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Regression Analysis of Cloud Computing Adoption for U.S. Hospitals

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This is to certify that the doctoral dissertation by

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Walden University
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Abstract

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Terence H Lee

MS, Warwick University of U.K., 1995

BS, Chinese University of Hong Kong, 1986

Dissertation Submitted in Partial Fulfillment

of the Requirements for the Degree of

Doctor of Philosophy

Applied Management and Decision Science

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Abstract

Industrial experts agree that cloud computing can significantly improve business and public access to low cost computing power and storage. Despite the benefits of cloud computing, recent research surveys indicated that its adoption in U.S. hospitals is slower than expected. The purpose of this study was to understand what factors influence cloud adoption in U.S. hospitals. The theoretical foundation of the research was the diffusion of innovations and technology-organization-environment framework. The research question was to examine the predictability of cloud computing adoption for U.S. hospitals as a function of 6 influential factors: relative advantage, compatibility, complexity, organizational size, structure, and culture. The research methodology included a cross-sectional survey with an existing validated questionnaire. A stratified random sample of 118 information technology managers from qualified U.S. hospitals completed the questionnaire. The categorical regression analysis rendered F statistics and R^2 values to test the predictive models. The research results revealed that all 6 influential factors had significant correlations with the public cloud adoption intent (adjusted $R^2 = .583$) while only the 3 technological factors had significant correlations with the private cloud adoption intent (adjusted $R^2 = .785$). The recommendation is to include environmental factors and increase sample size in the similar future research. The developed predictive models provided a clearer understanding among hospital IT executives and cloud service providers of cloud adoption drivers. The potential implications for positive social change can be the increase of efficiency and effectiveness in U.S. hospital operation once their speed of cloud adoption has increased.

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Dedication

I dedicate this dissertation to my wife, June Wong, who provides me endless support and encouragement so that I can keep my focus and energy to complete my doctoral program. I also dedicate this dissertation to my children, Timmy and Erica, who make life more meaningful for my wife and me.

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Table of Contents

List of Tables

List of Figures

Chapter 1: Introduction to the Study

A hospital information system (HIS) is a comprehensive and complex integration of various software applications, useful in managing the information required in hospital planning, operational, financial, legal, medical, and documentation processes. Typically, a HIS consists of patient scheduling, admission, discharge, payroll, accounts receivable, patient health record management, data analytics, and other functional modules to support the hospital's daily operation (Sheldon, n.d.). As the need arose for Health Insurance Portability and Accountability Act (HIPAA) compliance and continuous improvement on patient safety, many hospitals considered shifting from traditional paper-based information systems to paperless electronic data acquisition and reporting systems through modern mobile technologies. Nevertheless, according to Japsen (2013), only 1.8% of U.S. hospitals had a complete electronic medical records (EMR) system. With the ongoing government and public demand for service improvement and challenges in information technology (IT) budget for most hospitals, a push toward the adoption of cloud computing is imminent while the concern for data privacy and security persists.

Cloud computing may appear to be a new terminology in the IT vocabulary, but the foundational concepts of cloud computing have existed since the 1960s when IT experts introduced time sharing and virtual machine technologies for mainframe computers (Cusumano, 2010). Realistically, cloud computing is an accepted development in virtualization, service-oriented architecture, and utility-computing technologies (Clario Analytics, n.d.; Hill, 2013). Cloud computing is a consolidation of these proven technologies, theories, and business processes to allow a new form of IT outsourcing

(Williams, 2012). The rapid public acceptance of smartphones and other mobile devices has indicated the growing need for mobile applications and remote data access, with a record high of 1.3 trillion transactions each month (Tweney, 2013). This increase in the public use of cloud technology requires enormous processing power and storage at the back end so that high processing and storage applications can run on today's mobile device platforms. Technologists and economists have labeled cloud computing as the fifth utility after oil, gas, water, and electricity, as it is useful for achieving large computing power and storage on demand (Buyya, Yeo, Venugopal, Broberg, & Brandic, 2008).

According to several U.S. surveys (e.g., the 2009 International Data Corporation [IDC] cloud services study, the 2013 North Bridge's future of cloud computing survey, and the CDW 2013 State of the Cloud Report), many enterprises have not adopted cloud service. The main concerns are data security, data privacy, legal compliance, service availability, intellectual property protection, resource control, and vendor lock-in. Slow cloud adoption because of these concerns was surprising to most visionaries (Business Wire, 2011; CDW, 2013; Hickey, 2010).

The Tata Consulting Service (TCS) conducted a study of global cloud adoption and found that the health care industry was the slowest adopter among 16 key U.S. industrial segments surveyed (TCS, 2011). This slow adoption is problematic because higher administration work and skilled labor are deficient in the U.S. health care industry, particularly for hospitals, due to the compliance requirements of health care reform acts and aging workforce, respectively (Harrington & Heidkamp, 2013). Accelerating cloud adoption is one solution for improving administrative efficiency and redirecting capital investment to other facility improvements instead of expanding IT infrastructure.

With effective use of cloud computing services, hospitals can offer low cost EMR systems that allow their health care professionals to access patient health information from anywhere and anytime, beyond regular software tools for conferencing, collaboration, and office productivity. With highly scalable, low cost, agile, and pay-as-you-go service characteristics of cloud computing, hospital staff can implement newly innovative IT solutions with a fraction of IT infrastructure investment and implementation time (Roney, 2012a). Data privacy and security concerns for cloud computing services are among the major hindering factors for its adoption in hospitals. However, in reality, most cloud service providers can offer much higher security and privacy control than most small to medium hospitals due to their limited IT budget and lack of security expertise (Roney, 2012b). Furthermore, once data from medical institutions under the same health care network reside in the cloud, the hospital staff can provide a common medical and health information repository for the health care analytics. The analysis results are beneficial to the social communities that these medical institutions serve.

According to the CDW 2013 cloud computing adoption survey, 73% of surveyed participants answered that the increased personal use of cloud services is influential in their organization's decision to adopt cloud computing. Among these 1,242 surveyed participants are employees in the health care industry (13%) and hospital IT decision makers (10%). Within the health care industry, 35% responded that they were utilizing some forms of cloud computing services in 2012, which is only a 5% increase from usage rates in 2011. However, these uses are mainly for office collaboration and productivity (51%), instead of managing their core business processes (CDW, 2013). So far, the degree of influence of various factors on the intent of U.S. hospitals to adopt cloud services has been unclear, even some level of cloud computing adoption exists.

In this chapter, I discuss the background of this quantitative research, cloud computing concepts, adoption issues, and potential values provided to the U.S. health care industry, especially hospitals. Next is a discussion of the problem statement and purpose statements to illustrate the significance of the problem and the research goal to address the stated problem. Finally, subsequent sections include the research questions and hypotheses, the guiding theoretical framework, the nature of this quantitative research, term definitions, assumptions, scope, delimitations, and limitations. The ending section of this chapter contains the implications of this study to theory and practice along with a summary.

Background of the Study

The idea of interconnecting computers around the globe and allowing programs and data to be accessible began in the 1960s (Cantu, 2011). Nevertheless, only after the occurrence of broadband Internet in the 1990s did data transmission speed become fast enough for cloud computing technology to be feasible (Shimrat, 2009; Steddum, 2013). The development of cloud services started in the 1990s from the initial form of subscription and web-based software accessed through the Internet (e.g., customer relationship management system from Salesforce.com) to today's forms of cloud service offerings, such as software, storage, platform, and infrastructure (Mohamed, n.d.). Currently, four cloud deployment models and three service models are in use. Deployment models include public cloud, private cloud, hybrid cloud, and community cloud, which differ by what types of users can coexist and share the physical computing resources as tenants (Mather, Kumaraswamy, & Latif, 2009; Sonsinky, 2011; Williams, 2012). According to Aljabre (2012) and Finan (2012), service models consist of software as a service (SaaS), platform as a service (PaaS), and infrastructure as a service (IaaS).

Internet users can view cloud computing as a renewed medium of IT outsourcing. The main difference is that it has a much better scalability, agility, and cost-effectiveness with its resource democratization ability that allows many tenants to share a large IT resource pool (Mather et al., 2009). IT providers can allocate or misallocate this kind of resource pool to an individual client on demand, and the cloud service vendors only charge their clients a per usage rate (Himmel, 2012; Sosinsky, 2011; Williams, 2012). In today's highly competitive market, business agility and efficient operation are essential for business profitability and long-term survival.

These benefits seem to have not triggered high enterprise cloud adoption rates in U.S. industries, according to the *2013 Outlook on Technology: Cloud Computing Survey Results*, which the PC Connection conducted. Interestingly, 31% of the surveyed 500 U.S. companies from various industry segments responded that they have no plan to use cloud computing services (Bramwell, 2013). This phenomenon of slow cloud adoption is similarly evident in the U.S. health care industry. According to the CDW *2013 State of the Cloud Report*, health care ranked seventh out of eight surveyed U.S. industries in terms of cloud computing adoption speeds. Additionally, 65% of the health care respondents in the CDW survey replied that their corporations have no plan to use cloud services (Bowman, 2013).

To illustrate further the use of cloud computing within the health care industrial segment, another survey the research firm KLAS conducted in 2011 indicated that U.S. hospitals are laggards of cloud services adoption within the U.S. health care industry, as compared with other clinical offices (Terry, 2011). Only 4% of cloud service customers are health care related (Bowman, 2013; Good, 2013). Conversely, industrial experts have indicated that most health care corporations have to reduce their expenses by 20–40% (McNickle, 2011). Furthermore, U.S. hospitals have an urgent need to maintain productivity and service quality with the aging workforce by investing in better technology and facility support (Harrington & Heidkamp, 2013). For instance, according to HIPAA and the American Recovery and Reinvestment Act (ARRA) compliance requirements, by 2015 all health care providers will have to maintain their patient medical and health records electronically and retire their existing hard copy of patient record file systems (Good, 2013). Concerning the aging workforce, research has indicated that the current average age of registered nurses in the United States is 50, and more than 25% of physicians are over 60 years old (Harrington & Heidkamp, 2013).

Researchers have conducted numerous studies to determine the key factors hindering cloud computing adoption (Chebrolu, 2010; Hailu, 2012; Opala, 2012; Ross, 2010; Tweel, 2012). Concerns, such as data security, data privacy, integration complexity, legal compliance, and vendor lock-in, seem to be the reasons why corporations are unwilling to adopt cloud computing (Business Wire, 2011; Ekufu, 2012; Finan, 2012; Himmel, 2012; Mather et al., 2009; Ross, 2010). To encourage U.S. hospitals to explore the benefit of using cloud services, it is important for them to understand all critical factors that can affect the success of cloud computing adoption. For instance, cloud services may be useful for providing a cost-effective and practical platform to share patients' private health information if medical institutions authorizing the sharing of information can address the security and privacy concern of using the public cloud (Miliard, 2013).

In summary, there was a lack of specific scholarly research focusing on understanding the influential factors for U.S. hospitals' cloud adoption (Armbrust et al., 2009; Tweel, 2012). In this research, I used regression analysis to determine the significance of six technological and organizational factors in predicting the degree of the cloud computing adoption intent for U.S. hospitals.

Problem Statement

Among U.S. organizations, hospitals seem to be one of the slowest adopters of cloud computing services (TCS, 2011; Terry, 2011). Researchers have noted that the importance of cloud computing services in their primary capability is to (a) lower the need for IT investment, and (b) improve business agility and scalability with its on-demand, pay-as-you-go charging model (Armbrust et al., 2009; King, 2011a; Mather et al., 2009; Ross, 2010; Sosinsky, 2011). However, studies indicated that U.S. hospitals are not using cloud service advantages to improve their cost structure and operational efficiency. These hospitals are struggling to manage additional complexity and challenges due to issues such as the government-directed health care reform and an aging workforce (Harrington & Heidkamp, 2013; Parrington, 2010).

As cloud computing is still an emerging technology, scholarly research on cloud computing adoption is lacking (Armbrust et al., 2009; Tweel, 2012). An initial review of the literature revealed that several key or critical technological and organizational factors influencing cloud computing adoption seemed to be the cause of delay for IT managers to use cloud computing services (Chebrolu, 2010; Hailu, 2012; Opala, 2010; Ross, 2010; Tweel, 2012). The problem was in the limited understanding of these technological and organizational factors for predicting the adoption intention of cloud computing services in U.S. hospitals. If this study could clearly show this understanding, then it would be useful to IT managers and cloud vendors in identifying the gaps to address the concerns in accelerating the cloud computing adoption rate of U.S. hospitals.

Purpose of the Study

The purpose of my research was quantitative and explanatory in nature, as I attempted to explain the six variables and their degrees of significance in predicting cloud computing adoption intent. To do so, I developed a statistical model to predict the cloud computing adoption intent of hospital IT managers by using multiple linear regression (MLR) analysis. The analysis consisted of six internal (technological and organizational) innovation adoption influential factors as composite predictor variables: (a) relative advantage, (b) compatibility, (c) complexity, (d) organizational size, (e) organizational structure, and (f) organizational culture according to the diffusion of innovations (DOI) and technology-organization-environment (TOE) theories. I assessed each factor with one or more Likert-type survey questions constructed based on a validated and published instrument. This research could be informative and helpful in understanding how the six influential factors can affect the cloud computing adoption intention in U.S. hospitals. As a result, this research could be useful in developing a predictive cloud computing adoption model, which could serve as a tool for hospital IT managers. These IT managers would be able to create their cloud computing implementation strategy while cloud service vendors would be able to enhance their products and services based on their assessment of the six influential factors.

Additionally, as an IT professional working in a company offering cloud computing services, I planned to create a scientific model to predict cloud computing adoption intent based on the identified six influential factors for U.S. hospitals.

Research Questions and Hypotheses

The overarching research question for this study was: What are the technological and organizational factors (within the six selected factors) that strongly influence U.S. hospitals' cloud computing adoption intention?

To operationalize this research question into a number of related research hypotheses based on regression, it was necessary to explain the independent and dependent variables for the study briefly and use them to develop the hypotheses.

Research Variables

In this study, I developed a regression model consisting of six independent variables (X_1 to X_6) and one dependent variable (Y). As noted in subsequent paragraphs, some of these variables were fixed factors (i.e., categorical variables) while the rest were formed by summing specific survey Likert items. Such summation variables represented index or composite variables. Since each variable was the sum of ordinal variables, each one was equal to an interval variable. In summary, each composite interval variable score was the result of summing a series of related survey item scores with each survey item equally weighted. Table 1 shows the details of this alignment and calculation.

Table 1

Survey Items Alignment and Value Calculation Method for Composite Variables

Adoption influential factor (composite variable)	Survey item	Calculation	Data type of the final (composite) variable
X_1 = Relative advantage	Use 7-point Likert-type scale to measure from strongly disagree, disagree, neutral, agree to strongly agree for the following survey questions: Q_1 = Increase the profitability of my hospital. Q_2 = Allow your hospital to provide additional services. Q_3 = Allow for reduced operational costs. Q_4 = Allow better communication with my patients, staff, and medical partners. Q_5 = Require no up-front capital investment. Q_6 = Provide dynamic and high service availability.	$X_1 = Q_1 + Q_2 + Q_3 + Q_4 + Q_5 + Q_6$	Interval
X_2 = Compatibility	Use 7-point Likert-type scale. Measuring from strongly disagree, disagree, neutral, agree to strongly agree for the following survey questions: Q_7 = Cloud computing adoption is consistent with my hospital's beliefs and values. Q_8 = Attitudes towards cloud computing adoption in my hospital is favorable. Q_9 = Cloud computing adoption is compatible with my hospital's IT infrastructure. Q_{10} = Cloud computing adoption is consistent with my hospital's business strategy.	$X_2 = Q_7 + Q_8 + Q_9 + Q_{10}$	Interval
X_3 = Complexity belief of cloud computing	Use 7-point Likert-type scale. Measuring from strongly disagree, disagree, neutral, agree to strongly agree for the following survey questions: Q_{11} = Cloud computing service is cumbersome to use. Q_{12} = Using cloud computing services requires a lot of mental efforts. Q_{13} = Using cloud computing is often frustrating.	$X_3 = Q_{11} + Q_{12} + Q_{13} + Q_{14} + Q_{15}$	Interval

(table continues)

Adoption influential factor (composite variable)	Survey item	Calculation	Data type of the final (composite) variable
	Q_{14} = The user interface of cloud computing services is clear and understandable. Q_{15} = Cloud computing services are easy to purchase and startup.		
X_4 = Organizational size	It is measured by the number of staffed beds that are grouped in one to eight scale from: Q_{16} = 6 - 24 (= 1), 25 - 49 (= 2), 50 - 99 (= 3), 100 - 199 (= 4), 200 - 299 (= 5), 300 - 399 (= 6), 400 - 499 (= 7) and greater than 500 (= 8) staffed beds.	$X_4 = Q_{16}$	Interval
X_5 = Organizational structure	Use a multiple choice question to categorize into four types: Q_{17} = functional (= 1), divisional (= 2), matrix (= 3) and others (= 4).	$X_5 = Q_{17}$	Nominal
X_6 = Organizational culture	Use a multiple choice question to categorize into five types: Q_{18} = clan (= 1), adhocracy (= 2), hierarchy (= 3), market (= 4) and others (= 5).	$X_6 = Q_{18}$	Nominal
Y = Cloud computing adoption intent	Use 7-point Likert-type scale. Measuring from strongly disagree, disagree, neutral, agree to strongly agree for the following survey questions: Q_{19} = Intends to adopt cloud computing. Q_{20} = Likely to take steps to adopt cloud computing in the future. Q_{21} = Likely to adopt cloud computing in the next 12 months.	$Y = Q_{19} + Q_{20} + Q_{21}$	Interval

In this study, I utilized the variables above and aimed to predict the degree of innovation adoption (Y) as a function of several technological or organizational factors (measured by X_1 to X_6). Thus, the refined research question was: Does regression allow prediction of hospital IT managers' cloud computing adoption intent (Y) as a function of the six influential adoption factors, including relative advantage (X_1), compatibility (X_2), and complexity belief of cloud computing (X_3), organizational size (X_4), organizational structure (X_5), and organizational culture (X_6) in the United States?

The expression of the model could be represented by the equation $Y = b_0 + b_1X_1 + \ldots + b_6X_6$. Although the model was linear, it included a mix of interval and nominal independent variables; thus, I could not directly model with ordinary least squares (OLS) regression. Instead, I solved the model using categorical variables to dummy coding variables transformation procedure or SPSS/GLM. Due to the simplicity, I chose to use SPSS/GLM instead of dummy coding. I explain the modeling and execution details of using SPSS in Chapter 3.

Based on the research question, I operationalized the regression-related null and alternative hypotheses as listed below:

$H0_1$: X_1 = relative advantage is not a significant predictor of Y = intent to adopt; mathematically, $b_1 = 0$ in the resulting regression model.

$H1_1$: X_1 = relative advantage is a significant predictor of Y = intent to adopt; mathematically, b_1 != 0 in the resulting regression model.

$H0_2$: X_2 = compatibility is not a significant predictor of Y = intent to adopt; mathematically, $b_2 = 0$ in the resulting regression model.

$H1_2$: X_2 = compatibility is a significant predictor of Y = intent to adopt; mathematically, b_2 != 0 in the resulting regression model.

$H0_3$: X_3 = complexity belief is not a significant predictor of Y = intent to adopt; mathematically, $b_3 = 0$ in the resulting regression model.

$H1_3$: X_3 = complexity belief is a significant predictor of Y = intent to adopt; mathematically, b_3 != 0 in the resulting regression model.

$H0_4$: X_4 = organizational size is not a significant predictor of Y = intent to adopt; mathematically, $b_4 = 0$ in the resulting regression model.

$H1_4$: X_4 = organizational size is a significant predictor of Y = intent to adopt; mathematically, b_4 != 0 in the resulting regression model.

