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The Relationship between Nonprofit Organizations and Cloud Adoption Concerns

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This is to certify that the doctoral study by

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Walden University
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Abstract

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by

Dana Haywood

MS, Colorado Technical University, 2014

BS, Colorado Technical University, 2012

Doctoral Study Submitted in Partial Fulfillment

of the Requirements for the Degree of

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Abstract

Many leaders of nonprofit organizations (NPOs) in the United States do not have plans to adopt cloud computing. However, the factors accounting for their decisions is not known. This correlational study used the extended unified theory of acceptance and use of technology (UTAUT2) to examine whether performance expectancy, effort expectancy, social influence, facilitating conditions, hedonic motivation, price value, and habit can predict behavioral intention (BI) and use behavior (UB) of NPO information technology (IT) managers towards adopting cloud computing within the Phoenix metropolitan area of Arizona of the U.S. An existing UTAUT2 survey instrument was used with a sample of IT managers (N = 106) from NPOs. A multiple regression analysis confirmed a positive statistically significant relationship between predictors and the dependent variables of BI and UB. The first model significantly predicted BI, $F(7,99) = 54.239$, $p \leq .001$, $R^2 = .795$. Performance expectancy ($\beta = .295$, $p = .004$), social influence ($\beta = .148$, $p = .033$), facilitating conditions ($\beta = .246$, $p = .007$), and habit ($\beta = .245$, $p = .002$) were statistically significant predictors of BI at the .05 level. The second model significantly predicted UB, $F(3,103) = 37.845$, $p \leq .001$, $R^2 = .527$. Habit ($\beta = .430$, $p = .001$) was a statistically significant predictor for UB at a .05 level. Using the study results, NPO IT managers may be able to develop strategies to improve the adoption of cloud computing within their organization. The implication for positive social change is that, by using the study results, NPO leaders may be able to improve their IT infrastructure and services for those in need, while also reducing their organization’s carbon footprint through use of shared data centers for processing.

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Dedication

I want to dedicate this doctoral study to my friends and family. My family has put up with me despite several hardships for the duration of the process. My friends Kat Gray, Florri Faustino, and Janice Scott have shown different types of support over the years. Kat Gray has been a tremendous friend, and we have both evolved regarding our writing talents. Florri, my love, provided much moral support, which made it possible for me to do anything. Janice gave tremendous support as we exchanged horror stories of what we are facing with our studies.

Acknowledgments

I would like to acknowledge Dr. Jon McKeeby helped me steer my doctoral study from an incomplete prospectus to a completed study. Additionally, Dr. Steven Case helped me refine the project towards an IT problem with a defined scope that is simple and accomplishable within a timeline. Finally, I want to thank Dr. Miles who was critical of my writing and attitude in the different instances I had interactions with her. These three committee members gave me much guidance throughout the doctoral degree program; this study would not be possible without their assistance. Also, Dr. Karlyn Barilovits always provides motivational words at the residencies I attended, which helped me move forward with my study.

I would also like to thank the colleagues in my 8100 and 9000 classes for feedback, general information, and other items of importance. I was one of few quantitative students, yet my peer provided valuable insight that helped me in completing this project. Peers can often see things that other might not, which builds a stronger project. Finally, I want to thank the Walden Institutional Review Board for taking the time to answer my questions about issues that may pose ethical dilemmas. Their answers helped to ensure that I would be able to protect ethical and legal rights of my participants. There might have been lengthy delays without critical guidance from the IRB.

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Section 1: Foundation of the Study

Cloud computing may help organizations achieve cost-efficient enterprise architecture. Presently, cloud computing helps providers deliver services such as infrastructure, software, and platforms to the public in a cost-efficient manner; service providers can do by sharing underutilized resources with multiple clients (Tripathi & Jigeesh, 2013). Despite the cost efficiency of using cloud computing, Tripathi and Jigeesh expressed concerns about small and medium businesses not adopting cloud technology, which reasons range between cost issues and security concerns. However, the focus of this study will be for non-profit organizations (NPOs), which may have more budget concerns than for-profit businesses.

Background of the Problem

Use of cloud computing technology offers business and other organizations several advantages. Cloud computing is the latest iteration of distributed information technology (IT) systems; these systems allow companies to rent only the resources they need to meet task requirements, which reduces the cost of traditional infrastructure (Tripathi & Jigeesh, 2013). Additionally, cloud computing is ideal for lowering the organization’s carbon footprint by reducing the power requirements (Naserian, Ghoreyshi, Shafiei, Mousavi, & Khonsari, 2015). However, the adoption of cloud technology is lower globally than what analysts initially projected (Tripathi & Jigeesh, 2013). Additionally, Ward (2016) reported that 47.5% of NPO within the United States has no plans to adopt cloud computing but did not provide any quantitative or qualitative explanation for the lack of adoption. Therefore, it is instrumental to learn why NPOs are not adopting the technology.

The key issue regarding organizations' adoption of cloud computing technology lies not in the cost efficiency or integration of such technology, but in the total cost involved. For instance, many leaders of small and medium businesses (SMBs) claim that cost and integration issues have hindered their decision to switch from traditional computing to cloud computing (Tripathi & Jigeesh, 2013). NPOs have additional attributes that set them apart from their for-profits counterparts (Gartner, 2013). McDonald, Weerawardena, Madhavaram, and Sullivan-Mort (2015) noted that these organizations' funding attribute consists of grants and donations to help support mission-critical tasks. Walterbusch, Marten, and Tuetenberg (2013) uncovered hidden costs, which Gumbi and Mnkandla (2015) included that providers charge for the full hour for quantities of resources necessary despite actual time used. Based on my review of the literature, there is a lack of knowledge about NPO IT managers' perceptions of cloud computing and how such perceptions might affect adoption rates for this technology in NPOs. In the problem statement section, I focus on how these factors influence perceptions of cloud computing and how this technology relates to cost efficiency and integration.

Problem Statement

Schniederjans, Ozpolat, and Chen (2016) found that NPOs can increase IT collaboration efforts for the organization with cloud computing due to gains in both cost efficiency and integration. However, Islam and Rahaman (2016) reported that 36% of all organizations, including NPOs, globally have no plans to adopt cloud computing. The general IT problem is that NPOs are not fully using cloud computing to optimize cost efficiency and integration of components. The specific IT problem is that some IT managers of NPOs lack information on the relationship between the predictors of performance expectancy (PE), effort expectancy (EE), social influence (SI), facilitating conditions (FC), price value (PV), hedonic motivation (HM), and habit (H), and the dependent variables behavioral intention (BI) and use behavior (UB) regarding NPO's propensity to adopt cloud technology.

Purpose Statement

The purpose of this quantitative correlational study was to determine the relationship between predictors of performance expectancy (PE), effort expectancy (EE), social influence (SI), facilitating conditions (FC), price value (PV), hedonic motivation (HM), and habit (H), and the dependent variables behavioral intention (BI) and use behavior (UB) regarding NPOs' propensity to adopt cloud technology. The specific population was IT managers within NPO in the Phoenix metropolitan area of the U.S. state of Arizona. The predictors were (a) PE (b) EE, (c) SI, (d) FC, (e) PV, (f) HM, and (g) H. The dependent variables were (a) BI and (b) UB. An implication of my doctoral study for positive social change is that, by using my study findings, NPO leaders might be better able to optimize their IT services to benefit those in need of their humanitarian services as well as reduce their carbon footprint.

Nature of the Study

The methodology for the study was quantitative. Borrego, Douglas, and Amelink (2009) stated that researchers use quantitative methods because it allows for deductive reasoning (specifically, the ability to generalize findings from a larger sample to reflect a broader population). I determined that a quantitative method to be appropriate because my study required to generalize predictors for a broader population of Phoenix metro area in the U.S. state of Arizona. Using qualitative methods, researchers obtain rich data from interviews, documents, and other data sources, which, when analyzed, provide contextual information about the study phenomena (Leydens, Moskal, & Pavelich, 2004). A qualitative method was not appropriate because the contextual information would have been ineffective without first understanding what factors affected adoption of cloud computing in NPOs. Another option would have been to use mixed methods, in which a research investigation combines quantitative and qualitative methods (Kamalodeen & Jameson-Charles, 2016). I decided against using this method based on my earlier decision not to use the qualitative method.

The design of a study is imperative for obtaining the appropriate information. Correlation studies can help researchers to determine the association between a predictor and dependent variable (Mueller & Coon, 2013). I viewed a correlational design as appropriate because my study required understanding the relationship between perception of cloud computing technology and NPO IT managers adopting the technology.

Researchers use an experimental design to determine causation (Dulmer, 2016). I did not choose an experimental study (or quasi-experimental study by extension) design because my focus was not on determining causation. Mueller and Coon (2013) used descriptive statistics to find the amount of an independent variable within a dependent variable. I did not use descriptive statistics as the primary design because it does not produce a statistically significant relationship between predictors and dependent variables. For my study, I used a correlational design with a multivariate linear regression analysis.

Research Question

RQ1. What is the relationship between (a) PE (b) EE, (c) SI, (d) FC, (e) PV, (f) HM, (g) H, and (h) BI regarding NPOs' propensity to adopt cloud technology?

RQ2. What is the relationship between (a) FC, (b) H, (c) BI, and (d) UB regarding NPOs' propensity to adopt cloud technology?

Hypotheses

$H_0$1There is no relationship between (a) PE (b) EE, (c) SI, (d) FC, (e) PV, (f) HM, (g) H, and (h) BI regarding NPOs' propensity to adopt cloud technology.

H_a1There is a relationship between predictors of (a) PE (b) EE, (c) SI, (d) FC, (e) PV, (f) HM, (g) H, and (h) BI regarding of NPO's propensity to adopt cloud technology**.**

$H_0$2There is no relationship between (a)FC, (b) H, (c) BI and (d) UB regarding NPO's propensity to adopt cloud technology.

H_a2There is a relationship between predictors of (a) FC, (b) H, (c) BI, and (d) UB regarding NPO's propensity to adopt cloud technology**.**

Operational Definition

Cloud computing: A model of distributed computing that enables convenient and on-demand access to IT resources including computing applications over the Internet (Mell & Grance, 2011).

Non-profit organizations (NPO): An organization that does not distribute profits to the employee beyond salary (e.g. profit sharing; IRS, 2016).

Theoretical Framework

In 2003, Venkatesh, Morris, Davis, and Davis (2003) developed the unified theory of acceptance and use of technology (UTAUT). The goal of the theory was to integrate IT user acceptance models such as the theory of reasoned action (TRA), the theory of planned behavior (TPB), and technology acceptance model (TAM; Venkatesh et al., 2003). The purpose of the unification was to increase prediction ability in measuring how users adopt the technology. Additionally, Venkatesh, Thong, and Xu (2012) developed UTAUT2 as an extension in 2012 to include the consumer's perspective such as price value. I used UTAUT2 in this study because of my focus on cost efficiency, which required information about price value.

The focus of the model is how the key constructs of performance expectancy (PE), effort expectancy (EE), social influence (SI), facilitating condition (FC), hedonic motivation (HM), price value (PV), habit (H), and behavioral intention (BI) contribute to individuals' perceived use of technology (Venkatesh et al., 2012). Additionally, Venkatesh et al. (2012) provided the moderators of age, gender, and experience to help explain factors that might influence how the constructs might influence an individual.

The model shown in Figure 1 shows the constructs and relationships that I analyzed in this study. While PE, EE, SI, FC, HM, PV, and H interact with the dependent variable BI, the predictors FC, H, and BI interact with the dependent variable UB. Therefore, I conducted two multiple regression analyses to examine the relationship with BI and UB separately.

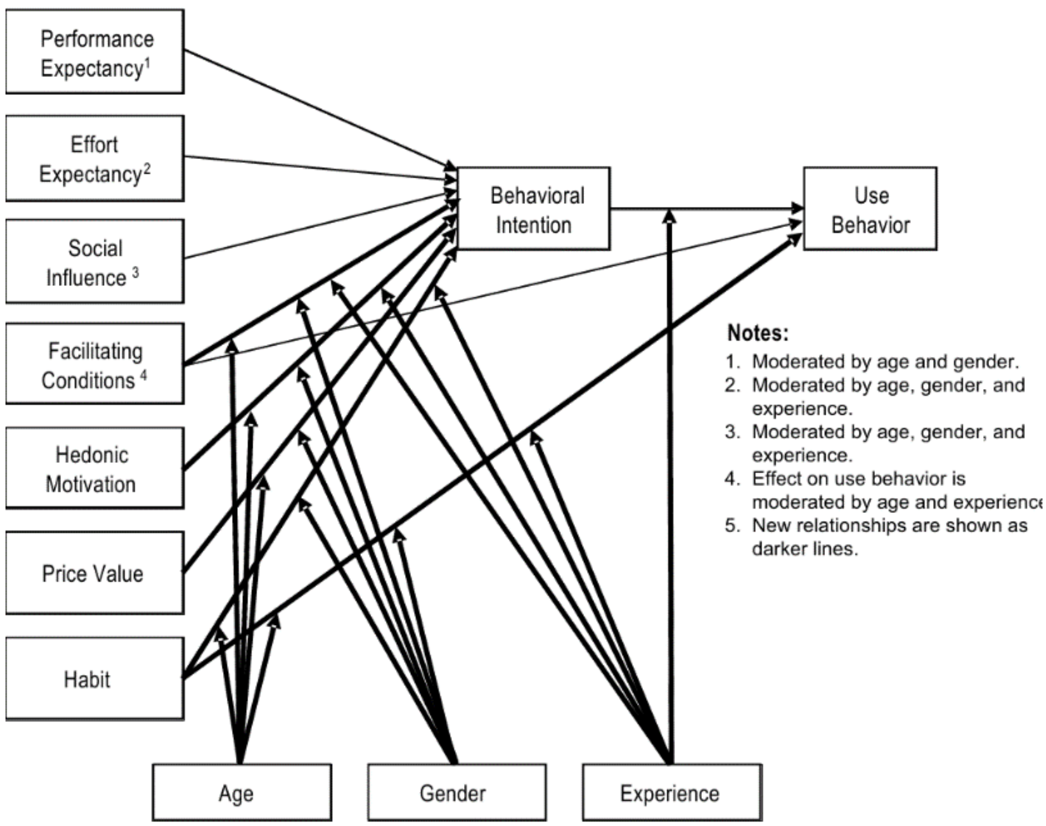

Figure 1. Conceptual model of UTAUT2. Reprinted from "Consumer Acceptance And Use Of Information Technology: Extending The Unified Theory Of Acceptance And Use Of Technology" by V. Venkatesh, J.L. Thong, and X. Xu. 2012, *MIS Quarterly, 36,* p. 160. Copyright 2012 Regents of the University of Minnesota. Reprinted with permission (Appendix C).

Both regressions included moderators to infer how a predictor might affect the dependent variable based on descriptive statistics. Venkatesh et al. (2012) included age, gender, and experience in the UTUAT2 model for demographic purposes. For example, Venkatesh et al. (2012) used gender statistics of PE to infer males have a high preference to improvement to job performance. I applied these constructs and moderators to the UTAUT2 survey I administered to help answer the research questions and test the hypotheses.

UTAUT2 was applicable because it combined known acceptance models, which applied to recent technological innovation. Venkatesh et al. (2012) described PV as how much value a technology provides to the consumer. However, NPOs are experiencing a lack of funding due to economic conditions, which affects technological purchases that might not show an immediate price value (Crump & Peter, 2013). Therefore, experts have advised that NPO leaders adopt technology that reduces operational expenses (Crump & Peter, 2013). Venkatesh et al. (2012) provided constructs, which can be used to explore the different dimensions of technology acceptance. Therefore, UTAUT2 provided me with enough measurable constructs to determine the relationships between my study variables.

Assumptions, Limitations, and Delimitations

This subsection includes a discussion of the assumptions, limitations, and delimitations for my study, I used these factors to create the foundation for the study to successfully collect and analyze data. Additionally, quantitative correlational design and the population also factored into assumptions and limitations. Finally, the delimitations set the boundaries based on the assumptions and limitations.

Assumptions

I made assumptions based on the requirements for the study. Haegele and Hodge (2015) focused on quantitative assumptions, which are statements that researchers believe to be true without affirmations. The first quantitative assumption is that hard reality exists and scholar-practitioners are required to discover the nature of that reality (Haegele and Hodge, 2015). To address this assumption, I removed myself from the subject of study to create an unbiased method of analyzing the predictors and dependent variables. Additionally, facts are distinctly different from values, which means that the researcher should avoid bias with fact finding rather than what they believe is true (Haegele & Hodge, 2015). Finally, this mindset encourages an appropriate research design that can lead to accurate statements, which may explain relationships between the different facts (Haegele & Hodge, 2015). Therefore, I designed the assumptions to facilitate fact finding rather than basing it on my values or previous knowledge.

The first assumption was that all NPOs have at least one IT manager, which will be the target participant. Additionally, I assumed that all invited participants will answer the survey honestly and that the data from the sample represented the population, which helped build an understanding amongst NPO. Furthermore, I assumed that each participant had at least the minimal knowledge of cloud computing and could answer key questions that related to non-profits propensity to adopt cloud computing. Finally, I assumed that using the quantitative approach would deliver enough raw data to use in developing future studies of cloud computing integration in NPOs.

Limitations

Despite the assumptions, limitations exist within the field. Denscombe (2013) described limitation as potential issues that may occur that defy assumptions. The limitations helped me remain open and honest about the data and findings.

I based the first limitation on the quantitative method. First, A quantitative method only provides empirical data rather than contextual information (Quick & Hall, 2015). Additionally, participants could not explain why they chose the Likert rating in the UTUAT2 survey. While UTAUT2 contain moderators to explain the different constructs (Venkatesh et al., 2012), there is a lack of contextual information and causal information about adoption issues within NPO. Therefore, I considered this limitation in building a case for future study to expand on the data.

I based the second limitation on correlational designs. First, correlational studies can only establish a relationship between variables, but cannot establish causation (Rogerson P. A., 2001). Additionally, this lack of causation does affect the external validity, which researchers use to generalise finding for a broader population (Fincannon, Keebler, & Jentsch, 2014). Therefore, I addressed external validity and statistical conclusion validity in the validity subsection of Section 2.

Delimitations

I developed the scope for collecting data. Delimitations are statements regarding the boundaries with inclusion and exclusion of the study (Denscombe, 2013). First, all participants had to be English speaking IT managers with at least a minimal knowledge of cloud computing. Health and Human Services (2009) prohibit the exploitation of non-English speaking minorities with an English language survey. Therefore, I excluded any NPOs that had a probability of non-English speaking IT managers, while also making this factor clear in the informed consent.

All non-profits need to comply by IRS 501(c) designation. The IRS (2016) defined non-profits as organizations that do not participate in profit sharing, which Kraft and Lang (2013) stated as employee bonuses that for-profit organizations issue. Therefore, I excluded all for-profit organizations.

I limited the population to the geographic location of Phoenix metropolitan of the U.S. state of Arizona. This scope also limits the sample to the confined area. Finally, this population sets the confined area to conduct a future study.

Significance of the Study

This subsection provides information on the contribution to IT practice as well as positive social change. I used this subsection describe the significance of the study, which I add knowledge for NPO IT managers. The positive social change expands on the last line of the purpose statement.

Contribution to Information Technology Practice

I focused on NPO IT managers optimizing their IT infrastructure. For instance, Lee, Jeong, and Jang (2014) stated that cloud computing increases IT efficiency by utilizing only the required resources for the specific period, which differs from continuously operating a server with limited function. Lee et al. stated the result was that organization would not have to provide support for underutilized servers. However, IT would have to address different adoption issues such as cost efficiency and integration.

NPO IT managers might require a different strategy than used to adopt conventional IT infrastructure technology. For example, Standardized virtual desktops can alleviate deviations for mission-critical tasks, but there is difficulty distributing the instances without a high-performance network (Zhang et al., 2016). Additionally, a distributed cloud can provide the high-performance network (Thackston & Fortenberry, 2015), but there are concerns on integrating the network into an organization (Tripathi & Jigeesh, 2013). However, the strategies noted in the article by Tripathi and Jigeesh (2013) apply to SMB. Therefore, NPO IT managers might create strategies to compensate for factors that affect adoption of cloud computing, which I used a multiple linear regression established the statistically significant factors from UTAUT2.

Implications for Social Change

The implication for positive social change is that increasing IT efficiency through cloud adoption may allow NPOs to increase the benefit towards those in needs whom they serve. For example, an NPO that relies on donations and grants may not have adequate resources to sustain an IT facility to sustain expanded operations, which would reduce the contribution to society whether it is a pet rescue, homeless shelter, aid to persons with disabilities, or legal aid. Therefore, the optimization of NPO’s IT infrastructure is essential to providing services to those in need.

Additionally, an NPO IT department may the reduce carbon footprint and paper usage by mitigating the challenging factors of adopting cloud computing. For instance, cloud providers consolidate services to serve multiple tenants, which reduces the overall consumption of energy by the consumer from coal power plants (Lee et al., 2014). Therefore, NPO can create an environmentally conscious group by lowering the carbon footprint.

A Review of the Professional and Academic Literature

The literature review includes in-depth information related to my central research topic along with a critical analysis and synthesis of journal articles concerning both cloud computing and UTAUT2. Additionally, I provide an overview of cloud computing, consider arguments about the cost efficiency and integration of cloud computing, and discuss how the theoretical framework of UTAUT2 ties the items together. While the constructs of UTAUT2 served as predictors and dependent variables in my study, the application subsection of Section 3 includes cost efficiency and integration, which makes the terms important to discuss these terms in this review. Discussion of the constructs within the framework subsection this review ties into the instrumentation subsection of Section 2.

The purpose of this quantitative correlational study was to determine the relationship between predictors of performance expectancy (PE), effort expectancy (EE), social influence (SI), facilitating conditions (FC), price value (PV), hedonic motivation (HM), and habit (H), and the dependent variables behavioral intention (BI) and use behavior (UB) in relation to NPOs' propensity to adopt cloud technology. The focal point of the literature review was the research questions:

RQ1. What is the relationship between (a) PE (b) EE, (c) SI, (d) FC, (e) PV, (f) HM, (g) H, and (h) BI regarding NPOs' propensity to adopt cloud technology?

RQ2. What is the relationship between (a) FC, (b) H, (c) BI, and (d) UB regarding NPOs' propensity to adopt cloud technology?

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

$H_0$1There is no relationship between (a) PE (b) EE, (c) SI, (d) FC, (e) PV, (f) HM, (g) H, and (h) BI regarding NPOs' propensity to adopt cloud technology.

H_a1There is a relationship between predictors of (a) PE (b) EE, (c) SI, (d) FC, (e) PV, (f) HM, (g) H, and (h) BI regarding NPOs' propensity to adopt cloud technology**.**

$H_0$2There is no relationship between (a)FC, (b) H, (c) BI and (d) UB regarding NPOs' propensity to adopt cloud technology.

H_a2There is a relationship between predictors of (a) FC, (b) H, (c) BI, and (d) UB regarding NPOs' propensity to adopt cloud technology**.**

This literature review consists of 108 articles and journals, which I found using databases such as Business Source Complete, CINAHL Plus, Expanded Academic ASAP, ScienceDirect, Social Sciences Citation Index, and SociNDEX. I primarily used Walden University Library's Thoreau search engine to access the various databases. I verified the peer review status of journal articles by using Ulrich's Global Serials Directory and analyzing the journal websites; 98 (91%) of articles were peer-reviewed. Finally, the number of articles published within 5 years of my anticipated graduation date was 99 (92%).

When searching the databases, I used 2013 and 2016 as the year range to maintain the 5-year time span required for the literature review. However, the strategy did not include any acceptance theories published before 2013. Finally, I used Google Scholar and ProQuest to locate additional content related to NPOs and items in the primary search.

I focused the literature review on four key areas: (a) NPOs and the lack of adoption of online technology, (b) the impact of cloud computing on NPO, (c) the cost-efficiency of cloud computing (d) the integration of cloud computing, and (e) the application of UTAUT2 to cloud computing. My research on cloud computing centered on the history, uses, NPO issues with using cloud computing, and arguments concerning cost-effectiveness and integration. In composing the subsection on the UTAUT2 framework, I focused on how the variables of performance expectancy, effort expectancy, social influence, facilitating conditions, hedonic motivation, price value, and habit towards behavior intention and use behavior of technology led to the application of cloud computing.

Nonprofit Organizations and Online Technologies

NPOs are different from businesses that run for a profit. The Internal Revenue Service (IRS; 2016) described NPO as an organization that does not distribute profits to its members beyond salary or participates for an individual's private interest. For example, Butler (2015) presented Hope Through Grace, Incorporated as a 501(c)(3) organization that works to increase awareness of colorectal cancer and create opportunities for screenings, which applies any profits towards this effort. Additionally, Levy (2009) described higher education facilities across the United States as falling under the categorization of nonprofit because these organizations use tuition and fees for the main source of supporting educational operations. Levy (2009) also included religion-based higher education, which fits the IRS categorization criteria for 501(c)(3). As McDonald et al. (2015) noted, NPOs encompasses different types of organizations, including humanities, environmental, economic development, health, education, safety, health, education, spiritual, and social justice. The charity organizations using the commonly used 501(c)(3) designation offer a wide range of services (IRS, 2016). Table 1 displays a few of the 501(c) organizations of varying sizes that are described in the IRS tax code.