$H0_5$: X_5 = organizational structure is not a significant predictor of Y = intent to adopt; mathematically, $b_5 = 0$ in the resulting regression model.

$H1_5$: X_5 = organizational structure is a significant predictor of Y = intent to adopt; mathematically, b_5 != 0 in the resulting regression model.

$H0_6$: X_6 = organizational culture is not a significant predictor of Y = intent to adopt; mathematically, $b_5 = 0$ in the resulting regression model.

$H1_6$: X_6 = organizational culture is a significant predictor of Y=intent to adopt; mathematically, b_5 != 0 in the resulting regression model.

$H0_7$: The linear model $Y = b_0 + b_1X_1 + \ldots + b_6X_6$ has no significant fit; mathematically, $R(Y \mid X_1 \ldots X_6) = 0$.

$H1_7$: The linear model $Y = b_0 + b_1X_1 + \ldots + b_6X_6$ has a significant fit; mathematically, $R(Y \mid X_1 \ldots X_6)$!= 0.

Theoretical Foundation

The theoretical framework of this study indicated a clear understanding of the nature and characteristics of the innovation adoption process. Such an understanding was essential to the determination of the predominant and predictive factors of cloud computing adoption in U.S. hospitals.

The technological innovation adoption process has been an important topic for years among researchers developing theories based on adoption behavior studies on the individual or enterprise level. According to Oliverira and Martins (2011), the developed applied technology adoption models for research practitioners include:

- diffusion of innovations (DOI) by Rogers in 1962,
- theory of planned behavior (TPB) by Ajzen in 1985,
- technology acceptance model (TAM) by Davis et al. in 1989,
- technology-organization-environment (TOE) framework by Tomatzky and Fleischer in 1990, and
- unified theory of acceptance and use of technology (UTAUT) by Venkatesh, Thong, and Xu in 2003.

Among these theories, only DOI and TOE are important to addressing the adoption process at the enterprise level while all others are useful in addressing individual levels of innovation acceptance (Oliverira & Martins, 2011). DOI contains insight on the attributes of an innovation itself that can have an effect on a social group's intent to adopt and on how peers can influence the willingness to adopt (Robinson, 2009). As stated in the DOI theory, prediffusion phase includes the factors of relative advantage, compatibility, complexity, trialability, and observability (Rogers, 2003). Under the TOE framework, DOI stated attributes that influence adoption fall into the technological context as they associate with technological innovation. Tornatzky and Fleischer (1990) argued that any innovation adoption process is not only affected by the technological context, but the organizational and environmental context also plays a significant role in influencing the acceptance and adoption speed of innovation. The TOE framework establishes a macroscopic view of innovation adoption according to these three key influential contexts, which group the influential factors in adoption underneath them (Tornatzky & Fleischer, 1990). A more detailed explanation of these theories is in Chapter 2.

Based on the literature review, combining the TOE and DOI methodology seemed to provide a stronger theoretical framework in explaining the influences on cloud computing services adoption created by various key factors than only using DOI theory (Tweel, 2012). The main benefit of using TOE was that its use compensated for the insufficiency in the DOI theory by adding emphasis on the organizational effect of innovation adoption. Additionally, TOE includes a better way to aggregate the level of influence generated by adoption factors into technological and organizational context. For this reason, I abstracted the six key innovation adoption factors from DOI and TOE theory under technological and organizational context as the core test elements in this study.

Nature of the Study

I selected a quantitative regression research method because I intended to quantify the degree to which six internal (technological and organizational) innovation adoption factors, as noted in the literature, can be useful in predicting the degree of cloud computing adoption intention. Qualitative research methods would have been inappropriate for quantifying the degree in which each variable can be a contributing factor to the adoption or for studying the simultaneous interaction effect of variables on the intention to adopt cloud computing technologies. Knowing the actual contribution of each variable is important to prioritize the variables leading to cloud computing adoption improvement.

In this study, I predicted the dependent composite variable (Y) capturing the intent of an IT manager in U.S. hospitals to adopt cloud computing services as a function of six independent composite variables (X_1 to X_6). Relative advantage, compatibility, and complexity fall under the technological context while organizational size, organizational structure, and organizational culture fall under the organizational context. The research not only created a predictive model for cloud computing adoption but also validated the DOI and TOE theoretical frameworks. In general, it would have been difficult to introduce experimental controls on any one of the six independent variables and in observing the impact to the cloud adoption intent (dependent composite variable) within the current hospital environment. Thus, a MLR analysis was a more appropriate research approach than experimental design (Balling, 2008).

The statistical regression design is not indicative of a precise causal relationship analysis between individual independent and dependent variables, as compared to experimental factorial design. However, this design was ideal for achieving a cost-effective way to analyze any combined effect of the six influential factors for adopting cloud computing for U.S. hospitals. Furthermore, its simple survey design structure can be useful for future longitudinal study. Researchers may then be able to determine the change of influential factors on cloud computing adoption as cloud computing technology progresses.

The data collection approach of this study was to use validated attitudinal measures to assess the variables. I collected the survey data through a self-administered online questionnaire and transferred the collected data to SPSS to calculate the composite variable value. Subsequently, I fed this value to a general linear model (GLM) for regression analysis to answer the research question and test the inferential hypotheses. The population of this study included IT managers of the qualified hospitals in the 48 continental U.S. states who have direct decision authority or influence on cloud computing adoption. I planned to select the survey participants by using a proportional stratified random sampling method with the sample framework set as the contacts retrieved from the company’s health care customer network. Chapter 3 includes the details of research design, methodology, instrumentation, and operationalization of constructs.

Definitions

Many terms and definitions are relatively new and especially relate to the latest IT and technology adoption theories. As they are rapidly evolving, a variety of definitions may exist. This section provides the definition of terms used in this study and gives a concise meaning for the random variables applied.

Cloud computing: An IT model that provides on-demand Internet access, self-service system configuration, rapid provisioning, and deprovisioning capability to common shareable computing resource pools. Internet users can easily share resources such as network, storage, servers, and applications without compromising the segregation of resource ownership. Currently, cloud computing supports three common service models (SaaS, PaaS, and IaaS) and four common deployment models (public cloud, private cloud, community cloud, and hybrid cloud) according to Mell and Grance (2011).

Community cloud: One of the current deployment models for cloud services. It is a cloud environment owned by the community with common objectives, needs, and requirements, such as security and regulatory compliance. Use of community cloud is common for U.S. federal agencies as well as health and medical industries (Finan, 2012; Williams, 2012).

Diffusion: A special type of two-way communication, which has the intent to trigger penetration of innovation and potentially cause changes to social systems. Due to the uncertainty and lack of structure in innovation ideas, diffusion can take much time (Rogers, 2003).

Electronic medical records (EMR): A digital form of a patient's complete medical record that tracks physicians' diagnostic and treatment history, vaccinations, medications, laboratory test results, long-term health data, and hospitalization records. The goal is to allow authorized access to patient health care information in a unified format for multiple health care providers to create and maintain for a patient (Garrett & Seidman, 2011).

Grid computing: A computing technology that involves the use of interconnected computer networks to accomplish a particular task by working on a common workload simultaneously. Every computer in the system is a contributing factor to its resources including processing power, memory, and storage with other computers in the same system. At the end user viewpoint, this system of computers resembles a supercomputer (Strickland, n.d.).

Health Insurance Portability and Accountability Act (HIPAA): In 1996, the U.S. Congress established and passed this Act to protect the use and disclosure of an individual's health information. All U.S. health care providers received the HIPAA-compliant guidelines with which they had the legal obligation to follow ("HIPAA – General Information," 2013).

Hybrid cloud: One of the current deployment models for cloud services. Under this model, the infrastructure has the nature of public, private, and community cloud. Hybrid cloud has the connections of these various cloud instances through a special interconnect technology, enabling the interoperability between different types of cloud services and the transfer of data and applications seamlessly among them (Finan, 2012). With the hybrid cloud, users can create an integrated business environment for which applications with high security and privacy requirements are operable in a private cloud and other applications in a public cloud (Williams, 2012).

Infrastructure as a service (IaaS): As one of the cloud services, the service providers package the infrastructure resources (server, network, and storage) and sell them as a subscription service. Clients can create virtual machines on demand with the hardware and operation system (OS) specification that they picked from the vendor's supported list (Finan, 2012; Mather et al., 2009; Williams, 2012).

Platform as a service (PaaS): As a cloud service, PaaS is useful in offering development and deployment platform for software developers to benefit from a pay-as-you-go charging plan. This service has a web browser through which users may access a set of vendor-provided standard software design, programming, testing, and integration toolkit (Finan, 2012; Mather et al., 2009; Williams, 2012).

Private cloud: Similar to the public cloud, private cloud is a kind of cloud deployment model that includes virtualization technology to encapsulate the physical hardware from the operating system layer. Multiple users within the same corporation can share the same pool of infrastructure resources, which resemble their physical machines. The corporation's internal IT can manage this cloud infrastructure on the premises, or cloud service vendors can serve it for their end users (Finan, 2012; Williams, 2012).

Public cloud: A kind of cloud deployment model with a virtualization capability similar to that of a private cloud. However, the cloud service vendor's data center contains its infrastructure to serve the public with multitenant security, application, and data control (Finan, 2012; Williams, 2012).

Software as a service (SaaS): As a cloud service, under SaaS, consumers will rent instead of purchase the software, based on subscription or pay-per-use charging scheme (Finan, 2012; Mather et al., 2009). Clients do not need to purchase their servers, which are helpful in reducing the complexity and cost of hardware infrastructure installation and maintenance (Williams, 2012).

Variable-radius measurement: This degree of competition measurement is equal to the calculated average of distance measurement from each customer's home location to the service provider location (to determine the radius of a service provider's market area). Service providers can then calculate the degree of competition by counting the number of providers servicing a given geographical area. This measurement is a common method used for business services (e.g., health care service) highly bounded by geographic locations (Gresenz, Rogowski, & Escarce, 2004).

U.S. region: A region of the United States is a geographical grouping of multiple U.S. states. According to U.S. Census Bureau (2014), the United States consists of five census regions—west, midwest, northeast, south, and pacific. The west, midwest, northeast, and south regions include the 48 continental states and one federal district (i.e., Washington DC). The pacific region consists of all noncontinental states, including Alaska, Hawaii, and all offshore U.S. territories and possessions.

Assumptions

Research assumptions are the underlying stated facts that researchers believe to be true (Leedy & Ormrod, 2005). Researchers can link them to the deployed theory, the observed phenomenon, the accuracy of the measuring system, the selection process for the research participants, and the analysis of the survey results (Simon, 2011a). Table 2 shows the assumptions of this research regarding these areas.

Table 2

Assumptions with Justifications, Risks, and Mitigations

Research component	Assumptions	Justifications	Risks	Mitigations
Theory	Innovation adoption theories—DOI and TOE—provide appropriate theoretical framework	The constructive elements for cloud computing adoption are similar to other technology adoptions for which have the application of innovation adoption theories.	DOI and TOE might not be the best innovation adoption theories to apply.	Compared various technological adoption theories. Only included the critical factors validated in other research studies.
Phenomenon	The actual slow cloud computing adoption phenomenon for U.S. hospitals is measurable by the low intention of their IT managers to adopt.	Survey results show cloud computing adoption rate and adoption intention have a causal relationship.	The actual behavior could be affected by perceived behavior control, and different from behavioral intention (Ajzan, 1985).	Analyzed survey results for cloud computing adoption studies to determine whether cloud computing adoption rate has a causal relationship with the adoption intention.
Methodology	Quantitative research is appropriate research method.	Examined what are the critical influential factors, instead of trying to answer the *why* or *how* of research.	The six selected critical factors might not be the most predictors for the U.S. hospitals' intention to adopt cloud computing.	Reviewed cloud computing adoption research to identify the six most critical factors.
Instruments	Online self-administrated survey questionnaire is a valid and reliable instrument.	It is cost-effective and fast method to reach a large sample population via emails and website.	Low response rate. Doubt on validity and reliability of the survey questionnaire construct.	Sent invitation letters and reminders to encourage survey participation. Used validated survey questionnaire.
Analysis	MLR is useful in making causal prediction on cloud computing adoption intention of U.S. hospital IT managers.	Expected normal distribution for collected response data based on sampling population method and size.	Omitted variable bias might exist due to missing critical factors	Reviewed cloud computing adoption research to identify the current six most critical factors. Used R^2 to measure model significance.

(table continues)

Research component	Assumptions	Justifications	Risks	Mitigations
Power of detection	Sufficient responses can come from all selected U.S. regions to make a proper statistical analysis.	The selected sampling framework provided sufficient population for sampling.	Typical low response rate (10—15%)	Set up a larger sampling size to anticipate low response rate. Used proportional stratified random sampling method to guarantee a certain number of sample candidates from each selected U.S. region.
Participants	Provide honest and unbiased responses. Have foundational understanding of cloud computing service and deployment models.	Participants were professionals, and their responses would be their best personal judgment according to organizational benefit and risk assessment.	Participants might be too stressful to provide rational and thoughtful answers.	Only picked IT managers with decision responsibilities for cloud computing adoption. Used validated questionnaire with clear survey questions.
Results	It is meaningful and sufficient to create a predictive adoption model to forecast cloud computing adoption intention for U.S. hospitals.	As the researcher utilizes a proper theoretical framework, an instrument, a sample group, and analysis, the expected result is to have strong external validity and generalization.	Unscholarly research	Followed proper research guideline and procedure. Reviewed and validated the intermediate results with research committee members.

Innovation adoption theories—DOI and TOE—comprise the appropriate theoretical framework for this research despite their limited applications for cloud computing adoption studies so far. The justification was that the constructive elements of behavioral intention for cloud computing adoption under an organizational context are similar to other types of innovation adoption. Therefore, these theories can be equally applicable. The risk was that the DOI and TOE might not be the best innovation adoption theories to apply. The challenge was that cloud computing is an emerging technology. Researchers have developed insufficient empirical methodologies to describe the adoption behavior (Armbrust et al., 2009; Tweel, 2012). The mitigation approach was to compare various innovation adoption theories, and I determined that combining DOI and TOE theories was most suitable for the core theoretical base for this research. In addition, this study included only the factors validated by other research studies that have statistically significant association with adoption intention.

As emphasized in the problem statement, the research phenomenon was the slow adoption of cloud computing for U.S. hospitals, even when IT managers recognize the numerous business and financial benefits of such adoption. The assumption was that the U.S. hospitals' cloud computing adoption intention has a causal relationship with the actual cloud computing adoption, and adoption intention is measurable. According to TPB, the actual behavior can be different from behavioral intention, which the perceived behavior control can affect (Ajzan, 1985). To mitigate possible issues with this assumption, I conducted a comprehensive literature review on cloud computing adoption rate and intention survey studies. So far, the results have shown that the actual adoption rate and degree of adoption intention for cloud computing have a predictive, causal relationship (CDW, 2013; North Bridge, 2013; TCS, 2011). Therefore, the use of cloud computing adoption intention in U.S. hospitals was safe to project its future adoption rate. I discuss the details of this survey study comparison in Chapter 2.

The quantitative methodology choice was the right choice of research method because the objective of this study was to examine the predictive power of the critical factors influencing the cloud computing adoption intention for U.S. hospitals. As the goal was to use the six selected factors to create a predictive model of cloud computing adoption intention for U.S. hospitals (instead of an exploratory study to identify all possible influential factors), quantitative research is more appropriate than qualitative research (Mora, 2010). The risk is whether the six selected dependent variables are the most essential factors to drive cloud computing adoption intention in U.S. hospitals. If not, omitted variables bias could exist, and the functional construct between the dependent variables and independent variable could not demonstrate statistical significance (Sykes, n.d.). To mitigate this bias risk, I reviewed research studies on cloud computing adoption to identify the six most critical factors that fit the DOI and TOE models. During the statistical analysis, the R^2 statistic was useful to measure to determine whether omitted variable bias exists.

The assumption was that an online, self-administrated survey questionnaire was an appropriate instrument due to cost and time constraints for this study and due to its ease of distribution to a large group of participants via e-mails and an Internet website. The risks included the traditional low response rate for online survey and the validity and reliability of the construct of survey questions. To mitigate this risk, I sent an invitation letter and reminders to selected sample candidates to encourage the survey participation. In addition, I used a validated survey questionnaire from another cloud computing adoption study and modified it to fit this study.

An essential assumption for conducting MLR analysis was that the collected data were under a normal distribution pattern. I expected the six selected critical factors to be linearly independent and that the variance of the error was random and constant across observations. Since sufficient number of sizes and types of hospitals exist in the United States, I expected the response to the survey items to follow a normal distribution pattern. According to innovation adoption studies, the six selected independent variables do not seem to have any correlated effect among themselves (Rogers, 2003; Tornatzky & Fleischer, 1990). As mentioned, unless there is omitted variable bias (detectable by the statistical R^2 value), the variance of the error should be random and constant.

To identify the significant relationship between the six selected influential factors for adoption and the adoption intention of U.S. hospital IT managers, I assumed I could receive sufficient responses to fulfill the minimum statistical sample size requirements for MLR. I assumed that I could invite sufficient sampling participants for my study within my sampling framework, as it should consist of most U.S. hospital IT contact information. To minimize the risk of generalization, I used a proportional stratified random sampling method to guarantee receiving enough return responses from IT managers of the hospitals in the selected regions that comprise the 48 continental U.S. states.

The assumption regarding participants was that they were willing to provide honest and unbiased responses. Additionally, I assumed that they have a fundamental understanding of cloud computing services and deployment models. Therefore, they gave their opinion and decision regarding acceptance or rejection of this technology according to their best personal judgment of their organization's benefit and risk instead of basing a decision on ignorance. The risk was that the participants are under a high-stress working environment and unable to provide thoughtful answers. The mitigation step to getting the best, unbiased, and meaningful responses was to select only IT managers who have the responsibility to make decisions or to influence cloud computing adoption to provide the survey responses, and I also used a validated survey questionnaire with clear survey questions.

Finally, the assumption for the research result was that it could be meaningful and useful to create a predictive model to forecast the cloud computing adoption intention in U.S. hospitals. As long as I followed the proper research method, this assumption should be achievable. To reduce the risk of unscholarly research results, I aligned my study with Walden University's research guidelines and procedures. In addition, I reviewed and validated the intermediate results with the research committee members.

Scope and Delimitations

The objective of this research was to determine whether any of the three selected technological factors (relative advantage, compatibility, and complexity as independent composite variables, X_1 to X_3) and the three organizational factors (organizational size, structure, and culture as independent composite variables, X_4 to X_6) under the innovation adoption theories (DOI and TOE) are causal predictors to the intent of hospital IT managers for cloud computing adoption (dependent composite variable, *Y*). The study included a focus on assessment at the organization level instead of at the individual decision maker's level regarding perceived relative advantage, complexity, and compatibility judgment on cloud computing technologies. The scope was a more cohesive view of influential factors on cloud computing adoption intent for U.S. hospitals, compared with the research for general U.S. industries. I measured each of the independent variables by one or multiple survey items corresponding to the aspects of that variable. Table 1 shows the detailed alignment of the survey items and the variables along with the score calculation method.

This study excluded trialability and observability, as they indicated little correlation with cloud computing adoption rate, according to Powelson (2012) and Tweel (2012). I did not study the environmental factors (e.g., industrial competition and support infrastructure), as they represent external factors that were outside the scope of this study. The research method for this study was a cross-sectional survey design involving an assumed representative sample from the population. The analysis involves regression, useful for predicting any possible causal relationship between the listed influential factors and the hospital's intent for cloud computing adoption, without the construct validity to conclude any absolute causal relationship (Lomax & Li, 2013).

In addition, the general competition measurement scheme applied in most industrial segments is not relevant for U.S. hospitals; thus, researchers have suggested using the variable-radius measurement method instead (Gresenz et al., 2004). Therefore, this study excluded the analysis of cloud adoption factors under the environment context of TOE due to data collection complexity and effort of measuring industrial competition for U.S. hospitals with the suggested variable-radius method. Other researchers may find the analysis of cloud adoption factors under environmental context a significant topic for future research endeavors.

The theoretical population boundary of this research included the IT managers, who have a direct influence or decision power on cloud computing adoption in qualified hospitals of the 48 continental U.S. states. The planned accessible population was the IT managers of qualified hospitals in the 48 continental U.S. states who were in the company's health care customer network. This company currently sells and supports its software products to almost all U.S. hospitals. Its health care customer network database should consist of sufficient IT contact information (e.g., e-mail address and office phone number) of hospitals in each U.S. state. I distributed survey request e-mails to hospital IT managers whom I selected through a proportional, stratified random sampling for each U.S. region within the accessible population. The sampling administration window closed after I received sufficient responses as according to the desired total sample size. This approach was to guarantee proper survey result representation from each U.S. region to provide sufficient statistical power for hypothesis tests (Trochim, 2001).

I conducted a pilot study to confirm the validity and reliability of the survey instrument and to ensure clarity of the survey questions. As I selected the survey participants from United States only, the research viewpoint on cloud adoption factors was U.S.-centric as expected. The research result of this study had limited generalization, which may be inapplicable in other countries.

I have listed each delimitation item together with the corresponding justification, risks, and mitigations in Table 3.

Table 3

Delimitations with Justification, Risks, and Mitigations

Research Component	Delimitations	Justifications	Risks	Mitigations
Objective	Predicted the possible causal relationship between the six critical factors and cloud computing adoption. Trialability and observability factors under DOI. I excluded the environmental factors under TOE.	Other researchers found the correlation between trialability and observability with cloud computing adoption intention insignificant. No simple way is suitable to measure factors (e.g., competition) under the environmental context for U.S.	The phenomenon of the six selected critical factors within the U.S. hospital environment was yet inexplicable.	The success results of other research studies and adoption theories were the basis for selecting the most relevant factors for this study.
Research question	What are the technological and organizational factors (within the six selected factors) that strongly influence the U.S. hospitals' cloud computing adoption intention?	The objective was facilitative for identifying the possible causal relationship between these factors and cloud computing adoption intention for U.S. hospitals.	MLR was not the proper analysis method that would be helpful in answering the research question	Compared and analyzed other statistical methods (e.g., factorial and correlational analysis) to conclude that MLR is the best method to create a predictive model.
Theoretical perspective	Technology adoption theories include the DOI and TOE	Provided the theoretical framework of what potential influential factors for new technology adoptions.	DOI and TOE were not the best choices for a theoretical framework.	Researched and analyzed other innovation theories based on the literature review to determine whether I could use combined DOI and TOE as my theoretical framework.
Population	IT managers of qualified hospitals in the 48 continental U.S. states registered in the company's health care customer database	I contributed to this research topic with a relevant and accessible population.	The IT managers within the company's health care customer network might carry a similar cloud computing adoption intent.	Used descriptive statistic to analyze whether the survey result values were under the normal distribution.

(table continues)

Research Component	Delimitations	Justifications	Risks	Mitigations
Geographical representation	Hospitals in the 48 continental U.S. states.	The statistical power of detection justified the external validity and generalization.	Sample candidates might not proportionally come from the selected U.S. regions, and the outcome might affect the generalization.	Used proportional stratified sampling method to ensure a presentable amount of sample candidates come each selected U.S. regions.

Limitations

As this research was a MLR study instead of an experimental study, I could only define predictor variables (the six selected adoption influential factors) and observe whether they have covariate effect with the outcome variable (cloud computing adoption intention of U.S. hospital IT managers). Therefore, I could not draw any absolute conclusion on the causal relationship between the predictor variables and the outcome variable (Singleton & Staits, 2005; Wijayatunga, n.d.).

In terms of the power of detection, due to the limited time, resource constraint, and required sample size, I chose the proportional, stratified random sampling method. I picked a small number of random sample candidates proportionally from each selected U.S. region and with a combined sample size large enough to provide sufficient statistical power for generalization based on the estimated response rate (Singleton & Straits, 2005). The selected participants only included the hospital IT managers who have registered contact information in the accessible population and located in the United States (sampling frame). The American Hospital Association (AHA) provided a list of 5,723 hospitals currently in the United States (“Your best source for hospital information,” 2013). In addition, my research had much narrower scope than in Tweel’s (2012) research. My research result only represents the analysis and prediction of the cloud adoption intent for U.S. hospitals, instead of for all U.S. industries as in Tweel’s (2012) research.

This sampling frame might have a potential bias. As I selected the study sample from the company’s health care customer network, these research subjects could be representing a group of IT management people who have similar, yet unknown backgrounds. These groups might have common subjective norms on technological preference, risk tolerance, and decision making. As a result, they might have a similar mindset toward cloud computing adoption. The descriptive statistic generated as part of the results analysis could be useful to confirm whether such sampling frame bias exists. Furthermore, self-administered online surveys usually have a low response rate. To compensate for this limitation, I sent invitation letters and reminder e-mails to encourage survey participation.

The population of this study only included the qualified hospitals in the 48 continental U.S. states (i.e., hospitals with 50 or more staffed beds). Therefore, the generalization power of this study only represented the cloud computing adoption intention of hospitals in the United States. According to Black (1999), without the right mix of views and opinions collected from the sample groups, the generality could be limited. However, for countries that have a similar socioeconomic environment as the United States, this research result could be useful for predicting the influential factors for their hospitals' intention to adopt cloud computing services. To demonstrate whether this study has an unbiased population sample, I discuss descriptive statistics such as hospital type and bed size in Chapter 4.

Finally, with increased need for cost containment and increased demand for patient data privacy, IT managers of U.S. hospitals are under pressure to find innovative and effective ways to manage their new financial and workforce challenges (McNickle, 2011; Parrington, 2010). This work pressure may influence their ability to make a rational decision on new technology adoptions. To mitigate this limitation and risk, I conducted a pilot study to determine whether the survey questionnaire was clear and easy to understand with minimal mental effort. Based on the pilot study result, I adjusted the survey questionnaire content as necessary.

As cloud computing is an emerging technology, its business model, value proposition, and constraints are rapidly changing. Therefore, quickly diminishing the predictive validity of this study could be possible, and the significance of each factor as a predictor of the cloud adoption intention could shift over time. To improve the generalizability of this research, besides MLR analysis on the six critical factors level, I concatenated and analyzed the independent variables under the technological and organizational context level. This approach should provide a better macro viewpoint.

Table 4 contains the summary of the limitation of this research study together with its justification, risks, and mitigation plans.

Table 4

Limitations with Justification, Risks, and Mitigations

Research component	Limitations	Justifications	Risks	Mitigations
Theory	DOI and TOE as a theoretical framework can only indicate planned behavior for adoption intention.	This study showed an analysis of cloud computing adoption that should be a rational decision for U.S. hospitals.	This study excluded some factors under DOI and environmental factors under TOE.	Declared as a future research opportunity. Used test statistic R^2 to determine whether there is significant omitted variable error exists.
Phenomenon	Other possible causes beyond planned behavior are not under consideration for slow cloud computing adoption for U.S. hospitals	Low cloud computing adoption intention from U.S. hospital IT managers is the major cause for slow cloud computing adoption.	More than adoption intention from U.S. hospital IT managers could be influential to cloud computing adoption.	Reviewed research studies to find evidence to demonstrate cloud computing adoption and adoption intention has a direct correlation. Used test statistics R^2 to detect possible omitted variable bias issue.
Methodology	Quantitative research can only be useful in determining influences, instead of why and how cloud computing adoption is slow for U.S. hospitals.	The objective was to examine which of the six selected critical factors have a significant influence on cloud computing adoption and to create a predictive model. Quantitative research is the commonly applicable method.	Statistical analysis was the basis of my research result, lacking in-depth exploratory power as in qualitative research methods.	I declared it as a future research option to explore further why and how the identified significant influential factors are affecting cloud computing adoption for U.S. hospitals.
Instrument	Online self-administrated survey questionnaire in this research only consists of Likert and multiple-choice type of questions. The survey has no open question to allow the	It is the most cost effective, objective way to collect large amount of survey data. It is a suitable method for quantitative statistical analysis. Open questions will require additional codification effort.	The research insight would have a very narrow focus on identifying the correlation between the selected six selected factors and cloud computing adoption intention	I informed the readers on the limitation of data collected via the online self-administrated questionnaire and provided the questionnaire details (see Appendix. A). The survey included a validated

(table continues)

Research component	Limitations	Justifications	Risks	Mitigations
	participants to provide more insight into the research on cloud computing adoption.		of U.S. hospital IT managers.	instrument to improve rationality and reliability.
Analysis	MLR analysis only fits data under the normal distribution. The included factors are linearly independent of each other.	The expectation in this study included the normal distribution of data.	The result of MLR was not permissible for claiming absolute causal relationship.	The six selected factors were the basis of objective for this research to identify the possible causal relationship and create a predictive model for cloud computing adoption intention. Future experimental researchers will need to confirm the cause-effect relationship for any factor that has shown a significant correlation.
Participants	As a behavioral study, total reliance on honesty and unbiased answers from the participants to provide in the survey are important. Since I shall select all participants from the company's health care customer network, they may carry a similar preexisting bias.	The selected participants were professional, who would provide honest and unbiased answers as expected.	Some participants might not be able to provide the best rational answers based on their organizational benefit and risk assessment due to the high-stress hospital environment.	Conducted a pilot study to determine whether the survey instrument is clear or may require any improvement.
Power of detection	The total number of U.S. hospitals is 5,723 (AHA, 2013), and only a relatively small sample size will be of use.	The current limitations involved cost, resource, and time constraint permissible to only a small number of selected hospitals in	The hospitals that would respond to the survey might fall under a few U.S. states, and the outcome might affect the	Used proportional stratified sample method to pick proportional number of sample candidates from the selected U.S. regions to

(table continues)

Research component	Limitations	Justifications	Risks	Mitigations
		this research.	generalization.	improve the overall generalization.
	I had much narrower research scope than in Tweel's research.	The scope of my research was to determine the IT manager's cloud computing adoption for U.S. hospitals only, instead of for the entire U.S. industry as in Tweel's research.	I could not generalize my research result to other U.S. industries besides U.S. hospitals.	Clearly stated the scope and generalization limitation of my study.
Results	Limited by the statistical analysis results on the independent and dependent variables	The selection of six factors was according to adoption theories and research studies. The adoption factors for cloud computing may be similar to another technology adoption as expected.	The values and constraints for cloud computing are rapidly changing, the predictive validity can diminish quickly.	I analyzed the technological and organizational context level to observe its generalizability on the technology and organizational context level.

Significance of the Study

Significance to Theory

This study included the underresearched area of cloud computing adoption in hospitals, focusing on the emerging technology, which is still in a rapid growth phase and in need of its own theoretical basis for business value and risk measurement (Ekufu, 2012; Himmel, 2012; Paquet, 2013; Powelson, 2012; Ross, 2010; Tweel, 2012). The output of this study was helpful in filling the knowledge gap, the lack of a predictive model to determine the expected cloud computing adoption intent for U.S. hospitals, based on six predefined influential factors regarding innovation adoption.

Significance to Practice

The purpose of this quantitative study was to examine the degree of influence of key technological and organizational factors in predicting the adoption intention of cloud computing in U.S. hospitals with MLR analysis. Cloud service providers may find this model useful as they seek ways to resolve the cloud adoption obstacles and improve the technology and service perception for U.S. hospitals. Furthermore, the model may also be useful to U.S. hospital IT managers to enrich the decision framework, including cloud adoption strategy, cloud computing service, deployment model selection, and implementation priority.

Significance to Social Change

Similar to the positive social change created by the adoption of broadband Internet, IT specialists anticipate the increase in technological innovation, improvement in business agility, scalability, and mobility of cloud computing services (Business Wire, 2011; Himmel, 2012; King, 2011b). Especially for U.S. hospitals, cloud computing service providers offer low cost commodity digital communication and document processing services, on-demand EMR software (SaaS), HIPAA compliant platform, and scalable infrastructure resources. These cloud services could be useful in tremendously reducing small hospitals' competitive disadvantage compared to large hospital chains by improving their operational efficiency and effectiveness. Instances may include the reduction of the required upfront capital funding for IT infrastructure or operational expenses for data security compliance, availability of in-house IT expertise, and the ability to maintain high IT resource utilization (Good, 2013). Based on Porter's five-force competition model, with effective rivalry supplier market, economic productivity will rise, along with more jobs that U.S. hospitals may generate in the future (Grundy, 2006). Ultimately patients, health care providers, and the entire health care industry can benefit by having better hospital services that tend to be more affordable, innovative, and transparent (Shimrat, 2013).

By consolidating the current scattered, end-user-owned computing infrastructure into cloud service vendors' mega data centers, overall computing resource utilization will greatly increase, which in turn reduces worldwide power consumption and carbon dioxide emission (Borja, 2012; Williams, 2012). Based on the industrial forecast, by 2020, cloud-related services will have an allocated 69% of the IT budget, and that will be equivalent to $12.3 billion of IT spending for large corporations with revenue greater than $1 billion. Besides the economic benefits, using cloud services can be a viable source of significant environmental benefit. According to an environmental study, the carbon footprint can also be reduced by 85.7 million metric tons per year after the current capacity of cloud computing services are fully utilized (Williams, 2012). Currently, the health care industry is only 4% of U.S. cloud service use (Good, 2013). This report has indicated that the opportunity for accelerating the cloud computing adoption is high, and the global economic and environmental improvement contribution can be enormous.

Summary and Transition

Based on many predictions of technologists, the social and financial effects created by cloud computing development can be as significant as for the broadband Internet adoption in the last decade. Surprisingly, the current adoption speed for enterprises is slower than expected (North Bridge Venture Partners, 2012), especially for U.S. health care organizations such as hospitals (Bowman, 2013; Gold, 2013). According to most of the general surveys and studies, the concerns seem to include the potential risks of immature technology; lack of standards, security, and data privacy; and regulation compliance (Ekufu, 2012; Himmel, 2012; Mather et al., 2009; Paquet, 2013; Ross, 2010; Sosinsky, 2011). Presently, scholarly quantitative research is limited; filling this research gap can be useful in providing sufficient validity and generalization to specify the degree of influence for key DOI and TOE factors on cloud service adoption.

The objective of this research effort was to close this research gap by examining the significant factors under technological and organizational contexts, based on DOI and TOE theories, and creating a predictive model, which can affect cloud service adoption intent for U.S. hospitals. The dependent composite variables in this study included (a) relative advantage, (b) compatibility, (c) complexity, (d) organizational size, (e) organizational structure, and (f) organizational culture. The outcome was a quantitative, MLR research with population sampling candidates retrieved from the company's health care customer network for hospital IT managers in the United States. I adopted to this study a validated online self-administered survey questionnaire, which I enhanced to fit this study in collecting research data. I invited a small, initial sample group to participate in the pilot study in order to validate and improve the survey instrument. The collected data passed through MLR analysis and hypothesis tests in order to draw research conclusions. As a result, the output of this research could be used to frame a decision framework to assist U.S. hospital IT managers in defining their cloud computing adoption strategy and roadmap.

I provide in Chapter 2 a detailed literature review on technology adoption theories, the nature and characteristics of cloud computing, their current available service and deployment models, architecture, benefit and risks, the current circumstance of U.S. hospitals in adopting new technologies, and the types of regression analysis methods. Furthermore, I discuss innovation adoption methodologies to provide a comprehensive viewpoint on their relevance to this study. In Chapter 3, I cover the research methodology.

Chapter 2: Literature Review

Cloud computing adoption in U.S. hospitals is slower than expected, and currently, only 35% of U.S. hospitals have indicated that they have a solid plan for future cloud services adoption (Terry, 2011). As U.S. hospitals are facing significant financial and legal compliance challenges, cloud computing services could provide the needed economic and technological advantages. Nevertheless, cloud service providers and hospital IT managers should firstly understand the technical and organizational factors that affect the adoption rate. The objective of this cross-sectional survey research was to predict hospital IT managers' intent to adopt cloud computing based on the six selected factors (predictors): relative advantage, compatibility, complexity, organization size, organizational structure, and organizational culture. The ultimate goal was to (a) provide an academic contribution to identifying the degree of influence of these factors on U.S. hospital's cloud computing adoption, and (b) create a predictive model of adoption to assist hospital IT managers to decide how they can accelerate their cloud adoption. In addition, this study may also be useful in providing cloud service providers the required insights related to slow cloud adoption in U.S. hospitals.

With this objective and goal, this chapter includes the literature review of more than 100 journal articles, reports, books, and academic research according to four themes. For the first theme, I describe classical technology adoption theories and provide a justification for the selection of DOI and TOE frameworks as the theoretical foundation of this research. For the second theme, I provide the concepts and development of cloud computing with a focus on its architecture, services, business, social benefits, risks, and constraints. For the third theme, I review the current business challenges and status of IT adoption in U.S. hospitals. For the fourth theme, I present an overview of regression methods and the process to create a statistical predictive model. Finally, I conclude with a summary and transition to Chapter 3.

Literature Search Strategy

As cloud computing is an emerging technology, and U.S. hospital technology adoption is continuously evolving, online blogs, wikis, and journal articles contain the most up-to-date information that was important for this research. Most relevant and peer-reviewed journals related to the research topic came from *Healthcare IT News, Gartner Research, International Journal of Business and Social Science, Business Wire, Forbes, Computer Weekly, International Journal of Information Management, SERI Quarterly, Journal of Internet Law, znet.com, Journal of Information Systems, Journal of High Technology Management Research, Global Journal of Business Research*, *Informatica Economica,* and *Financial Executive*. The recent scholarly and dissertation research papers were among the sources I searched and retrieved from ProQuest dissertation database. The main keywords I used included *cloud services*, *cloud computing*, *health care cloud*, *hospital cloud*, *hospital information system*, *cloud adoption*, *technology adoption*, *adoption theories*, and *statistical regression*. The scope of most research papers or journal articles was within the last five years to ensure their content included the most recent aspects of the research topics. The main search engines for articles and research papers were Bing, Google Scholar, and Walden University library’s database searches.

Theoretical Foundation

The common challenge for new technology adoption is that no universal guidance for decision makers is in line with critical factors. The lack of universal guidance reduces the technology adoption intent and hinders the adoption decision progress (Tornatzky & Fleischer, 1990). In this respect, scholars and researchers have conducted multiple studies based on individual and social behavior viewpoints to identify the most influential technology adoption factors instead of judging the adoption by the technology itself. Within the last two decades, scholars have developed several technology adoption theories to address this concern. These theories include the technology acceptance model (TAM) by Davis et al. (1989), the theory of planned behavior (TPB) by Ajzen (1985), the unified theory of acceptance and use of technology (UTAUT) by Venkatesh et al. (2003), the diffusion of innovations by Rogers (2003), and the technology-organization-environment framework (TOE) by Tomatzky et al. (1990). In the following sections, I briefly describe each of these adoption theories and provide justification on why I chose DOI and TOE for this research.

Technology Acceptance Model (TAM)

The TAM model includes three key influential factors—perceived usefulness, ease of use, and attitude toward using—affecting the perception of an individual, which is, in turn, influential to the behavioral intention to accept a new technology (Chuttur, 2009; Powelson, 2012). As illustrated in Figure 1, external variables are technology features, user training, user involvement in the design, and implementation process influential to user's perceived ease of use and usefulness. Once these perceptions are set, they then become the driving factors for a user to accept or reject the new technology. The perceived usefulness and attitude toward using a new technology have a direct correlation with the behavioral intention to use technology (Davis et al., 1989).