Table 1

Different Types of NPOs

Code	Type of Organization
501(c)(2)	Title-Holding Corporations for Single Parent Corporations
501(c)(4)	Civic Leagues and Social Welfare Organizations
501(c)(5)	Labor, Agricultural, and Horticultural
501(c)(6)	Business leagues, etc.
501(c)(7)	Social And Recreational Clubs
501(c)(12)	Local Benevolent Life Insurance Associations, Mutual Irrigation and Telephone Companies, and Like Organizations.
501(c)(13)	Cemetary companies
501(c)(14)	Credit Unions and Other Mutual Financial Organization
501(c)(19)	Veterans Organization
501(c)(20)	Group Legal Services Plan Organizations

Note: *(IRS, 2016)*

Many organizations are not applying cost-effective technology despite lower financial support according to researchers. Crump and Peter (2013) stated that grants might sustain these organizations, but noted that the grants are dependent on the economic conditions of the country that hosts the NPO. Crump and Peter also established that economic conditions were poor, which leads to fewer grants available. Additionally, McDonald et al. (2015) noted that competition for donation has increased as the number of NPOs has grown in the United States, which means that NPOs need to be successful with their services despite decreasing funds. Furthermore, Arthur and Rensleigh (2015) stated that small churches often lacked engagement in online technologies. Crump and Peter (2013) also observed the lack of engagement toward shared services with other NPOs in comparison to for-profit organizations. In the context of absent funding, NPOs should invest in technology to lower back-office expenses, but the evidence shows the lack of adoption.

The absence of knowledge might also contribute to not effectively employing technology. First, Arthur and Rensleigh (2015) stated the results of their quantitative study found that their sample of small churches does not utilize online technologies effectively. Additionally, Alfaro and Watson-Manheim (2015) reported that social media jobs are highly influential within marketing any organization, but the highest concentrations came from the service industry, manufacturing, and retail trade rather than NPO. Therefore, some NPOs are not utilizing online technology effectively.

The lack of adoption and effective use does not mean the lack of availability of technology that might benefit NPO. First, Paul, Karn, Chatterjee, and Poovammal (2014) suggested technologies for nonprofits such as MySQL, which increases functionality and has a lower online. Additionally, Pichardo et al. (2016) experimented with creating an online mobile application for a local food pantry to increase functionality between event planners and volunteers, which used PHP, Java, MySQL, and JSON. Finally, Bhatkal, Jajodia, Bhandari, and Sankhe (2014) stated that PHP and MySQL could work efficiently as web-based content management systems with NPOs. Despite the availability of low-cost online technology for NPOs, there is a hesitancy for NPOs to use technology, which leads to other causes.

The success or failure of implementing online technology might impede the adoption within NPOs. First, Lee, Li, Shin, and Kwon (2016) found that organizations base their decisions to adopt the technology on the success within another organization. Although there is justification for adopting online technology such as cloud computing, significant issues that lead to unsuccessful implementation for the organization will dissuade other groups from engaging in technology. Additionally, success is an important metric because Raman (2015) stated that NPOs need to optimize its financial status by not wasting spending on excessive infrastructure. Furthermore, Ohmann et al. (2015) reported problems such as lack of asset control, industry volatility, security issues, suitability issues, and uncertainties of legal jurisdiction have led to the unsuccessful adoption of cloud technology in NPOs. Therefore, cloud computing requires a further exploration of literature for the review.

Cloud Computing

The understanding of cloud computing is important before applying it towards NPO. Cloud computing is the latest iteration of a computing paradigm where providers consolidate and share resources with tenants that rent the services (Ai et al., 2016). Also, providers reduce the overall cost to the tenant by providing infrastructure requirements at a fraction of the cost of building the infrastructure within their organization (Tripathi & Jigeesh, 2013). Futhermore, Mell and Grance (2011) defined cloud computing as a model that enables convenient and on-demand access to shared computer resources over the Internet, which Batista et al. (2015) confirmed the method allows the renting of infrastructure as `pay for what you use` model. Therefore, this paradigm could allow a NPOs without facilities or large capital to utilize enterprise level architecture.

Cloud computing is not a single service for all organizations. Yuvaraj (2015) described diverse deployment models that include public, private, community, and hybrid models. First, The service provider runs public clouds to sell resources on a pay-per-use model to the general public (Garrison, Wakefield, & Kim, 2015), while a private cloud stays behind a company firewall to constrain resources for internal users (Brueque Camara, Moyano Fuentes, & Maqueira Marin, 2015). Additionally, a community with common objectives own, share, and support community cloud systems, while a hybrid cloud combines the benefits of both private and public cloud deployment (Yuvaraj, 2015). Finally, Shin (2015) explained organization should analyze different deployment models to address the challenges that cloud computing presents. Therefore, the application of the deployment model will make a difference based on the type of organization.

The different deployment models also provide different types of services, which Batista et al. (2015) included infrastructure as a service (IaaS), software as a service (SaaS), and platform as a service (PaaS). Additionally, Mell and Grance (2011) described the concepts as services available to the consumer through the Internet, which includes any conceivable application such as disaster recovery as a service. However, the difference between the models may make a difference in the application of the UTAUT2 constructs, which are discussed later in this literature review. Therefore, the understanding of the services and impact on NPOs is critical for this review.

IaaS. Infrastructure as a Service is a baseline service that provides support for an organization. Mell and Grance (2011) described IaaS as a delivery of basic resources that consumers need for IT functionality. Additionally, Garrison, Wakefield, and Kim (2015) stated that IaaS providers supply servers, networking equipment, operating systems, and storage via an Internet connection to businesses that require IT operations. Furthermore, the on-demand service reduces the need for organizations to purchase and maintain such equipment (Garrison et al., 2015). Finally, Akar and Mardiyan (2016) did a study in Turkey and noted that 61.4% of respondents prefer to use IaaS. Therefore, this factor shows that IaaS is potentially increasing viability for organizations based on the analysis of the study.

SaaS. Software as a Service provides tools for consumers that they need to operate the business. Mell and Grance (2011) stated SaaS delivers a provider's application through a client application. First, Goutas, Sutanto, and Aldarbesti (2016) stated that SaaS relieves providers from low-level IT tasks in setting up the infrastructure to deploy the applications. Additionally, Raja and Raja (2013) noted that the optimization and minimization of costs occur because multiple deliveries of the software can function from the same hardware. While there may be a difference based on providers, SaaS focuses on an optimized delivery of software from the provider to the client (Tripathi & Jigeesh, 2013). Therefore, SaaS can deliver unique tools that organizations need to operate.

PaaS. The platform as a service (PaaS) model takes a different route than SaaS. Mell and Grance (2011) described PaaS as a platform for the tenant to develop and deploy applications. Additionally, Shorfuzzaman, Alelaiwi, Masud, Hassan, and Hossain (2015) used the Virtual Computing Laboratory (VCL) where students use MatLab and Autodesk to develop and deploy applications. Therefore, PaaS provides an opportunity to deliver platforms that were previously difficult to create individually.

Application to nonprofits. As discussed earlier, NPO needs to save money. Raman (2015) stated that IaaS, SaaS, and PaaS could decrease spending on infrastructure and more on social change expenses. However, Ward (2016) noted that 47.5% of all NPO in the United States are not adopting any of the models, which requires an explanation due to how cloud computing may decrease their costs. For instance, Lee, Li et al. (2016) provided the goal contagion theory to suggest technology adoption based on success or failure of integration into another organization. Therefore, the theory could extend to NPO not adopting cloud computing based on the failure of another NPO's integration of cloud technology.

Functional elements of cloud computing. While there are deployment models and XaaS configuration, the examination of functional elements of cloud computing help establishes the relationship between tenant and provider. Zota and Petre (2014) examined the NIST reference model, which include the terms of cloud consumer, cloud provider, cloud auditor, cloud broker, and cloud carrier. Additionally, the consumer and the provider establish a relationship with terms and agreements on different levels (Zota & Petre, 2014), which Walterbusch et al. (2013) stated the importance of the relationship for determining the total cost of ownership (TCO) of adopting cloud technology. Finally, the relationship can also assist in understanding how NPOs may engage with providers, which ties into understanding adoption issues in the context of the theoretical framework.

Cloud consumer. Cloud consumer is an integral part of the relationship with cloud computing providers. Zota and Petre (2014) consumers described as users that consume the services. Additionally, J.H. Chen et al. (2015) expanded this definition by stating the consumer negotiates for services with the provider. Therefore, NPOs as consumers can negotiate with the provider for specific needs regarding IaaS, PaaS, and SaaS.

Although the consumer is an integral part of the negotiation, Ohmann et al. (2015) noted that NPOs are at a disadvantage with a volatile industry. Cloud providers may cease operations without the ability to transfer data to another provider (Ohmann et al., 2015). Additionally, Tripathi and Jigeesh (2013) highlighted this issue as vendor lock-in, which prevents the interchange of information between two providers. Finally, NPOs have an ethical responsibility for handling data, which has caused organizations not to trust remote services (Ohmann et al., 2015). Therefore, the NPOs are at a disadvantage using cloud computing vs. traditional IT infrastructures regarding data ownership.

NPOs also face a lack of understanding legal jurisdiction with cloud computing. Ohmann et al. (2015) reported that cloud providers might host data globally, which creates issues in applying a specific legal framework for arbitration. Additionally, Mosweu, Bwalya, and Mutshewa (2016) indicated that ISO 15489 standardize the need for an appropriate legal framework for managing organizational records. Despite Ward (2016) stating that laws such as health insurance portability and accountability act (HIPAA) are important to some NPOs, Ohmann et al. (2015) stated that enforcing those laws is difficult when data is offshore. Therefore, the evidence presents a risk exists for NPOs that have data protected by different laws.

The legal issues also included the lack of accountability for providers. Ohmann et al. (2015) stated that consumer's evaluation of legal compliance was difficult due to the lack of disclosure of cloud arrangements. In addition to HIPAA, Bendovschi and Ionescu (2015) noted that Sarbanes-Oxley (SOX) act of 2002 required a financial snapshot of IT systems, which the current lack of disclosure of cloud providers makes that snapshot difficult. Therefore, the legal ramifications from the lack of disclosure for the consumer can lead to penalties under these laws.

Cloud provider. The understanding of the consumer relationship requires a review of the cloud provider. Zota and Petre (2014) described cloud provider as the source of cloud services for consumers to utilize. Additionally, Suneel and Guruprasad (2016) suggested the comparison of cloud computing with utilities, which the water company negotiate a fee with consumers for usage and delivery to the home. Similarly, Yuvaraj (2015) described cloud computing as a customer paying a subscription fee to have services delivered for as long as the customer needs it. Finally, the benefit is that consumers avoid wasting investment on infrastructure after any project (Suneel & Guruprasad, 2016). Therefore, a cloud provider can provide an advantage to its clients.

Despite the advantage provided, there are issues with the providers. First, Ohmann et al. (2015) reported that cloud providers are the target of cyber attacks despite the investment in security. Additionally, Ring (2015) reported that 70% of 2000 organizations spent less than 10% of the budgets towards cloud services due to security risks. Furthermore, clients that handle sensitive government data require security against cyber attacks (Liotine, Howe, & Ibrahim, 2013). Therefore, these security issues present a challenge with consumers that need data assurance.

Data assurance within cloud computing is more difficult than conventional IT infrastructure due to the limitation of access. Ohmann et al. (2015) mentioned that the provider manages the data invisibly, which takes the control away from the consumer. In addition to cyber attacks and inability to confirm legal compliance, these items generate an issue with NPOs that are trying to comply with regulations such as HIPAA and SOX (Bendovschi & Ionescu, 2015; Ohmann et al., 2015). Therefore, there are complications towards NPO adopting cloud computing.

Cloud auditor and broker. Cloud auditor and broker are constructs that exist between consumers and providers. First, Zota and Petre (2014) stated that the auditor serves as the provider's quality assurance function that assesses and maintain the cloud performance, which Batista et al. (2015) established the quality measures such as quality of service (QoS) and service level agreements (SLA) as focal points. Also, the auditor's role is to ensure that the goals are optimal and mutually beneficial for both parties (Chen, J.H. et al., 2015). Therefore, the auditor serves to control expectations between the consumer and the providers.

The cloud broker serves as an entity to deliver the expectations to the consumer. Zota and Petre (2014) described brokers managing the usage, performance, and provisioning of services. Furthermore, the cloud broker is instrumental in the integration of cloud services into the consumer's network (Zota & Petre, 2014). Additionally, Mohaupt and Hilbert (2013) described the hampering of integration cloud computing with legacy systems. Therefore, cloud broker needs to ensure that the actual connectivity occurs with the systems.

However, the cloud auditor does not always succeed in delivering to the consumer. Ohmann et al. (2015) highlighted a problem with cloud provisioning costs that might exceed the cost of delivery of data. Additionally, Crump and Peter (2013) expressed that IT provisioning of services should include a wide array of services, while Kuada and Hinson (2015) highlighted the importance of provisioning remaining flexible. Therefore, the lack of provision flexibility can hinder the cloud provider's ability to maintain an effective quality of services.

Cloud carrier. The cloud carrier serves as a physical connection between cloud consumers and providers, which Zota & Petre (2014) described as a transmission medium such as the Internet. Additionally, Lo, Yang, and Guo (2015) highlighted the advantage of cloud computing only requiring a high-speed Internet connection with basic equipment for functionality, which Tripathi and Jigeesh (2013) noted the same transmission lines could exist for other Internet functionality in a company. Despite cloud computing using the Internet, the previous section that demonstrated how some NPOs do not use online technology effectively presents an issue. Therefore, factors cloud computing as an online technology require exploration.

Arguments on cost efficiency. The first exploratory concept for the study is cost efficiency with NPOs. Puri and Yadav (2016) defined cost efficiency as the ratio between the minimum observed cost and the actual observed cost. Additionally, cost efficiency can include a company's projected TCO and the actual TCO (Walterbusch et al., 2013), which Crump and Peter (2013) stated that an NPO requires cost efficiency due to lack of funding for IT services. Therefore, the cost efficiency of cloud computing required investigation, which includes how it affects NPOs.

Dispelling the hype of cloud computing. There is a need to separate what marketers promote and what exists. Walterbusch et al. (2013) explained that marketers tend to promote cost efficiency with the ‘pay for what you use’ model and the reduction of servers required by an organization. Furthermore, the reduction of serves requires fewer staff members for maintenance, which attracts SMBs wanting enterprise level of IT support (Tripathi & Jigeesh, 2013). While Yuvaraj (2015) stated the requirement of training for cloud computing, Tripathi and Jigeesh (2013) suggested that less IT staff means fewer expenses for training than traditional infrastructure. Furthermore, Van Dyk and Fourie (2015) explained that NPOs seek fewer expenses due lack of adequate funding. Therefore, the challenge presents an opportunity for cloud computing adoption due to cost efficiency.

However, there are caveats for these promising statements. Walterbusch et al. (2013) studied the TCO for using Amazon Web Service (AWS), which the authors uncovered indirect or hidden costs from service providers that extend the bill further than anticipated. Additionally, Gumbi and Mnkandla (2015) stated that cloud providers charge by the hour regardless if the company does not use the full hour, which also includes a charge for the quantities of resources to complete the task. While the statement on quantity does adhere to `pay what you use,' the charge by the hour does not. Due to the funding challenges that Crump and Peter (2013), McDonald et al. (2015), and Van Dyk and Fourie (2015) had warned about in context for NPO, the contradiction of ‘pay what you use' and charge by the hour could make it cost inefficient for NPO usage. Therefore, the review requires an investigation beyond the hype.

Elasticity. One main topic found in previous sections is the need for flexibility with NPO. Ai et al. (2016) described elasticity as a function that will increase or decrease the number of resources based on demand. Additionally, Coutinho, Rego, Gomes, and De Souza (2016) stated elasticity would increase the number of server instances during the period of traffic increase, which Ai et al. (2016) explained the method helps maintain cost efficiency by reducing the cost to only what the consumer uses. Furthermore, Carcary, Doherty, Conway, and McLaughlin (2014) highlighted this factor is a major adoption issue because elasticity creates an on-demand computing power that different level of organizations require. Finally, Pichardo et al. (2016) used online resources to support their NPO mobile application, which required networking support to handle requests. Therefore, the flexibility of elasticity provides the necessary cost-efficient computing ability to meet the demands of organizations.

Another theme related to flexibility is doing more with less funding. Abouelhoda, Issa, and Ghanem (2013) highlighted that that cloud computing elasticity makes large workflows affordable by dynamically increasing and decreasing virtual machines. Additionally, Thackston and Fortenberry (2015) extended the concept of large workflows by demonstrating how cloud computing can lower the cost of performing extensive chemical calculations by reducing the number of hours or equipment required. Furthermore, Van Dyk and Fourie (2015) expressed that NPO faces a challenge with long-term budget concerns, which is similar to Thackston and Fortenberry (2015) concerns before moving towards the cloud. Finally, the goal for elasticity is to analyze the amount of work required by the task, which the system assigns resources to complete it in an optimized time frame (Abouelhoda et al., 2013). Therefore, the authors presented examples of having less financial resources and utilizing cloud computing to maximize the cost efficiency.

However, the model is not perfect. Abouelhoda et al. (2013) reported that overheads exist with dynamically changing the quantities of available resources. Additionally, Coutinho et al. (2016) highlight that the lack of standardization with elasticity tools at cloud providers make it difficult to make the appropriate calculation for resource management. Therefore, this lack of appropriate calculation can cause provisioning issues, which makes it difficult for NPOs to control costs.

Performance and availability. The flexibility is useless if it is not available or unable to perform. For example, Thackston and Fortenberry (2015) noted that a high-performance server blade cost more than $5,000, while older machines cannot handle the processing required for chemical calculations. Additionally, Brueque Camara et al. (2015) highlighted that cloud computing could significantly increase the performance of the supply chain within an industry and reduce the costs. Furthermore, Muelder, Zhu, Chen, W., and Ma (2016) stated that this option is due to the service-oriented approach that can add or subtract servers dynamically to handle the workload, which Thackston and Fortenberry (2015) concluded can reach high-performance quality without excessive spending on equipment. After Crump and Peter (2013) and McDonald et al. (2015) demonstrated that funding for NPO could be short due to lack of grants and increase of donation competition, the cost optimization that cloud computing presents is a desirable approach for doing more operations with less funding.

However, there is a likelihood that performance can be impaired. For example, Xiwei, Liang, and Yanping (2016) noted a significant performance decrease could occur due to random resource failure. Additionally, Muelder et al. (2016) presented a 24-hour analysis of cloud utilization that included a gap in the middle of the chart, which can include an inappropriate maintenance affecting overall performance issues. Therefore, the lack of resources available due to failure limits the elasticity function, which lowers the cost-efficient appeal of cloud computing.

Failing systems can cost an organization attempting to complete a task. Change, Tsai, Chen, C.Y., and Tsai (2015) stated automatic migration from a failed node to a new virtual machine is necessary for high availability of services. Additionally, Lango (2014) highlighted that the transition from failed nodes to another active VM with all the data could improve the SLA between the consumer and provider. Furthermore, this factor can translate in not restarting the process, which reduces the number of resources required to finish the job (Lango, 2014). However, the quantification of resources and per-hour rates increases the service charges (Gumbi & Mnkandla, 2015). Therefore, ensuring the performance and availability of resources is essential for optimizing the cost-efficiency of cloud computing for NPOs.

However, availability is not always a guarantee. For example, Somani, Gaur, Sanghi, and Conti (2016) reported a large number of distributed denial of service (DDoS) attacks against major service providers, which caused an average of $444,000 of damage.

Additionally, Batista et al. (2015) noted that business needs to maintain confidence by ensuring availability, which includes geo-distributions to ensure global availability. However, there are mobile applications that might depend on the consistent availability of services (Pichardo et al., 2016). Therefore, an entire data center becoming unavailable due to an attack lowers the cost-efficient appeal.

Energy efficiency. Data centers require power for continual service. Whitney and Delforge (2014) estimated that energy consumption for data centers would reach an aggregate total of 140 billion kilowatt-hours by 2020 or $13 billion per year. Additionally, Naserian et al. (2015) highlighted that energy costs are the largest portion of cloud computing expenses, which providers share the resources with clients to reduce the overall cost of the subscription. Furthermore, this process makes an essential difference to reduce the cost of electricity within an organization, which can allow it to reallocate funds to expand its operations (Stamas, Kaarst-Brown, & Bernard, 2014). Therefore, the burden of energy costs can either limit operational performance or the organization ability to deliver to the community.

Some of the energy costs may be avoidable. For example, Whitney and Delforge (2014) noted that data centers are not using power management to cycle unused servers down, which create an energy inefficiency. Additionally, Horri, Mozafari, and Dastghaibyfard (2014) confirmed that cloud computing data centers need to lower power consumption to meet green computing standards. Finally, Liu, Li, and Yang (2015) added that cloud computing providers that support multimedia need to find a balance between performance and energy cost. Therefore, cloud computing providers need to perform energy optimization to improve its expenses to deliver cost efficiency.

Arguments on integration. Systems are useless unless the public can use it. Yin, Lu, Pu, Wu, and H.W. Chen (2015) stated that cloud providers need to design services to enable consumer integration into existing IT infrastructure. Furthermore, this factor allows organizations to supplement its current IT infrastructure with gaps that it is not serving (Tripathi & Jigeesh, 2013). However, there are obstacles to examine regarding integration of cloud computing that might impede adoption (Garrison et al., 2015). Therefore, integration requires exploration as it may affect the perception for non-profit IT managers.

Standardization. Standardization has a role in how the cloud functions. S. Chen (2016), as well as Tripathi and Jigeesh (2013), stressed that open standards ensure the interoperability of components across the Internet. Additionally, Mell and Grance (2011) attempted to standardize concepts of cloud computing, and Zota and Petre (2014) noted the NIST does have a standardized reference model for relationships in the cloud computing concept. However, Tripathi and Jigeesh (2013) stated that providers and developers have not fully realized standardization within cloud computing. Therefore, the lack of standardization may hinder the benefits of cloud computing.

The function of standardization in any technology is to create a simple interface. S. Chen (2016) defined standardization as two or more items communicating without special adaptation or effort. However, Tripathi and Jigeesh (2013) stated a problem with vendor lock-in, which they describe as the inability to communicate information from one provider to another. Additionally, Li et al. (2013) highlighted this issue by remarking that companies that use one community cloud service vendors will have difficulty transferring information to a new provider. Therefore, the lack of open standardization in cloud computing complicates the usage of the services.

The lack of standardization can lead to a lack of adoption. Walterbusch et al. (2013) include vendor lock-in as a potential risk for adoption that may affect the TCO for an organization. While TCO may measure cost related functions, integration does have a relationship with cost (Walterbusch et al., 2013). Additionally, TCO accounts for all factors that go into making the finished product, which includes effort during integration (Visani, Barbieri, Di Lascio, Raffoni, & Vigo, 2016). Therefore, the effort aspect of TCO reflects on the integration concepts as well as the standardization of component.

However, standardization is not limited to a single system. Li et al. (2013) attribute lack of standardization to application program interface (API) of different cloud providers. Additionally, Tripathi and Jigeesh (2013) stated that each cloud provider uses a different API, which makes it difficult to port or manage information from one provider to another. Therefore, the different API is creating a conflict with standardization, which makes communication between two cloud providers difficult.

The lack of standardization presents an issue for NPO attempting to adopt cloud computing. Ohmann et al. (2015) included that there is always a possibility of vendor closure. However, the lack of standardization prevents NPO from migrating data from one provider to another (Ohmann et al., 2015). Additionally, Liotine et al. (2013) presented a different viewpoint where organizations that handle crisis management requires integration of different cloud tools. Therefore, standardization is necessary because of the need to transfer information to different systems.

Different paradigm. Different technology represents different challenges with integration. Yin et al. (2015) stated that integrating cloud and enterprise level applications is amongst those challenges. Additionally, Yin et al. (2015) stated that there are assumptions about traditional computing environments that do not apply to cloud computing. Furthermore, Raja and Raja (2013) stated that porting a local database, software librations, and configuration presents a challenge with integration, which requires rigorous testing to ensure replication between cloud and local systems. Therefore, the different paradigm creates a significant challenge in the attempt to utilize the cloud.

Security. Integrating cloud computing into an organization should always have security concerns. While Drew (2013) highlights that malware may not spread to desktops from the cloud, he stated the malware might spread across cloud platforms. Additionally, the spread of malware through the cloud platform should prompt clients to adequately evaluate the vendors for security plans to ensure the safety of the data (Drew, 2013). However, Ring (2015) states that some experts claim that security is an afterthought for cloud providers, which contests that Drew (2013)'s data that the big name providers are developing high-level security plans. Furthermore, this factor might be a problem since public cloud computing has providers storing all the data (Tripathi & Jigeesh, 2013). Therefore, there is a risk in storing sensitive and confidential information within the cloud platform.

NPO faces different security issues than for-profit organizations. Ohmann et al. (2015) stressed the significance of IT security in an NPO environment due to sensitive and confidential information stored on cloud servers (e.g. clinical trials). Additionally, clinical trials introduce issues with laws such as 45 CFR 46, which provides ethical and legal guidelines for biomedical researchers to protect the privacy of human participants (Health and Human Services, 2009). Furthermore, an unauthorized release of information will create an ethical violation that researchers are held accountable (Health and Human Services, 2009). While the example pertains to research NPO, the example does stress the need to ensure that cloud computing can protect confidential and sensitive information.

Training. The integration of technology must account for training. Walterbusch et al. (2013) stated training affects the TCO of IT. However, the approach to making the staff aware of the training required might differ, which Yuraraj (2015) reported that reported that 69% of Banaras Hindu library staff was encouraged to attend conferences or events covering cloud computing for library services. However, 14% stated they attended the event on their initiative, but 17% stated that the university provided training towards the new system (Yuvaraj, 2015). Furthermore, 60% of the staff stated they wanted more knowledge about emerging technology, which can include development in cloud computing (Yuvaraj, 2015). However, the author does not specify if employees enhanced their knowledge of new system by attending training sessions. Finally, the qualifications of the trainers are absent in the article.

The availability and persistence of training are necessary to lower TCO. Walterbusch et al. (2013) stated that TCO should include a view into training because improvement of staff proficiency will determine end cost. However, Van Dyk and Fourie (2015) noted that training employees are difficult due to the funding required for materials. Therefore, there is a need to understand how IT members perceive how the performance and effort to integrate cloud from different experience perspectives, which leads to the discussion of the theoretical framework for this study and how it will focus the study of cloud computing.