Researchers have widely used this methodology in various technology adoption studies and demonstrated that it is a valid and reliable theory to provide a reasonable prediction on user acceptance for new technology deployment (Lule, Omwansa, & Waema, 2012). However, several researchers argued that the TAM model is more suitable for technology adoption studies with the voluntary use of a system instead of mandatory applications, such as in the commercial business environment. TAM does not indicate further explanation on the reasons for success or failure of technology adoption beyond showing the correlation with perceived usefulness and ease of use. Therefore, TAM has limited practical use (Chutter, 2009), as it also lacks any relation to external factors as demonstrated in other technology adoption theories, such as organizational size, competitive pressure, and system compatibility. As the research environment of this study is within a corporation setting, external factors besides perceived usefulness, and ease of use are influential to IT managers' intention to adopt cloud computing services. TAM appears to be an inappropriate theory to apply.

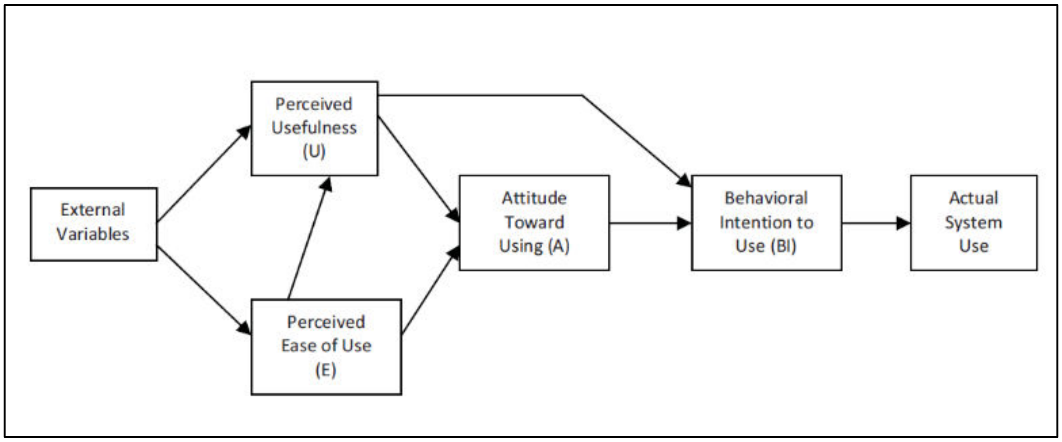


Figure 1. Technology acceptance model. It shows the interrelationships between adoption factors. Adopted from "Perceived Usefulness, Perceived Ease of Use, and User Acceptance of Information Technology," by F. D. Davis, *MIS Quarterly, 13*(3), 1989, pp. 319–314. Copyright 2010 by MISRC. Reprinted with permission.

Theory of Planning Behavior (TPB)

The TPB model is an attempt to link an individual's beliefs with individual's behavior and intention. This theory is the successor of the theory of reasoned action (TRA) with modification to include perceived behavioral control as a way to address the limitation of TRA. According to Ajzen (1985), TRA is only suitable to predict deliberate behavior when the intention is 100% voluntary and under an individual's control. As illustrated in Figure 2, TRA consists of three types of beliefs that align independently with three theoretical components: (a) attitude toward the behavior, (b) subjective norm, and (c) perception of behavioral control. In combination, these three beliefs comprise the components for the formation of an individual's behavioral intention. Many health-related research studies validated the TRA theory by showing a high correlation of attitudes and subjective norms to behavioral intention (Sheppard, Hartwick, & Warshaw, 1988). However, personal intention and decision assessment based on individual's beliefs and behavior is still this theory's main application, instead of business decision assessment. Furthermore, Dutta-Bergman (2005) argued that emotion could heavily influence an individual's behavior at a given time for then the behavioral intention may not be rational. Therefore, TRA is not the right choice as the foundational theory for my research study because, for a business-oriented research within a workplace setting, this theory is lacking any objective organizational and environmental measure. Similar to the constraint for applying TAM, the research result may indicate insufficient details to highlight critical characteristics of cloud computing and organizational factors to predict the IT managers' intention for adoption.

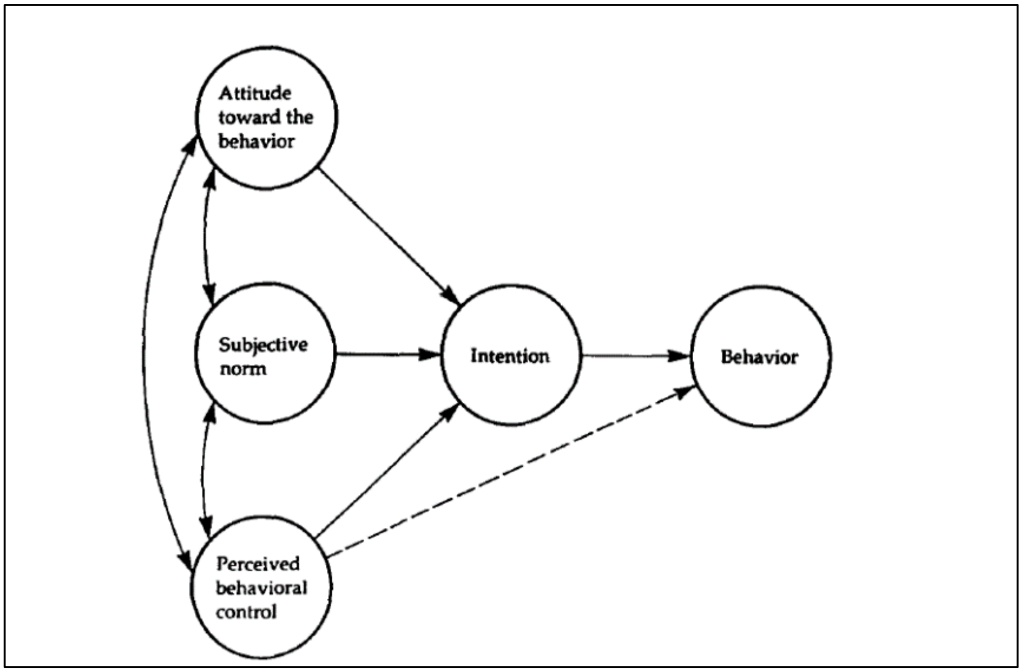


Figure 2. Theory of planned behavior. It shows subjective norm, attribute toward the behavior, and perceived behavioral control are three key factors to drive intention. Adopted from "The Theory of Planned Behavior," by I. Ajzen, *Organizational Behavior and Human Decision Processes, 50*, 1991, pp. 179–211. Copyright 1997 by Elsevier. Reprinted with permission.

Unified Theory of Acceptance and Use of Technology (UTAUT)

UTAUT, Venkatesh and his associates developed in 2003, is another well-accepted technology adoption theory. UTAUT is a combination of eight innovation adoption theories, including TRA, TAM, TPB, DOI, motivational model (MM), combined TAM and TPM (C-TAM-TPB), model of PC utilization (MPCU), and social cognitive theory (SCT). This new unified theory indicates the behavioral intention to accept and use new technology (Sundaravej, n.d.; Venkatesh et al., 2003). As illustrated in Figure 3, UTAUT consists of four key constructs: (a) performance expectancy, (b) effort expectancy, (c) social influence, and (d) facilitating condition.

Gender, age, experience, and voluntariness are moderation components that interact with the four constructs to influence the behavioral intention. Since UTAUT is a consolidation of adoption theories, it has significant conceptual similarity with those theories. For instance, its social influence is equivalent to the subjective norm in the TPB, performance expectancy and effort expectancy are similar to the perceived usefulness and ease of use under the TAM model. Although UTAUT is a more comprehensive technology adoption model as compared with TAM and TPB, it is very difficult to apply because it consists of 41 and more than 8 independent variables to predict adoption intention and behavior respectively (Bagozzi, 2007). Due to its unnecessary complexity, I do not consider this theory as part of my research theoretical framework.

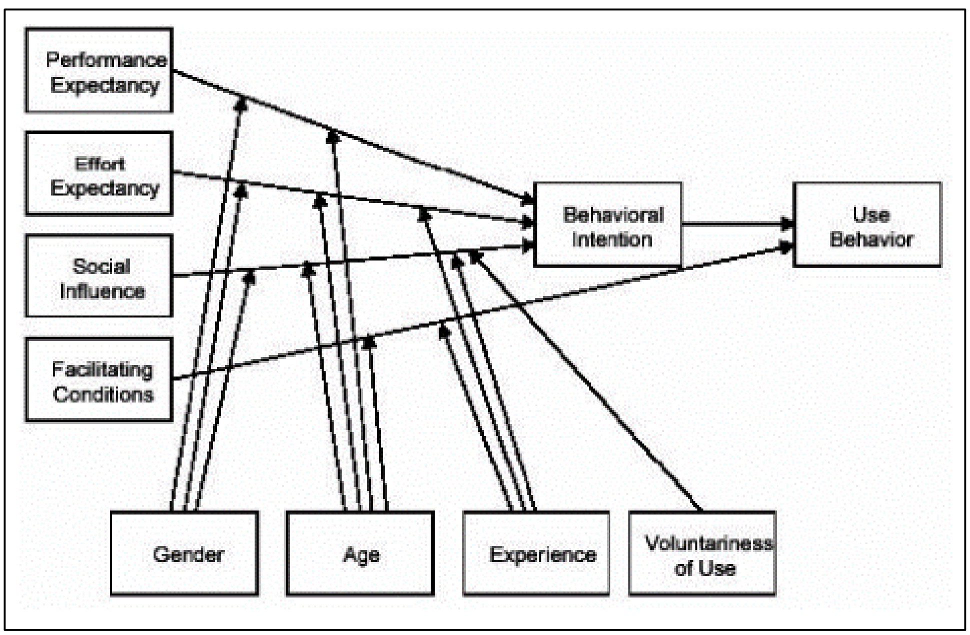


Figure 3. Unified theory of acceptance and use of technology. It shows two-dimensional influence to behavioral intention. Adopted from "User Acceptance of Information Technology: Toward a Unified View," by V. Ventakesh, M.G. Morris, F.D. Davis, and G.S. Davis, *MIS Quarterly, 27*, 2003, pp. 425–478. Copyright 2014 by MISRC. Reprinted with permission.

Diffusion of Innovations (DOI)

DOI states that several factors are influential to the technology adoption rate: (a) leadership style, such as attributes to change; (b) organization structure, such as centralized versus decentralized control, slack size, structure formalization, and internal collaboration versus competition model; and (c) external characteristics of an organization, such as system openness (Powelson, 2012; Roger, 2003; Ross, 2011).

Specifically for norm similar to Ajzen (1985), Rogers (2003) explained that a social system has a structure where chief users can create and set the standard behavior to guide the behavior of most members. Therefore, besides individual’s preference, the social system can also be directly influential to the adoption rate of innovation. The reason is that social system is a venue where users can maintain a formal and informal structure to constrain people in ways they should interact with each other to solve common problems and provide a sense of regularity and stability (Roger, 2003). Even norm and communication channels seem to be important in innovation adoption; Rogers’ research did not prove them as most critical factors.

In his study, Rogers (2003) concentrated on the influential factors of technology itself and created a five-factor influential model. Rogers argued that the main objective of an innovation-decision process was to reduce the uncertainty about consequences. The five influential factors are essential for an individual to gain better understanding of potential consequences. Rogers claimed that these five factors indicated 49–86% explanation behind the innovation adoption, as follows:

- Relative advantage. It represents the perceived extra value of using a new technology, compared with an existing solution. For example, financial and social status benefit can be part of the relative advantages. According to Rogers (2003), relative advantage is the strongest predictor of an innovation adoption rate. As Powelson (2012) highlighted, cloud computing is an emerging innovation, and its elasticity capacity feature has significant relative advantage for the business, particularly for small corporations that lack strong financial position to invest on IT capitals.
- Compatibility. It refers to the degree of synchronization with an existing value, method, and experience. It means it does not include conflict to the current social system value and norms. When an innovation is compatible with an individual's belief and value system, the individual's uncertainty about technology will diminish, and a higher rate of adoption is permissible (Shin, 2006).
- Complexity. The perceived technological solution is simple to understand and apply. Researchers can use the perceived functional points and process steps to perform a specific function to measure complexity (Tornatzky & Fleischer, 1990). Besides this scientific calculation, researchers can estimate the complexity of technology innovation by the amount of physical and behavioral knowledge aggregation through observation of cause–effect understandings in real world scenarios. According to Tornatsky and Fleischer (1990), technological solutions with less perceived knowledge aggregation required (i.e., less complex) normally indicate higher adoption rate.

- Trialability. When someone tries a new technology, the trialability of that technology increases because it shows the possibility to do incremental adoption instead of full adoption. As an investment, training and change management risk become minimal, trialability typically has a high degree of adoption. Additionally, with trialability, the user could gain the opportunity for reinvention and customization during the trial period, which has a positive effect to encourage adoption (Shin, 2006).
- Observability. It represents the result of a new technological solution that is highly visible, and its result value is ready for assessment. This positive visible effect can be influential to peers, causing faster adoption of the similar technology.

According to Rogers (2003), relative advantage and compatibility are the most important among the five key influential factors for technology. Rogers concluded that if an individual or corporation perceived an innovation as having high relative advantage, no compatibility issue, and simple to apply, then it would have a high adoption rate without too much consideration on trialability and observability.

Due to the DOI's strong theoretical base on revealing the critical factors for innovation adoption at the individual and organizational level with vital research-supported validity, I had chosen it as one of the foundational theories for this research. Compared with other innovation adoption theories, with DOI, people can address the adoption at the enterprise level instead of only at the individual level (Oliverira & Martins, 2011).

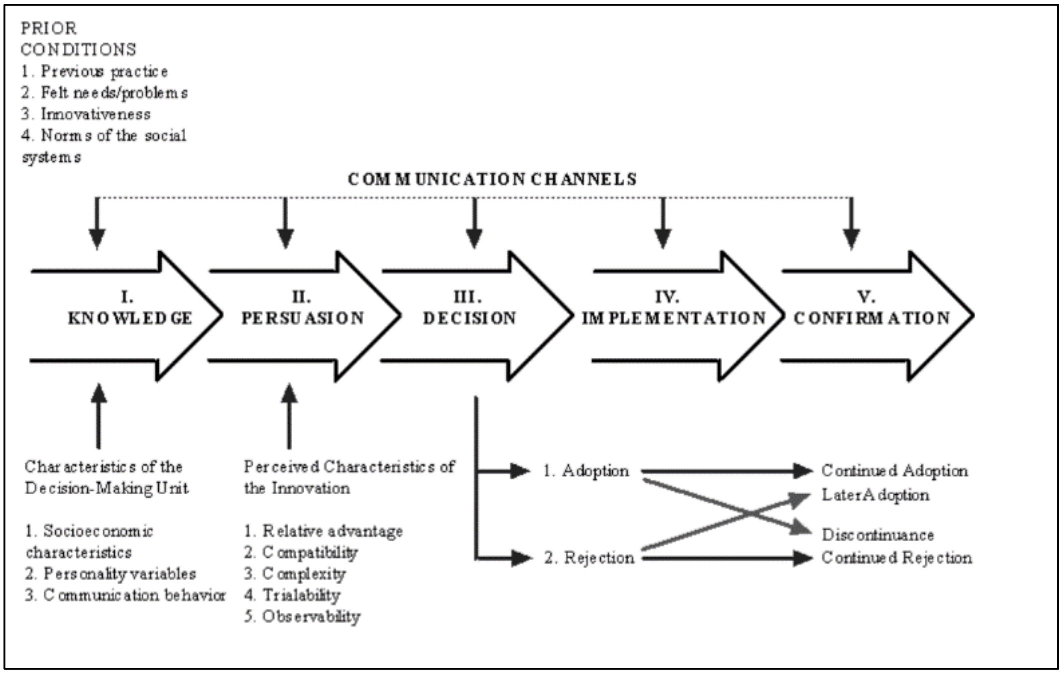


Figure 4. Diffusion of Innovation (DOI)—a model of Five Stages in the innovation-decision process. Adopted from *Diffusion of Innovations* (p. 170), by E. M. Rogers, 2003, New York, NY: Free Press. Copyright 2003 by E. M. Rogers. Reprinted with permission.

Technology–Organization–Environment (TOE) Framework

The distinction of TOE from other innovation adoption theories is that it does not include technology innovation itself. Moreover, TOE shows an influence analysis of other factors under organizational and environmental context and their interrelationship affecting the result of adoption. As a summary illustrated in Figure 5, under the TOE framework, the factors in three interconnected contextual areas affect technology adoption process (Oliverira et al. 2011; Tornatzky & Fleischer, 1990):

- Technological context. It shows how the internal and external availability of different technologies affect a new technology adoption. The justification or rejection for adoption usually relates to the perceived direct and indirect benefits, perceived barriers, interoperability and interconnectivity, required IT infrastructure, and expertise of the technology itself.

- Organizational context. It indicates the degree of effect of organizational size, culture, and structure influential to the technology adoption. It shows the level of satisfaction of the existing technology base, adoptability, financial power, management support, commerce strategy, and view on the return of investment relating to the decision of a new technology adoption.
- Environmental context. It shows the influence caused by its industrial segment, competitors, and government. To measure, it indicates whether perceived government–pressure; market uncertainty; competitive pressure; the need for regulatory policy compliance; and assessment of consumer, trading partner, and vendor support readiness are in favor of a new technology adoption.

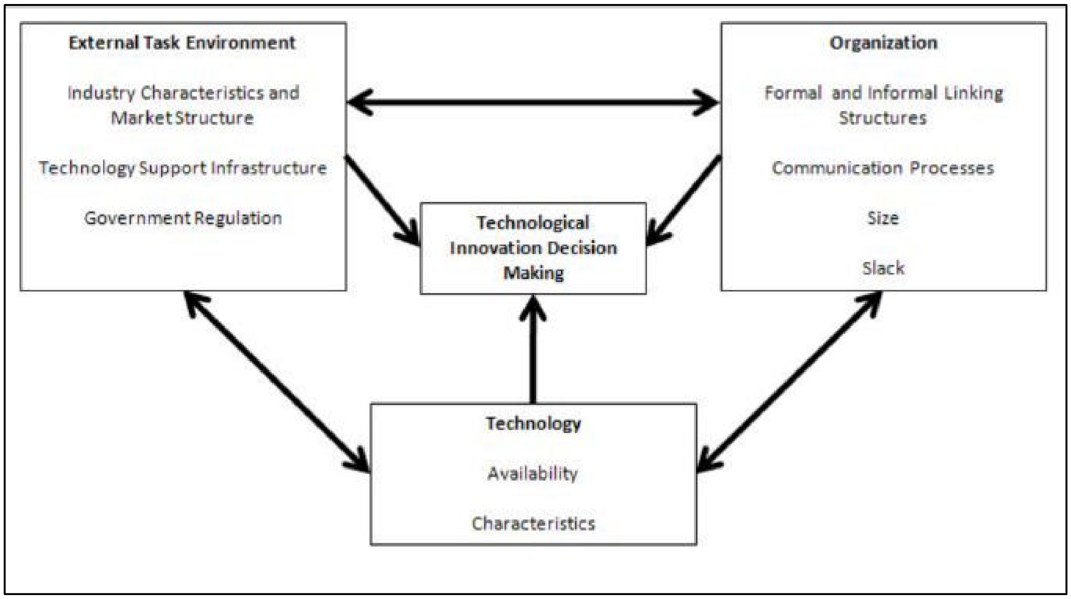


Figure 5. Technology–organization–environment (TOE) framework. Adopted from *The Processes of Technology Innovations* (p. 153), by L. Tornatzky and M, Fleischer, 1990, Lexington, MA: Lexington Books. Copyright 1990 by Lexington Books. Reprinted with permission.

For this research, I was interested in how organizational factors become influential to the adoption of cloud computing as an emerging technology, in addition to the technical context. Organizational sizes, organizational structure, and organizational culture are three predictor variables within the organizational factors. Specifically for organizational cultures, I measured them using two core competing value dimensions and simplified them into four forms: clan, adhocracy, hierarchy, and market. These two dimensions represented two orientations to measure an organization's people management (from flexibility to stability) and business management (from the internal capability to external positioning focus) styles. According to Cameron, Quinn, DeGraff, and Thakor (2003), by intersecting these two dimensions, organizational cultures can be under the classification of a clan (i.e., focus on flexibility and internal capability), adhocracy (i.e. focus on flexibility and external positioning), hierarchy (i.e. focus on stability and internal capability), and market (i.e., focus on stability and external positioning).

As highly regulated and structured U.S. hospitals carry their social responsibilities parallel to their revenue generation or cost recovery goals, their IT managers' intention on cloud adoption is not be voluntary. Therefore, I believed combining the DOI and TOE theory strengthened the relevance of my study due to their coverage of organizational context. It can also be useful in providing a strong theoretical framework to develop a predictive model to determine the cloud computing adoption intent, according to a set of influential factors described in these two theories.

Literature Review

Concepts and Development of Cloud Computing

What is cloud computing? Cloud computing is a progressive technological evolution of grid computing and virtualization. Its functions include virtualization to support a transparent encapsulation of resources from a physical server (memory, CPU, and storage) to a segregation of multiple virtual servers. Assigned tenants can allocate and control these resources similar to physically owning a server (Mather et al., 2009; Reese, 2009; Williams, 2012). To extend the virtualization capability further, cloud computing has another essential concept called *service abstraction*, in which cloud users access the service through a self-service web interface via the Internet. As the underlining infrastructure is virtual and built on top of a shared resource pool, cloud computing is helpful for providers to support multitenant charge per usage and provide instant scalability with agility (Sosinsky, 2011).

By definition, cloud computing includes the functions of IT services, which a third party provides. Cloud computing, which carries the attributes of multitenancy, massive scalability, rapid elasticity, metered usage charge, and self-provisioning for shared IT resources, runs on a distributed network and is accessible with common Internet protocols (Mather et al., 2009; Sosinsky, 2011). In the business viewpoint, cloud computing is a new IT resource subscription model (instead of just an Internet-enabled IT infrastructure virtualization technology) because it is useful for enabling businesses to eliminate their need to provide capital investment on IT infrastructure (Williams, 2012). Figure 6 shows a brief summary of cloud computing's deployment models, service models, and service attributes with the explanations included in the subsequent sections.

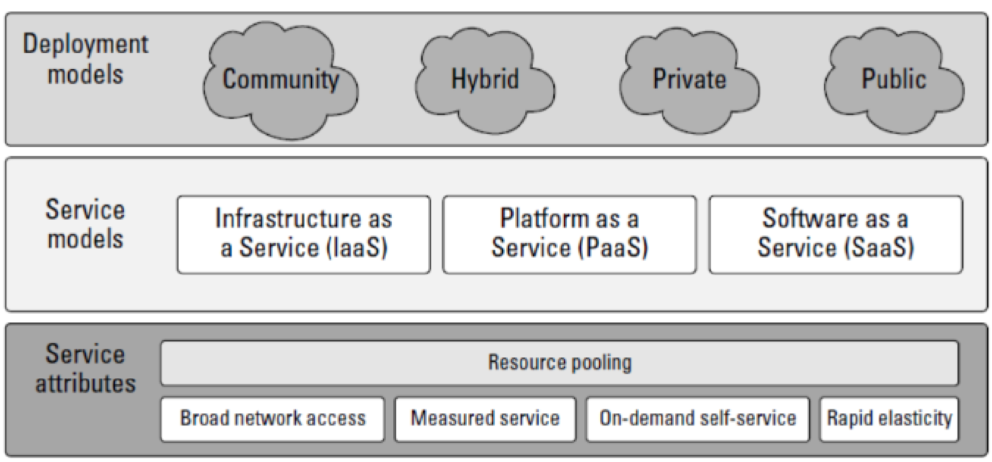


Figure 6. NIST (National Institute of Standard and Technology) Cloud Computing Definitions. Adopted from *Cloud Computing Bible* (p. 6), by B. Sosinsky, 2011, Indianapolis, IN: Wiley Publishing, Inc. Copyright 2011 by Wiley Publishing, Inc. Reprinted with permission.

Key characteristics of cloud computing service. As cloud computing is an emerging technology, its business model, characteristics, and underlying technology are continuously evolving. Currently, the cloud computing characteristics are as follows:

- Cloud service providers use Internet broadband network access and a web browser to connect services to their clients (Reese, 2009; Smith, 2013; Williams, 2012). Therefore, its service is accessible from anywhere as long as Internet is available (Finan, 2012).
- The service includes special on-demand and self-serve tools and portals to allow subscribers to manage provisioning and back office functions with a service-oriented approach (Armbrust et al., 2009; Finan, 2012; Jackson, 2011; Reese, 2009; Smith, 2013; Wilder, 2012; Williams, 2012).
- It has multitenant resource pooling by virtualization technologies to reduce charges to individual subscribers and maximize its own resource utilization (Jackson, 2011; Reese, 2009; Sosinsky, 2011; Wilder, 2012; Williams, 2012). Each tenant can only access its allocated resource without interfering others under the same sharing physical infrastructure (Smith, 2013; Wilder, 2012; Williams, 2012).
- The individual subscriber receives all monitored, measured, and reported resource consumption to check usage visibility and associate with charge amount (Reese, 2009; Wilder, 2012; Williams, 2012). The providers bill the service usage on a

pay-as-you-go scheme to their clients. The billing scheme is similar to general utility services (Finan, 2012; Smith, 2013; Sosinsky, 2011).

- The cloud providers do not require users to sign any long-term commitment contract for the services received. Therefore, the cloud service has a low entry cost to try out or pilot (Armbrust et al., 2009; Sosinsky, 2011).
- The biggest strength of the services is rapid elasticity (Finan, 2012; Williams, 2012). Under the end user perspective, the cloud resource is near infinite (Sosinsky 2011; Wilder, 2012), which avoids unnecessary infrastructure charges for its subscribers due to underutilization and decreasing time to market (Smith, 2013; Williams, 2012). Cloud-provisioned servers can have the auto-scaling capability to turn the service on when the load is high, or shut itself down when the server is idle (Reese, 2009).

Cloud computing service models. Understanding the common service and deployment models of cloud computing is important. As cloud computing is rapidly developing, more service models will be available in the future. Nevertheless, most providers, as illustrated in Figure 7, commonly offer three service models:

- Software as a service (SaaS). The cloud providers offer application software through subscription base, and subscribers can run it under the cloud provider's infrastructure instead of theirs (Finan, 2012; Sosinsky, 2011; Williams, 2012). As a result, subscribers experience reduced complexity and cost of installation and maintenance (Williams, 2012). Subscribers only need to do some application configurations and not carry any responsibility to manage and support the software and hardware for a specific business function. Microsoft Office 365, Google Mail, QuickBooks Online, Dynamics CRM Online, and Salesforce.com for customer relationship management are a few of many popular SaaS (Sosinsky, 2011).

- Platform as a service (PaaS). The cloud providers set up infrastructure, operating systems, and required development toolkits for subscribers to use as their development platform without the cost and lead time to build up and tear down the dynamic infrastructure instances to support their software development life cycle (Finan, 2012; Sosinsky 2011; Williams, 2012). The service is supportive of the idea behind the rapid design, development, test, and new application deployment. Currently, this service has the highest growth rate among the three services (Williams, 2012). Microsoft Azure, Google AppEngine, and Force.com are the three popular PaaS due to ease of use, low cost, and comprehensive tool sets for development, test, and deployment (Sosinsky, 2011).
- Infrastructure as a service (IaaS). The cloud providers package virtualized infrastructure (server, network, and storage) as a service for subscription and allow subscribers to use them to run their applications (Finan, 2012; Sosinsky, 2011; Williams, 2012). This service does not require the initial capital expense, procurement and installation lead time, ongoing maintenance charge, and implementation complexity (Sosinsky, 2011; Williams, 2012). Microsoft Azure, Amazon AWS, Verizon Terremark, and RackSpace are a few cloud service providers that offer IaaS (Sosinsky, 2011).

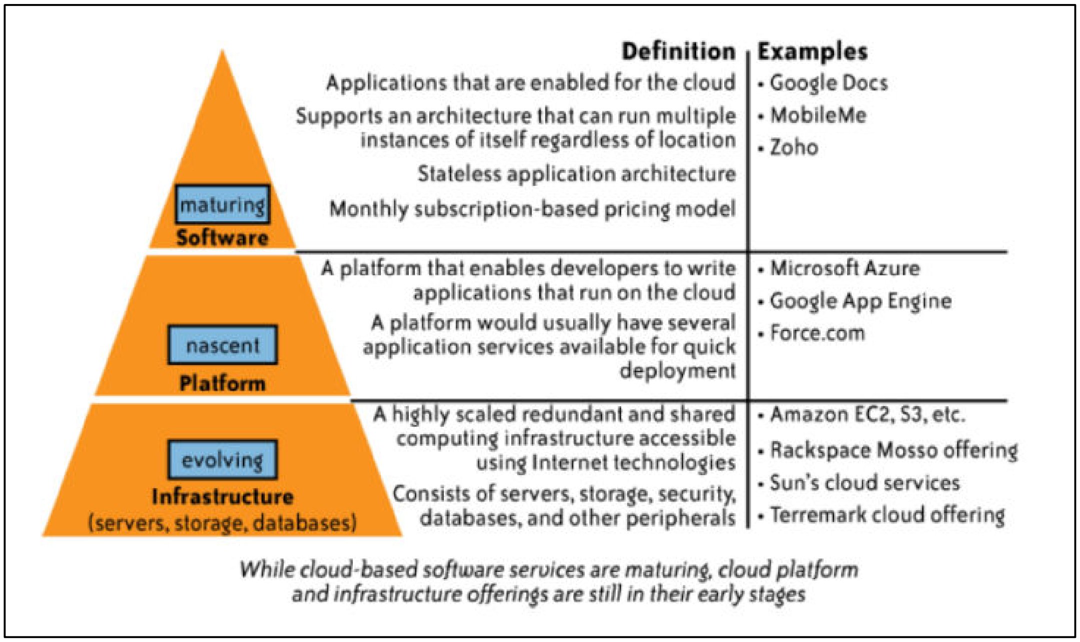


Figure 7. Cloud service models. Adopted from *Cloud Security and Privacy: An Enterprise Perspective of Risks and Compliance (Theory in Practice)* (p. 17), T. Mather, S. Kumaraswamy, and S. Latif, 2009, Sebastopol, CA: O'Relly Media, Inc. Copyright 2009 by O'Relly Media. Reprinted with permission.

Cloud computing deployment model. Cloud providers usually run the three service models under a deployment model called public cloud. Nevertheless, due to the data privacy and security concern, cloud providers developed other deployment models to accommodate the needs of subscribers. Nowadays, consumers and enterprises highly adopt four deployment models, mainly distinguished by tenant strategy under the foundational infrastructure layer, in terms of segregation of physical resource and data. These four deployment models include:

- Public. A cloud service provider owns the cloud infrastructure with a design specifically for public use (Finan, 2012; Sosinky, 2011).

- Private. The cloud infrastructure design is exclusively for one client to fulfill multiple departmental needs (Finan, 2012; Sosinky, 2011). It can be on or off-premise, and the management is under an in-house technical staff or a third party (Sosinky, 2011).
- Community. The cloud infrastructure design is useful for serving a group of clients with common objectives, functions, or under the same organizational group (Finan, 2012; Sosinky, 2011).
- Hybrid. It is a combination of multiple types (public, private, and community) of cloud infrastructure, connected seamlessly through specific application program interface (Finan, 2012; Sosinky, 2011).

Perceived benefits and barriers for cloud computing adoption. As mentioned in Chapter 1, even though cloud computing seems to have tremendous benefits for enterprises, its adoption is lower than expected, particularly for U.S. hospitals. Researchers are interested exploring this phenomenon to identify the critical factors influential to the cloud computing adoption. Based on my literature review, the summary of perceived benefits and barriers for cloud computing adoption can be a significant source of hints and association with the influential factors described in the DOI and TOE technology adoption theories.

The benefits of adopting cloud computing services can be on the global socioeconomic and individual business enterprise level. The global socioeconomic level has a focus on the potential impacts of cloud computing development and adoption for the overall global economy and environmental changes. These benefits are as follows:

- As cloud computing applies a virtualization and multitenant approach, which has an allocation of IT infrastructure resource to a large group of customers, it can have a high operational efficiency and resource utilization. With tremendous economies of scale, cloud service providers can offer IT services at low price points (Armbrust et al., 2009; William, 2012). With the ability to access advanced IT services without the need for high upfront capital investment, many small and medium companies can compete against large corporations (Aljabre, 2012; Armbrust et al., 2009; Campbell, 2010). In addition, with the reduced infrastructure investment, the business entry points are lower and the competition via innovation increases (Jackson, 2011).
- Besides the cost-saving benefit, cloud computing adoption also accelerates information sharing, accessing latest technology innovation, enabling data analytics, future cost transparency, and predictability (Aljabre, 2012; Finan, 2012).
- Cloud computing adoption can shorten the IT sourcing time for enterprises that in turn improves time to market as no more hardware deployment lead time is needed. As cloud service clients improve overall time to market for their products, their new product innovation cycle also improves (Finan, 2012; Jackson, 2011). As a result, cloud users experience better, more affordable, and faster cycles of new products and service creation. This IT technological and service model will ultimately be helpful in improving the quality of human life (Williams, 2012).

- On the enterprise business level, the largest benefits of cloud computing services are its resource elasticity, scalability, and low cost, flexible pay-as-you-go billing model (Aljabre, 2012; Armbrust et al., 2009; Jackson, 2011).
- With fast provisioning speed (for scale up or scale down), users benefit from reduced infrastructure maintenance time and solution implementation (Campbell, 2010; Jackson, 2011; Williams, 2012)
- Users can avoid the cost of infrastructure overprovisioning or the risk of opportunity lost due to infrastructure underprovisioning (Armbrust et al., 2009; Campbell, 2010).
- Users can transform their capital expense to operational expense so that the cash flow can match with total infrastructure cost (Finan, 2012; Jackson, 2011; Williams, 2012).
- Adopting cloud service is an opportunity for businesses to redeploy company resources on their core capabilities to provide business values to their customers instead of worrying about IT infrastructure (Aljabre, 2012; Campbell, 2010).
- On the end users' viewpoint, cloud service offers almost an infinite computing resource and support on demand for complex data processing needs that require a huge amount of parallel computing power (Aljabre, 2012; Finan, 2012).
- Subscribing to a cloud service can be the best time to streamline the IT supply chain process and provide a unified way to acquire, consume, maintain, and pay for IT infrastructure as global resources (Williams, 2012).

- Cloud users can be recipients of a reliable, secure and high-quality IT services that may not be implementable by small and medium corporations with limited IT funding and internal expertise (Aljabre, 2012; Jackson, 2011).
- Acquiring cloud service may be helpful for users improve internal and external business collaboration with the ease to use mechanism to access information anywhere at any time and via any device (Aljabre, 2012; Armbrust et. al, 2009; Jackson, 2011; Williams, 2012).

While cloud computing has benefits for businesses in terms of cost, technological innovation, and flexibility, many scholars argued that cloud service is still immature in several areas, and thereby put businesses at risk. These concerns include:

- Data security and privacy. Under the public cloud model, company data are in the safe keeping of the cloud service providers' data centers. Corporations may feel out of control to protect their data and have to rely on third party's security policies and technologies to do so (Ekufu, 2012; Williams, 2012; Sosinsky, 2011).
- Network bandwidth and security. Unlike companies' infrastructure on-premise, cloud computing services depend on the public Internet infrastructure, for which performance can be unpredictable due to uncontrollable network traffic via Internet communication pipelines (Reese, 2009; Sosinsky, 2011). When the Internet reaches saturation, such as in some special event days (e.g., Thanksgiving Black Friday), the low availability of cloud services may be the cause of jeopardizing a company's operational efficiency. Furthermore, as cloud services include multitenant virtualization technologies, implementing security intrusive

detection can also be challenging due to a virtualized network environment (Reese, 2009).

- Vendor lock-in. Currently, cloud service providers do not provide an industrial standard on how to integrate cloud services and resources (Himmel, 2012). Once companies adopt a specific cloud service from a cloud vendor, migrating their applications and data to other service providers can be difficult and time-consuming (Sosinsky, 2011).
- Legal and service level compliance. For some industries (e.g., health care, financial, and law advisory corporations), legal and service level compliance is specifically important due to public impact of their services and the large amount of customers' private and commercial sensitive data withholding. Nevertheless, not all cloud service providers have internal legal compliance expertise to satisfy regulatory requirements, such as U.S. HIPAA and EU data protection laws (Canellos, 2013; Paquet, 2013; Williams, 2012). Once the migration of data to the cloud environment is complete, the corporations providing data may have to bear the risk of legal and service level compliance violation if the cloud service contracts have not stated clearly the legal and service level responsibilities (Sosinsky, 2011). In addition, the physical location of data will be difficult to track after their transfer to the cloud data center (Paquet, 2013; Reese, 2009).
- Existing IT investment. Many large corporations have existing investments in their data centers, platforms, or applications. These investments may not fully depreciate. Even moving to the cloud environment does not involve upfront

capital investment but may indicate increasing the IT operational cost and underutilizing owned infrastructure (Reese, 2009). Furthermore, the modern cloud infrastructure may not be compatible with the existing infrastructure on premise and application design (Williams, 2012; Reese, 2009).

- Software licensing and infrastructure cost. In general, clients expect cloud services to be scalable and demand elasticity (i.e., clients can ramp up and down their service needs on demand). Nevertheless, as most cloud services are still premature, the licensing schemes for required software are not yet in line with the new cloud computing model (Reese, 2009; Sosinsky, 2011). In the cost control standpoint, the dynamic resource allocation flexibility provided as a cloud selling feature can be unfavorable to customers trying to avoid a highly fluctuated IT operational expense (Sosinsky, 2011).
- Fear of job loss. As corporations consider cloud computing services as a new medium of IT outsourcing, IT staff may resist migrating existing IT services and infrastructure to the cloud due to job loss fear (Williams, 2012).

Even though plenty of tangible and intangible benefits and concerns come with the cloud service adoption that IT managers have to consider, to most extent, the adoption choice will still matter according to the perception of whether the benefits are much higher than the cost and risks. Therefore, having a relevant predictive model can be helpful to cloud services providers and IT decision makers in analyzing and changing the status of critical adoption factors, as a way to accelerate the adoption. For instance, the benefits and barriers can be directly relevant to the three technical factors of this research:

- Relative advantage: Financial benefit and cost, security and data privacy risk, scalability, deployment cycle time, and flexibility for future change.
- Compatibility: Existing infrastructure and technologies deployed, and compliance requirement in legal and public regulation.
- Complexity: Ease of use, training requirement, and self-service capability.

Current Development and Status of Technology Adoption for U.S. Hospitals

Similar to other industries, U.S. hospitals and the entire health care industry are active in introducing new medical and information technologies in terms of new equipment, medications, and systems for improving effectiveness and efficiency on patient sickness diagnostic and treatment. With this research focused on information technology for U.S. hospitals such as cloud computing, I reviewed more than 30 related articles to understand its development and status. From the mega trend perspective, I found three important aspects:

- Creation of the interconnected electronic HIS with streamlined workflows and medical data hubs, integrating internally with all departments and externally with other health care providers and payers.
- The introduction of mobile devices with intuitive user interfaces (e.g., voice and handwriting recognition), which physicians and nurses use in rendering service.
- Acceleration on the outsourcing hospital administrative operation and systems to third-party vendors, such as cloud service providers and business process outsourcing (BPO) vendors.