Unified Theory of Acceptance and Use of Technology (UTAUT)

The original UTAUT theory was the basis for the theoretical framework. Venkatesh et al. (2003) developed the theory in 2003 to combine popular acceptance models such as the technology acceptance model (TAM) into a unified theory. Additionally, Sharifan et al. (2014) noted that UTAUT integrates vital constructs from other theories and help explain the variance that might exist in individual theories. Furthermore, Chauhan and Jaiswal (2016) stated that TAM only accounted for 50% in predictive power in tested cases, while Kim, Lee, Hwang, and Yoo (2016) found that that UTAUT averages on 20-30% greater explanatory power than TAM. However, Oh and Yoon (2014) noted the original model did not contain consumer-related items such as trust and flow experience, which limits explanatory power on a consumer level. Despite this limitation, the original model contains key constructs that are vital for measuring acceptance of the technology.

The constructs are the predictors and dependent variables for the study. Venkatesh et al. (2003) provided performance expectancy, effort expectancy, social influence, facilitating condition, behavioral intention, and use behavior. Additionally,

Table 2 illustrates how Venkatesh et al. (2003) used the constructs as predictors and dependent variables. Furthermore, Wu, Huang, and Hsu (2014) stated that the generalizability of the constructs permits it to capture adequate predictors that relate to the adoption of new technology. Therefore, the constructs are applicable for recent technological developments such as cloud computing.

Table 2

Constructs: Predictors and Dependent Variables

Type	Construct
Predictors	Performance Expectancy
	Effort Expectancy
	Social Influence
	Facilitating Conditions
Dependent	Behavioral Intentions
Variables	Use Behavior

Note: (Venkatesh et al., 2003)

Performance expectancy. Performance is a vital measurement towards how efficiently an individual completes a task. Venkatesh et al. (2003) stated the construct measures the individual’s perception on how technology may improve their performance in an activity. Additionally, Rempei and Mellinger (2015) applied this construct towards the ability for graduate students to maintain their references and increase academic performance, which the data showed an improvement in academic performance. Furthermore, Oliveira, Faria, Thomas, and Popvic (2014) accepted a hypothesis that performance expectancy positively influenced the adoption of mobile banking. However, Attuquayefio and Addo (2014) rejected a hypothesis that performance expectancy was a positive influence towards the adoption of technology, but Karimi (2016) explained these situations might occur due to different influence in the environment. Therefore, the environment of the population can affect the influence of performance expectancy.

Performance expectancy requires a method to infer an understanding. Venkatesh et al. (2003) used age and gender as moderators to determine the effect of constructs. The focus was on the propensity that certain age or gender groups might respond to technology, which provides an inferential answer towards the scores that participants enter (Venkatesh et al., 2003). Alotaibi (2016) found that SaaS had an increased performance expectancy amongst young working males, which does infer some projections towards other demographic groups. However, Dajani and Yaseen (2016) and Thomas et al. (2014) noted that UTAUT was only developed and tested with Western and Asian civilization, which will change the reflection of technology based on the groups in other populations. Therefore, the appropriate usage of UTAUT requires an understanding of culture.

Performance expectancy may not provide statistically significant results for all technology. Hew and Kadir (2016) expanded their study into cloud-based virtual learning environments (VLE) with self-determination theory, which the authors chose based on compatibility with UTAUT. Additionally, Sumak, Polancic, and Hericko (2010) reported a statistically non-significant result for the relationship between PE and BI, while Hew and Kadir (2016) reported that other authors found no relationship between PE and BI within the same types of studies. Furthermore, Hew and Kadir (2016) accepted the hypothesis that delivery of rich media content improves performance on cloud-based platforms. Despite the different theory, Hew and Kadir (2016) noted the similarities of the hypothesis to the construct of performance expectancy. Therefore, performance expectancy is viable if limited construct when studying cloud computing.

Effort expectancy. Venkatesh et al. (2003) stated that effort expectancy focuses on the ease of use of a particular system. For example, Van der Vaart, Atema, and Evers (2016) used effort expectancy to understand the relationship between ease of use and adoption of guided online psychological self-management interventions, which the data showed a positive correlation. Additionally, Šumak, Pušnik, Heričko, and Šorgo (2016) provided support by stating too much complexity deters potential users from engaging technology. Despite Wu et al. (2014) stating that perceived ease of use would positively affect the acceptance of technology, Schniederjans (2017) stated the possibility that effort expectancy is given less weight on perception by early adopters. Therefore, each author directed attention towards ease of use affecting the use of technology, but the perception of a particular technology can manipulate and reduce the reliability of effort expectancy.

In addition to age and gender, the user's experience is a contributing factor towards ease of use. Venkatesh et al. (2003) labeled this moderator as experience. Alotaibi (2016) found supporting evidence that experience has a high influence on effort expectancy for software as a service (SaaS). While Alotaibi (2016) found that female participants have a strong effect on effort expectancy, there was insufficient evidence to support the hypothesis that elderly workers provide adequate influence towards the same construct. Additionally, Hamoodi (2016) found a statistically significant relationship between effort expectancy and behavior intention in adopting cloud computing, which included a high quantity of user of reporting their expertise of computer usage between good to excellent. Therefore, researchers can use effort expectancy to evaluate cloud computing adoption.

Social influence. The surrounding colleagues can contribute to the acceptance of the technology. Venkatesh et al. (2003) created the construct social influence to measure the perception of surrounding colleagues. For example, Chauhan and Jaiswal (2016) used the perception of business student's colleagues towards the importance of learning enterprise resource planning (ERP), but the authors did not find a statistically significant relationship. However, Escobar-Rodriguez and Carvajal-Trujillo (2014) found support for the hypothesis that the social influence regarding low-cost carrier websites affects online purchases. Therefore, the evidence demonstrated that social influence can affect the purchase of items, but might not influence learning technology.

Similar to effort expectancy, age, gender, and experience moderate social influence. Hamoodi (2016) found social influence had a significant impact on cloud adoption, which had a high quantity of population that are ages 18-24 and proficient in using computers. Additionally, Alotaibi (2016) provided support for this conclusion with social influence having an impact on adopting SaaS, which younger highly educated individuals are adopting the technology. Therefore, the consensus is that younger generation with high experience with computing technology tends to adopt cloud computing in the environment of the studies.

Facilitating conditions. Every technology requires support for functionality. Venkatesh et al. (2003) defined facilitating conditions by the perception that the infrastructure has the support it needs for the system. First, Huang and Kao (2015) noted that researchers reported that any issues with support for technology affect adoption. Additionally, Magsamen-Conrad, Upadhyaya, Joa, and Dowd (2015) found supporting data that age differences affect the perception of facilitating condition for tablets. Furthermore, Attuquayefio and Addo (2014) extended the need for facilitating condition with a relationship towards the adoption of information and communication technology, which the highest groupings were individuals that are 20-30 with their first degree. Therefore, the authors provided evidence that younger generations with considerable experience prefer infrastructure support to adopt the technology.

Hew and Kadir (2016) found supporting data that facilitating condition significantly improves the intention to adopt cloud-based VLE. Additionally, Alotaibi (2016) supported this conclusion by showing support that facilitating conditions improve the adoption of SaaS. Therefore, cloud computing adoption improves when there is significant infrastructure support by the vendor.

Behavior intention and use behavior. Each predictor leads to intention to adopt and actual adoption. Alotaibi (2016) confirmed that behavior intention and use behavior are dependent variables, which Aldrich (2015) defined as variables affected outside factors. Additionally, behavioral intention measures the intent of users to adopt the technology, which leads to use behavior that describes the actual usage of technology (Venkatesh et al., 2003). Furthermore, Mtebe and Raisamo (2014) simplified the concept by connecting the four influencing constructs from UTAUT to the behavioral intention, which leads to actual use. Finally, this simplification does help illustrate the relationship between the predictors and dependent variables of UTAUT.

The construct behavioral intention provides an insight toward how each predictor affects user's adoption intentions. Mtebe and Raisamo (2014) focused their research on the behavioral intention to adopt the new technology of open educational resources (OER) but found that EE was the only predictor that had a significant influence on BI in that study. Additionally, Oliveira et al. (2014) found that PE and FC are significant in influencing BI for the new technology of mbanking, while EE and SI remained statistically non-significant. Therefore, each of the predictors of UTAUT can help isolate a pattern for a particular technology that affects BI.

However, the above examples are only measuring behavior intention. Venkatesh et al. (2003) created use behavior as the transference from considering to use technology to actual adoption. Additionally, Oliverira et al. (2014) found that behavior intention had a significant influence in adopting the mbanking technology. Therefore, the examples thus far demonstrate how each predictor of UTAUT that might strengthen the behavior intention and lead to use behavior for the NPO adoption of cloud computing.

Behavioral intention does not always lead to the use of technology. Hamoodi (2016) found in a study that intention to adopt cloud computing did not make a lead to actual use. However, Alotaibi (2016) found that BI and FC has a positive influence on UB, which indicates that the situation that exists in that study promoted the usage of cloud computing adoption. Therefore, the authors supported that UTAUT provides useful predictors and dependent variables for analyzing adoption issues with cloud computing.

Extension of UTAUT

The constructs of UTAUT provide ample information about users. However, Oh and Yoon (2014) found that the theory lack consumer-related constructs such as trust and flow control. Additionally, Lian (2015) highlighted the issue by adding trust, security concerns, and perceived risks in conjunction with the initial constructs of UTAUT to study a cloud computing e-invoice system. Furthermore, Venkatesh et al. (2012) understood the absence of consumer-level constructs and provided price value, hedonic motivation, and habit as predictors for the extension of UTAUT. Finally, the additional constructs help address purchase behavior with new technology, which is part of the explanatory process (Venkatesh et al., 2012). Therefore, the consumer-related constructs add dimensions towards studies.

Price value. The value of technology is an important factor towards adoption. Venkatesh et al. (2012) described price value as for how the consumer evaluates the perception of quality vs. the actual quality of the product. Additionally, Puri and Yadav (2016) defined cost efficiency as the minimum costs compared to perceived costs of the system, which affects the adoption of technology. Finally, these two definitions focus on the consumer's perception of a product that influences the purchase.

There is significant value in determining how PV affects adoption. First, Huang and Kao (2015) found that PV has a positive contribution towards the adoption of phablets, which consumers considered the cost efficiency of the devices upon reaching a purchasing decision. Additionally, Escobar-Rodriguez and Carvajal-Trujillo (2014) found that PV can provide a statistically significant effect on behavior intention to adopt low-cost airplane fare systems, but value does not provide the same effect towards adoption. Therefore, the positive effect of PV for phablets did not have the same effect for adopting low-cost airplane fare systems over traditional systems.

Researchers use PV in determining the adoption of cloud technology within consumer groups. First, Pan, Luo, Liu, Gao, and Rao (2014) found that cost influenced the acceptance of Chromebook and MacBook as a cloud terminal, but only found support for Chromebook for the influence of purchasing for cloud services. Additionally, Dhulla and Mathur (2014) found support for the relationship between price value and behavioral intention for cloud computing amongst college students. Finally, Nguyen, Nguyen, and Pham (2014) found support for price value having a positive effect on the adoption of cloud-based learning systems. Therefore, the construct PV is a viable tool to anticipate the adoption of cloud computing for this study.

Hedonic motivation. The utility of technology is not the only factor that drives adoption. Venkatesh et al. (2012) described hedonic motivation as pleasure or fun that comes from using a certain technology, which Oh and Yoon (2014) extended this definition as deriving pleasure through visual or fantasy stimulation. Additionally, Huang and Kao (2015) provided evidence that enjoyability of a phablet positively links to behavioral intention. However, Parker and Wang (2016) stated that consumers tend to purchase products based on utilitarian value vs. hedonic motivation, which Yim, Yoo, Sauer, and Seo (2014) added that utilitarian purchases are ones that are task oriented and serves a purpose rather than pleasurable indulgences. While consumers will purchase items that serve a task, some consumers purchase items that are a new style of similar technology, which is hedonic motivated shopping (Yim et al., 2014). Finally, Venkatesh et al. (2012) implemented hedonic motivation to understand how consumer accepted a new style of technology. Therefore, the consensus of the authors is that new technology needs a measurement of hedonic motivation because it is unclear how it will immediately apply to utilitarian usage.

The pleasant experience that cloud technology provides determines how it is adopted. Dhulla and Mathur (2014) found that hedonic motivation positively affects the adoption of cloud services amongst college students. Additionally, Nguyen et al. (2014) found that hedonic motivation positively influences behavioral intention to adopt cloud-based learning environments. Furthermore, Nguyen, Nguyen, and Cao (2014) conducted a study focused on cloud computing in Vietnam and found hedonic motivation also positively influences behavioral intention to adopt cloud-based learning systems. While utilitarian usage does have a role in adoption, there is a significant influence of hedonic motivation in studying cloud computing acceptance and use.

Habit. Consumers have purchasing habits that determine what they will buy. Therefore, Venkatesh et al. (2012) provided the construct of habit to understand how habitual tendencies influence the adoption of technology, which Escobar-Rodriguez and Carvajal-Trujillo (2014) provided evidence that habit influences the behavior intention for the adoption of low-cost airline fare vs. traditional airline fare. Additionally, Huang and Kao (2015) stated that consumers might automatically purchase an item based on habit rather than price value, but also concluded that consumers make a conscious decision on adopting the technology. Despite the previous claim, Yen and Wu (2016) stated that habit is directly linked towards how consumers adopt new technology, which justifies Venkatesh et al. (2012) inclusion of the construct. Therefore, the authors provided ample evidence that the construct can measure how the consumers affect the adoption of technology.

Consumers may have purchasing habits that will determine if they adopt cloud technology. Unlike hedonic motivation and price value, Dhulla and Mathur (2014) did not find support for habit positively influencing the adoption of cloud computing amongst college students. However, Nguyen et al. (2014) contrast this result by showing support for habit as positively influencing the behavioral intention to adopt a cloud-based learning system. Additionally, Nguyen, Nguyen, and Cao (2014) found secondary support with habit positively influencing adoption of cloud-based learning systems in Vietnam. Therefore, habit is dependent on the application of the technology.

Moderators

The predictors and dependent variables need to drive towards meaning within this study. While the constructs capture key attitudes towards technology, any indication is absent as to why the participant chose the answer, which is why moderators are necessary to help explain the attitudes (Venkatesh et al. 2012). For example, the moderators can include how age might affect how the population might react to aspects of technology (Khechine, Lakhal, Pascot, & Bytha, 2014). Additionally, the moderators for UTAUT2 are gender, age, and experience, which serve as a tool to predict how certain parties will react towards the constructs (Venkatesh et al., 2012). Finally, these moderators will provide a descriptive statistic to help understand the perceptions towards the predictors.

The moderators will create considerations in the evaluation of data. For example, Venkatesh et al. (2012) noted that female participants tend to focus on existing support structures while male participants do not have as strong of a tendency. However, Thomas, Singh et al. (2014) noted that the studies for UTAUT focused on Western and Asian countries, which Dajani and Yaseen (2016) stated that studies require culture awareness to account for this issue. Therefore, The consideration will lower the invariance in the study.

The purpose of the age moderator is to analyze how different demographics affect behavioral intention and actual use. For example, older consumers may have difficulty adapting to new systems versus a younger generation (Venkatesh et al., 2012). Additionally, Khechine et al. (2014) used age difference as an assumption that younger individuals were concerned about new skills taught in a webinar, while older individuals focused on ease of use concerns. Furthermore, the evidence presents an adequate picture of how different age brackets of consumers may respond to cloud computing. Therefore, the moderator can serve as an analytic tool to understand how different generations of individuals might react towards cloud computing within an NPO.

Experience is a strong moderator against items such as habit, which the varied range of experiences can explain the formation of a participant’s actions (Venkatesh et al., 2012). Lu and Lee (2012) used different experience levels to study how it affects the usage of blogs, which is an online technology that writers use to distribute information.

However, Chauhan and Jaiswal (2016) make different connections that lower levels of experience will increase behavior intention to learn enterprise resource planning. Furthermore, experience along with the other moderators can serve to understand behaviors towards technology on an inferential level (Venkatesh et al., 2012). Therefore, the moderators are important to the study to deliver an acceptable generalization of the population, but the framework is not without limitations.

Limitations. While UTAUT2 has an increased prediction range in comparison to other frameworks, some factors limit the usage. Thomas et al. (2014) included cultural aspects due to limited testing in the Western and Asian countries. Therefore, a hindrance can occur if there are multi-cultural groups within the population. Additionally, UTUAT2 may not address all consumer and user-related variables, which has caused researchers like Oliveira et al. (2014) to combine multiple theories to address their research. Finally, Bagozzi (2007) argues that technology acceptance theories, in general, are becoming chaotic, which include UTAUT presenting 41 independent variables for predicting intentions and eight variables predicting behavior. While this limitation may hinder certain investigations and other theories might apply to cloud computing, Kim et al.(2016) noted that UTAUT provides 20-30% greater explanatory power than TAM. Therefore, UTAUT2 explanatory power provides a balance for the limitations, which makes UTAUT2 suitable for this study.

Other Frameworks

While there is a need to discuss competitive frameworks, there are eight acceptance theories that tie into UTUAT, which Venkatesh et al. (2003) included constructs from theories such as the theory of reasoned action (TRA) and TAM. Additionally, Table 3 contains the acceptance models incorporated into UTAUT as a foundational basis. Therefore, a discussion of TAM and TRA is necessary as well as why the theories are not adequate for the study.

Table 3

Comparison of UTAUT with Root Constructs

UTAUT Constructs	Root Constructs
Performance Expectancy	Perceived Usefulness (TAM) Extrinsic motivation (MM) Job Fit (MPCU) Relative Advantage (IDT) Outcome Expectation (SCT)
Effort Expectancy	Perceived Ease of Use (TAM) Complexity (MPCU) Ease of Use (IDT)
Social Influence	Subjective Norm (TRA/ TAM2/ TPB/DTPB/C-TAM-TPB) Social Factors (MPCU) Image (IDT)
Facilitating Conditions	Perceived Behavioral Control (TPB/DTPB/C-TAM-TPB) Facilitation Conditions (MPCU) Compatibility (IDT)
Behavior Intention/Use Behavior	Attitude toward Behavior (TRA/TPB, C-TAM-TPB) Intrinsic Motivation (MM) Affect Toward Use (MPCU) Affect (SCT)

Note: *(Venkatesh et al., 2003)*

Technology acceptance model. Davis (1989) developed the technology acceptance model (TAM) in 1986 to explain computer usage, which was adapted from TRA to establish perceived usefulness and perceived ease of use. Furthermore, the main constructs are perceived usefulness, perceived ease of use, attitude towards use, behavioral intention to use, actual system use (Davis, Bagozzi, & Warshaw, 1989). Finally, Table 3 shows how TAM contributes to UTAUT/UTAUT2, which explains the familiarity between UTAUT and TAM.

Dajani and Yaseen (2016) used TAM to study the lack of Internet adoption in Arab culture, which the authors evaluated the economic and cultural dimension behind the low adoption. However, their review found that that the modified model only predicted 40% of actual use (Dajani & Yaseen, 2016). Furthermore, Arab organizations may exist within the target population that may have different ideal than other sample targets, which makes the discussion necessary for viability outside Western and Asian countries.

External factors. The external factors construct is a generic variable that consists of any outside influences that might affect perceived usefulness and perceived ease of use (Davis et al., 1989). For example, Esmaeilpour, Hoseini, and Jafarpour (2016) reviewed organizational barriers, technical barriers, and environmental barriers to describe issues that might affect the adoption of e-commerce in small and medium enterprises in Bushehr, Iran. Additionally, the authors did state that simplicity reflects positively on perceived ease of use, which helps people adopt e-commerce. Also, Kansal (2016) used perceived risk factors as external factors to study the acceptance of self-service banking, which includes financial risk, performance risk of cash, social risk, time risk, and security risk. Furthermore, the author demonstrated the usage of the external factors by using a correlation test, which shows no statistically significant relationship between financial risk and intention to use and a statistically significant relationship between the other four dimension (Kansal, 2016). Therefore, the two respective studies show the value of external factors by showing it can add modularity for different items that can affect technology acceptance.

However, the modularity of external factors could also create an issue. Kansal (2016) ran an exploratory factor analysis (EFA) to test the reliability of the each construct, which the test show it only accounts for 75.588% variance. Therefore, the author had to refine the survey questions to ensure that the results were reliable. Additionally, Iqbal and Bhatti (2015) used an EFA to study the reliability of the student readiness external factor, which the author had to adjust to handle it for measurement appropriately. While external factors present the ability to add different items that might affect perceived usefulness and perceived ease of use, it also demonstrates that TAM does not address enough general factors for technology adoption. Finally, Venkatesh et al. (2012) included seven predictors to address different validated dimensions that UTAUT did not include. However, the previous EFA tests demonstrate that external factors provide an additional effort that a validated UTAUT/UTAUT2 does not require.

Perceived usefulness and perceived ease of use. Davis et al. (1989) stated the constructs of perceived usefulness and perceived ease of use are important factors in predicting the acceptance of the technology, which also affects the interest in the technology. Additionally, Yeou (2016) used perceived usefulness to describe how a student thinks Moodle improves their academic performance, while perceived ease of use was used to describe how students think about the effort required to use the application. As a result, perceived usefulness was a strong determinant for technology acceptance. Furthermore, Butt, Tabassam, Chaudhry, and Nusair (2016) added that perceived ease of use has a positive effect on the usage of online shopping. Therefore, these two studies demonstrate the usefulness of these two constructs towards a study on cloud computing.

The perceived use and perceived ease of use can translate to UTAUT as performance expectancy and effort expectancy respectively (Venkatesh et al., 2003). However, UTAUT does not have the external factors construct that that can be defined by the researcher (Venkatesh et al., 2012). Instead, UTAUT uses defined constructs that can capture relevant factors such as social influence, facilitating conditions, hedonic motivation, habit, and price value. Additionally, the constructs are validated so that researchers can use UTAUT2 survey items without extensive modification (Venkatesh et al., 2012). Therefore, this factor adds strength to an argument of using UTAUT2 over TAM.

Theory of reasoned action. Fishbein and Ajzen developed the theory of reasoned action (TRA) in 1975 as a social psychology approach to understanding the actions of an individual by their behavioral intention (Davis et al., 1989). In conclusion, Fishbein and Ajzen found that attitude and social norms influence the intention to perform an action, which helps develop the model (Davis et al., 1989). Additionally, the key constructs are belief and evaluation, normative belief and motivation to comply, attitude toward the behavior, subjective norm, behavioral intention, and actual behavior. Furthermore, Ajzen did create an extension called the theory of planned behavior (TPB) in 1991, which Newton, Newton, and Ewing (2014) noted that both theories are critical in health sciences. Therefore, there is a need to understand how both theories apply to IT.

Subjective norms change the intention to perform an action, which is viable to understanding how and why that construct does this action (Newton et al., 2014). Additionally, Hussain, Rahman, Zaheer, and Saleem (2016) used TRA to study the usage of Halal within the Muslim community, which focuses on attitudes and subjective norms. Therefore, these examples of constructs serve as to understand how general it is, which could apply towards cloud computing adoption.

Variance. Ackermann and Palmer (2014) stated that TRA and its extension TPB only account for 39% of the variance in behavioral intention and 27% of actual behavior. However, Burak, Rosenthal, and Richardson (2013) provided a different variance of 70% regarding the intention to use exercise as a punishment. Finally, these ranges of variances support Kim et al. (2016) statements that UTAUT increases explanatory power because of the lower variance in the answers.

Constructs. Davis et al. (1989) described beliefs as a subjective probability that consequences will result from performing a behavior, while evaluation provided a focus on the response to the consequences. Additionally, the subjective norm is the compliance with norms generated by a peer or a group (Salt & Semira, 2016). Finally, attitude is the negative or positive emotion towards action (Davis et al., 1989). Furthermore, each of these constructs will culminate towards behavioral intention, which is the strength of the intention to act. Finally, the focus is towards the displayed behavior of the subject (Davis et al., 1989). Therefore, these psychological items may explain how participants react to different web-based technology, which is outside the normal health field.

Barman and Barman (2016) used attitude, subjective norm, behavior intention, actual use, and perceived belief control in a study, which the authors also included knowledge and skill as additional constructs. Additionally, perceived belief control is a construct from TPB, which measures how much an individual perceives that behavior is under their control (Tavousi et al., 2015). However, Ackermann and Palmer (2014) added implicit measures of attitude because the authors felt that explicit measure did not account for attitudes that occur spontaneously, which people store in memory. Furthermore, Ackerman and Palmer (2014), as well as Barman and Barman (2016), ran validity and reliability checks to ensure that the changes did not negatively affect the framework. While this factor is not a negative aspect, it does suggest that TRA/TPB is not complete enough to study the surrounding perceptions of cloud computing.

Concluding Remarks

The review of NPO was essential because the organizations operate financially different than for-profit organizations, which might affect the adoption of cloud computing with its benefits and challenges for the organization. Additionally, the study will require predictors that include how each factor might affect cost efficiency and integration of cloud computing, which was the aim of the review of the professional and academic literature. Finally, the factors might provide a focal point towards how different acceptance might occur.

While TRA, TPB, and TAM are viable frameworks for studying technology, there is lacking consistent constructs to measure the different aspects towards adopting cloud technology. Additionally, the studies have shown that additional outside constructs are added to extend the framework to suit the needs, which always requires validity and reliability tests. However, UTAUT2 provides ample constructs to provide measurements to study cloud computing without the need to add additional frameworks, which Venkatesh et al. (2012) already conducted reliability and validity on the base instrument. Therefore, UTAUT2 is the best fit to conduct this study.

The constructs will help with an inferential report. For example, consumers might perceive a technology as taking too much effort to learn and operate, which leads to effort expectancy influencing the ease of use in use behavior (Venkatesh et al., 2012). Additionally, this factor can note that too much effort to secure data in the cloud could hinder adoption in non-profits. Therefore, effort expectancy is integral to explaining integration.