Creation of the interconnected HIS. In recent years, HIS have expanded from its original goal of managing cost and handling billing to now including patient prescription, examination, and medical instruction functions. The main difference between a HIS and other information systems is that the former serves as a sociotechnical system because its tasks involve a lot of human interaction, information exchange and processing (K. Zarour & Zarour, 2012). The basic objective of a HIS is to improve patient service and care, hospital planning and management, safety and quality assessment, medical research and epidemiology by providing accurate patient data at the right time in the right place and to the right people (Li, Wu, Chen, Zhou, & Wu, 2011; K. Zarour & Zarour, 2012). According to Hosseini, Nordin, Mahdiani, and Rafiei (2014), the HIS should consist of the minimal four functional subsystems: (a) clinical operation and nursing management; (b) laboratory information management; (c) pharmacy information management; and (d) radiology information management. K. Zarour and Zarour (2012) mentioned that it should also include EMR and medical image retrieval and archiving. Additionally, Lee, Ramayah, and Zakaria (2012) stated that the HIS should have a real-time monitoring capability for patients.

Haque, Kayadibi, Rafsanjani, and Billah (2013) later believed that hospital financial management, outpatient information management, and health information exchange (HIE) subsystems are also essential for a HIS to be fully functional. Furthermore, Yang, Zheng, and Wang (2011) alleged that patient registration, health check management, surgery management, anesthesia management, drug management, and blood transfusion management are the other six core subsystems for large-scale HIS.

This list of diversity corresponding to HIS and functionalities indicates no consensus on which capabilities are essential. Most likely, it depends on the process and technological maturity of a hospital.

The improvement of patient safety is possible with effective HIS while hospitals can have better communication with patients, nurses, and doctors. Timely and accurate medical information is available at the point of service without the need to coordinate multiple support staff to retrieve the information (K. Zarour & Zarour, 2012; Mirabootalebil, Malaekeh, & Mahboobi, 2012). Besides immediate patient safety and financial benefit, redundant task elimination, common processes, employee job satisfaction, enhancing patient trust, available data for medical research, and the notion of personal lifetime health plan (PLHP) can be the other intangible values of HIS (Hosseini et al., 2014; Lee et al., 2011; Mirabootalebil et al., 2012; Siegel, 1968). Furthermore, hospitals with information systems can have reduced time in reporting statistical data for public health safety (Anema, Kievit, Fischer, Steyerberg, & Klazinga, 2013), which in turn can be a contributing factor in disease prevention and chronic-disease management (“Health Information Technology,” 2005).

Disregard with the benefits and the availability of required technologies, the adoption of HIS was slow according to published public statistics in 2009. During that period, only 17% of U.S. hospitals and 21% of U.S. physicians were using electronic order entry forms and EMR (Lee et al., 2011). Mirabootalebil et al. (20012) reported that the low adoption rate might be because many HIS designs are only supportive of financial and management point of view and exclude the usability assessment for the end users, including physicians and nurses. Besides the system interoperability and system design issues, a suspected reason for low hospital investment in information systems is that improving patient care efficiency might have an effect on hospitals' incomes due to reduced patient bed days ("Health Information Technology," 2005).

In the past three to four years, the adoption of HIS indicated significant improvement. Within different functional areas of a HIS, Optum Institute (2012) highlighted that the biggest acceleration for recent HIS development is from the EMR and the HIE. As the Optum Institute's 2012 CIO survey reported, 87% of surveyed hospitals now have EMR and 70% have been using HIE technology. The EMR system includes incredible convenience and improved safety measurement to medical staff and patients with a complete patient medical and treatment records stored online (Morris, Savelyich, Avery, Cantrill, & Sheikh,2005). Other dominated factors for EMR's recent rapid adoption are Obama administration's 6.5 billion incentive payment for health care institutions to convert health care providers' existing paper systems to EMR and the coming 2015 penalty for noncompliance with the U.S. government health IT regulation (Freudenheim, 2012).

Nevertheless, even though more hospitals now have EMR system and HIE, technology concerns still arise in that existing medical data lack the required effectiveness and interoperability (Optum Institute, 2012). For instance, some EMR implementations are still difficult to use, arguably slowing physicians and nurses' daily work efficiency. Hospital staff can easily make mistakes based on point-on-click user interface design. Any system downtime can be the cause of a life-or-death situation for the patient (Freudenheim, 2012). These barriers for the adoption of EMR and HIE indicated issues on raising cost; insufficient implementation time; lack of data accuracy and completeness; and legacy system and process incompatibility. The overall resistance to the adoption of a HIS was due to lack of required mobility, intuitive user interface, staff training, and uncertainty about its system reliability, according to Hanada, Shusku, and Kobayashi (2010). K. Zarour and Zarour (2012) further added that the development and deployment of a HIS include several challenges: (a) the enhancement pace cannot keep with the new technology changes, (b) lack of unified information exchange standard, (c) the system lacks accurate and sufficient data to support day-to-day hospital decision making and execution, and (d) patients' trust on data privacy is low.

Some of the challenges are due to the amount, diversity, and complexity of information that stakeholders require in hospital operation. Hosseini et al. (2014) identified that the key factors for the adoption of information system for hospitals are system, service, and information quality; perceived usefulness; and perceived ease of use based on the TAM framework. Chow, Chin, Lee, Leung, and Tang (2011), in their research on HIS adoption in a Hong Kong private hospital, discovered that nurse attitude and satisfaction of using HIS play a significant role in hospitals. The primary factors are work units, perceived usefulness, and the level of support that nurses receive pertaining to the HIS.

A good HIS should be scalable, flexible, stable, robust, requiring low maintenance effort, easy and open for customization to fit for hospital operation (Yang et al., 2011). In a case study research article, Patrick (2011) argued that using an enterprisewide, off-the-shelf HIS (e.g., Firstnet) might lack the critical design features, as compared with in-house, developed best-of-breed solution. Conducting a risk assessment of a HIS before its adoption is the responsibility of the hospital IT manager, to ensure patient safety and confirm the expected results and future workflow productivity. One way to improve the operational efficiency and effectiveness design of a HIS is to use critical path analysis to define optimal process flows with preset standard service quality and lead time (Hanada et al., 2010).

Haque et al. (2013) proposed two new conceptual HIS solution selection methods for a HIS. The first method is a rapid learning system, which has a special algorithm for analyzing the foundational patient needs and search for proven solutions. The second method is useful for analyzing the capability and process domains of a HIS and for identifying the critical elements essential for its effectivity. For the creation of an in-house HIS, Damij (1998) recommended the use of a methodology called *tabular application development*. This method consists of five phases for the design and implementation of a HIS: (a) problem analysis with entity diagram, (b) business process analysis with activity–task table, (c) data analysis with object modeling technique, (d) system design, and (e) implementation.

In terms of the architectural design development of a HIS, history indicated two stages. In the first stage, a HIS only operates under one centralized database. While in the second stage, a HIS consists of many components with built-in databases. The data exchange relies on the extraction of data from various modules into a centralized data warehouse after data cleansing and conversion (Li et al., 2011). K. Zarour and Zarouor

(2012) as well as Li et al. (2011) proposed a similar technical architecture of a HIS that consists of three layers: user interface, system function, and data access. It has seven critical components that are useful for reducing the design complexity and improving the interoperability of a HIS. The seven components include (a) web portal, (b) user–system communication agent, (c) local database for the core function of every HIS, (d) peer-to-peer interconnection network, (e) data warehouse with shared hospital data, (f) user profile ontology, and (g) access control module.

Another major development for HIS was the use of workflow engine, which is facilitative in providing more seamless integration among processes and systems of hospitals and health care partners. This new approach is called *process-oriented hospital information system* (Tavakol, Hachesu, Rezapoor, & Rezazadeh, 2013). It is helpful in satisfying the need to connect heterogeneous system environment at the process level and enable health care service providers to exchange data in varying data formats. It can improve operational efficiency and data quality of a HIS by means of a better process management and control (Yang et al., 2011). Additionally, if this technology combines with the convenience of wireless handheld devices, users can further enhance the data query and entry capability at the point of service (Tavakol et al., 2013). In general, a workflow engine of a HIS should include three architectural components: workflow management system, process modeler, and application integration bus (Yang et al., 2011).

Computer -aided decision support in a clinical operation is another area, which show major improvement in recent years. With this capability included in appropriate clinical workflows, a HIS can directly provide patients with specific recommendations (e.g., medication and treatment assignment at the time and location needed), and reduce redundant data entry and query (Kawamoto, Houlihan, Balas, & Lobach, 2005).

Interestingly, the outpatient capability of a HIS is expected to increase significantly due to the common availability of broadband Internet and continuous price drop of home-based health monitoring devices, such as portable weight, blood pressure and blood sugar monitoring and alert systems. As a pilot project, the Intel Digital Health Group sponsored, program patients can take a daily health measurement with their home-based health monitoring device. Patients will send, through the device, the digital health data and share their EMR directly with their physicians and hospitals (Olson, 2009).

According to Hanada et al. (2010) as well as K. Zarour and Zarour (2012), the success factors for creating and sustaining EMR are data confidentiality, integrity, and availability. At the same time, for a HIS, other success factors include the use of normalized information distribution standard (e.g., XML) and unified interagent communication protocols (e.g., HL7). As suggested, to improve the interoperability of a HIS with other health care systems, the federal government should create common data protocol and access standard (“EHR Report: Health IT isn't delivering,” 2013). Establishing a national data repository for EMR was highly recommended (Anema et al., 2013).

As Tavakol et al. (2013) stated, due to the lack of reliable technology to send, receive, present, and transfer medical information to an authorized medical staff, the triggered medical errors became the cause of mortality (nearly 98,000 annually), according to the U.S. Institute of Medicine. Potentially the recorded 200,000 adverse drug events could be avoidable if physicians could have received early alert before the issuance of a drug prescription (“Health Information Technology,” 2005). Despite the rapid improvement in user interface and mobility of a HIS as hardware and software technology continue to advance, the main challenge for the development and adoption of a HIS remains with the interoperability of other health care partners and patients’ home-based health monitoring devices. If a HIS can be useful in ultimately delivering seamless patient information exchange among health care providers, then doctors can review the patient’s historical health condition and make the best treatment decision (Chow et al., 2011).

The introduction of mobile devices for hospital applications. Until recent years, the electromagnetic interference among medical devices was the biggest concern in using wireless data and voice communications system in hospitals. Researchers helped mitigate this concern with their continuous evaluation, and it had finally been mitigated (Hanada et al., 2010). With this constraint removed, a HIS is now workable with a wireless network and mobile devices in tracking the location of expensive medical equipment through a method called *RF-ID technology*. Physicians and nurses can carry their cell phones at work and be able to contact their medical teams easily during an emergency (Hanada et al., 2010).

With the introduction of smartphones and tablets, physicians and nurses can now use them to make necessary real-time data entry and query from a remote location (Karahoca, Bayraktar, Tatoglu, & Karahoca, 2009). With advancing technology in mobile devices, the health care industry can create different applications suitable for hospital users and allow them to integrate well with their existing HIS. For FDA to approve these applications, software application developers need to comply with the FDA-published mobile health application guideline. The most valuable mobile application usages surveyed for doctors and nurses are the remote access to patient's EMR; lab result and medical image enquiry; appointment schedule setting and alert; and drug application assistance (McNickle, 2011).

With hospitals extending their outpatient services, mobile applications for patients become more vital than the traditional desktop computer applications. Applications such as medication intake reminder and remote health monitoring are increasing (Fong & Chung, 2013). These applications can capture the patient health data and send them remotely to the EMR module of a HIS. With the continuous development of this mobile technology with cloud computing platform (e.g., centralized information hub), hospitals are able to extend their outpatient service by reducing the hospital pressure to have enough beds available at all times.

Acceleration on the hospital IT outsourcing. As the cost of structure and pressure of global competition in the health care industry continue to increase, qualified health care resource shortage in the United States becomes a significant issue to resolve. Four particular segments in health care have the urgency to improve their innovation and cost position are: (a) health care providers, (b) payers and governments, (c) life science and pharmaceutical companies, and (d) medical device manufacturers (Cisco, 2014). Health care providers such as hospitals have been seeking to outsource their IT hardware and software infrastructure to third party cloud service providers. Many even consider outsourcing their routine and administrative tasks to vendors offering business process as service.

Nevertheless, according to Presti (2013) and Bowman (2013), despite the key cost, scalability, and reliability benefit of hiring cloud service providers, cloud computing adoption in health care industry is still slower than expected. As highlighted in Chapter 1, the main barriers are still system reliability, data backup, disaster recovery, interoperability, privacy, and security compliance concern (Shimrat, 2009; Hirsch, 2012). As hospitals must be able to operate 24 hours and 365 days per year, any outsourced IT solutions must be agile enough to handle change requests from internal medical operation, hospital management, and external regulation bodies effectively (Siegel, 1968). The general perception is that software reliability offered by cloud services remains unsuitable for the requirements of hospitals, according to the software error rate measured by other industrial software products. For instance, the prediction of 60,000 adverse events can happen based on existing software reliability statistics, which is unacceptable in health care industry (Freudenheim, 2012). Since most cloud service providers have legal clause in their contract to defer their responsibility and accountability for incidents caused by program bugs, it makes hospitals more skeptical to deploy a cloud-based solution such as the EMR (Freudenheim, 2012).

With the new HIPAA and ARRA requirements, hospitals and other health care service providers now have to keep the patient records electronically and make them accessible online by 2015. Otherwise, they will have to pay penalties (Good, 2013).

Under the 2013 HIPAA revision, cloud service providers as business associates for any health service providers must report any disclosure of patient data even it may not cause significant financial risk to themselves or their customers (Smith, 2013). Addressing some existing concerns of health care providers is helpful and facilitative of the need for infrastructure outsourcing to cloud service providers. Based on the current estimation, the cloud computing market will grow to $5.4 billion in 2017 due to this U.S. regulation (Good, 2013). To further relieve the security and privacy concerns, hospitals and cloud service providers with HIPAA certification have been active in resolving the data ownership, integrity, confidentiality, and availability concerns, and in starting to provide adequate audit measurement and data archiving strategy (Chen, Lu, & Jan, 2012). Many cloud service providers also utilize external independent audit to enforce privacy and security compliance in order to boost trust (Miliard, 2013).

The Optum Institute (2012) reported in its CIO survey, that 60% of the surveyed hospitals, currently having EMR system and HIE, had planned to invest in a new cloud-based environment. They anticipated cloud technology would be helpful in providing the needed applications and additional infrastructure in the future. As long as hospitals and the entire health care industry are progressing to adopt cloud computing, the development of cloud-based software will grow. For instance, having an integrated cloud-based EMR system that is assessable by all health care providers of a patient is helpful to each health care practitioner in making accurate diagnosis to create an appropriate patient treatment plan. The cloud technology involves low-cost, low-maintenance, and interconnected environment (Chen et al., 2012). Applications for the EMR, drug prescription, clinical operations and administration, and physician order-entry systems will become more popular (Shimrat, 2009).

Presti (2013) shared that health care institutions adopting cloud computing platforms mostly demand a private cloud architecture first, instead of a multi-tenant public cloud environment. This technological requirement is an adoption barrier symptom since the full trust on cloud security is still lagging. According to Shimrat (2009), more than 300 software manufacturers have been providing some forms of cloud-based electronic health care system since 2009. Google and Microsoft invested heavily in electronic health care systems under the brands as Google health and Microsoft HealthVault, respectively. These two corporations are competing for the leadership role to create an alliance with health care providers and IT solution builders. Nowadays, over 58% of health care CIOs started to realize the cloud benefits. They began to believe it could significantly transform their business as well as improve service quality and cost structure (Miliard, 2013). For cloud service providers to be a success to attract health care customers, they must offer more HIPAA-compliant solutions. Specifically, hospitals can then realize the following vital benefits:

- Improved security. Cloud service providers most likely have more security experts, data encryption, authorization/authentication control, and backup/restore service than most IT departments in hospitals.
- Highly scalable infrastructure can correspond with the rapid increase of patient data due to the data retention policy imposed by government regulation.

- Improved data mobility. Once hospitals store their data in the cloud, physicians can access the data remotely with the use of mobile devices, such as cell phones and tablets.
- Lower cost for patients and hospitals. Patients can avoid duplicated laboratory and radiology tests due to loss of their test records. At the same time, hospitals also receive the benefit by not investing in new hardware, software, and their in-house IT experts.
- Better data sharing. Patients can easily share their EMR with other health care partners without much administration effort (Good, 2013).

The rapid development of cloud computing and Internet technology is facilitative of enabling the business process outsourcing model for U.S. hospitals and other health care providers. Hospitals can have a back office workforce provided by a BPO vendor that has operational staff in other countries (e.g., India), at a low cost. Besides the classical SaaS, PaaS, and IaaS benefits, this outsourcing model is supportive to hospitals in managing the operational cost, avoiding staff training on new software, and enabling hospital staff to focus on their core health care services (Steve, 2010). Overall, it can be useful for improving the society by making the health care industry more efficient. Scholars reported that 16% of the U.S. GDP was from the health care sector in 2009 (Fong & Chung, 2013).

Overview of Statistical Regression Methods

Traditionally, many quantitative correlation studies used factorial methods. Nevertheless, as Balling (2008) and LaMorte (n.d.) described, MLR is a more efficient statistical method than factorial analysis. They explained that the MLR could be a viable tool for measuring the effect of multiple independent variables simultaneously without the need to set all variables under control except the one under examination.

By definition, regression methods are statistical tools useful in predicting the relationship between variables. Similar to other nonexperimental correlation analyses, these statistical tools cannot ascertain any causal relationship (Flom, 2011). Many types of regression analysis classification are according to relationship, number of predictor variables, and outcome variable. The objective of MLR is to model the mean response of the dependent variable as a function of a set of independent variables. Under linear regression, researchers use a linear function to build a prediction model (Washington State University, 2007; Yale University, 1998).

Types of regression methods. With a single linear regression, the researchers use one independent variable (also called *explanatory*, *predictor*, *covariate*, or *confounding variable*) to predict the dependent variable (also called *outcome* or *criterion variable*) value and expect that their relationship is linear. Since the analysis using this method may ignore other important correlated factors, the result regression Equation 1 as illustrated below can have a significant omitted variable bias (LaMorte, n.d.; Sykes, n.d.).

$$Y = b_0 + b_1 X + \varepsilon \tag{1}$$

Where Y is the dependent variable, X is the independent variable, b_0 is the value of Y when X is equal to zero, b_1 is the coefficient of X to Y, and ε is the noise including omitted variable bias value and random errors. Also described as residual, ε is equivalent to the deviations of the observed values from the mean value of Y (LaMorte, n.d.). The noise due to random variance includes the errors that are not controllable (Balling, 2008).

When X value is plotted against Y value on a two-dimensional graph, Equation 1 shows a straight line that carries the best estimated b_0 and b_1 based on the least sum of square distance between the line and the plotted X–Y pairs. Corresponding to the interception and scope of the equation line are b_0 and b_1 (Balling, 2008; Holmes, 2011; Lane, n.d.; Sykes, n.d.). In other words, the equation result has the minimum sum of the squared difference between the predicted and actual value points of the dependent variable (Holmes, 2011).

Under the MLR, researchers use more than one predictor variables in the regression analysis to calculate the outcome variable value and expect that their relationships are linear (Griffin, 2013; Holmes, 2011; LaMorte, n.d.; Lane, n.d.). Multiple regression is more appropriate than single regression as it reduces omitted variables bias (Sykes, n.d.). The MLR in Equation 2 is quite similar to a single linear regression, except that it has more independent variables Xi and corresponding coefficient factors. Each coefficient represents the independent influence (or *individual contribution*) of associated predictor variable X_i to the value of the outcome variable Y (Holmes, 2011; LaMorte, n.d.).

$$Y = b_0 + b_1X_1 + b_2X_2 + \ldots + b_nX_n + \varepsilon \quad (2)$$

In general, the dependent variable Y and independent variable X_i for single or MLR require the continuous type of data values, such as interval and ratio (Flom, 2011). In the case that the dependent variable Y has continuous data values but one or more independent variables have discrete data values, such as ordinal and nominal, the researchers will need to transform those independent variables by using a dummy coding method. This type of regression is called categorical regression, and those independent discrete variables are also known as *categorical variables* (Griffin, 2013). Under the circumstances that the dependent variable Y has discrete data values, researchers will need to use logistics regression method (LaMorte, n.d.). The logistics regression method includes three subtypes (binary, ordinal, and multinomial logistics regression practices) depending on the data type of dependent variable (Flom, 2011).

Besides linear regression methods, nonlinear regression is another category of regression that researchers can use to predict the response of the dependent variable, based on the nonlinear relationships with a set of independent variables. The three common types of nonlinear regressions are Cox proportional hazard regression, Poisson regression, and negative binomial regression. When the outcome variable is time value of a specific event, researchers should use Cox proportional hazard regression method. Adversely if the outcome variable is the number of counts, researchers can use either Poisson or negative binomial regression because in either case, only positive number can be the outcome variable value, which follows a Poisson distribution curve (Griffin, 2013). Nevertheless, Poisson regression has more restricted assumption including the relationship between conditional mean and variance. However, the assumption for negative binomial regression is more relaxed. Furthermore, when many zero counts exist, zero-inflated Poisson and zero-inflated negative binomial regression methods can have better prediction (Flom, 2011).

In my research paper, I had a set of six predictor variables to predict the hospital IT managers' intention to adopt cloud computing. I assumed their relationship with the dependent variable (hospital IT managers' intention) is linear, and I validated this assumption during the research analysis. The data type of four of them (relative advantage, complexity, compatibility, and organizational size) is interval, which I could simply apply to my MLR model. Nevertheless, the other two predictor variables (organizational structure and organizational culture) had the data type as nominal. That means they are categorical variables. Therefore, I must first transform the survey response data under these two categorical variables by using dummy coding method. Since I am using SPSS for my statistical analysis, which provides the GLM capability to create the best set of dummy variables automatically. By using GLM, I avoided to performing the dummy coding manually. Therefore, I skip its detailed explanation in this section.

Process to build a regression model. The two common processes to determine the best-estimated set of independent variables are (a) standard and (b) forward-backward stepwise approach. Under the standard approach, researchers use the literature review approach to identify theoretical predictor variables. Apparently, under the forward-backward stepwise approach, researchers utilize statistically significant tests to determine whether an independent variable should be in or out of the regression equation (Holmes, 2011). Under the forward stepwise approach, by comparing the statistical R^2 value of the original set of predictor variables with the R^2 after an additional variable added to the equation, researchers can determine the effect of the latter variable, whether it should be in the model.

To get a better evaluation of the prediction effectiveness of the regression model, the adjusted R^2 can provide a better result, as researchers can take the sample size and number of predictors into consideration (Holmes, 2011). Under the backward stepwise approach, after completing the initial statistical analysis and determining the R^2, the researcher will exclude some independent variables from the regression equation and rerun the statistical analysis. If the result of the second analysis has less prediction power, it implies that the excluded variables are more significant to the model, and they should stay in the model (Lane, n.d.). I must highlight one important aspect: For all statistical tests to drive a significant conclusion, researchers must set the desired confidence level first (Sykes, n.d.). Furthermore, as a general rule of thumb, the sample size should be greater than ten times the number of independent variables (Holmes, 2011). The regression model result should be unbiased, consistent, and efficient. In other words, the mean of estimated outcome value should be close enough to represent the true value (unbiased). The regression model should indicate an accurately estimated result at all times (consistent). The estimated outcome value should have minimal variance (efficient) with the observed outcome value (Sykes, n.d.).

Another essential step is to eliminate outliers to improve the normality of the regression model. Otherwise, the coefficient estimation is not accurate. The most common way to reduce outliers is by removing observed points with a value greater than two standard deviations. However, this method has no guarantee to produce a better *p* value in the normality test. Courvoisier and Renaud (2010) recommended using robust analysis that applies *M* estimation regression as according to Tukey's biweight method. As a result, the effect of the outlining observation will have less effect on the estimation of the regression coefficients. The only disadvantage is that it has less statistical power than the standard R^2 method.

Similar to statistical analyses, proper sample sizing setting is critical for developing a valid and reliable regression model. Shieh (2013) argued that the classical sample size calculation method by Bonet and Wright for MLR is inaccurate. Since the statistical distribution curve of R^2 is always skewed, researchers should calculate the sample size based on the required confidence intervals, magnitude of squared multiple correlation coefficients, and the number of independent variables, instead of by confidence intervals as stated in Bonet and Wright's sample sizing method.

Basic assumptions for MLR. Similar to other statistical methods, the MLR has assumptions that researchers have to be aware of and examine as to ensure that their created model has the required construct validity and reliability. The basic four principal assumptions that a valid MLR should include independence, linearity, normality, and homoscedasticity:

- *Independence* means each predictor variable is independent with other predictor variables (Sykes, n.d.). As a consequence of having highly correlated independent variables, the outcome changes explainable by the individual independent variable are relatively small in compared with the overall variance for all independent variables explained together (Lane, n.d.). It affects the degree of significant measurement for each independent variable. Furthermore, each observed sample object must be independent and not interference with the others (Holmes, 2011; Sykes, n.d.).

- *Linearity* means the relationships between the independent variables and dependent variable are linear (Lane, n.d.; Holmes, 2011).
- *Normality* means the variation (also called noise, errors, or residuals) of the outcome variable changes should follow a standard normal distribution (LaMorte, n.d.; Lane, n.d.).
- *Homoscedasticity* means the variances of errors are the same no matter of their predicted outcome values (Holmes, 2011; Lane, n.d.).

Validation tests for MLR. To ensure that the MLR assumptions are valid, researchers must conduct multiple statistical tests for confirmation. As explained, if the predictor variables are highly correlated, it implies difficulty to detect which variable is generating the effect with the independent variables. This situation is called *collinearity*. To diagnosis this problem, researchers can use multiple statistical tests, such as variance inflation factors, condition number, determinant, and *k* value (Balling, 2008; Piña-Monarrez, 2011). As recommended by Balling (2008), when the *k* value is higher than 30, the collinearity of a regression model is high. Nevertheless, these tests cannot distinguish the severity of collinearity under different correlation structures. Therefore, the R^2 scheme to determine the regression equation is not accurate when collinearity is present. One common way to solve the collinearity issue is to take two highly correlated variables and construct them under a different simple linear regression model. Once researchers determine the coefficient between those two variables, they can simplify the original regression equation by substituting one correlated variable by another one (Balling, 2008). Alternatively, Piña-Monarrez (2011) suggested using Ridge regression method to overcome the collinearity situation by calculating the correlational effect among the predictor variables. This approach requires less number of statistical analysis iterations.

For the linearity test, the simplest method is to create multiple scatter plots with each to detect the relationship between the outcome variable and a particular predictor variable in the regression model. Under each graph, the *Y* axis and *X* axis represent the observed outcome values and the corresponding input values for the predictor variable under examination. Researchers can detect the linearity visually (Griffin, 2013).

As described in the section on using R^2 for determining whether a predictor variable should be included or excluded as part of the stepwise regression model building approach, R^2 is an essential statistical value to measure how many variations of the outcome variable was due to the changes of predictor variables as a whole. R^2 is simply the square of the correlation coefficient (R), that is the mathematical evaluation of how close is the regression line fit into the sampled X_i–Y pairs (Judge, 2014). A high R^2 indicates the regression model has sufficient statistical power to predict the outcome value (Sykes, n.d.). By examining R^2 in F test, researchers can determine the percentage of variation in the outcome variable attributed by the variation of the regression model (i.e., the combined variation effect of all predictor variables). Researchers normally set the null hypothesis to be the combined variance effect of the independent variables on the dependent variable equal to zero, that is R^2 is zero (Holmes, 2011).

Besides validating the significance of the entire regression model, researchers use t test on the coefficient factors—b_i of each predictor variable—to determine their individual contribution to the variation of the outcome variable. The null hypotheses are set to state that the variation effect of a particular predictor variable on the dependent variable is equal to zero (Holmes, 2011).

Recent quantitative researches on applying MLR. Even though many scholars have applied the MLR in their quantitative research studies, I can only find a few that relates to HIS technology or cloud computing adoption. I picked a few of those that could represent the good use of the MLR, or provide research contribution to apply MLR method for predictive model creation.

Arieshanti, Purwananto, Ramadhani, Nuha, and Ulinnuha (2013) compared theories and methodologies to build a reliable predictive model to provide a leading indicator for corporation bankruptcy. They illustrated the use of MLR together with a multiple layer perception (MLP) method to create a bankruptcy predictive model with financial indices as predictors. As the result, the model generated the second best prediction and identified 74.5% of corporate bankruptcy in their research test.

Ilgan (2013) demonstrated a classical use of MLR in his research. He developed a MLR model to predict the final examination result for college students basd on gender, study time, perceived importance of a school course, student attitudes on the course, and teachers. An important aspect of this paper is that Ilgan illustrated on how to use other statistical analysis methods to supplement the standard approach for creating a multiple linear model. He used (a) exploratory factor analysis to discover underlying structure and develop a scale, which is a set of questions for quantitative research measure, (b) principal component analysis to identify the essential independent variables, and (c) confirmatory factor analysis to confirm the significance of selected factors. According to Ilgan's research result, his MLR model could predict 33% of the outcome variance.

Thaweewannakij et al. (2013) conducted a research study for the critical factors that affect Thai senior citizens' functional ability. The predictor variables included weight, height, age, and sex while the measurements of the outcome variable came from several different physical tests. The key difference of their MLR research among others is the use of post hoc analysis to discover patterns from the data pairs. Most scholars argued that this is not an effective method and creates data dredging (Deng, 2009).

Pathak (2012) applied the MLR to predict the groundwater quality based on dissolved oxygen level as an outcome variable with a set of physicochemical substances in the water as predictors. The scholar used forward stepwise approach and R^2 to find the suitable regression equation. As the result, Pathak identified SO4, HCO3, CI and Mg as critical predictor variables that could affect the ground water quality (i.e., DO level).

Cerruti and Decker (2011) built a predictive model for estimating the degree of utility equipment damage (including poles, transformers, primary wires, etc.) caused by adverse weather. The predictor variables included maximum window gust, maximum temperature, liquid–water–equivalent precipitation (LWE), 10-day accumulated LWE, 3-day maximum temperature sum, severe weather report count per region, and other storm factors. Since the data type of the dependent variable is countable, the researchers did logarithmic transformation so that the MLR can be applicable. The researchers also used the perfect prognosis method to create the MLR equation. Their research result seems provide better adaptability for a future model upgrade. To eliminate irrelevant predictors, the researchers applied the backward stepwise approach.

In another study, Kabaasaki and Totan (2011) investigated the relationship between elementary school students' mental issues and social–emotional training needs. The studied mental issues included substance abuse, depression, anxiety, violence, and aggressiveness; and social–emotional training needs included self-awareness, emotional control, arrangement skills, and social relationships with others. Firstly, the data went through Pearson product moment correlation coefficient calculation to determine the correlation among the independent variables and dependent variable as part of the collinearity test. The researchers then used multivariate Mahalanobis distance method to identify and eliminate outlier observation points. To ensure linearity, the researchers reviewed the scatter plots for confirmation. As the result of the MLR analysis, the researchers determined that depression, anxiety, negative self-concept, somatization, and hostility have negative significant relationships with the social and emotional training needs.

Shepherd and Yu (2011) researched on an approach to estimate data error rate that can affect the accuracy of the MLR model, and developed a corrective procedure. As the result, the researchers recommended conducting two rounds of data accuracy audit with the sample size of the second audit based on the mean squared error calculation of the

MLR. By applying this data audit and cleanup approach, the MLR model can become more precise with a better estimation of the data error for the researchers to deploy the right amount of effort to correct the data mistakes, as according to the desired confidence level.

Stan (2011), in his research, created a MLR model to predict the economic rate of return based on tangible and intangible assets as predictor variables. In the past, the rate of return calculation only included tangible assets (e.g., cash, physical assets, shareholder equity, etc.) because they are easy to measure. Due to the rapid change in today's global economic model, some intangible assets (e.g., employee skillset, corporate knowledge, corporate image, brand, etc.) are critical for a company's future return. The research result showed that the new MLR model could explain 63.9% of research observations. Stan used variance inflation factors and adjusted R^2 to test collinearity and validate the model significance respectively.

Noh, Kwon, Yoon, and Hwang (2011) conducted a medical field research on 89 Korean hospitals to determine the internal and external factors that affect hospital-based home nursing care. The internal factors included managerial resources, core hospital capability, organization structure, and culture. The external factors consisted of market and community aspects. The researchers used cross-sectional survey and forward stepwise approach of MLR to create the predictive model. To determine any collinearity, the researchers deployed the independent variable tolerance and variance inflation factors to examine the independent variables. As the result, the researchers showed that managerial resource factors (except hospital cash flow), service development, unified

HIS, and nurse passion had significant effects on home nursing care. Since this research relates to new service adoption for hospitals, some of the identified predictive factors may be indirectly relevant to my research on hospital cloud computing adoption.

Côté, J. Gagnon, Houme, Abdeljelil, and Gagnon (2011) conducted another medical field research to predict the intention of nurses to apply research evidence in their clinical decision making. This study was an adoption theory research with the goal of identifying the critical adoption factors by using MLR. The study was similar to my research in terms of predicting the hospital IT managers' intention on cloud computing adoption with the six technological and organizational factors. In my research, I used DOI and TOC as my theoretical framework. However, Côté et al. applied TPB and used subjective norm, perceived behavioral control, and attitudes as their MLR foundational predictor variables, and added moral norm, pass behavior, gender, and education level as extended predictor variables. To confirm the validity of their survey questionnaire, they instrumented a panel of four experts to review. They used traditional validation tests and approach to develop their MLR models.

Côté et al. (2011) included Pearson correlation coefficient calculation to determine the relationships among independent and dependent variables, and stepwise approach to identify individual contribution of each independent variable in predicting the outcome and the criteria for inclusion or exclusion. According to Côté et al., moral norm, perceived behavioral control, normative beliefs, and past behavior were significant predictor variables for the intention of nurses to use the research findings for clinical decision making. Moral norm and perceived behavioral control factors related to about

70% of the outcome variance. Nevertheless, the generalization of the research was limited because it showed all collected samples from one hospital.

Summary and Conclusions

In this chapter, I reviewed four major themes: (a) comparison of different technology adoption theories; (b) overview of the latest cloud computing technologies; (c) recent development and adoption of HIS; and (d) review of various regression methods to create predictive models. From the literature review, I identified that the combination of DOI and TOE adoption theories was the most appropriate theoretical foundation for my research. The combination of these theories contained the required technological and organizational factors to construct a predictive model to forecast the hospital IT managers' intention of cloud computing adoption.

Beyond reviewing the latest cloud computing technologies, I analyzed the current benefits and barriers for its adoption. From the recent development and adoption of HIS, I realized the current preferences and challenges for hospitals to adopt new technologies. The above literature review provided the confirmation on my predictor variables selection. Under the final theme of reviewing regression methods, I confirmed that MLR was a suitable method and provided guidance for a detailed procedure to build and validate an effective predictive model. As the conclusion of my literature review, limited researchers had done studies on cloud computing adoption; so far, all of them applied correlational analysis, and none of them considered including organizational structure and culture as critical factors. Furthermore, I did not find a study showing the application of MLR to create cloud computing adoption predictive model for U.S. hospitals. In

Chapter 3, I provide a detailed explanation of the research method and design, including the sample group selection, sizing, data collection, data analysis, and required validation tests.

Chapter 3: Research Methods

In this explanatory quantitative study, I utilized a cross-sectional survey design to gather the data needed to examine the relationship between the intent of IT managers in U.S. hospitals to adopt cloud computing (the dependent variable) as the function of six identified critical technological and organizational factors (the independent variables). The basis for the theoretical framework of this study was the two innovation adoption theories: DOI and TOE. The relationship between the independent and dependent variables was a predictive model based on MLR. This predictive model could be useful in assisting (a) hospital IT management to develop their cloud computing implementation strategy and (b) cloud service vendors to enhance their products and services. The research question was: Does regression allow us to predict the cloud computing adoption intent of U.S. hospital IT managers (Y) as a function of the six influential adoption factors, including relative advantage (X_1), compatibility (X_2), and complexity belief of cloud computing (X_3), organizational size(X_4), organizational structure (X_5), and organizational culture (X_6) in the United States?

Corresponding to the RQ, the regression-related null and alternative hypotheses were set as follows:

$H0_1$: X_1 = relative advantage is not a significant predictor of Y = intent to adopt; mathematically, b_1=0 in the resulting regression model.

$H1_1$: X_1 = relative advantage is a significant predictor of Y = intent to adopt; mathematically, b_1 != 0 in the resulting regression model.

$H0_2$: X_2 = compatibility is not a significant predictor of Y = intent to adopt; mathematically, $b_2 = 0$ in the resulting regression model.

$H1_2$: X_2 = compatibility is a significant predictor of Y = intent to adopt; mathematically, $b_2 != 0$ in the resulting regression model.

$H0_3$: X_3 = complexity belief is not a significant predictor of Y = intent to adopt; mathematically, $b_3 = 0$ in the resulting regression model.

$H1_3$: X_3 = complexity belief is a significant predictor of Y = intent to adopt; mathematically, $b_3 != 0$ in the resulting regression model.

$H0_4$: X_4 = organizational size is not a significant predictor of Y = intent to adopt; mathematically, b_4=0 in the resulting regression model.

$H1_4$: X_4 = organizational size is a significant predictor of Y = intent to adopt; mathematically, $b_4 != 0$ in the resulting regression model.

$H0_5$: X_5 = organizational structure is not a significant predictor of Y = intent to adopt; mathematically, $b_5 = 0$ in the resulting regression model.

$H1_5$: X_5 = organizational structure is a significant predictor of Y = intent to adopt; mathematically, $b_5 != 0$ in the resulting regression model.

$H0_6$: X_6 = organizational culture is not a significant predictor of Y=intent to adopt; mathematically, $b_5 = 0$ in the resulting regression model.

$H1_6$: X_6 = organizational culture is a significant predictor of Y = intent to adopt; mathematically, $b_5 != 0$ in the resulting regression model.

$H0_7$: The linear model $Y = b_0 + b_1X_1 + \ldots + b_6X_6$ has no significant fit; mathematically, $R(Y \mid X_1 \ldots X_6) = 0$.

H1$_7$: The linear model $Y = b_0 + b_1X_1 + \ldots + b_6X_6$ has a significant fit; mathematically, $R(Y \mid X_1 \ldots X_6)$!= 0.

This chapter has five main sections. Under the research design and rationale section, I explained the study variables and the research design choice as associated with the research question. Under the methodology section, I described the population, sample size, sampling method, participant recruitment procedure, data collection process, survey instruments, and operationalization of constructs. Then followed by the threats of validity section, in which I discussed the potential threats to internal, construct, and external validity; the chosen statistical tests to discover these threats; and the procedures to minimize their effect on the research result. Under the ethical procedure section, I illustrated the process I followed to (a) get data access agreement; (b) maintain the data privacy and confidentiality for participants; and (c) collect data protection. Finally, I concluded this chapter with a summary section.