The conclusion from the literature review provides ample evidence that issues exist with the adoption of cloud computing within NPOs, but there is a gap towards the extents. Additionally, Ward (2016) stated that 52.5% of NPOs in the United States considered or have adopted cloud computing despite issues that exist. Therefore, there is justification to explore the relationship between the predictors and dependent variables to find what might increase or decrease adoption of cloud computing within NPOs.

Transition and Summary

This section contains an introduction to the topic of cloud computing within organizations. Additionally, the purpose of the study is to determine the relationship between performance expectancy (PE), effort expectancy (EE), social influence (SI), facilitating conditions (FC), price value (PV), hedonic motivation (HM), habit (H), behavioral intention (BI), and use behavior (UB) in relation to non-profits' propensity to adopt cloud technology within non-profits organizations. By utilizing UTAUT2 as the underlying theoretical framework for exploring the relationships, it will provide an appropriate statistical analysis to understand how the independent variables relate to the dependent variable. Finally, the literature review focused on the defining properties of cloud computing, arguments on cost efficiency, arguments on integration, defining UTAUT2 and how it applies to the study.

Section 2 will expand on the study with sections such as the role of the researcher, the participants, the justification for a quantitative method and correlational design, the population and sampling methods, how to ethically conduct a study, data collection methods and techniques, data analysis method, and the validity of the study. Additionally, section 3 will present the data as well as the analysis of information, which will include findings, application for professional practice, the implication for social change, and recommendation for future study. Finally, I included a reflection of conducting the study as a completion of the draft.

Section 2: The Project

Section 2 contains a detailed discussion of the project itself. In the Role of the Researcher subsection, I discuss how I was involved in the study; the researcher will be involved in the study, while in the Participant's subsection I fully defined the eligibility requirements for participating in the study. Additionally, in the Research and Design subsection, I discuss applicable methods and designs. The Population and Sampling subsection includes discussion of the study population and sampling procedures. Furthermore, the subsection on ethical research contains information on how I maintained ethical boundaries to protect participants and abide by Walden University's Institutional Review Board (IRB) requirements. Finally, I provide details on my data collection and analysis procedure and discuss the issue of validity.

Purpose Statement

The purpose of this quantitative correlational study was to determine the relationship between predictors of performance expectancy (PE), effort expectancy (EE), social influence (SI), facilitating conditions (FC), price value (PV), hedonic motivation (HM), and habit (H), and the dependent variables behavioral intention (BI) and use behavior (UB) regarding NPOs' propensity to adopt cloud technology. The specific population was IT managers within NPO in the Phoenix metropolitan area of the U.S. state of Arizona. The predictors were (a) PE (b) EE, (c) SI, (d) FC, (e) PV, (f) HM, and (g) H. The dependent variables were (a) BI and (b) UB. An implication of my doctoral study for positive social change is that, by using my study findings, NPO leaders might be better able to optimize their IT services to benefit those in need of their humanitarian services as well as reduce their carbon footprint.

Role of the Researcher

The role of the researcher in any quantitative study is to collect, compile and analyze the data to test the hypotheses, and, subsequently, answer the research question (Larson-Hall & Plonsky, 2015). I collected UTAUT2 surveys from a sample of the population; the survey contained questions with a Likert scale, which I used to measure the predictors and dependent variables. Boari and Ruscone (2015) stated that a Likert scale is useful for yielding ordinal data from survey questions. Additionally, I used Statistical Package for Social Science (SPSS) v.23 to store and calculate the data; Sebjan and Tomic (2015) confirmed that SPSS provides suitable calculations for quantitative studies. I used this software to perform multiple linear regressions and determined whether a relationship existed between the predictors and dependent variables.

I also collected demographic information on participants' gender, age, and experience in the UTAUT2 survey. Venkatesh et al. (2012) explained that these variables could be used as frequency variables to help explain the participant's perceptions of different constructs. Additionally, Venkatesh et al. (2012) created the moderators to strengthen an inferential report for any study that used UTAUT2. Therefore, I performed a frequency check using SPSS to create an inferential report of the findings.

Before completing this study, my experience with cloud computing was purely academic, which my perception of cloud computing could present bias into the study. Vydiswaran, Zhai, Roth, and Pirolli (2015) stated that researchers should always examine evidence that may support or contradict a claim and their doing so helps lessen their bias when researching a topic. Therefore, I grounded my study with the literature review, which provided both support and contradiction to marketing claims about cloud computing to maintain an objective viewpoint.

I was involved with Arizona Golden Rescue between 2009 to 2017, where my father served as an IT director to optimize the infrastructure to assist golden retrievers. I avoided coercion by not selecting groups for whom I had served as a stakeholder or people whom I knew on a personal or professional basis. By avoiding coercion, researchers can avoid an ethical violation as stated in the Belmont Report (Miracle, 2016). I needed to avoid coercion to ensure the ethical validity of the study.

Ethics in research is important to protect all members in the study. Members of the Nuremberg war crime trials created the Nuremberg code to judge ethical standards for biomedical experimentation due to unethical behavior towards vulnerable population in biomedical studies (Office for Human Research Protections [OHRP], 1979). Authors of the Belmont Report extended the protection to include respect for the person, beneficence, and justice for all subject, which helps resolve the vagueness introduced by the Nuremberg code (OHRP, 1979). Additionally, the Health and Human Services (2009) codified these tenets as an enforceable code labeled 45 CFR 46, which provides legal protections to vulnerable populations. In conclusion, both the Belmont Report and 45 CFR 46 were critical to this study to avoid any violation of basic human rights.

Respect for a person includes the tenet that participants are autonomous, and individuals with diminished capacity require additional protections (OHRP, 1979).

Presently, diminished capacity includes any state that leaves a participant vulnerable to coercion (OHRP, 1979). Additionally, the subparts of 45 CFR 46 include protection for prisoners, minors, members of a minority, pregnant women, and people with disabilities (Health and Human Services, 2009). Furthermore, 45 CFR 46 includes the right to refuse and withdraw because research always has the possibility of harming the participant (Health and Human Services, 2009). Miracle (2016) added that coercion violates the right refuse and withdraw, which include using subordinates and colleagues. Therefore, I did not use any organization in which I had an active role. Additionally, I ensured that the informed consent and UTUAT2 instrument conveyed the right to refuse and withdraw. Finally, I did not actively seek out any vulnerable participants.

Beneficence concerns the balance of benefit from research and risk to the participant (OHRP, 1979), which Miracle (2016) simplified as ensuring minimal harm to participants. Additionally, Miracle provided an example of harm arising from the disclosure of private information to outside parties without consent. Accidental disclosure of sensitive information can create stigma, which harms the participant socially and financially. Therefore, my role was to minimize any risks, which included limiting the collection or disclosure of personally identifiable information (PII) to anyone outside the study.

The issue of stigma was a potential issue that could occur with my research. Stigma can occur if a party discovers information related to a study and uses against the participant (Miracle, 2016). Therefore, the Belmont Report included provisions that require protections from reprisal (OHRP, 1979). Accordingly, all participants in my study were anonymous to prevent any issues from disclosure of study data to outside parties.

Participants

The initial eligibility requirement was that participants were not minors. Health and Human Services (2009) stated in 45 CFR 46 Subpart D to limit minor participants unless necessary for the study (Health and Human Services, 2009). Therefore, I have excluded minors from the study.

I required participants to serve as NPO IT managers within the U.S. state of Arizona as well as having at least a minimal familiarity with cloud computing. Additionally, the IT manager must also serve with a valid non-profit with a 501(c) designation from the IRS. By definition, the 501(c) designates the organization not include any sharing profits to employees such as bonuses (IRS, 2016), which Kraft and Lang (2013) defined employee bonuses as features for for-profit organizations. Therefore, I excluded IT managers from for-profit organizations.

The key eligibility requirements for inclusion was determined using the population and research questions. Stern, Jordan, and McArthur (2014) stated that role and population could help specify requirements for participants filling out a survey. While Gumbi and Mnkandla (2015) stated there is a lack of standardization for cloud computing that makes it difficult to determine between different viewpoints, there is enough information to constitute basic cloud computing functionality. Therefore, NPO IT managers must have at least researched or have experience with different cloud computing concepts as it relates to any organization.

I obtained approval to access participants from Walden Institutional Review Board (IRB). Accordingly, this group evaluates all research studies to ensure that it adheres to Belmont Report protocols (Walden University, 2015). Consequently, any access to participants without IRB approval may jeopardize the safety of human subjects and cause penalties towards the researcher (Walden University, 2015). Therefore, I submitted the proposal, IRB application, certificate obtained during training for ethical treatment of human subjects, informed consent forms, and the UTAUT2 survey that demonstrated the collection process. Accordingly, this process was consistent with the submission requirements for the IRB review (Walden University, 2015). After the approval, I contacted the participants.

Upon IRB approval, I aggregated email and web form addresses from websites listings on pac911.org, greatnonprofits.org, and handsonphoenix.org, which contain listings of relevant NPO in the Phoenix metropolitan area. Then, I stored the contact information in a password-protected Microsoft Excel® workbook to comply with Belmont report tenant of justice, which the OHRP (1979) stated that PII required protected storage. Therefore, I secured the Microsoft Excel® workbook to protect the participant’s PII.

The purpose of the electronic contact was to increase the anonymity of the participants on UTAUT2 survey submission. Additionally, the IRB application has questions referencing the researcher's knowledge of participants, which helps the university understand the legal and ethical implications of the study (Walden University, 2015c). Finally, the IRB prefers the anonymity of the participants, which decreases with awareness of the participants (Walden University, 2015c). Therefore, I excluded listings of NPO without an email or web contact form.

I created a brief invite email message that linked to the informed consent form on the first page of the online survey on SurveyMonkey. Then, I distributed the emails using my Walden University email address, which served as a means of contact during the study. Additionally, I used blind carbon copy (BCC) to hide all the participants to ensure confidentiality, which Sietsma and Apt (2013) elaborated that BCC allows a sender to transmit a message without sending the list of recipients for anonymity. Finally, I transmitted the same brief invite with informed consent link to web forms to comply with limited character space.

The informed consent email contained a brief introduction to the study, potential benefits of the study, confidential protocols, convenience of the study, and a link to the survey on SurveyMonkey. Additionally, this information was consistent with wording from the IRB for informed consent (Walden University, 2015). Furthermore, there was a statement in the informed consent that clicking on the link implied that the invitee had read the information and consented to the study, which included a notice about the exit button on the upper-right hand corner of the survey. Accordingly, this method ends the survey and submit only data from prior pages (SurveyMonkey Inc., 2016b). Therefore, I used this method to automate the exit procedure without the need for the participant to contact myself.

Research Method and Design

I conducted a quantitative correlation study to determine the relationship that NPOs have between the predictors and the dependent variable. Additionally, the method and design did help provide a focus for the theoretical framework and tie the relationship each predictor has to the significant final variable, which was BI and UB. Furthermore, Tripathi and Jigeesh (2013) summarized available quantitative and qualitative evidence on adoptions factors small and medium businesses encounter, which the authors focused on for-profit organizations. However, NPOs operate significantly different from SMB, which organization cannot pay stakeholders any share of the profits after business expenses (IRS, 2016). Incidentally, Ward (2016) reported that 47.5% of NPOs did not adopt cloud computing, but did not provide any quantified information on reasons for this percentage. Therefore, I conducted a quantitative correlation study to understand adoption issues further.

Method

I utilized the quantitative method to guide the collection of data. Quick and Hall (2015) signified that quantitative methods yield empirical results, which means that researchers measure a variable using scales rather than analyzing contextual themes. Additionally, Tripathi and Jigeesh (2013) consolidated different studies on cloud computing within SMB, which suggests there is information about that population for quantitative and qualitative data. However, Ward (2016) reported quantitative information about NPOs using cloud technology that had gaps of information about factors that impeded adoption. Therefore, the gap justified using a quantitative approach to distinguish what affects adoption. For example, the report did include that state of Texas, Colorado, New Mexico, Utah, and Arizona collectively represents six percent of survey respondents, which was part of the 47.5% that did not decide to adopt cloud technologies (Ward, 2016). Therefore, I collected quantitative data within central Arizona to determine why the rate of non-adopters is at 47.5%.

Bettany-Saltikov and Whittaker (2014) expanded the discussion by stating that quantitative methods rely on the testing of hypotheses. Additionally, De Magalhaes (2016) noted that a hypothesis is an educated guess made with a thorough analysis of environment and literature. Furthermore, Sartarelli (2016) stated that researchers could use empirical instruments to collect data to test the variables to reject or fail to reject a hypothesis. While Ward (2016) provided statistical information, there was not a clear hypothesis to test. Therefore, I performed an academic inquiry using quantitative methods, sampling, and survey strategies to determine acceptance issues with cloud technology in NPOs. Finally, the null and alternate hypothesis help develop the study for testing the research question, which the null hypothesis will either reject or fail to reject (Bettany-Saltikov & Whittaker, 2014). Therefore, I have included the null and alternate hypothesis in section one.

The inclusion of predictors and dependent variables also separates the quantitative method from qualitative. Aldrich (2015) defined the dependent variable as an item that changes based on outside influence, which is independent variables or predictors. Therefore, the dependent variables were BI and UB, which makes the predictors PE, EE, SI, FC, HM, PV, H. Furthermore; the variables provided aspects of technology for measurement, which assessed the acceptance of technology (Venkatesh et al., 2012). Additionally, hypothesis testing can help determine the predictors that are viable in inferring what is possibly occurring in the environment (Sartarelli, 2016). Therefore, a quantitative method was useful in determining the construct that positively and negatively influences adoption of cloud computing.

Qualitative methods are ideal for gathering contextual information. The gathering involves the researcher using active listening skills to gain more information about the subject matter (Munn, 2016). Additionally, any qualitative design can gain contextual information (e.g. strategies) regarding the topic, which may garner more information than empirical numbers regarding implementing cloud computing. Ultimately, the purpose of gaining contextual information is to obtain knowledge from a small collection of individuals that implemented the project (McCusker & Gunaydin, 2015). However, Ward (2016) did not present any information about what influenced the decision not to adopt cloud technology. Therefore, participants may not provide adequate strategies for overcoming non-existent obstacles.

A qualitative method was not selected for this study because there was not enough information to collect contextual information in an efficient method. For instance, qualitative researchers have used interviews to develop common themes, which translate into variables for empirical data (Pedron, Picoto, Dhillon, & Caldeira, 2016). However, there are other cases where researchers required empirical evidence before doing a contextual investigation due to the lack of key components related to the subject matter (Visani et al., 2016). Finally, the qualitative method would require prior research or literature to construct the design because researchers need to fill the void with valid contextual information (McCusker & Gunaydin, 2015). Despite the discovery of Ward (2016) report on NPOs and cloud technology, there was a lack of information on what might cause a lack of adoption. Therefore, there is not enough information to warrant a qualitative study.

Mixed method studies help researchers triangulate the results by using both quantitative and qualitative data (Platt, 2016). Additionally, the method does this by including empirical and contextual information into the study, which can provide a complete analysis of the subject matter (Ingham-Broomfield, 2016). Furthermore, the key to the mixed method is that it is not two separate studies, but the deployment of two methods (Ingham-Broomfield, 2016). Researcher's address both contextual research questions as well as a quantitative hypothesis to develop a complete answer towards a subject matter (Babones, 2016). Finally, the triangulation of these methods would be viable to discovering the lack of adoption rate and strategies that might overcome those limitations.

I could use the qualitative method to collect contextual information about cloud computing, which I can use quantitative methods to verify it with hypothesis testing. For instance, Pedron et al. (2016) used the mixed method to gain context on CRM technology and verify it with a survey of 210 individuals. However, the lack of information about cloud computing as indicated in the qualitative discussion was the leading cause not to use the mixed method. For example, Pedron et al. (2016) had information backed by literature to support the qualitative portion of that study. Incidentally, Ward (2016) had only explored the growth of non-profit, which is viable information to consider. However, there is an absence of supportive literature that a combination of quantitatively and qualitatively explains the possible reasons why there are NPOs that are not adopting cloud technology. Therefore, the mixed method query was not an appropriate method for this study.

Research Design

The research design was crucial to constructing the study because each design collects a different type of data, which include correlation, experimental/quasi-experimental, and descriptive studies. Furthermore, each of these designs was viable options in quantitative methods, which required exploration to decide the suitable type for this study. In conclusion, I used the correlation design for constructs and descriptive design for the moderators.

The purpose of correlation is to determine if two or more variables have a positive, negative, or no relationship (Rogerson P. A., 2001). First, a positive correlation means that variables increase and decrease at the same time, while a negative correlation indicates that a decrease of variable occurs when another variable increase (Blasig et al., 2016; Shen, Zhang, Liu, Zhao, & Yuan, 2015). However, no correlation means that there is no relationship between the variables (Longo & Morcom, 2016). Therefore, I used the relationships to determine how the different predictors related to each dependent variable, which helped focus on the possible link between the cost efficiency, integration, and adoption rates in the application portion of Section 3. Furthermore, I gained an understanding of the importance of each construct by analyzing the type of relationship it has with the dependent variable. Finally, I will remove any *ns* variables from future studies to focus on statistically significant factors.

The drawback to correlation is the lack of causation (Rogerson P. A., 2001). Incidentally, the reason is that correlation relies on statistical information that may form an inferential conclusion (Bleske-Rechek, Morrison, & Heldtke, 2015), but Ryan and Iago-McRae (2016) stated causation would require an experimental approach with control and test groups. However, I did not look for the cause for the lack of adoption. While experimental studies are viable, correlation studies were the most appropriate for this study to isolate testable variables in an experimental situation.

Experimental design is a viable option for testing for cause and effect of an event (Lázaro et al., 2016), which Ryan and Iago-McRae (2016) explained the design randomly divides the sample into control and testing group to analyze the variables. For example, two groups would be set up with cloud simulations. However, the testing group would include an intervention to see if it improves a situation (Lázaro et al., 2016). Additionally, a researcher can enact controls to ensure that the groups are blind to each other, which helps avoid validity issues to compare the testing and control group (Zhang & Zhou, 2016). However, I did not have enough information for viable variables to test with an intervention. Furthermore, experimental design for cloud computing might require an isolation of variables through statistical tests and an intervention generated through a qualitative study. Therefore, the experimental design was not appropriate for this study.

The difference with quasi-experimental is that random selection of participants does not exist or the constraints of a true experiment cannot exist within the environment

(Dutra et al., 2016). Consequently, this approach may have validity issues because the baseline between the groups will not have an equal chance at the measurement levels (Hancock, 2011). However, the design does require independent variables to create a cause and effect environment for the dependent variables (Farhoudi et al., 2016). Therefore, the design was not appropriate in a similar way as experimental design.

Descriptive statistics provides summary information that can help in making inferential reports about subject matters (Dos Santos, Barroso, Macau, & De Godoy, 2015). Additionally, UTAUT2 included moderator variables, which does help create an inferential report on the constructs (Venkatesh et al., 2012). For example, the frequency can infer an aspect that occurs among survey participants (Kestin, 2015), which Venkatesh et al. (2012) made the moderators to discover the frequency of participants answering a survey. Therefore, descriptive statistics was appropriate for this study for measuring the moderators.

Population and Sampling

In this subsection, I provide an overview of the population and sampling for the study. After establishing the population, I established a sampling strategy to select a range of participants for data collection. Therefore, the goal ensured the validity of the study by having enough participants.

Population

The target population for this study was approximately 5928 IT managers within NPOs in the Phoenix metropolitan area of Arizona, which I derived the approximate total of NPOs from greatnonprofits.org, pac911.org, and handsonphoenix.org.

Greatnonprofits.org aggregates organizations that exist under a non-profit designation (GreatNonProfits, 2016). Additionally, PAC911 aggregates animal rescue NPOs within Phoenix area (PAC911, 2016), while HandsOnPhoenix.org is an organization that promotes and lists non-profits organization in the Phoenix, U.S. state of Arizona area (HandsOn Greater Phoenix, 2017). Furthermore, a single individual can affect the decision to adopt technology within an organization (Pedron et al., 2016). Therefore, one IT manager per organization was a feasible population decision. Finally, I made the selection of NPOs using tax law 501(c) as a qualifier, which the IRS (2016) identified as any organization that does not participate in profit-sharing such as bonuses. In conclusion, the population made a pool to select a sample.

Sampling

Selection of simple random sampling. I used the simple random sampling method to create a probabilistic sample of the population. The probability theory is a branch of mathematics that deals with the random distribution of numbers (Athreya, 2015). Additionally, the probability theory aligns with quantitative studies by delivering a sample through random distribution, which may represent the population (Athreya, 2015). In conclusion, probability theory was appropriate for this quantitative study.

Simple random sampling occurs by giving a population an equal chance of selection (Leahy, 2013). However, simple random sampling has a weakness of not distinguishing between different groups within the population (Leahy, 2013). For example, Leahy (2013) discussed using a population of car enthusiasts, drivers, and professionals, but could not distinguish between each group. In conclusion, this weakness might hinder any inference about specific types of NPOs.

The alternative sampling strategy was stratified sampling. This sampling strategy divides participants into groupings called a strata (Shields, Teferra, Hapij, & Daddazio, 2015). Incidentally, the purpose of stratified sampling is to create a random distribution amongst a grouping of individuals with a specific characteristic, which balances selection of participants amongst different characteristics for an inference into different types of subjects (Shields et al., 2015). However, the UTAUT2 survey does not contain any items for identification (Venkatesh et al., 2012). While I could list NPO types, participant anonymity was in the best interest of maintaining ethical research. Additionally, de-identifying participants provide protections that are critical for ethical research (Angiuli, Blitzstein, & Waldo, 2015). However, a validity threat occurs if the sample does not adequately represent the population (Fincannon, Keebler, & Jentsch, 2014). Consequentially, the validity threats was a deciding factor because I did not have a method to ensure the representation of particular strata. Therefore, a simple random sampling of all NPOs was appropriate for this study.

The method of random assignment. I used Microsoft Excel® to list and select the participants' email addresses for the study. Microsoft Excel® provides the option to protect sensitive information with a password (Callahan, 2007). The reason was to protect the email addresses stored within the worksheet, which Angiuli et al. (2015) classified as PII that requires protection. Therefore, I used the password protection feature to ensure that email addresses of the potential candidate did not leak to unauthorized personnel.

I provided participants an equal chance by alphabetizing all collected emails from the different cities, Jelen (2013) described as possible with the Microsoft Excel® sorting feature that allows alphabetization of worksheet items. Additionally, Morey (2007) described the RAND() function in Microsoft Excel® to create random numbers to select a random sample. Therefore, I used the RAND() function to create a random number, which I sorted from smallest to largest. Finally, I selected the number of participants based on the sample number.

Sample. I used two methods to gain sample sizes for the study. First, I used a simple algebraic formula to produce a minimum sample number. Then I used G*Power to create a range of participants. Finally, I consolidated these calculations to produce a sample range to conduct the study as well as address validity threats.

Simple algebraic formula. Tabachnick and Fidell (2007) used a formula of n=50+8(m) for a multivariate linear regression analysis, which n is the sample and m are the numbers of predictors. Additionally, UTAUT2 contains seven predictors, which are PE, EE, SI, FC, PV, HM, and H (Venkatesh et al., 2012). As a result, the formula was n=50+8(7), which comes to n=106 as a sample size. While the model requires a separate analysis for the UB, the number of predictors is three, which are BI, FC, and H (Venkatesh et al., 2012). Therefore, the sample size obtained by the formula was adequate for meeting the needs for both multiple regression analysis.

G*Power. I used G*Power to do a power analysis. Lapresa, Alvarez, Anguera, Arana, and Garzon (2015) described G*Power as a statistical software that can determine a priori sample size. Additionally, I conducted a power analysis using software version

3.1.9 to analyze another appropriate sample size for this study. Finally, I used *F* test based on relevant information such as effect size, α, and the number of predictors.

Thomas, Ott, and Liese (2011) used non-government organizations (NGO) for its quantitative studies, which they describe as non-profit. Additionally, the methodology section of the article contained the estimated effect size as d = .5 (medium), α = 0.05 and power = .8 (Thomas, Ott, et al., 2011). However, multiple regression uses Cohen's criteria of f^2 having a medium effect size of .15 (Faul et al., 2007). Furthermore, Jafri (2013) provided support for this by stating $f^2 = .31$ is medium and $f^2 = .11$ is low in his study, which Faul et al. (2007) stated stated the thresholds is between .15 and .35. Therefore, I confirmed .15 is medium effect size and converted d = .5 to f^2 =.15 to create an appropriate sample size.

I had used multiple linear regression for the power analysis. Additionally, G*Power requires the number of predictors in the power analysis for multiple regression. Therefore, I used the seven predictors for the power analysis.

The initial calculation led to a minimum sample size of 103 with the power of .80 and maximum sample size of 153 with the power of .95. First, the maximum number was generated to mitigate type I errors or incorrectly rejecting the null hypothesis. However, Smith (2012) warned against using the power of .99 due to an increased chance of type II errors or incorrectly failing to reject the null hypothesis. Therefore, I did not use the result of .99, which was 203 participants. Furthermore, Shetty et al. (2016) used 95% confidence level and 5% significance level for their multivariate regression study to alleviate type I and type II errors. Therefore, I used the sample range of 106 to 153, which the former is above .80. Finally, a discussion on Type I and Type II validity is in the Validity subsection.

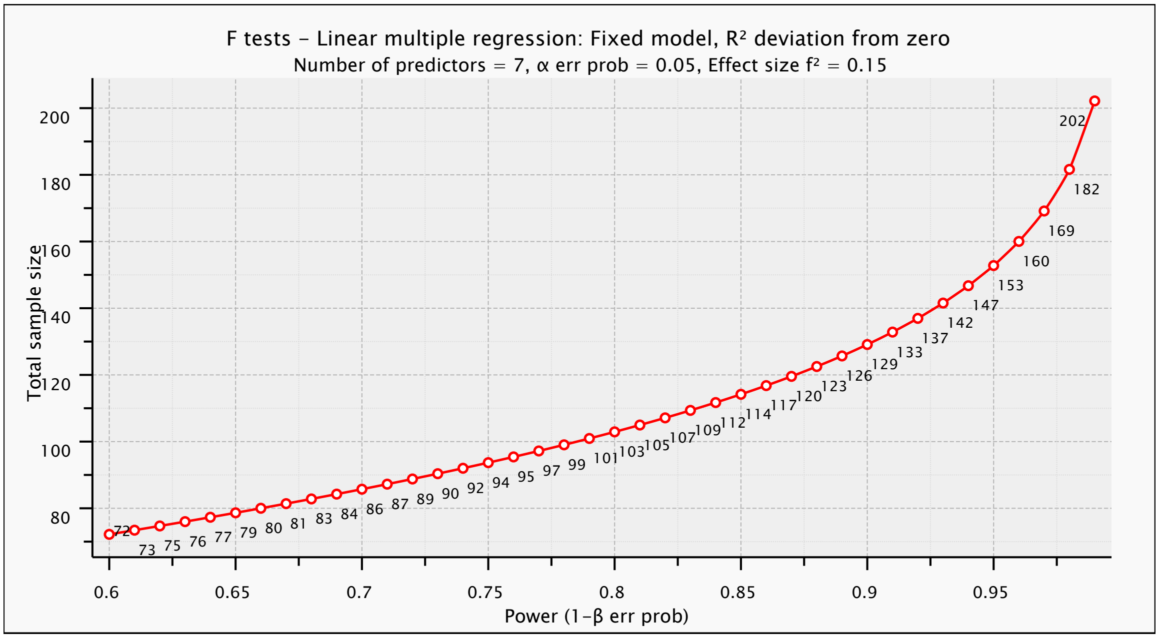

Figure 2. Graphic display of power analysis**.**

Ethical Research

I was required to conduct the research using ethical standards from both the Belmont Report and 45 CFR 45. First and foremost, the U.S Department of Health and Human Services uses the regulation 45 CFR 46 to place legal protections for human participants, which includes any social and financial risks that participants might experience if PII is inappropriately disclosed (Health and Human Services, 2009). Additionally, PII is information that can directly link to an individual, which includes name, address, phone numbers, and more (Angiuli et al., 2015). Furthermore, the release of this information along with the raw data can jeopardize the protection of the participant, which is among the reasons why 45 CFR 46 exists with legal consequences

(Health and Human Services, 2009). As a result, I completed the National Institutes of Health (NIH) training for protecting human subjects, and a copy of the certification is in Appendix A with certificate number 1908332. Ultimately, the goal of the training is to raise awareness of ethical behavior and instill the value of informed consent (Health and Human Services, 2009). Therefore, I used these considerations to protect my participants from any exploitation.

Informed consent is disclosing the potential harm and benefits of the research to the participants. Nishimura et al. (2013) stated that informed consent includes divulging rights as a human subject, a description of protecting rights, and disclosure of the nature of the research. Additionally, researchers need to use the informed consent process to explain the right to withdraw without any repercussions (Health and Human Services, 2009). Therefore, I simplified and explained the withdrawal process in the informed consent, which participants can click on the exit button in the survey to end the collection without any notification.

The survey was set up with a web link with an anonymous response, which eliminates any potential linking of participants to data. Additionally, the form also included an explanation that there were no monetary incentives for participating in the study, which removes the possibility of coercion as well as possible PII. Finally, I placed the link at the end of the informed consent form, which the participants implied their consent by clicking. In conclusion, I used this process to avoid collecting PII via signatures as well as ensuring participants could withdraw without contact.

Other agreement forms were not necessary for this study. First, the study only had an online survey, which participants implied consent through a web link. Additionally, Parental consent and children assent are only necessary when minors are involved (Health and Human Services, 2009), which I did not need due to the exclusion of minors. Furthermore, confidentiality agreements are required if more than one researcher is working on the project (Cooper & McNair, 2015). However, I was the only researcher who handled the data, while the supervisory committee only viewed the results. Therefore, confidentiality agreements were not required. Also, I would require an agreement of cooperation if I performed the study on a site (Walden University, 2015c). However, I had used the Internet and did not interfere with a participant's work environment, which meant that a cooperation agreement was not required. Finally, there is an agreement required if a researcher is operating within their work setting, which requires dual roles (Walden University, 2015b). However, this agreement was not required because I did not contact any organizations that I belonged to for a period.

I downloaded an SPSS compatible file for analysis and digitally shredded it upon completion using File Shredder. First, File Shredder® deletes files beyond the point of recovery (File Shredder, 2007). Additionally, SurveyMonkey maintains a stringent security policy on its data centers, which follows PCI-DSS standards to avoid the release of information to unauthorized users (SurveyMonkey Inc., 2016d). Therefore, the organization maintains a higher standard of security than I can maintain my systems for secure storage.

I will keep all raw information on SurveyMonkey for five years after the completion of the study, which only I will have access. Then, I will delete the survey after that period. Furthermore, this deletion will erase the data from SurveyMonkey, which will require the account holder to contact SurveyMonkey for restoration (SurveyMonkey Inc., 2016a). However, I will not request the restoration of the survey and results to ensure the protection of participants.

The informed consent form underwent an IRB evaluation and a change of procedures. Incidentally, the previous informed consent had the potential to allude participants to purchasing cloud technology and then take the survey. Therefore, I simplified the language to make it clear that only the survey was necessary. Finally, the IRB approved the study with approval code 03-06-17-0521783, which expires March 5, 2018.

Data Collection

Data collection is essential to discovering answers to the research question as well as rejecting or failing to reject the null hypothesis. This process occurs by using instruments to obtain information about the topic (Boulden, 2015). For instance, I used an instrument as well as data collection techniques to accomplish this task. Therefore, this subsection will focus on defining the data collection process for this quantitative study.

Instrument

The UTAUT2 survey was the instrument for this study. Venkatesh et al. (2012) published the UTUAT2 survey instrument for UTAUT2. Additionally, the UTAUT2 survey is in Appendix B, and the permission to use the instrument is in Appendix C.

Furthermore, I used the instrument to collect data for determining the relationship between the predictors of (a) PE (b) EE, (c) SI, (d) FC, (e) PV, (f) HM, (g) H and the dependent variables of (a) BI, and (b) UB.

The study required an instrument that was reliable and valid. Incidentally, Venkatesh et al. (2003) combined the reliability and validity of the models that they combined to form the original UTAUT. Additionally, Venkatesh et al. (2003) performed an internal consistency reliability (ICR) on the constructs, and all readings were greater than .70. Futhermore, Arzglou et al. (2015) explained that ICR is a test that examines items within a construct to ensure it is capturing information reliability. Therefore, a greater than .70 means all questions have a high-reliability rating. Also, this testing is important for a study because it ensures that it captures the correct information with reliable measures (Doody & Doody, 2015). Venkatesh et al. (2012) used ICR on UTAUT2 survey, which produced numbers of .75 or greater. The ICR indicates that that UTAUT2 survey maintains the reliability, which makes it useful for this study.

Venkatesh et al. (2003) tested the square roots of shared variance between constructs and measures, which lead to the square roots being higher than the correlation across the constructs. Additionally, The test revealed that the instrument meets convergent and discriminant validity (Venkatesh et al., 2003). Furthermore, convergent validity focuses on ensuring that two measures that should be related are proven to have a relationship with testing results (Ekstrand, Lexell, & Brogårdh, 2016). Contrastly, discriminant validity provides a test to ensure that unrelated items are proven to be unrelated after testing (Cicero et al., 2016). Also, multiple regression requires a low multicollinearity value, which means that the constructs used for independent variables do not show a strong correlation to each other (Zainodin & Yap, 2013). Therefore, both validity tests show that each construct is unique with its measures (Venkatesh et al. , 2003), which helps determine predictors and dependent variable without interference. Finally, the uniqueness of each construct was important for determining how the predictors individually affected the dependent variables.

Venkatesh et al. (2012) performed a partial least-squares test to determine the discriminant validity of the extended model. In fact, Dino & de Guzman (2015) stated that PLS identifies variance and relationships between constructs, which can help determine the validity of an instrument. For validity, Venkatesh et al. (2012) found that the average extracted variance (AVE) was above .70, which supports discriminant validity of the instrument. As discriminant validity helps remove unrelated items from a construct (Cicero et al., 2016), Venkatesh et al. ensured that hedonic motivation, price value, and habit were valid and captured the correct information. Therefore, the validity and reliability of the instrument were important to ensure the capture and analysis of information reflected the population of the study.

I did not conduct a pilot study for this study. A pilot study is used to test instrument to ensure it is collecting the correct information (Doody & Doody, 2015), which Venkatesh et al. (2012) had performed an ICR to test for reliability. In fact, Ekstrand et al. (2016) declared that ICR is a standard tool for reliability. Furthermore, discriminant validity helps instrument authors to drop any unrelated questions (Cicero et al., 2016), which Venkatesh et al. (2012) did perform on UTAUT2. Therefore, a pilot study was not necessary for this study.

I did have to adapt the UTAUT2 survey for the study. While Venkatesh et al. (2012) provided a UTAUT2 survey instrument, statement 2 for H was "I am addicted to mobile Internet." Because Coors (2012) declared addiction as a sensitive psychological issue, the scope of addiction could stem into significant psychological boundaries, which Miracle (2016) stated that sensitive subject requires additional ethical controls. As sensitive psychological issues are outside the scope of this study, I removed statement number 2 from habit on the UTAUT2 survey. Additionally, I had changed hedonic motivation and habit to pleasant experience and habitual tendency on the participant viewing survey to clarify the statements. The purpose of clarity is to ensure the maintenance of reliability and validity (Doody & Doody, 2015). Finally, I had provided instructions for each construct to improve clarity.

The minor changes in the UTAUT2 survey could affect the reliability and validity of the scores received from the participants. In fact, Barry, Chaney, Piazza-Gardner, and Chavarria (2014) concluded testing the validity and reliability of the scores received from participants is best practices for researchers. Additionally, Zachariadis, Scott, and Barrett (2013) stated that reliability of data ensures that measurements can generalize an inferential analysis, which Fincannon (2014) stated that generalization is the goal using quantitative research. Therefore, I performed Cronbach's alpha to test the reliability of the scores.

Concepts of UTAUT2. The constructs of UTAUT are performance expectancy (PE), effort expectancy (EE), social influence (SI), facilitating conditions (FC), hedonic motivation (HM), price value (PV), habit (H), behavioral intention (BI), and use behavior (U), which also include moderators of age, gender, and experience (Venkatesh et al., 2012). First, I used PE, EE, SI, FC, HM, PV, and H as predictors, while the dependent variables were BI and UB. Additionally, I tied the data from the constructs into concepts in the application subsection of Section 3. Furthermore, Table 4 displayed how the constructs and concepts will apply. Finally, the moderators help explained the relationship between certain constructs (Venkatesh et al., 2012). Thus, I excluded from the predictors, but I included it as descriptive statistics to assist with an inferential explanation.

Table 4

Association of Constructs, Cost Efficiency, and Integration

Type	Construct	Concept
Predictors	Price Value Social Influence Facilitating Conditions	Cost Efficiency
	Hedonic Motivation Habit Performance Expectancy Effort Expectancy	Integration
Dependent Variables	Behavior Intention Use Behavior	Non-Profit propensity to adopt cloud technology

Likert scale. I used a Likert scale to measure items, which ranged between 1 (strongly disagree) and 7 (strongly agree) for PE and UB, but EE, SI, FC, HM, PV, and H used a five-item scale with the removal of slightly agree and slightly disagree. For instance, Boari and Ruscone (2015) noted that participants could use a Likert scale to note their perception with on an ordinal scale. Furthermore, the purpose of using a five-item and seven-item Likert scale is to make it viable for a continuous scale (Foroughi, Werner, & Boehm-Davis, 2016), which Hazra and Gogtay (2016) stated that linear regression requires variables to scale such as ratio or interval measures. Additionally, the Likert scale can occur as a metric if it has enough items (Foroughi, Werner, & Boehm-Davis, 2016), which Hazra and Gogtay (2016) expanded on the use of metrics to create linear plots with regression. Therefore, I chose this method to support the multiple linear regression analysis. However, the intention was to make survey seven-item, but I noticed the error of the five-item scale after the data collection period. Still, the discrepancy did not seem to affect the analysis.

I used PE, EE, SI, FC, PV, HM, and H as my predictors. Aldrich (2015) described predictors as manipulated variables that attempt to change the dependent variable. Additionally, each predictor is a force that may change the acceptance of technology (Venkatesh et al., 2012). Therefore, the predictors were viable to analyze factors of consumer use of cloud computing.

PE was an ordinal predictor to study performance expectancy. Venkatesh et al. (2003) used PE to measure how a user believes a system will enhance job performance. Additionally, this perception included how sampled NPO IT managers perceived integrating cloud computing might increase or decrease the efficiency of their performance. Furthermore, this construct contained three statements on the instrument that allowed participants to assess their perception of performance gains due to technology (Venkatesh et al., 2012). Finally, I labeled the predictor PE.

EE was an ordinal predictor to study effort expectancy within cloud computing and NPO. Venkatesh et al. (2003) used EE to measure the ease of integration and use of a system. Additionally, this perception included how the IT manager perceived the effort involved in using and integrating cloud technology into an NPO. Furthermore, this construct contained four statements on the instrument that allows participants to assess their perceptions of the amount of effort that the technology requires (Venkatesh et al., 2012). Finally, I labeled the predictor EE.

SI was an ordinal predictor to study social influence/ Venkatesh et al. (2003) stated SI measured the perception of how colleagues influence the intention to adopt the technology. Additionally, this perception included how influenced the participant's colleagues are into integrating cloud technology into non-profits. Furthermore, the construct contained three statements on the instrument that focuses on how the social network around the participant influence the adoption (Venkatesh et al. 2012). Finally, I labeled the predictor SI.

FC was an ordinal predictor to study facilitating conditions. Venkatesh et al. (2003) described FC as providing a focus on how the user perceives the available support for the technology. Additionally, participants analyzed the current infrastructure of the NPO and determine if there is enough support to utilize cloud technology. Furthermore, the instrument contains four statements about support for technology (Venkatesh et al. 2012). Finally, I labeled the predictor FC.

PV was an ordinal predictor to study price value. Venkatesh et al. (2012) described PV as providing a focus on how the user perceives the cost and value of the technology. Additionally, participants evaluated the current cost of cloud technology and evaluated if the technology will deliver the value. Furthermore, the instrument contains three statements about price value of technology (Venkatesh et al. 2012). Finally, I labeled the predictor as PV.

HM was an ordinal predictor to study hedonic motivation. Venkatesh et al. (2012) used HM to provide a focus on how enjoyable the technology. Additionally, the participant evaluated their perception of how enjoyable cloud technology is versus other technology. Furthermore, the instrument came with three statements related measuring user enjoyment of the technology (Venkatesh et al. 2012). Finally, I labeled this predictor as HM.

H was an ordinal predictor to study habit. Venkatesh et al. (2012) used H to measure the habitual tendencies that consumers use to make decisions toward adopting the technology. For example, the participant noted their perception how often they would use the cloud technology. As noted in changes, I dropped one of the three statements from the survey. Finally, I labeled the predictor as H.

The dependent variable is what the predictor attempts to change (Aldrich, 2015), which Venkatesh et al. (2012) used PE. PE, EE, SI, FC, PV, HM, and H as predictors for UTAUT2. Therefore, BI was a dependent variable. Additionally, the above constructs, as well as BI, influence the use behavior (Venkatesh et al. 2012). Finally, this factor made UB a dependent variable.

BI was an ordinal dependent variable to study behavior intention. Venkatesh et al. (2003) used BI to measure users' intention to adopt the technology. For example, the participants stated whether they would use cloud computing within a specified period. Additionally, there are three statements within the instrument related to this construct (Venkatesh et al., 2003). Finally, I labeled the dependent variable as BI.

UB was an ordinal dependent variable to study use behavior. The construct of UB provides a measurement of the frequency that participants will commonly use technology in their everyday activities (Venkatesh et al., 2003). For example, the participant noted how often they use IaaS, PaaS, or SaaS in their daily lives. Therefore, I noted the dependent variable as UB to the measure the frequency of the three main cloud models.

Gender, age, and experience were moderators that tied into the constructs, which I used to create an inferential report. For example, Venkatesh et al. (2003) made a statement about how an older user might have a different opinion on technology than younger users. First, I used gender as dichotomous nominal variables to distinguish the frequency between male or female participants, which Assari, Lankarani, and Burgard (2016) stated that dichotomous nominals are appropriate categorical variables for only two categories. Additionally, I used a four-item ordinal categorical variable to collect data on different age and experience ranges, which Van der Palm, Van der Ark, and Vermunt (2016) noted that ordinal variables are appropriate for ordering information without requiring a scale for mathematical calculations. Additionally, Iannario and

Piccolo (2015) noted stated that ordinal values do not have a significant difference between two values. Therefore, I used categorical, ordinal variables because the moderators do not require regression or linear plots.

I summated the scores for each construct to simplify the analysis. Gilboa, Jaffe, Vianelli, Pastore, and Herstein (2015) noted the use of summated scores in studies when there are multiple item-level measures per constructs. Therefore, the item-level scores are consolidated into a construct-level score to predict the influence between predictor and the dependent variable (Gilboa et al., 2015). For example, performance expectancy has three statements associated with the construct (Venkatesh et al., 2012). Furthermore, each Likert item has a scoring between 1 to 7 or 1 to 5, which I combined into a summated total. Finally, Table 5 helps explain the summated scoring matrix.

Table 5

Scoring Matrix for Summated Score

Construct	Min	Max
PE	3	21
EE	4	20
SI	3	15
FC	4	20
HM	3	15
PV	3	15
H	2	10
BI	3	15
UB	3	21

Note. PE = performance expectancy, EE = effort expectancy, SI = social influence, FC = facilitating conditions, HM = hedonic motivation, PV = price value, H = habit, BI = behavioral intention, and UB = use behavior

The summated score of the Likert scale helps determine the influence of the predictors and dependent variables (Jaisridhar, Sankhala, & Sangeetha, 2014). For example, a summated score of 15 for PE would likely equal a slightly agree for the entire construct. Additionally, the discriminant validity of the statements allows the even scoring for the entire construct (Cicero et al., 2016; Venkatesh et al., 2012). Therefore, I used the data cleaning process to ensure that each summated value was valid.

I adapted the UTAUT2 survey from the UTAUT2 theory, which created an alignment with the theoretical framework to determine the perception towards adopting cloud technology. Particularly, Venkatesh et al. (2012) provided the instrument as part of the UTAUT2 theory, which Huang and Kao (2015) used to collect predictions on the acceptance of phablets with using a nominal measure with agreeing or disagree. While the measure type differed from those used for this study, the dichotomous nominal provided a demonstration of how agreement and disagreement answers applied to predictions. Additionally, Escobar-Rodriguez and Carvajal-Trujillo (2014) used the UTAUT2 instrument to measure the acceptance of low-cost airlines within a population of Spanish fliers. Furthermore, Tripathi and Jigeesh (2013) described cloud computing as a low-cost service in comparison to traditional infrastructure. Therefore, the application of the instrument was appropriate for this study with the context of the service. Additionally, Chauhan and Jaiswal (2016) used UTAUT instrument to determine the acceptance of ERP within Indian business schools. While UTAUT2 included hedonic motivation, price value, and habit (Venkatesh et al., 2012), the authors were still able to use the statements for the constructs to assess the acceptance of ERP (Chauhan & Jaiswal, 2016). Finally, these examples present evidence that the instrument was appropriate to measure the perceptions towards cloud computing.

First, I stored all raw data on SurveyMonkey as detailed in Ethical Research, which I will only release upon request from researchers after acknowledgment of confidentiality. More importantly, the legal tenets of 45 CFR 46 stated that information from the research should not jeopardize the individual (Health and Human Services, 2009). Despite de-identifying information, my duty is to ensure that I protect any information participants provide during the study.

Data Collection Technique

After IRB approval, I distributed the UTAUT2 survey to participants based on the sample range, which the initial maximum distribution was 765 or 153 * 5. Additionally, I hosted the survey on SurveyMonkey, which SurveyMonkey Inc. (2016c) described their service as an online platform to design surveys, collect data, and store raw data for analysis. Finally, I used my university email address as both contact and user account, which Walden University (2015c)'s IRB process required the contact information to be the university email address.

The primary reason for the online survey was a paper reduction, which Cole and Fieselman (2013) described as a social initiative to create sustainable supplies rather than wastes in the environment. Therefore, I cannot ethically condone a study that does not minimize the usage of paper. Additionally, online survey increases the convenience for the participants (Dykema, Jones, Piché, & Stevenson, 2013). SurveyMonkey can run on any device that has an Internet connection, which Dykema et al. (2013) stated that Internet functionality reduces the response time from sending invitations to complete surveys. Furthermore, SurveyMonkey provides an automated withdrawal function for exiting a study (SurveyMonkey Inc., 2016c), which Health and Human Service (2009) requires as part of the right to refuse and withdraw from a study. Above all, these advantages made SurveyMonkey distribution applicable for the study.

The primary disadvantage is coverage limitation, which could result in the lack of accurate email addresses (Dykema et al., 2013). Specifically, coverage limitations occur with surveys when certain parts of the population are inaccessible, which can create bias in the reporting (Eisele et al., 2013). For example, Greatnonprofits.org aggregates NPO information for locations around the United States (GreatNonProfits, 2016). While I did perform an additional Google search for any entries that were missing a website, there were NPO that did not have a web presence, electronic contact, or closure of the organization. Therefore, I used a sampling strategy that overcame the lack of access to specific areas to avoid bias.

The secondary disadvantage of web surveys is the low amount of responses (Dykema et al., 2013). For example, some cause for low response rates is biased questions and lengthy survey with boring questions (Orr, 2005). However, The instrument for UTAUT2 contains short statements for each construct that was pilot tested and adjusted to ensure a reasonable response rate (Venkatesh et al., 2012). Therefore, I concisely used the instrument to avoid the leading factor in low response rate, which includes placing each construct on a single page for a 12 question survey. Finally, I distributed 2514 invites, which returned 106 responses (4.22%).

I generated a web link collector on SurveyMonkey with parameters, which SurveyMonkey Inc. (2016e) created the option to create an anonymous access point to the survey via email or other document distribution. Additionally, a web link provides the convenience of distribution through e-mail or a web page (Dykema et al., 2013). Finally, I used this method to place a link at the bottom of the informed consent form for ease of use for the potential participants.

My key goal was to distribute an anonymous survey. For instance, the UTAUT2 survey instrument does not present many opportunities for collecting PII (Venkatesh et al., 2012). Additionally, I enabled anonymous response for the web link collector, which SurveyMonkey Inc. (n.d.) created to remove the IP from the raw data to anonymize the participants with a code number. However, the link provided to the potential participants does capture an IP address for SurveyMonkey's security records, but SurveyMonkey encrypts this information due to PCI-DSS 3.1 specification (SurveyMonkey Inc., 2016d). Furthermore, The three moderator variables were generalized not to specify the identity of any specific participant. Finally, SurveyMonkey does not release records to a third-party, which excludes a subpoena from a court of law (SurveyMonkey Inc., 2016c). However, the study did not include elements (e.g. recording illegal activities) for a subpoena to be necessary.

I ran the data collection phase for 13 weeks to collect 106 responses. While Dykema et al. (2013) stated online survey has a lower response time than mailing a survey, Eisele et al. (2013) stated that maximum response requires best practices within a particular population. Therefore, three weeks was adequate time between invitation and taking the survey, but best practices for the unsolicited survey with NPOs was unavailable to maximum the results. Therefore, I used the minimum sample of 106 after three weeks and sent additional invites to meet this requirement As discussed in the Population and Sampling subsection; this sample size was calculated using G*Power to obtain a reasonable sample size to gain information and limit Type I and Type II errors.

Data Analysis Technique

Upon the completion of data collection, I downloaded an SPSS-compatible file from SurveyMonkey and loaded it into SPSS v.23 for analysis. Additionally, all the variables stated in Instruments subsection transferred into the program to assist with analyzing the data. Therefore, this section is a transition from collecting data to deriving meaning from it.

Research Question

RQ1. What was the relationship between (a) PE (b) EE, (c) SI, (d) FC, (e) PV, (f) HM, (g) H, and (h) BI regarding NPOs' propensity to adopt cloud technology?

RQ2. What was the relationship between (a) FC, (b) H, (c) BI, and (d) UB regarding NPOs' propensity to adopt cloud technology?

Hypotheses

$H_0$1There is no relationship between (a) PE (b) EE, (c) SI, (d) FC, (e) PV, (f) HM, (g) H, and (h) BI regarding NPOs' propensity to adopt cloud technology.

H_a1There is a relationship between predictors of (a) PE (b) EE, (c) SI, (d) FC, (e) PV, (f) HM, (g) H, and (h) BI regarding NPOs' to adopt cloud technology**.**

$H_0$2There is no relationship between (a) FC, (b) H, (c) BI and (d) UB regarding NPOs' propensity to adopt cloud technology.

H_a2There is a relationship between predictors of (a) FC, (b) H, (c) BI, and (d) UB regarding NPOs' propensity to adopt cloud technology**.**

Missing Data

I checked for any missing data before the analysis because no response to a question could impair the ability to make an accurate inferential report. Furthermore, Osborne (2013) described missing completely at random (MCAR), missing at random data (MAR), or missing not at random (MNAR) as the forms of missing data that occurs in data collection. Additionally, missing data can create bias if it is systematic such as MNAR (Wolkowitz & Skorupski, 2013). Therefore, I need to discuss MCAR, MAR, and MNAR.

The first kind of missing data is MCAR. Osborne (2013) described MCAR as any missing data that is unrelated to the variables. Additionally, Wolkowitz and Skorupski (2013) supported this statement by noting that missing data occurs randomly across all observations. For example, researchers can survey a sample and retest a fraction of the sample, which would cause missing data since part of the sample was not retested (Osborne, 2013). Similarly, Wolkowitz and Skorupski (2013) used the example of a phone survey where a database application randomly selects a phone number. If the application does not dial a phone number at the end of the survey period, the data is missing that independent of the question (Wolkowitz & Skorupski, 2013). Therefore, participants may have read the invitation and chose not to participate in the survey, which created an absence of data.

Osborne (2013) stressed that a minimal sample needs to be maintained to ensure validity, which includes sending out a large number of invitations. For example, Pedron et al. (2016) provided an example of 210 responses from 2000 invites. Therefore, I sent out 2514 invites to meet the minimum sample range. However, MCAR would occur on the person-level, which data is missing from a participant (Newman, 2014). Finally, the purpose of reaching the sample number is to maintain validity levels (Fincannon et al., 2014). Therefore, I sent out invitations until I met a minimum of 106 responses.

MAR and MNAR referred to any missing answers from items or constructs on the survey. First, MAR occurs when data is randomly missing that is partially dependent on other observed data (Osborne, 2013), which Newman (2014) state that the dependency makes it likely that an item-level or construct-level missing data event occurred. Additionally, item-level missing data means a single question is missing an answer, while construct-level missing data would include all questions within a specific construct (Newman, 2014). For example, “I find mobile Internet useful in my daily life” is an item on the UTAUT2 instrument, which exists within the performance expectancy construct (Venkatesh et al., 2012, p. 178). Additionally, SurveyMonkey saves partial information if the participant leaves the survey after completing a page (SurveyMonkey Inc., 2016b), which Newman (2014) described partial survey contribute to both construct and item-level missing data (Newman, 2014). Therefore, the lack of systematic missing data means that deleting the participants or multiple imputations is viable (Wolkowitz & Skorupski, 2013). However, I had to choose the method of handling missing data carefully to maintain validity.

The purpose of deleting participants with partial information is to draw inference on observed data (Rosenkranz, 2015). However, the problem with deleting participants with missing data is that it requires an appropriate sample size to complete a statistically significant analysis (Wolkowitz & Skorupski, 2013). Therefore, I did not delete participants because MCAR might present a lack of participants for analysis.

Researchers use imputation to provide an estimate that would stand in as a value for the missing data. For instance, single imputation can use the mean of each participant to fill in for the answer, but this method can create a bias for both MCAR and MAR (Newman, 2014). Multiple imputations fill in the missing data multiple times to achieve an appropriate estimate for analysis (Wolkowitz & Skorupski, 2013), which Van Ginkel and Van der Ark (2014) stated that SPSS has the functionality to perform multiple imputations. Therefore, I used SPSS with five iterations to ensure the use of multiple imputations is accurate, which I aggregated into a single dataset.

MNAR. MNAR occurs when there are systematic missing data that depends on the missing data rather than observed responses (Newman, 2014). For instance, Osborne (2013) used an example about teachers went through a satisfaction intervention and likely not to fill out a survey if their satisfaction did not increase. Therefore, missing data might occur on the construct-level. For example, performance expectancy measures how a participant feels a technology improves their performance within an environment (Venkatesh et al., 2003). Therefore, a participant might not feel that performance expectancy applies to their use of technology and decide to skip the construct.

I used multiple imputations to resolve issues with MNAR. While Newman (2014) stated that Heckman's selection model is popular, the author also stated that the model uses assumptions that are not testable. Additionally, Heckman's selection model tends to have worse performance than multiple imputations (Newman, 2014). Furthermore, deleting either case-wise or list-wise could produce bias information, which is not ideal for any study (Osborne, 2013). Finally, Wolkowitz and Skorupski (2013) provided support that multiple imputations can work for MNAR, which will help fill in data points and reduce bias. Therefore, I used multiple imputations for both MAR and MNAR.

Summate and Recode

After ensuring complete data sets, I summated item-level data into a construct-level scoring. For instance, each item in the UTUAT2 survey reflects the constructs, which the construct predicts BI and UB (Venkatesh et al., 2012). Additionally, the purpose of the study was to understand the relationship between the constructs. Furthermore, summated scoring of each construct can provide a more meaningful analysis than separate Likert scale items (Jones, Gemeinhardt, Thompson, & Hamilton, 2016). Therefore, I summated each item-level Likert scale in the data set into a construct-level Likert scale to provide a meaningful evaluation of the dependent variables.

The steps I followed to accomplish the summation of Likert scale:

1. Open Data in SPSS
2. Go to Transform>Compute Variables.
3. Create a name for the new variable.
4. Select Sum from the Function groups.

5. Enter the question columns to summate.

6. Click Ok (Patel, 2013).

The summation of variables did present an issue with not presenting whole numbers, which did create an incomplete analysis. Therefore, Dedu (2014) stated that recoding variables help clean the data to make it viable for a clear understanding. While Jones et al. (2016) did not specify recoding variables, the authors did stress the necessity of ensuring the clarity of the survey scores. Venkatesh et al. (2012) also highlighted that clarity among the constructs and moderators were crucial to explain behavioral intention best and use behavior. Therefore, I recoded the data into different variables as described in Table 6.

Table 6

Scoring Recode for Summated Scores

Construct	Recode
PE and UB	1 to 3.5 = 1, 3.6 to 6.5 = 2, 6.6 to 9.5 = 3, 9.6 to 12.5 = 4 12.6 to 15.5 = 5, 15.6 to 18.5 = 6, 18.6 to 21 = 7
SI, HM, PV, and BI	1 to 3.5 = 1, 3.6 to 6.5 = 2, 6.6 to 9.5 = 3, 9.6 to 12.5 = 4 12.6 to 15.5 = 5
EE and FC	1 to 4.5 =1, 4.6 to 8.5 = 2, 8.6 to 12.5 = 3, 12.6 to 16.5 = 4, 16.6 to 20.5 = 5
H	1 to 2.5 = 1, 2.6 to 4.5 = 2, 4.6 to 6.5 = 3, 6.6 to 8.5 = 4, 8.6 to 10.5 = 5

Note. PE = performance expectancy, EE = effort expectancy, SI = social influence, FC = facilitating conditions, HM = hedonic motivation, PV = price value, H = habit, BI = behavioral intention, and UB = use behavior

Analysis Methods

I used multiple linear regression for analyzing the data. Hidalgo and Goodman (2013) described multiple linear regression as testing two or more predictors with one dependent variable. While Venkatesh et al. (2012) describe BI and UB as dependent variables, figure 3 shows that BI, FC, and H influence UB as predictors. Additionally, Aldrich (2015) described dependent variables as a variable that predictors influence, which means that BI is a predictor for the dependent variable UB. Therefore, I performed two standard multiple linear regression to account for BI and UB accurately.

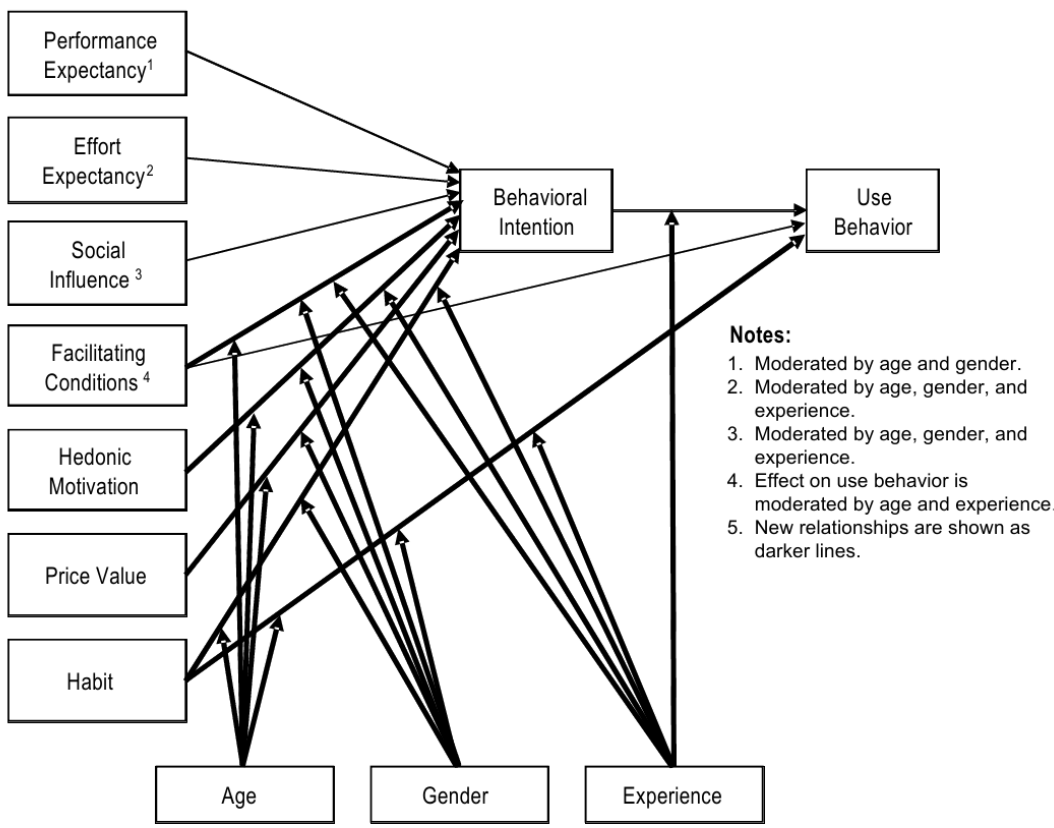

Figure 3. Explanation of Two Regressions for UTAUT2. Reprinted from "Consumer Acceptance And Use Of Information Technology: Extending The Unified Theory Of

Acceptance And Use Of Technology" by V. Venkatesh, J.L. Thong, and X. Xu. 2012, *MIS Quarterly, 36*, p. 160. Copyright 2012 Regents of University of Minnesota. Reprinted with permission (Appendix C).

There are multiple forms of regression analysis such as linear, logistic, and ordinal regression. First, Hazra and Gogtay (2016) described linear regression as an option when the predictors are continuous. Additionally, the predictors would exist on the x-axis, which the dependent variable would consist of the y-axis on a plot chart (Jantschi, Pruteanu, Cozma, & Bolboaca, 2015). Furthermore, the purpose is to use a best-fit line, which forms a straight line to describe a relationship based on a formula of $y = mx + c$, which x equals the predictor and y equals the dependent variable (Casson & Farmer, 2014). Finally, linear regression was appropriate because I was trying to determine the relationship between continuous numbers.

Another option was a logistic regression. Lapresa, Arana, Anguera, Perez-Castellanos, and Amatria (2016) described logistic regression as establishing the relationship with dichotomous dependent variables. While BI could use true or false for the statement "I intend to continue using mobile intent in the future.", Venkatesh et al. (2012, p. 178) also use statements that count how often participants use a different form of mobile Internet. As continuous variables associated with counting, linear relationships are a more appropriate option (Casson & Farmer, 2014). Therefore, this analysis was inappropriate for the study because the dependent variable requires more than two possible answers.

Ordinal regression was also a consideration. Feng, Wu, and Song (2015) described ordinal regression analyzes a relationship of predictors that order a sequence of answers. While Boari and Ruscone (2015) stated Likert scale could use an ordinal measure to rate a question positive, neutral, and negative, Foroughi et al. (2016) stated Likert scale could also support scale measures. As I am using scale measures rather than ordinal measures, ordinal regression was inappropriate for this study.

Multiple linear regression contains assumptions for operation, which includes linearity, outliers, multivariate normality, multicollinearity, autocorrelation, and homoscedasticity (Williams, Grajales, & Kurkiewicz, 2013). Additionally, the assumptions affect how researchers can infer about the results, which means a violation can create an incorrect inferential report (Williams et al., 2013). Therefore, I tested the assumption and resolved any violation with bootstrapping function in SPSS to correct the analysis.

The first assumption was a linear relationship, which means both predictors and dependent variables form a straight line (Jantschi et al., 2015). In this case, predictors are X, and dependent variables are Y on the plotline, which can show a straight line to demonstrate a positive, negative, or no relationship on a chart as shown in Figure 3 (Jantschi et al., 2015). A violation would be a lack of a straight line such as Figure 4 (Jantschi et al., 2015), which Hazra and Gogtay (2016) stated that a scatterplot is useful for regression because it plots all data with a fit line in a visual method to show the relationship. Therefore, I used a scatterplot with a fit-line to determine if the data was linear.

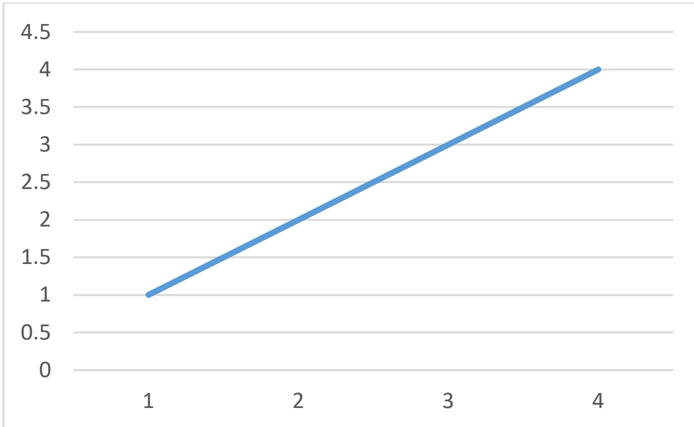

Figure 4. Example of a linear relationship (Jantschi et al., 2015).

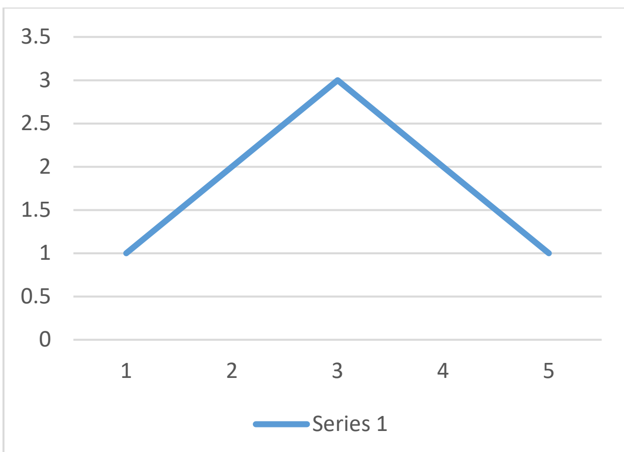

Figure 5. Example of linear relationship assumption violation (Jantschi et al., 2015).

The next assumption was outliers. Brereton (2015) stated that outliers could affect the standard error as well as the inferential analysis. Therefore, the Mahalanobis distance (MD) measures the variances of a multivariate dataset (Brereton, 2015), which IBM (2016) supplies the probability formula of 1-CDF.χ^2 (MD, *df*) to test for outlier existence (IBM, 2016). Additionally, Tabachnick and Fidell (2007) recommend using $p < .001$ to determine if outliers exist, which anything greater than .001 is not an outlier. Therefore, I used this formula on the dataset to discover outliers.

The third assumption was multivariate normality to assure random distribution with the variables to ensure accurate inference (Sheikhi & Tata, 2013). Furthermore, Marmolejo-Ramos and Gonzalez-Burgos (2013) used bell curves to test the probability of X on the positive and negative side of the X plotline, which uses the mean for the center as well as a variance for the width. Additionally, Kim, Shin, Ahn, and Heo (2015) used the coefficient of skewness to measure the distribution between -1 and +1, which serves as a statistical version of the bell curve. Furthermore, Käärik, Käärik, and Maadik (2016) stated +1 and -1 are the threshold for multivariate normality, which any exceeding coefficient will violate the assumption. Therefore, I ran a skewness coefficient to test this assumption.

The fourth assumption is multicollinearity, which Zainodin and Yap (2013) described as a high correlation between constructs within an instrument. Additionally, multicollinearity also mean that predictors are not independent of each other because of the high relationship between the predictors (Nimon & Oswald, 2013). Therefore, researchers might have a difficulty determining the level of relationship that each independent variable has with the dependent variable if each is related to each other (Sinan & Alkan, 2015). Therefore, I ensured that this assumption was not violated to gain viable insight into the variables.

The framework has multicollinearity as a consideration, which Venkatesh et al. (2003) and Venkatesh et al. (2012) performed discriminant validity tests to ensure that each construct is independent of each other. Therefore, I did not perform a pilot study to test multicollinearity. However, I tested the survey data using variance inflation factor (VIF), which Sinan and Alkan (2015) stated that VIF measures the increase in the variance of a regression coefficient related to its collinearity. Incidentally, a VIF greater than 10 indicates a problem with multicollinearity in a regression model (Sinan & Alkan, 2015). Therefore, I used VIF in collinearity diagnostics to measure if VIF ≤ 10 to indicate if the data sets met the multicollinearity assumption.

The fifth assumption relates to autocorrelation. Linnainmaa, Torous, and Yae (2016) explained autocorrelation as an occurrence when the correlation of values is dependent on another value, which violates the independence of the variable. For an example of autocorrelation, a change in PE might affect the change in EE. Consequently, the lack of independence defeats the purpose regression due to the difficulty of determining how each predictor independently affect the dependent variable. Therefore, I tested the assumption of autocorrelation with the Durbin-Watson statistic test, which Bercu, Portier, and Vazquez (2015) describe as testing a range between 0 to 4 for autocorrelation. Additionally, The critical values are 1.5 and 2.5, which is the acceptance range for no autocorrelation (Linnainmaa et al., 2016). Furthermore, any independent falling outside of this range indicates that autocorrelation exists (Dette, Munk, & Wagner, 2000). Therefore, I used the Durbin-Watson statistic test to test for autocorrelation

The last assumption is homoscedasticity, which Schützenmeister, Jensen, and Piepho (2012) described as the same variance occurring throughout the dependent variable. Additionally, the purpose is to test the relationship between the standardized residuals (error) and predicted values of the dependent variable, which homoscedasticity occurs when the variance on a plot is consistent rather than erratic (Schützenmeister et al., 2012). Furthermore, the Breusch-Pagan and Koenker test can determine heteroscedasticity in a dataset, which can turn into *p*-values for rejecting if heteroscedasticity exists within a dataset (Srivastava & Misra, 2015). Whereas if heteroscedasticity exists with a dataset, Schützenmeister et al. (2012) stated it violates the homoscedasticity assumption. Therefore, I used Breusch-Pagan and Koenker test to create *p*-values to determine if the dataset meets the assumption of homoscedasticity.

I handled any violations of the assumptions using Bootstrap in SPSS, which Montoya and Hayes (2016) explained that SPSS Bootstrapping enables the ability to increase accurate analysis despite assumption violation. While IBM (2010) did create functions to reduce skewness, there is a possibility that function could affect the other assumptions in a negative occurrence. However, Bootstrap provides an efficient way to overcome the violations by resampling the data and providing information through bootstrap factor analysis (Lu, Miao, & McKyer, 2014). Therefore, I used SPSS Bootstrap to handle the violation of homoscedasticity, which I will discuss further in the Presentation of Findings subsection.

Next, I analyzed the moderators as measures of central tendency rather than as predictors. Venkatesh et al. (2012) used age, gender, and experience to explain how PE, EE, SI, FC, HM, PV, and H interact with BI and UB, which provides a method for using descriptive statistics. Additionally, measures of central tendency provide mean, median, and mode to calculate summary statistics (Dos Santos et al., 2015). Therefore, I used mean for the moderators. Smothers, Sun, and Dayton (1999) described obtaining mean and standard deviation as a method to determine the average of scores and the variance between the scores. Third, median provides the middle value in a data set (Kestin, 2015). Therefore, I used mean to determine the l level of influence each moderator had based on the answers with the predictors. Finally, the median was not appropriate because I was not searching for a middle number.

I used confidence intervals (CI) to create an inferential report. First, sampling is done to represent a population, but there is always the chance that a different result may occur with a different sample (Eisele et al., 2013). Additionally, the purpose of CI is to provide a range of mean scores for an inferential report (Pritikin, Rappaport, & Neale, 2017). Therefore, I used CI to create a range to create an accurate inferential report in Section 3.

Validity

Type I error, also known as alpha or α, is the incorrect conclusion that a difference exists, which means an error in rejecting the null hypothesis. Additionally, the common acceptance for error is probability is less than .05, which means that anything less than .05 is an acceptable level to reject the null hypothesis (Smith, 2012). Therefore, I set the study parameters to a power of .95 and $\alpha = .05$. Additionally, these numbers mean that if probability value (*p*-value) >= α, the null hypothesis that there is no relationship between (a) PE (b) EE, (c) SI, (d) FC, (e) PV, (f) HM, (g) H, (h) BI, and (i) UB in terms of non-profit propensity to adopt cloud technology is rejected. Furthermore, Type I error can contribute to external validity, which are threats that hinder the ability to apply the results towards the population (Fincannon et al., 2014). Therefore, I will consider the type I error to maintain the external validity of the study. Finally, the incorrect rejection of a null hypothesis will imply the wrong generalization for the population (Kang, 2016). Therefore, any study needs to compare the *p*-value and α to avoid false positives (Rogerson & Kedron, 2016), which I used the comparison of *p* and α to test type I validity.

A variable sample size can lead to problems with Type I error because common power analysis takes into account of the α (García-Pérez, 2012). Additionally, if there is an optional stop of sample rating, there is an increased chance that the null hypothesis can incorrectly be rejected (García-Pérez, 2012). Therefore, the sample size for this study was discovered using multiple power analysis, which I found the sample range to be 106 to 153. Furthermore, the sampling method is important because it lessens the type I error, which is necessary to increasing external validity (Fincannon et al., 2014). Finally, a higher sample reduces the chance for a false positive to occur (Smith, 2012). Therefore, I used the range from the sampling calculations to reduce the amount of type I risks.

Type II errors occur when the statistics show there is an incorrect fail to reject the null hypothesis (Smith, 2012). Additionally, this error means that statistical analysis would reveal that there is no relationship between (a) PE (b) EE, (c) SI, (d) FC, (e) PV, (f) HM, (g) H, (h) BI, and (i) UB regarding NPO propensity to adopt cloud technology. However, a Type II error would reveal it as a false negative, which leads to incorrect conclusions (Evans & Glenn, 2015). Furthermore, a false negative can also lead to statistical conclusion errors, which threatens external validity of a study (García-Pérez, 2012). Therefore, I must lower the risk of type II errors within this study.

Similar to type I errors, sample sizes can affect type II errors. Sample size strongly influences type II errors, which means that a higher sample can limit the error (Smith, 2012). Therefore, the same step to reduce type I error is similar to reducing type II, which is ensuring an appropriate sample size (García-Pérez, 2012). Furthermore, I used the sample range of 106 to 153 to reduce the amount of type II errors. Additionally, the correct evaluation of α decreases the likelihood that a false negative, which is essential to external validity (Evans & Glenn, 2015). Therefore, I used the power of .95 and α of .05 to produce the sample and evaluate the *p*-value to reach a probable conclusion.

I can generalize the results to NPOs with significant accuracy. While each NPO may have different functions, there is a possibility that the groups do have common requirements with IT systems. However, there is also a possibility each group might differ enough to cause an external validity threat. For example, animal rescue group could present different answers than legal aid based on requirements for the groups. Additionally, the inability to generalize towards the population is an external validity issue (Fincannon et al., 2014). Therefore, I need to ensure that there is a good representation of groups within the sample.

I used a simple random sampling of a large selection of NPOs to reduce the risk. Incidentally, a simple random sampling provides an equal opportunity for participant selection (Leahy, 2013). While the instrument for UTAUT2 does not provide necessary demographics to determine the type of organization (Venkatesh et al., 2012), simple random sampling can select an adequate collection of disparate groups to generalize towards the population (Leahy, 2013). Finally, a good sampling method can lower external validity threats (Fincannon et al., 2014). Therefore, I used the sampling range to ensure that I can generalize the non-profit sample with other non-profit groups in the Phoenix metropolitan area.

Transition and Summary

Section Two restated the purpose statement, which provided a starting point to discuss the participants, population and sampling, and research methodology and design decisions for the study. Additionally, the section included ethical consideration, which is critical to abide by ethical practices and legal obligations as researchers. Furthermore, I provided a discussion on how UTAUT2 contributes to the setup of the mechanism for data collection. Finally, the discussion on validity focused on Type I errors that can cause a statistical conclusion error, which would invalidate the entire study. Therefore, the section provides a method that will decrease the occurrence of Type I errors from occurring.

Section Three will present analysis from the collected raw data. Additionally, the reporting will include multiple regression models as well as frequency tables to assist with an inferential report. Finally, the study will conclude with discussion the application to professional practice, the implication to social change, recommendation for action and future study, reflection, and a summary to conclude to doctoral study.

Section 3: Application to Professional Practice and Implications for Change

I used a correlational quantitative research method to analyze the relationships between the predictors of performance expectancy (PE), effort expectancy (EE), social influence (SI), facilitating conditions (FC), hedonic motivation (HM), price value (PV), and habit (H); and the dependent variables behavioral intention (BI) and use behavior (UB). I will present the findings of the multiple linear analysis and descriptive statistics in this section. The data from the online surveys administrated via SurveyMonkey provide the basis for the analysis.

Overview of Study

The purpose of this quantitative correlation study was to determine the relationship between predictors of PE, EE, SI, FC, PV, HM, H, and the dependent variables BI and UB regarding NPOs' propensity to adopt cloud technology. Tabachnick and Fidell's (2007) formula of $n = 50 + 8(m)$ was used to gain the minimum sample for a multiple regression, with $m = 7$ resulting in a sample size of 106. Additionally, I used G*Power to perform an F test with an effect size of .15, numbers of predictors = 7, and $\alpha = .05$; the software calculated a range between 103 and 153. To collect 106 responses, I sent 2,514 invitations to IT managers of NPOs in the Phoenix metropolitan area during a 13 week period. The response rate was 4.22%.

I performed a standard multiple linear regression analysis on the survey data. The model for BI show a statistically significant positive slope for predictors PE, SI, FC, and H, However, the model for UB only shows a statistically significant slope for H. The moderators for H present descriptive statistics that a total of 7.4% of female participants in the 18-50 year age group with 1 to 10 years of experience agreeing that habitual tendencies compel them to adopt cloud technology. However, only 6% of male participants in the same age group with 11 to 20+ years of experience made the same assessment.

Additionally, the moderators for PE show that 10.3% of male participants and 17% of female participants in 18-50 year age group agreed that cloud computing increases their job performance. However, the moderator for SI showed that 18% of female participants in the 18-50 years age group with 1 to 10 years of experience and 13% of male participants in the 18-50 years age group with 11-20+ years of experience neither disagreed or agreed that their colleagues compel them to adopt cloud computing. Finally, 8.9% of female participants in the 18-50 years age group with 1 to 10 years of experience agree that existing technology infrastructure contributes to the adoption of cloud computing, while only 13.3% of male participants in the 51-80 years age group with 11-20+ experience were in agreement.

Presentation of the Findings

This subsection includes an analysis of how I handled missing data and reliability to ensure an accurate analysis. Additionally, I will present information related to my assumptions, descriptive statistics of the sample, and inferential results from the multiple regressions analysis. Finally, I will tie the analysis into the literature review based on the theoretical framework because the quantitative analysis does not provide contextual information to relate to the topic discussion of the literature review.

Missing Data

Before performing testing and analysis, I checked the data for MAR and MNAR. Table 7 shows a summary of missing data, and Appendix E has the full SPSS output for the missing data analysis. Next, I corrected the missing data using multiple imputations, which allowed me to estimate the values which were not filled out on an item-level or construct-level by participants. Finally, the multiple imputation results were aggregated to perform reliability testing, assumption evaluation, and multiple linear regression.

Table 7

Statistics for Missing Data

Variables	Count	Percent
PE	4	3.8%
EE	20	18.9%
SI	17	16.0%
FC	24	22.6%
HM	19	17.9%
PV1	19	17.9%
H	13	12.2%
BI	20	18.9%
UB1	22	20.7%
Gender	7	6.6%
Age	7	6.6%
Experience	7	6.6%

Note. *N* = 106. PE = performance expectancy, EE = effort expectancy, SI = social influence, FC = facilitating conditions, HM = hedonic motivation, PV = price value, and H = habit. The aggregate count was based on missing data from each item.

Reliability

Due to minor changes I made with the UTAUT2 survey such as changing mobile Internet to cloud computing, I used Cronbach's alpha to perform a reliability test. Appendix H includes the item-total statistics for Cronbach's alpha. The Cronbach's alpha for this study was .966 (96.6%) for standardized items and .971 (97.1%) for standardized items based on 28 items, which Ain, Kaur, and Waheed (2016) declared .70 is the benchmark for Cronbach's alpha. I determined from the benchmark that the scores for the study are reliable for this study.

Assumptions

In the Data Analysis subsection of Section 2, I defined the tests of assumptions for multiple linear regression that were used to help ensure accuracy in my analysis. These tests included linearity, normality, multicollinearity, autocorrelation, and homoscedasticity. In the next section, I will examine each of these tests and present the findings.

Linearity. Figure 6 shows an overlay scatterplot with a fit line to test the linearity of each predictor and dependent variable. Each predictor and dependent variable form a straight line, which Jantschi et al. (2015) stated that a straight line on the graph indicates a linear relationship. Therefore, no violation occurred for the assumption of linearity.

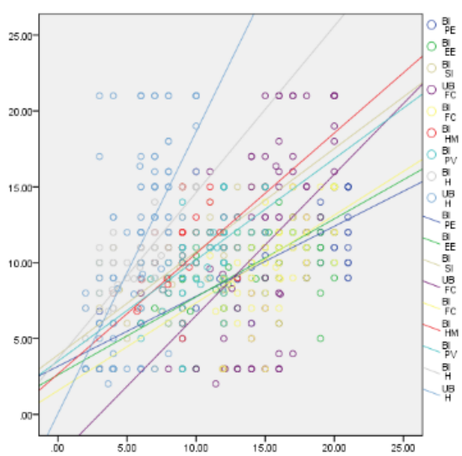

Figure 6. Linear assumption scatterplot of predictors and dependent variables.

Multivariate normality. I ran a skewness test, which I found the numbers of -.758 (PE), -.631 (EE), -.296 (SI), -.933 (FC), .025 (HM), .487 (PV), and .027 (H). Each number falls between the -1 and +1 thresholds, which Käärik et al. (2016) stated as the threshold for multivariate normality. The scores do skew on both the positive and negative, but it does not exceed the thresholds. Therefore, the multivariate assumption remains valid.

Multicollinearity. I used collinearity diagnostics to generate VIF scores, which help determine if multicollinearity exists. Table 8 displays the VIF scores for predictors affecting BI, and Table 9 displays the VIF scores for predictors affecting UB. All scores were below 10, which Sinan and Alkan (2015) state is the threshold for multicollinearity issues. Therefore, the multicollinearity assumption remains valid.

Table 8

Multicollinearity VIF Scores Based on BI as a Dependent Variable

Predictor	VIF
PE	4.0
EE	3.0
SI	1.7
FC	2.9
HM	2.2
PV	1.7
H	2.2

Note. *N*=106 PE = performance expectancy, EE = effort expectancy, SI = social influence, FC = facilitating conditions, HM = hedonic motivation, PV = price value, and H = habit.

Table 9

Multicollinearity VIF Scores based on UB as a Dependent Variable

Predictor	VIF
FC	2.2
H	2.2
BI	3.4

Note. N=106. FC = facilitating conditions, H = habit, and BI = behavioral intention.

No Outliers. I used the formula of $1 - CDF.\chi^2(MD, 7)$ to test for outliers, which I measured against the threshold of .001. Each participant exceeds the .001 threshold, which indicated that no outliers exists. Therefore, the outlier assumption was met.

Autocorrelation. I used the Durbin-Watson test to determine if autocorrelation exists within the dataset, which I used the values between 1.5 and 2.5 as thresholds. The score for BI was 2.316 and UB was 1.950, which remain in critical range. Therefore, the dataset aligns with the assumption.

Homoscedasticity. I used the Breusch-Pagan and Koenker test to analyze homoscedasticity, which the χ^2 significance of less than .05 indicates the existence of heteroscedasticity. Table 10 displays the scores and significance fall below .05. Therefore, heteroscedasticity exists and the homoscedasticity assumption is violated.

Table 10

Breusch-Pagan and Koenker Tests for Heteroscedasticity

DV	Breusch-Pagan	Koenker	Sig [Breusch-Pagan, Koenker]
BI	23.846	15.609	[.0012, .0289]
UB	23.846	15.609	[.0000,.0014]

Note. N=106. BI = behavioral intention, and UB = use behavior.

Bootstrapping. I used bootstrapping because heteroscedasticity will create an error in multivariate regression. I used SPSS bootstrapping functionality, which accounts for violations and minimizes the errors with 1000 samples. After accounting for the errors, I continued to the multivariate linear regression.

Descriptive Statistics

A total of 106 participants sent in surveys through SurveyMonkey. Instead of removing surveys with missing data, I used SPSS multiple imputations with five iterations to estimate answers for the missing data. Next, I used the data aggregate function of SPSS to consolidate the simulated data. Finally, I summated and recoded the item-level scores into construct-level scores to simplify the comparisons with the moderators such as age. Table 11 contains the values and standard deviation for predictors and dependent variables.

Table 11

Means and Standard Deviation for Quantitative Study Predictors and Dependent Variables

Variable	*M*	*SD*	Bootstrapped 95% CI(M)
PE	4.9623	1.92193	[4.5851,5.3113]
EE	3.6604	1.12873	[3.4623,3.8771]
SI	3.0189	1.04180	[2.8116,3.2075]
FC	3.8019	1.02743	[3.6226,3.9811]
HM	3.1132	.96925	[2.9340,3.3019]
PV	3.2830	1.02125	[3.0946,3.4623]
H	2.9434	1.10264	[2.7361,3.1509]
BI	3.4811	1.06217	[3.2736,3.6698]
UB	3.6886	2.15302	[3.2925,4.0849]

Note *N=106.* PE = performance expectancy, EE = effort expectancy, SI = social influence, FC = facilitating conditions, HM = hedonic motivation, PV = price value, H = habit, BI = behavioral intention, and UB = use behavior.

I also analyzed the moderators to create an inferential report. The total sample size was 106. The number of male participants was 45 (42.5%), while the number of female participants was 61 (57.5%). Additionally, the number of participants between the ages of 18 and 50 were 52 (49.1%), while the number of participants between the ages of 51 to 80 was 54 (50.9%). Finally, the number of participants with no experience was 16 (15.1%) participants had no experience, which contrasts the 44 (41.5%) participants with 1 to 10 years of experience and 46 (43.4%) participants with 11 to 20+ years of experience. The descriptive statistics will help create an inferential report in the next subsection.

I used the moderators to create descriptive statistics to help explain PE, SI, FC, and H, which I will discuss later in the inferential report. Age and gender influence PE within the UTAUT2 model (Venkatesh et al., 2012), which Table 12 shows the percentages grouped by gender and age. The statistics show that 10.3% of male participants between ages 18-50 agree that cloud computing increases their job performance, whereas 17% of female participants in the same age show a similar sentiment towards cloud improving job performance. Additionally, the age group 51-80 show 17.9% of male participants and 16% of female participants believe that cloud computing improves job performance. Finally, the prominent gender moderator was female (33%), while the prominent age group was 51-80 (33.9%).

Table 12

Percentage of Means for BI grouped by Gender and Age answering PE

Gender	Age	1	2	3	4	5	6	7
Male	18-50	.9%	.9%	.9%	2.8%	2.8%	2.8	4.7%
	51-80	1.9%	0%	0%	2.8%	4.7%	4.7%	8.5%
Female	18-50	1.9%	3.8%	0%	4.7%	2.8%	6.6%	8.5%
	51-80	4.7%	.9%	2.8%	4.7%	3.8%	7.5%	4.7%

Note: *N=106, Scale 1-7 = Strongly Disagree, Disagree, Slightly Disagree, Neither Disagree/Agree, Slightly Agree, Agree, Strongly Agree.*

Gender, experience, and age moderate the construct of SI, which Table 13 shows the *M* percentage for the moderators for participants answer for SI. The zero years of experience showed 1.5% of male participants from age 51-80 neither disagreed or agreed that SI compels them to adopt cloud technology, while 6.2% of female participants from both age groups state that SI compels them to consider cloud computing. Additionally, the 1 to 10 years of experience field shows 8.2% of male participants and 10.20 % of female participants in both age groups neither disagreeing or agreeing that SI compels them to consider cloud computing. Furthermore, the experience group 11-20+ show 7.3%

of male participants from 18-50 age group neither disagreeing or agreeing that SI compels them to adopt cloud technology, while 6.8% of female participants in the 51-80 age group agreed that social influence does compel them to adopt cloud technology. Finally, the prominent experience group was female participants with 1-10 years of experience in the 18-50 age group (18%), while the prominent male participant experience group was 11-20+ years in the both age groups (13% and 13%).

Table 13

Percentage of Means for BI grouped by Gender and Age answering SI

Gender	Experience (Years)	Age	1	2	3	4	5
Male	0	18-50	0%	0%	0%	0%	0%
		51-80	.6%	0%	1.5%	1%	0%
	1-10	18-50	0%	1.2%	6.4%	2%	0%
		51-80	0%	1.1%	1.8%	1.2%	1.4%
	11-20+	18-50	0%	0%	7.3%	4.3%	1.4%
		51-80	1.7%	2.8%	2.4%	5.3%	1.1%
Female	0	18-50	.3%	.6%	1.7%	.8%	0%
		51-80	.6%	.8%	2.3%	5.4%	0%
	1-10	18-50	0%	3.6%	8.2%	4.4%	1.4%
		51-80	0%	2.1%	2.0%	1.3%	1.1%
	11-20+	18-50	0%	0%	6.0%	5.5%	0%
		51-80	2.2%	.5%	3.4%	6.8%	1.4%

Note: *N=106, Scale 1-5 = Strongly Disagree, Disagree, Neither Disagree/Agree, Agree, Strongly Agree.*

Gender, experience, and age moderate the construct of FC (Venkatesh et al., 2012), which Table 14 shows the *M* percentages for the moderators of FC. The zero years of experience shows 2.5% of male participants from age 51-80 as well as 3.4% of female participants from the 51-80 age group, who neither agreed nor disagreed that facilitating condition affect the decision to adopt cloud technology. Additionally, the 1 to 10 years of experience field shows 4.6 % of male participants and 8.9% of female participants in the 18-50 age group agreeing that FC is an important consideration for adopting cloud computing. Furthermore, the experience group 11-20+ show 9.9% of male participants and 9.7% of female participants from the 51-80 age group agreeing that that facilitating condition is important for considering adopting cloud technology. Finally, the prominent experience group was female participants with 1-10 years of experience in the18-50 age group (18.6%), while the prominent male experience group was 11-20+ years in the 50-80 age group (13.3%).

Table 14

Percentage of Means for BI grouped by Gender, Experience, and Age answering FC

Gender	Experience (Years)	Age	1	2	3	4	5
Male	0	18-50	0%	.6%	0%	0%	0%
		51-80	.6%	0%	2.5%	0%	0%
	1-10	18-50	0%	.9%	1.5%	4.6%	2.9%
		51-80	0%	0%	0%	4%	1.4%
	11-20+	18-50	0%	0%	.9%	3.8%	8.4%
		51-80	0%	0%	0%	9.9%	3.4%
Female	0	18-50	.3%	0%	1.7%	1.3%	0%
		51-80	.3%	0%	3.4%	0%	0%
	1-10	18-50	0%	1.4%	3.4%	8.9%	4.9%
		51-80	0%	.6%	3.1%	2.7%	3.3%
	11-20+	18-50	0%	0%	.9%	2.5%	4.0%
		51-80	.3%	1%	.3 %	6.7%	4.7%

Note: *N=106, Scale 1-5 = Strongly Disagree, Disagree, Neither Disagree/Agree, Agree, Strongly Agree.*

Gender and age moderate the construct of H (Venkatesh et al., 2012), which Table 15 shows the *M* percentages for the moderators of H. The zero years of experience shows 1% of male participants from age 51-80 agreeing that habit compels them to adopt cloud technology, while 2.2% percent of female participants in the 18-50 age group disagreed that habit compels them to adopt cloud technology. Additionally, the 1 to 10 years of experience field shows 3.8% of male participants in 18-50 age group neither agreed or disagreed that H compels them to adopt cloud technology, while 7.4% of female participants in the 18-50 age group agreed that H compels them to adopt cloud technology. Furthermore, the experience group 11-20+ show 6.6% of male participants in the 51-80 age group disagree that H compels them to adopt cloud technology, while 5.4% of female participants in the 51-80 age group agree that habit compels them to adopt cloud technology. Finally, the prominent experience group was female participants with 1-10 years of experience in the 18-50 age group (19%), while the prominent male participant experience group was 11-20+ years in the both age group (13% and 13%).

Table 15

Percentage of Means for BI/UB grouped by Gender and Age answering H

Gender	Experience (Years)	Age	1	2	3	4	5
Male	0	18-50	0%	0%	0%	0%	0%
		51-80	.6%	.9%	.6%	1%	0%
	1-10	18-50	0%	1.8%	3.8%	2.5%	1.4%
		51-80	0%	1.8%	2.2%	0%	1.4%
	11-20+	18-50	0%	3.4%	.9%	6.0%	2.9%
		51-80	0%	6.6%	3.3%	3.4%	0%
Female	0	18-50	.3%	2.2%	.9%	0%	0%
		51-80	.6%	1.4%	1.7%	0%	0%
	1-10	18-50	0%	3.1%	6.7%	7.4%	1.4%
		51-80	0%	4.3%	1.1%	4.2%	0%
	11-20+	18-50	0%	0%	.9%	5.1%	1.4%
		51-80	1.7%	1.2%	3.2%	5.4%	1.4%

Note: *N=106, Scale 1-5 = Strongly Disagree, Disagree, Neither Disagree/Agree, Agree, Strongly Agree.*

Inferential Results

I used a standard multiple linear regression, α = .05 (two-tailed), to examine the effectiveness of PE, EE, SI, FC, HM, PV, and H in predicting the BI to adopt cloud technology. The predictors were PE, EE, SI, FC, HM, PV, and H. The dependent variable was BI. The null and alternative hypothesis was:

$H_0$1There is no relationship between (a) PE (b) EE, (c) SI, (d) FC, (e) PV, (f) HM, (g) H, and (h) BI regarding NPOs' propensity to adopt cloud technology.

H_a1There is a relationship between predictors of (a) PE (b) EE, (c) SI, (d) FC, (e) PV, (f) HM, (g) H, and (h) BI regarding NPOs' propensity to adopt cloud technology**.**

The first model could predict BI significantly, (F (7,99) =54.239, p=.000, R^2=.795 (Table 16), which the R^2 value indicates that the model could explain 79.5% of the total variability in behavioral intention. Additionally, Table 17 shows the first model with PE, SI, FC, and H being statistically significant. Further, H (t=3.624, $p < .000$) is the biggest contributor to the prediction, which was higher than PE (t=3.238, p < .002), SI (t=2.472, p < .015), and FC (t=3.129, $p < .002$). Finally, Table 19 shows the semi-partial coefficients for this analysis.

The final regression equation for BI is:

BI = .038 + (.163) PE - (.014) EE + (.151) SI + (.254) FC + (.104) HM + (.075) PV + (.236) H

I also used a second standard multiple linear regression, α=.05, to examine the effectiveness of FC, H, and BI in predicting the actual adoption of cloud computing within NPOs. The predictors were FC, H, and BI, which the dependent variable was UB. The null and alternative hypothesis was:

$H_0 2$ There is no relationship between (a) FC, (b) H, (c) BI and (d) UB regarding NPOs' propensity to adopt cloud technology.

$H_a 2$ There is a relationship between predictors of (a) FC, (b) H, (c) BI, and (d) UB regarding NPOs' propensity to adopt cloud technology**.**

The second model could significantly predict UB, *F (*3,103*)* = 37.845, p = .000, R^2 = .527 (Table 16), which the R^2 value indicated an explanation of 52.7% of the total variability in use behavior. Additionally, the regression analysis (Table 18) show H was statistically significant with H (*t* = 4.247, *p* < .000*)*. Finally, Table 20 shows the semi-partial coefficients for this analysis.

The final regression equation for UB is:

UB = -1.663 + (.348) FC + (.839) H + (.442) BI

Table 16

Model Summary for Dependent Variables BI and UB

Model	R	$\boldsymbol{R^2}$	Adjusted $\boldsymbol{R^2}$	Std. Error	F	*p*
1	.892	.795	.780	.49765	54.334	.000
2	.726	.527	.513	1.50274	37.845	.000

Note. *N*=106

Table 17

Regression Analysis Summary for Predictor Variables against BI

Predictor	*B*	*SE B*	*β*	*t*	*p*	*B 95% Bootstrap CI*
(Constant)	.038	.199		.174	.849	[-.359, .449]
PE	.163	.058	.295	3.219	.004	[.063, .264]
EE	-.014	.093	-.015	-.183	.855	[-.180, .175]
SI	.151	.07-	.148	2.492	.033	[.019, .298]
FC	.254	.096	.246	3.154	.007	[.053, .420]
HM	.104	.076	.095	1.367	.179	[-.032, .260]
PV	.075	.072	.068	1.226	.315	[-.061, .218]
H	.236	.064	.245	3.573	.002	[.102, .359]

Note. *N*=106 PE = performance expectancy, EE = effort expectancy, SI = social influence, FC = facilitating conditions, HM = hedonic motivation, PV = price value, and H = habit

Table 18

Regression Analysis Summary for Predictor Variables against UB

Predictor	*B*	*SE B*	*β*	*t*	*p*	*B 95% Bootstrap CI*
(Constant)	-1.663	.448		-2.865	.005	[-2.790, -.496]
FC	.348	.193	.166	1.657	.071	[-.051, .699]
H	.839	.208	.430	4.247	.001	[.424, 1.256]
BI	.442	.253	.218	1.723	.085	[-.015, 1.004]

Note. *N*=106 FC = facilitating conditions, H = habit, and BI = behavioral intention

Table 19

Semi-partial Coefficients for BI

Predictor	Semi-Partial Coefficients
PE	.147
EE	-.008
SI	.114
FC	.144
HM	.062
PV	.056
H	.163

Note: N=106 PE = performance expectancy, EE = effort expectancy, SI = social influence, FC = facilitating conditions, HM = hedonic motivation, PV = price value, and H = habit

Table 20

Semi-Partial Coefficient for UB

Predictor	Semi-Partial Coefficient
FC	.113
H	.289
BI	.117

Note: N=106. FC = facilitating conditions, H = habit, and BI = behavioral intention

PE shows a positive slope (.163) for BI, which indicates that PE positively affects BI. Additionally, the squared semi-partial coefficient (sr^2) was .147, which means that PE explains 14.7% of the variance for BI if EE, SI, FC, HM, PV, and H are controlled. The statistically significant correlation represents that a focal point for a future causal study on how PE affects BI for cloud computing.

SI shows a positive slope (.151) for BI, which means that SI positively affects BI. Additionally, the sr^2 = .114 means that SI can account for 11.4% of the variance for BI if PE, EE, FC, HM, PV, and H are controlled. Finally, this statistically significant correlation represents that a focal point for a future causal study on how SI affects BI for cloud computing.

FC shows a positive slope (.254) for BI, which means that FC positively affects BI. Additionally, the sr^2 = .144 means that FC can account for 14.4% of the variance for BI if PE, EE, SI, FC, HM, and PV are controlled. Finally, this statistically significant correlation represents a focal point for a future casual study on how FC affects BI for cloud computing.

H shows a positive slope (.236) for BI (.236) and UB (.843), which indicates that H positively affects BI and UB. Additionally, the sr^2 = .163 means that H can account for 16.3% of the variance for BI if PE, EE, SI, FC, HM, and PV are controlled. Furthermore, the semi-partial coefficient with UB was .289, which means that H explains 28.9% of the variance for UB if FC and BI are controlled. This statistically significant correlation represents that a focal point for a future causal study on how H affects BI and UB for cloud computing.

I used *ns* to remove any potential predictors that do not significantly affect the dependent variables. EE (p = .894), HM (p = .104), and PV (p = .075) exceeds α in the multiple linear regression of BI, which makes the predictors *ns.* Additionally, FC (p = .348) and BI (p = .442) exceed α, which makes the variables *ns* for UB. Finally, I will exclude these predictors in a future causal study for NPO adoption rate of cloud computing.

Analysis summary. The purpose of the quantitative correlational study was to determine the relationship between predictors of PE, EE, SI, FC, PV, HM, H, and the dependent variables BI and UB regarding NPOs' propensity to adopt cloud technology. The study was divided into two research questions and sets of hypotheses to work the UTAUT2 model, which I used standard multiple linear regression to analyze the relationships. Additionally, I evaluated the assumptions surrounding multiple regression, and only found a violation of homoscedasticity. Finally, I handled this violation by implementing bootstrapping with 1000 samples into the SPSS analysis.

The first model significantly predicted BI, (F (7,99) = 54.334, p=.000, R^2 = .795. Additionally, the findings in this study rejects the first null hypothesis showing that there is a relationship between predictors of (a) PE (b) EE, (c) SI, (d) FC, (e) PV, (f) HM, (g) H, and (h) BI regarding NPO propensity to adopt cloud technology**.** Finally, PE, SI, FC, and H could provide significant predictive information about BI. However, EE, FC, HM, and PV do not significantly predict BI with cloud computing adoption.

Age and gender moderate PE, which 33% of female participants in 51-80 age group found the construct useful in determining their intention to adopt cloud computing. Additionally, age, gender, and experience moderate SI, which shows that 8.2% of female participants with 1-10 years of experience in the 18-50 age group and 7.3% of male participants in the 18-50 age group with 11 to 20+ years of experience neither disagreed or agreed that SI compels them to adopt cloud computing. Furthermore, gender, experience, and age moderates FC, which shows that 8.9% of female participants in the 18-50 age group with 1-10 years of experience agreed that FC influences their adoption of cloud technology. However, 9.9 of male participants in 50-80 age group with 11-20+ years of experience agreed that FC influences their decision to adopt cloud technology.

Finally, gender, experience, and age moderate H, which shows that 7.4% of female participants in the 18-50 age group with 1-10 experience and 6% of male participants in the 18-50 age group with 11-20+ years of experience agreeing that H influences their decision to adopt cloud technology.

The second model could predict UB significantly, (*F (*3,103*)* = 37.845*, p* = .000, R^2 = .527. Additionally, the finding of this study help rejects the second null hypothesis due to a relationship existing between predictors of (a) FC, (b) H, (c) BI, and (d) UB regarding NPOs' propensity to adopt cloud technology**.** Furthermore, H could provide predictive information about BI. However, FC and BI were *ns* in predicting predicting UB in cloud computing adoption.

The moderators for H show that 7.4% of female participants in the 18-50 age group with 1-10 experience agreed that H influences their decision to adopt cloud technology. However, only 6% of male participants in the 18-50 age group with 1-10+ years of experience agreed that H influences their decision to adopt cloud technology. Furthermore, I will discuss H further in the Further Research subsection.

Theoretical Framework

Both models from the data analysis demonstrated that UTAUT2 statistically significantly predicted BI and UB for the NPOs' propensity to adopt cloud computing technology. Additionally, the first model showed that H was the most statistically significant predictor (p = .001), while H was the only statistically significant predictor for UB. Furthermore, both PE and FC showed a statistical significance with BI with *p*-values at .002, while SI had a lower statistical significance for BI with a *p*-value of .014. Finally, EE, HM, and PV were *ns* for BI, while BI and FC were *ns* for UB.

BI being *ns* in a regression with UB was important because Hamoodi (2016) indicated that intention to adopt did not always equate to actual adoption of technology. Additionally, De Moura, De Sevilha Gosling, Christino, and Macedo (2017) reported that BI was not a significant factor in UB with using technology to choose a tourism destination. However, Alalwan, Dwivedi, and Rana (2017) found that BI was statistically significant in predicting UB for a mobile banking solution. Therefore, the usage of technology is dependent on the usage platform.

The statistical significance of H in both BI and UB help determine how influential habitual tendencies was in this study. The influence of habitual tendencies in both BI and UB was the purpose for H inclusion into UTAUT2 (Venkatesh et al., 2012). Additionally, Huang and Kao (2015) stated that consumers might automatically purchase an item based on habit, which Yen and Wu (2016) tied into explaining the UTAUT2 framework and directly linking habit to adopting new technology. Furthermore, De Moura et al. (2017) confirmed that habit positively influences both BI and UB. Finally, these statements support the data showing a statistically significant influence that habit has with cloud computing within the NPO community.

I used PE to demonstrate the perception that NPO IT managers have towards cloud computing. The statistically significant predictor reflects a positive relationship towards adopting cloud computing regarding job performance. Additionally, Herrero, San Martín, and Del Mar Garcia-De Los Salmones (2017) found that social networks improved the job performance of the participants, which delivers content from distributed servers to users. Furthermore, Mell & Grance (2011) declared the description of cloud computing as a remote collection of servers delivering content to remote users, which Herrero et al. (2017) stated that social networking performs this task function. Finally, De Moura et al. (2017) found similar results in a study using PE with BI. Therefore, the results of PE in this study aligns with literature related to the framework.

FC was statistically significant for BI, but *ns* for UB. Venkatesh et al. (2003) created FC to measure how participants felt about the supporting resources for the technology. Additionally, Attuquayefio and Addo (2014) found a significant grouping of participants in the 20-30 age range with their first degree wanted infrastructure to support new technology, but Magsamen-Conrad et al. (2015) found the support that age difference had a different impact on the perception of facilitating conditions. Finally, Alotaibi (2016) noted that facilitating conditions improves the adoption of technology such as SaaS.

While 8.9% of the female participants for FC were between 18 to 50 and had 1 to 10 years of experience for agreed, the FC answers changed with 9.9% of males in the 50-80 age group with 11 to 20+ years of experience. Additionally, the different age groups and experience groups confirmed that those two moderators could shift based on cultures, which Dajani and Yaseen (2016) warned could occur with the instrument. Finally, FC was useful in predicting BI for adoption. Therefore, the data conforms to the theory's construct.

EE, HM, and PV were *ns* for predicting BI, but do yield useful information. Table 21 presents total percentages for the remainder of the constructs for the discussion on theory. Additionally, EE and PV show a high percentage of agreed, but HM remains within the neither disagrees or agree range. Therefore, the numbers are viable for discussing how the study still aligns with the theory.

Table 21

Total Percentage for Remaining Predictors

Construct	Strongly Disagree	Disagree	Neither	Agree	Strongly Agree
EE	1.40%	10.10%	17.00%	39.00%	32.10%
PV	3.70%	11.10%	29.60%	44.30%	11.20%
HM	1.70%	11.90%	50.40%	23.90%	12.10%

Note: *N=106* EE = effort expectancy, PV = price value, and HM = hedonic motivation.

Seventy-one percent of the participants agreed that EE is an important factor towards the intention to adopt cloud technology. Šumak et al. (2016) suggested that too much complexity will deter users from adopting the technology, which Wu et al. (2014) supported by stating perceived ease of use positively affect adoption of technology. Additionally, Venkatesh et al. (2012) created the statements on the instrument for users to declare whether they found a particular technology easy to use. Additionally, Venkatesh et al. (2003) created the construct as an influential predictor of behavioral intention. Therefore, the number of agreements aligned with the theory.

PV was an important factor towards an intention to adopt cloud technology for 55.5% of the participants. Venkatesh et al. (2012) described PV as how the consumer evaluates the perception of quality versus the actual quality of the product. Therefore, this factor can equate to cost efficiency, which Puri and Yadav (2016) stated was the minimum purchasing cost compared to the perceived cost of the system. Additionally, Dhulla and Mathur (2014) and Nyugen, Nyugen, and Pham (2014) both support that PV is influential in determining behavioral intention. Although PV was *ns*, the majority being in agreements does stress the importance participants placed on PV, which aligns with the theory.

Of the participants, 50.4% neither disagreed or agreed that HM influenced their behavioral intention. HM focuses on pleasure derived from the use of technology rather than a focus on utilitarian functions (Venkatesh et al., 2012). However, Parker and Wang (2016) stated that consumers tend to purchase products based on utilitarian value versus hedonic motivation, which Yim et al. (2014) defined the former as a task-oriented technology that serves a purpose rather than pleasurable indulgences. Despite the evidence, HM can positively influence the adoption of cloud technology (Dhulla & Mathur, 2014; Nguyen et al., 2014; Nguyen, Nguyen, & Cao 2014). For example, the remainder of the sample found 36% in agreement and 13.6% in disagreement that hedonic motivation influences the behavioral intention construct. Although the majority were ambivalent, the 36% does conform with the theory and statements about the positive influence of hedonic motivation versus utilitarian usage.

Applications to Professional Practice

I aimed at examining the relationship between the predictors PE, EE, SI, FC, HM, PV, H and the dependent variables BI and UB regarding the NPO propensity to adopt cloud technology. Additionally, the focal points of the analysis were cost efficiency and integration, which I used the literature review to tie the concepts to the impact on NPOs. Therefore, the discussion of these two items in professional practice is crucial.

Cost Efficiency

Cost efficiency was a concept tied to PV, which Venkatesh et al. (2012) reflect on cost efficiency in adopting the technology. Regarding NPOs, Crump and Peter (2013) and McDonald et al. (2015) stated that economic conditions and competition for funding set the requirement for cost efficiency at NPOs. Although PV was *ns*, there was an abundance of participants agreeing that cloud computing is reasonably priced and a good value for the money as an influence towards adoption. Therefore, IT managers for NPOs that do not use cloud-based products should evaluate their infrastructure to see if it is performing all the necessary services such as communications and databases with a cost efficiency compared to cloud providers. Finally, IT Managers will be able to create strategies for evaluating and selecting the services to switch to cloud-based services based on an infrastructure review to address funding challenges.

The evaluation of existing knowledge and resources may make adoption of cloud computing more cost-efficient, which makes the statistical significance of FC in BI important. First, this factor means that IT managers at NPOs should evaluate their current infrastructure and knowledge before intending to adopt cloud technology. Accordingly, the infrastructure review should include legacy systems or other hindrances that might require replacements or updating, which would increase the cost to implement cloud computing. Additionally, a careful review might be required to ensure that cost efficiency not reduced by too many legacy systems. Therefore, the significant relationship of FC may allow IT managers to create strategies for replacing appropriate systems with cloud-based services based on current infrastructure and knowledge. Finally, the additional focus should also include what colleagues recommend.

The evaluation of the IT manager's professional social network may also influence the intent to adopt systems, which I used SI to measure how colleagues factor into adopting the technology. Additionally, the IT manager's professional social network might include friends, colleagues at another NPO, or colleagues at for-profit organizations. Then, colleagues at a similar type of NPO might recommend similar systems that increased production and lower costs for the organization. Furthermore, SI was significant in predicting BI, which means the IT manager should create a strategy to evaluate the professional social network to decide to implement any cloud technology based on the needs of their NPO. Finally, the IT manager should also evaluate the recommendations with cost efficiency, which functions based on their home NPO's budget.

The ideal strategy is to consider PV, FC, and SI into the decision of adopting the technology. While only FC and SI were statistically significant, the IT managers would make an error if they did not consider PV as well. Therefore, the strategy to create a cost-efficient replacement of traditional infrastructure to cloud-based system relies on those predictors. However, cost efficiency is only one factor that an IT manager needs to consider. The IT manager still needs to integrate the systems.

Integration

Integrating current infrastructure with cloud-based systems require a strategy to gain any benefits. One critical element is performance expectancy, which the IT manager needs to ensure the cloud system improves the performance of the staff who use the systems. Additionally, there is a need to ensure the integration also meets the performance expectations, which includes eliminating misconfiguration or lack of appropriate systems to handle cloud-based output on end-user systems. Therefore, the IT manager needs to create a strategy to ensure that the integration does not decrease any possible performance enhancements that cloud-based systems may promise. However, IT managers also need to consider the habit of IT staffing and users.

IT managers may use a system because there is a trained habit, which influences the behavioral intention and actual use of a system. If an NPO IT manager changes the system and it becomes unfamiliar to the users, there is a chance that the system will not integrate with the end-users. Therefore, the IT manager should create a strategy to manage the integration based on the familiarity of both the NPO IT staff as well as the end users. Ultimately, the strategy would include the introduction of systems that are like current systems as well as introductory training into the new cloud-based system. Finally, the strategy is important for the acceptance of the integration, which includes the utilitarian function of the system.

Although HM was *ns* and 50.4% of participants neither disagree nor agree that HM was a contributing factor, there is potential evidence that utilitarian is a consideration. While the results for cloud-based systems may differ outside of a non-profit organization, the statistics show that most IT managers do not consider the user's enjoyment of cloud-based systems over functionality. Therefore, IT managers should focus the integration of cloud-based systems into the organization based on the function it needs to serve. For example, health organizations should focus on integrating electronic health care systems based on serving the needs of the patients and allowing the providers to increase their ability to provide the service. Finally, the creation of a strategy to enable utilitarian cloud-based services may improve the integration of cloud-based systems as well as help increase the adoption rate of cloud services.

Implications for Social Change

The implication for positive social change is that strategies to consolidate and transition services to cloud provider data centers may reduce the carbon footprint of the organization. Ai et al. (2016) explained that cloud computing providers consolidate and share resources with clients so that services are used only when needed. Therefore, this factor may help an NPO reduce its energy use by sending servers to a data center which reduces local fossil fuel emissions. Additionally, current development studies and strategies are focused on how to increase the energy efficiency of cloud data centers without a significant decrease in performance (Singh & Chana, 2016). Therefore, the consolidation of services to data centers may decrease localized carbon emission while strategies to improve energy efficiency at data centers may decrease global carbon emissions. In conclusion, this impact may allow all NPOs to operate in an environmentally sound manner while efficiently delivering services.

The additional benefit may be that NPOs can increase the performance of systems and increase the benefit to the population who need their services. For example, clients of veterans' organizations may require medical and social aid to function in society. Additionally, Rodin et al. (2017) reported an increase in veterans with combat-induced PTSD from serving in Iraq and Afghanistan that require treatment to maintain functionality. However, the usage of cloud-based services may help provide additional services for all veterans with PTSD and other difficulties through optimized communication and information delivery, which can also extend to a various organization serving public needs. Therefore, the social change enhanced by transitioning to cloud-based technologies may positively affect the well-being of people, animals, and environmental causes supported by NPOs by optimizing the mass delivery of information.

Recommendations for Action

I used the UTUAT2 model to determine if PE, EE, SI, FC, HM, PV, and H could predict the intention and actual adoption of cloud technology in NPOs. Therefore, this study serves as a correlation analysis that benefits IT managers within NPOs to show the factors that affect NPOs, which may differ from published factors that affect for-profit organizations. First, I will send the statistical results via https://danahaywood.wixsite.com/doctoralstudy to invited participants for public dissemination of the results. Additionally, I will publish a concise version of the study to a relevant journal for consumption of NPOs, which include will include a discussion and recommendation for action.

My recommended actions include producing strategies to maximize the integration and cost efficiency of installing cloud computing services based on the perceptions of the participants. Additionally, the actions include analyzing the habits of the end users and designing a system that end users will not reject due to unfamiliarity by strategically analyzing the resources and knowledge available to implement the cloud-based technology successfully. Therefore, the recommended actions may help the organizations benefit those who depend on their services, which strengthens the positive social impact of the study.

Recommendations for Further Study

There were limitations as stated in Assumptions, Limitation, and Delimiters sub-section in section one. First, Quick and Hall (2015) stated that quantitative methods do not provide contextual information for empirical data. Furthermore, PE, FC, SI and H require contextual information on how it affects intention to adopt, which will also include how H affect use behavior. For example, I could state that FC is statistically significant and that 8.9% of the female participants in this 18-50 age group with one to ten years of experience agree FC is important for adopting cloud technology, but there is not any statement as to why. Furthermore, the high percentage of males and females in the 18-50 demographic between 11 to 20+ years are ambivalent to SI impact on adopting cloud technology require a contextual explanation. Finally, the high variance of habit for both BI and UB require exploration. Therefore, the next step in studying cloud computing in NPOs would be a qualitative case study to deliver contextual information or strategies about the statistical information, which Akers and Amos (2017) stated that case studies could provide detailed contextual information.

The first limitation also leads to the limitation of correlation studies, which Rogerson P.A. (2001) stated that the design does not lead to causation. Additionally, the lack of causation may fail to generalize the information for a larger population (Fincannon et al. 2014). For example, the population will include NPO globally located, which could benefit learning how cloud computing may improve their services. Therefore, the next phase after multiple case studies would be an experimental study, which Lazaro et al. (2016) noted the design uses to test and controls groups to determine cause and effect of phenomena. Then, a control group would continue to use their current infrastructure, while the testing group would employ an intervention based on the case studies, which could help determine if strategies improve adoption amongst the population. Finally, the results from the experimental study would continue to evolve NPO's adopting cloud computing research.

Reflections

The focus on NPO stems from involvement with an animal rescue group that included continuous reports of medical expenses between $2,000 to $4,000. While the organization held fundraisers, other animal rescue groups in the Phoenix metropolitan area also competed for funding, which led to analyzing data of predictors that tie into cost efficiency. Additionally, IT effectiveness in integration was exploration based on reflections of the animal rescue group as well as findings in the literature review. Each concept relates to predictors within the UTAUT2 framework, which I used to reduce bias by analyzing different NPOs empirically.

My knowledge of cloud computing before the doctoral study was academic. First, my BSIT and MSIT provided textbook knowledge of cloud computing. Additionally, the literature review on NPO, cloud computing, and UTAUT2 helped the transition towards an applied scientific understanding. Furthermore, the data collection also provided a glimpse of what NPO use in the cloud-based systems and how integrated those systems are currently. While I might have had a bias based on the animal rescue organization and textbook understanding, the doctoral study had to change my opinions with scientifically supported data.

My effect on participants was minimal due to the anonymous survey. However, there were a few that replied and wanted to me to know that they want my study to succeed. Therefore, I am under the impression that there are NPOs want to know what influences adoption of cloud computing as well as future transitional strategies. In conclusion, this doctoral study has expanded my mindset to future possibilities and hopefully more than a few participants as well.

Summary and Study Conclusions

Despite the analysis showing that EE, HM, and PV were *ns* for BI and FC and BI was *ns* for UB, the UTAUT2 model did help confirm some predictors influence the behavioral intention and use behavior of cloud computing within NPO. Additionally, these are predictors that NPO IT manager should focus on when trying to effectively integrate the cloud-based system into their organization with cost efficiency also in mind.

Furthermore, cost-efficiency and integration can help improve NPO operational capacity, which will better serve those in need that a group services. Finally, the transition from traditional infrastructure to the cloud-based system may help the NPO become environmentally friendly by lowering the local carbon footprint.

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Appendix A: Certification of National Institute of Health Training Completion

Certificate of Completion

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

Date of completion: 11/02/2015

Certification Number: 1906332

Appendix B: UTAUT2 Survey Instrument

On my instrument, I included survey questions from Venkatesh et al.'s (2012) UTAUT2 instrument. Copyright © 2012, Regents of the University of Minnesota. Used with permission.

1. Welcome to the Study.

Thank you for agree to participate in this study. As mentioned in the informed consent, this survey is stored securely at SurveyMonkey and you can withdraw at any time by clicking on the Exit button in the upper right-hand corner. The survey should take no more than 30 minutes and the majority is setup with a rating system from strongly disagree to strongly agree.

2. Performance Expectancy

This section will ask you how you feel cloud computing would enhance your performance within your organization.

* 1. Performance Expectancy of Cloud Computing.

	Strongly Disagree	Disagree	Slightly Disagree	Neither Disagree or Agree	Slightly Agree	Agree	Strongly Agree
I find cloud computing useful in my daily life.	○	○	○	○	○	○	○
Using cloud computing helps me accomplish things more quickly.	○	○	○	○	○	○	○
Using cloud computing increases my productivity.	○	○	○	○	○	○	○

3. Effort Expectancy

These questions reflect on the amount of effort it would take to integrate cloud computing into the organization.

* 2. Effort Expectancy of Cloud Computing.

	Strongly Disagree	Disagree	Neither Disagree or Agree	Agree	Strongly Agree
Learning how to use cloud computing is easy for me.	◯	◯	◯	◯	◯
My interaction with cloud computing is clear and understandable.	◯	◯	◯	◯	◯
I find cloud computing easy to use.	◯	◯	◯	◯	◯
It is easy to me to become skillful at using cloud computing.	◯	◯	◯	◯	◯

4. Social Influence

These questions reflect how your colleagues influence your opinion on cloud computing.

* 3. Social Influence of Cloud Computing

	Strongly Disagree	Disagree	Neither Disagree or Agree	Agree	Strongly Disagree
People who are important to me think that I should use cloud computing.	◯	◯	◯	◯	◯
People who influence my behavior think I should use cloud computing.	◯	◯	◯	◯	◯
People whose opinions that I value prefer that I use cloud computing.	◯	◯	◯	◯	◯

5. Facilitating Conditions

These questions reflection on how much support you feel is available for cloud computing within your organization.

* 4. Facilitating Conditions of Cloud Computing

	Strongly Disagree	Disagree	Neither Disagree or Agree	Agree	Strongly Agree
I have the resources necessary to use cloud computing.	○	○	○	○	○
I have the knowledge necessary to use cloud computing.	○	○	○	○	○
Cloud computing is compatible with other technologies I use.	○	○	○	○	○
I can get help from others when I have difficulties using cloud computing.	○	○	○	○	○

6. Pleasant Experience

These questions are about your perception on how enjoyable cloud computing is.

* 5. Pleasant Experience of Cloud Computing.

	Strongly Disagree	Disagree	Neither Agree or Disagree	Agree	Strongly Disagree
Using cloud computing is fun.	○	○	○	○	○
Using cloud computing is enjoyable.	○	○	○	○	○
Using cloud computing is entertaining.	○	○	○	○	○

7. Price Value

These questions are to gauge your opinion on how cloud computing is priced vs. its overall value.

* 6. Price Value of Cloud Computing

	Strongly Disagree	Disagree	Neither Disagree or Agree	Agree	Strongly Agree
Cloud computing is reasonable priced.	○	○	○	○	○
Cloud computing is a good value for the money.	○	○	○	○	○
At the current price, cloud computing provides a good value.	○	○	○	○	○

8. Habitual Tendencies

These statements reflect about your habitual tendencies to use cloud technologies vs. other similar or diverse technologies.

* 7. Habitual Tendencies of Cloud Computing.

	Strongly Disagree	Disagree	Neither Disagree or Agree	Agree	Strongly Agree
The use of cloud computing has become a habit for me.	○	○	○	○	○
I must use cloud computing.	○	○	○	○	○

9. Behavioral Intention

These questions measure how you will use cloud computing in the future.

* 8. Behavioral Intentions of Cloud Computing.

	Strongly Disagree	Disagree	Neither Disagree or Agree	Agree	Strongly Agree
I intend to continue using cloud computing in the future.	○	○	○	○	○
I will always try to use cloud computing in my daily life.	○	○	○	○	○
I plan to continue to use cloud computing frequently.	○	○	○	○	○

10. Actual Use

These frequency measure how often you cloud computing.

* 9. How often do you use cloud computing services?

	Never	Once a Year	Once a Month	Once a Week	Once a Day	Once a Hour	Always
Software as a Service	◯	◯	◯	◯	◯	◯	◯
Infrastructure as a Service	◯	◯	◯	◯	◯	◯	◯
Platform as a Service	◯	◯	◯	◯	◯	◯	◯

11. Demographics

These are demographic information that will help understand the previous questions from an analysis standpoint. It will not be used to obtain personally identifiable information and will be securely stored to avoid disclosure.

* 10. Gender

◯ Male ◯ Female

* 11. Age

◯ 18-30 ◯ 40-50 ◯ 50-60 ◯ 70-80

* 12. Experience Level

◯ No Experience ◯ 1-5 years ◯ 6-10 years ◯ 10-15 years ◯ 15-20+ years

12. Thank You for your time.

The survey is concluded, and there is nothing more you need to do regarding this study. Your participation is greatly appreciated. All raw data shall be stored on SurveyMonkey for five years, which is the policy of Walden University. SurveyMonkey has stringent security and privacy policies, which helps ensure that all information is kept private.

Appendix C: Permission to Use UTAUT2 Model and Instrument

MIS Quarterly
Carlson School of Management
University of Minnesota
Suite 4-339 CSOM
321 19th Avenue South
Minneapolis, MN 55455

January 6, 2017

Dana Haywood
Walden University

Permission to use material from
MIS Quarterly in Dissertation Research

Permission is hereby granted for Dana Haywood to use material from "Consumer Acceptance and Use of Information Technology: Extending the Unified Theory of Acceptance and Use of Technology," V. Venkatesh, J. Y. Thong, and X. Xu, *MIS Quarterly* (36:1), 2012, pp. 157-178, in her doctoral dissertation examining the relationship between nonprofit organizations and cloud adoption concerns.

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Janice I. DeGross
Manager

Appendix D: Invitation to Participants to View Study Results

Recently, you were invited to take part in a research study about adopting cloud computing within a non-profit environment. This email is to inform you that the analysis is complete and posted on https://danahaywood.wix.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.

Contacts and Questions:

You may ask any questions you have now or later by contacting the researcher at [redacted]. If you want to talk privately about your rights as a participant, you can call the Research Participant Advocate at my university at [redacted]. Walden University's approval number for this study is 03-06-17-0521783 and it expires on March 5, 2018.

I thank you for your time,

Dana Haywood

Doctoral Candidate at Walden University

Appendix E: Missing Data Statistics

Univariate Statistics

	N	Mean	Std. Deviation	Missing		No. of Extremes[a]	
				Count	Percent	Low	High
PE1	104	5.01	1.968	2	1.9	0	0
PE2	104	4.72	1.948	2	1.9	11	0
PE3	106	4.73	1.969	0	.0	11	0
EE1	100	3.58	1.174	6	5.7	5	0
EE2	101	3.48	1.230	5	4.7	8	0
EE3	101	3.55	1.144	5	4.7	6	0
EE4	102	3.53	1.166	4	3.8	6	0
SI1	100	2.95	1.038	6	5.7	0	0
SI2	100	2.87	1.079	6	5.7	0	0
SI3	101	2.91	1.069	5	4.7	0	0
FC1	100	3.75	1.158	6	5.7	0	0
FC2	100	3.66	1.191	6	5.7	0	0
FC3	100	3.64	1.069	6	5.7	5	0
FC4	100	3.31	1.178	6	5.7	9	0
HM1	99	3.09	.959	7	6.6	7	0
HM2	101	3.16	.987	5	4.7	6	0
HM3	99	2.86	.958	7	6.6	0	6
PV1	100	3.12	1.037	6	5.7	0	0
PV2	99	3.21	1.023	7	6.6	7	0
PV3	100	3.16	1.022	6	5.7	7	0
H1	99	3.09	1.221	7	6.6	0	0
H2	100	2.55	1.218	6	5.7	0	0
BI1	99	3.60	1.133	7	6.6	8	0
BI2	99	2.96	1.142	7	6.6	0	0
BI3	100	3.34	1.139	6	5.7	9	0
UB1	100	3.90	2.389	6	5.7	0	0
UB2	98	3.26	2.281	8	7.5	0	0
UB3	98	3.39	2.273	8	7.5	0	0
Gender	99			7	6.6		
Age	99			7	6.6		
ExperienceLevel	99			7	6.6		

a. Number of cases outside the range (Q1 - 1.5*IQR, Q3 + 1.5*IQR).

Appendix F: Reliability Statistics

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
PE1	90.9100	681.788	.854	.	.963
PE2	91.1918	680.324	.879	.	.963
PE3	91.1796	678.396	.881	.	.963
EE1	92.3295	723.884	.760	.	.964
EE2	92.4453	718.211	.817	.	.964
EE3	92.3614	722.720	.801	.	.964
EE4	92.3802	724.453	.754	.	.964
SI1	92.9909	738.872	.588	.	.965
SI2	93.0569	736.926	.603	.	.965
SI3	93.0286	733.110	.665	.	.965
FC1	92.1796	728.801	.690	.	.964
FC2	92.2645	724.323	.739	.	.964
FC3	92.2928	729.254	.748	.	.964
FC4	92.6382	736.159	.553	.	.965
HM1	92.8400	733.749	.740	.	.964
HM2	92.7645	731.900	.751	.	.964
HM3	93.0569	739.907	.614	.	.965
PV1	92.7871	737.189	.627	.	.965
PV2	92.6985	737.584	.632	.	.965
PV3	92.7378	737.501	.630	.	.965
H1	92.8464	722.065	.763	.	.964
H2	93.3745	730.505	.630	.	.965
BI1	92.3483	719.461	.870	.	.963
BI2	92.9696	724.797	.776	.	.964
BI3	92.6041	719.502	.855	.	.963
UB1	92.0569	675.950	.748	.	.965
UB2	92.6241	683.963	.710	.	.965
UB3	92.5041	691.218	.655	.	.966

Note: N=106, PE = performance expectancy, EE = effort expectancy, SI = social influence, FC = facilitating conditions, HM = hedonic motivation, PV = price value, H = habit, BI = behavioral intention, UB = use behavior.