Research Design and Rationale

Study Variables

Statistical data have three types: numerical, categorical, and ordinal. Numerical data are measurable and can further be distinguishable as discrete and continuous. Discrete data are countable as integers while continuous data are representable as intervals with real numbers. Categorical data mean the classification of certain characteristics, such as gender and marital status. Scholars can even represent them through integer values, as they do not have any mathematical meaning. Ordinal data are mixes of numerical and categorical data. They represent a set of categories and indicate the meaning of numerical order by their values (Rumsey, 2011).

According to the definition of Singleton and Straits (2005), dependent variable is the object of study that researchers want to explain its outcomes as the change in the value of the corresponding independent variables. My study included one dependent variable and six independent variables, also known as predictor variables. The objective of my study was to predict the correlated responses behind the hospital IT managers' intention to adopt cloud computing (dependent variable Y) as according to the changes in three technological and three organizational factors (independent variables X_1 to X_6). The predictors were relative advantage (X_1), complexity (X_2), compatibility (X_3), organizational size (X_4), organizational structure (X_5), and organizational culture (X_6). Four independent variables (X_1 to X_4) were composite in nature and assessed by summing a subset of related questions. Two of these variables were categorical in nature (X_5 and X_6). Following are the definition of the six independent variables and their corresponding subset of survey items.

Technological predictors.

- Relative advantage (X_1) represents the perceived business and financial value (positive or negative) of cloud computing technology in compared with other existing technologies in used (Rogers, 2003). Six survey items included financial benefit (reduction in capital investment, a potential increase in profitability, and operational cost saving), new service opportunities, and existing service improvement in terms of service satisfaction and availability.

- Complexity (X_2) as Rogers (2003) stated, is the factor that has a negative effect on innovation adoption. The higher perceived complexity triggers a lower adoption rate. Similar to the technology acceptance model (TAM) of Davis (1986), ease of use is a typical way to measure complexity. Five survey items for ease of use measurement were cumbersome to use, required mental effort, user frustration, intuitive to use, and ease of purchase and startup.
- Compatibility (X_3) can be subjective or objective measurement from decision makers to determine whether cloud computing matches with their social value, faith, knowledge and perceived needs (Rogers, 2003). This study included four survey items: business strategy alignment, adaptability with existing IT infrastructure, cloud technology favorability, and consistency with hospitals' faith and value system.

Organizational predictors.

- Organizational size (X_4) is one of the several factors, which most scholars apparently ignored as a critical factor for cloud computing adoption. As the size of an organization can affect its financial position, marketing, and business strategies, it may set some default preference to accept or reject cloud computing services. In this study, I used a common measurement for the hospital size, which was the number of staffed patient beds. The survey included a question asking survey participants to provide this information.

- Organizational structure (X_5) can typically be categorized as functional, divisional and matrix structure (White, n.d.). Functional and divisional organizations usually use a top-down decision model (Gillikin, 2013; Johnson, 2013) while matrix organizations use consensus decision model (Guzman, 2013). As it is one of the most important factors to consider the organization's characteristics and nature, the survey included one survey question asking survey participants to identify the most appropriate organizational structure associated with their hospitals.
- Organizational culture (X_6), in general, includes perceived value, subjective norm, communicating style, and belief systems. It seems no consistent way existed to measure an organization's culture; thus, this research used one of the general organizational culture theories that Cameron et al. (2003) developed. It classified four types of organizational culture (clan, adhocracy, hierarchy, and market) based on two conflicting dimensions of organization value, that was, flexibility versus stability and internal maintenance versus external positioning, according to Cameron et al. By intersecting these two dimensions, organizational cultures can be classified as clan (i.e., focus on flexibility and internal capability), adhocracy (i.e., focus on flexibility and external positioning), hierarchy (i.e., focus on stability and internal capability), and market (i.e., focus on

stability and external positioning). The survey included a question asking survey participants to classify their hospital's organizational culture based on the definition of organizational culture.

Design to Address Research Questions

I used a cross-sectional survey research design approach to achieve the research objective of confirming the preselected critical factors that influenced the IT managers' intention to adopt cloud computing, and to create a corresponding MLR model to predict the future cloud adoption. As my research goal was explanatory instead of exploratory, it suited for quantitative instead of qualitative research (Amora, 2010). As an explanatory research, my study included answers to my correlational hypotheses using the dependent and independent variables. In addition, a cross-sectional instead of the longitudinal design suited for studying changes over time is appropriate (Singleton & Staits, 2005). Based on my literature review, this research could be the first baseline study to determine the critical factors for cloud computing adoption in U.S. hospital environments. In the future, other scholars could reuse the survey instrument and composite variables in their longitudinal research if they are interested to study the shift of critical factors due to the technological and social environment changes over time.

As highlighted in Chapter 1, my primary research question was whether the six independent variables retrieved from the DOI and TOE methodologies could be useful for predicting the criterion variable (i.e., the intention of hospital IT managers to adopt cloud computing services). By theory, to determine any causal relationship, the best research design should be randomized experimental design (Trochim, 2001).

Nevertheless, such design was not possible in my study to preset and control the research condition in U.S. hospitals. Therefore, the appropriate and cost effective research design for my study was nonexperimental. To detect causal linkage among the six influential innovation factors and the cloud adoption intent for U.S. hospital IT managers, I had to rely on statistical regression modeling approach.

Among the regression models, MLR is a statistical method for estimating the linear relationship between a dependent variable and a set of independent variables (two or more) with prediction and explanation as purpose (Holmes, 2011). Researchers use MLR when the dependent variable is continuous, and the expected relationship is linear. The goal is to predict the value of the dependent variable as a function of one or more predictor variables (Griffin, 2013). In a MLR design, examining multiple variable effects simultaneously is feasible, without the need to control other independent variables except the one under examination as in factorial analysis (Balling, 2008). MLR shows extreme efficiency in measuring the effect of multiple independent variables and in eliminating the strict control between groups of experimental items (LaMorte, n.d.), which it is not possible in the U.S. hospital environment as explained earlier.

Time and Resource Constraints

I had limited time and resource for my dissertation research. With the consideration of allocating one year to complete my dissertation, I did not plan to conduct a pilot qualitative research first to review the insight of cloud computing adoption phenomenon. I could only count on my theoretical and literature review to determine the list of potential critical factors and hypotheses influential to the cloud adoption for U.S.

hospitals. To provide an in-depth understanding of the cloud adoption under the health care industry, I limited my research to U.S. hospitals. Therefore, my analysis and conclusion had limited generalization applicable to other countries. Further validity tests may come from other scholars to confirm the similarity and difference between hospitals in the United States and other countries.

Due to the expected busy work life of most U.S. hospital managers, I considered their limited time to answer any survey questionnaire. For this reason, I had to make my survey questionnaire simple and only included questions for the seven study variables based on a validated survey questionnaire. I excluded the environmental factors to reduce my research effort.

Methodology

Population

The target population of my research was IT managers of qualified hospitals in the 48 continental U.S. states with key levels of IT decision makers, including CIOs, IT directors, and IT departmental managers. Their roles include decision-making authority for determining the adoption of new technologies. My study excluded hospitals in Alaska, Hawaii, and all other offshore territories and possessions of the United States. To qualify in my research, hospitals needed to have 50 or more staffed beds. The reason was to be sure IT is relevant to their operation. According to the 2012 AHA survey, the United States has 5,723 registered hospitals, which include 4,999 community hospitals, 211 federal government hospitals, 413 nonfederal psychiatric hospitals, 89 nonfederal long-term care hospitals, and 11 hospital units of institutions (AHA, 2014). 4,000 hospitals have registered IT manager contact information in the company's customer contact database, 3,915 reside in the 48 continental U.S. states, and 2,866 fulfill the qualification criteria. Table 5 shows the geographical distribution of these hospitals within the 48 continental U.S. states.

Table 5

Number of Registered and Qualified Hospitals per State

U.S. state	Number of hospitals	Number of qualified hospitals
AL - Alabama	93	68
AR - Arkansas	50	39
AZ - Arizona	73	48
CA - California	348	284
CO - Colorado	53	36
CT - Connecticut	34	31
DC - Washington D.C.	8	7
DE - Delaware	8	6
FL - Florida	212	167
GA - Georgia	116	95
IA - Iowa	40	29
ID - Idaho	17	10
IL - Illinois	140	124
IN - Indiana	98	71
KS - Kansas	60	35
KY - Kentucky	76	60
LA - Louisiana	113	66
MA - Massachusetts	80	57
MD - Maryland	50	41
ME - Maine	22	15
MI - Michigan	106	85
MN - Minnesota	56	45
MO - Missouri	88	65
MS - Mississippi	72	48
MT - Montana	15	10
NC - North Carolina	105	82
ND - North Dakota	10	6
NE - Nebraska	29	18
NH - New Hampshire	14	13
NJ - New Jersey	73	64
NM - New Mexico	37	19

(table continues)

U.S. state	Number of hospitals	Number of qualified hospitals
NV - Nevada	28	21
NY - New York	202	168
OH - Ohio	152	114
OK - Oklahoma	102	48
OR - Oregon	36	26
PA - Pennsylvania	176	139
RI - Rhode Island	12	11
SC - South Carolina	66	47
SD - South Dakota	28	10
TN - Tennessee	116	83
TX - Texas	379	214
UT - Utah	35	19
VA - Virginia	90	76
VT - Vermont	7	5
WA - Washington	64	43
WI - Wisconsin	76	59
WV - West Virginia	37	30
WY - Wyoming	13	9
Total	3,915	2,866

Sampling and Sampling Procedures

As I had no direct access to the IT manager contacts via AHA, I had to use another contact access point for my research sampling. My original sampling frame was the customer contact database of a software manufacturer that sold products to most of all U.S. hospitals. My study population included the IT manager of qualified hospitals in the 48 continental U.S. states, who had contact information available in my sampling frame. I excluded hospitals in Alaska, Hawaii, and all other offshore territories and possessions of the United States, and as a qualification criterion, hospitals needed to have 50 or more staffed beds.

Sampling methods has two main types: purposive (nonrandom) and random. The nonrandom sampling has a serious limitation on generalization, and its statistical inferences are difficult to estimate (Banerjee & Chaudhury, 2010). To demonstrate sufficient statistical generalization power for my research results, I decided to use a proportional stratified random sampling method for selecting survey participants (IT managers), who work for hospitals in one of the four regions of the 48 continental U.S. states (west, midwest, northeast, and south). I used the U.S. census region to state classification as published by U.S. Census Bureau (2014) as illustrated in Figure 8.

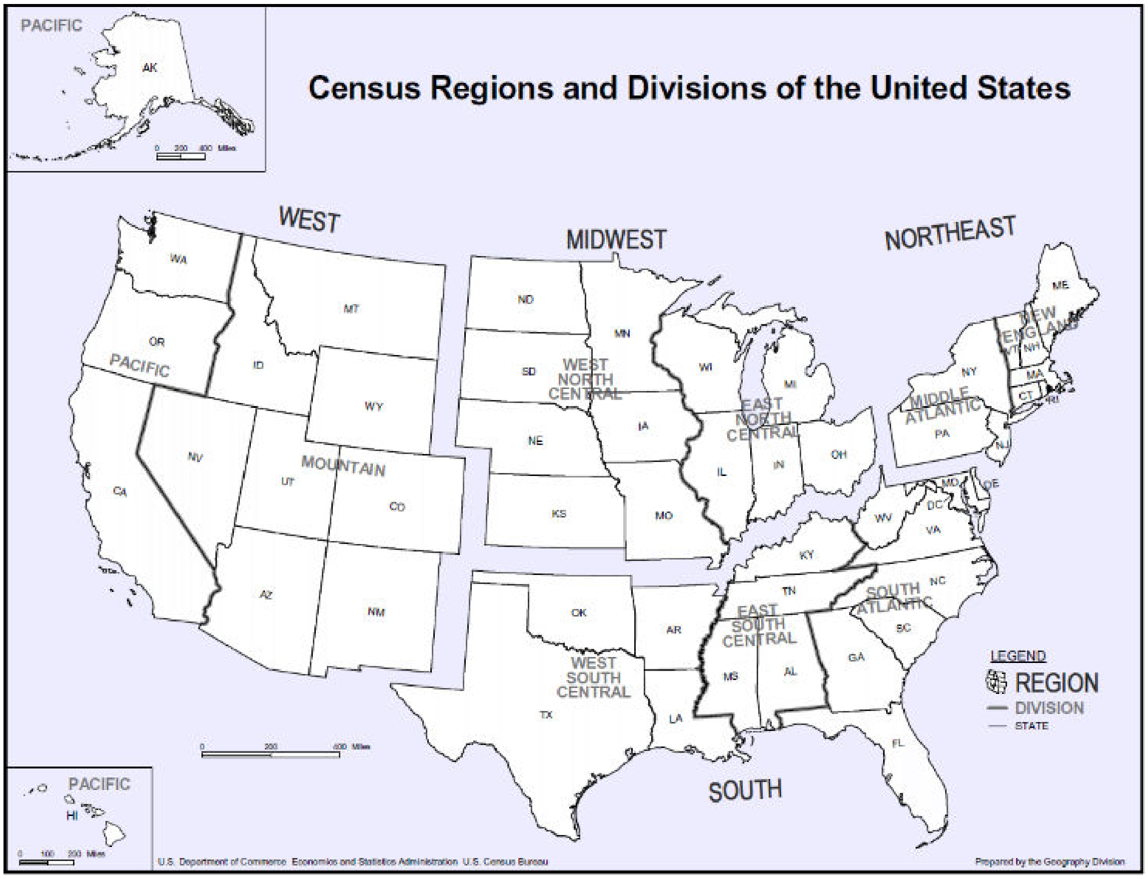


Figure 8. U.S. regions to states map. The United States includes five regions—west, midwest, northeast, south, and pacific. The west, midwest, northeast, and south regions consist of the 48 continental states and Washington D.C. of the United States. The pacific region includes Alaska, American Samoa, Guan, Hawaii, Northern Mariana Islands, Puerto Rico, and Virgin Islands, which I excluded in my research. Adopted from *Census regions and divisions of the United States*, by U.S. Census Bureau (2014). Retrieved from https://www.census.gov/geo/maps-data/maps/pdfs/ reference/us_regdiv.pdf.

One of the advantages of stratified random sampling above simple random sampling is that it is facilitative to ensure sufficient selected sample subjects from each region. Stratified random sampling has higher statistical precision based on the assumption that within the regional variability is less than simple random sampling (Crossman, 2014a). These two stratified sampling advantages were important for this research because hospitals in different regions most likely had social beliefs and environmental differences. This phenomenon might reduce the predictability of the regression model due to less homogeneity among subjects if selected by a simple random sampling. By using this sampling strategy, the generalization power of this research would be higher, having the opportunities to do further statistical analysis and comparison within and among regions.

As the basic statistical principle, when the sample size increases, the standard errors will decrease, and the confidence interval will be narrow. It denotes a higher statistical power (Field, 2013). Nevertheless, having a large sample may not be feasible considering financial and time limitations. Therefore, to determine the proper sample size for my study, so that the corresponding statistical tests can have results with statistically significant confidence, first, I must make several research design decisions. They included the values for acceptable Type 1 error (α), required statistical power, (i.e., 1), Type 2 error (β), and expected effect size.

Type 1 error is the probability to reject the null hypothesis while it is true. Type 2 error is the probability of not rejecting the null hypothesis while it is false. These two errors are negatively related. It means that when ones try to reduce Type 1 error, Type 2 error will increase (Taylor, 2014). Setting the levels for Type 1 and 2 errors is a balanced act, but normally reducing Type 1 error is more important than Type 2 error, and it should be set to a low value. Such as .05, it implies 95% confidence that the rejection of the null hypothesis is correct. As Field (2013) described, maximum Type 2 error should be .2, that is, 80% chance that the acceptance of the null hypothesis is correct, based on the recommendation of Cohen (1992). In this research, I set .05 as the value of Type 1 error to provide high confidence in the statistical result, which gauged the confidence level to 95%.

Effect size for a MLR model represents the magnitude of variance of the dependent variables is relevant to the variance of the independent variables, and coefficient of determination, $R^{2,}$ is commonly useful for measuring the effect size for regression model. Based on Fual, Erdfelder, Buchner, and Lang's (2009) explanation, the effect size for GLM is measurable with the population correlation coefficient of the alternative hypothesis, H1 p^2. To determine its appropriate value, the estimated total sample size (110), number of predictors (11), observed R^2 (.3), confidence level ($1 – \alpha = 1 – .5 = .95$), and relative central interval position (.5) must be supplied to the G*Power screen as illustrated in Figure 8. The reason to set R^2 as .3 was to ensure the effect size would be large enough. As a general guideline, which Nandy (2012) and Field (2013) provided, R^2 must be larger than .14 and .26, respectively if a large effect size is expected.

As described in the previous section, this research study had four continuous (relative advantage, complexity, compatibility, and organizational size) and two categorical (organizational structure and organizational culture) predictor variables. To calculate the total number of predictors, the number of required dummy variables must be determined and then added to the number of continuous predictor variables. For the categorical variable – organizational structure, it consisted of four categories – functional, divisional, matrix, and others, requiring three dummy variables (i.e., 4 – 1). For the categorical variable—organizational culture with five categories—clan, adhocracy, hierarchy, market, and others, requiring four dummy variables (i.e., 5 – 1). Therefore, the total number of predictors was 11 (i.e., 4 + 3 + 4).

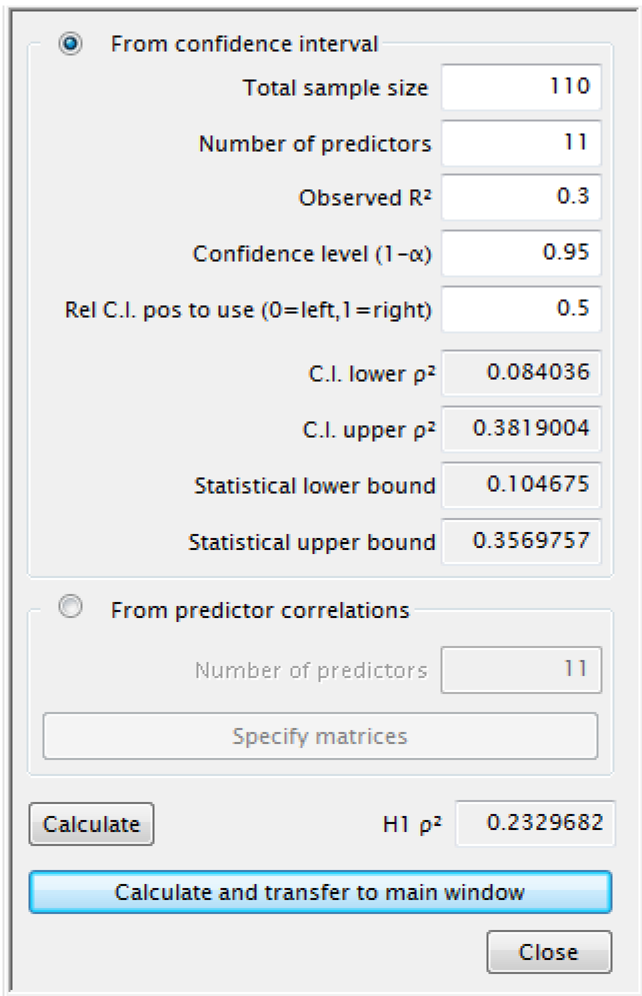


Figure 9. G*Power H1 p^2 determination. It is determined by estimated total sample size, number of predictors, observed R^2, confidence level, and relative central interval position as input parameters.

To avoid complex manual calculation, I used G*Power 3.1 utility to determine the sample size. G*Power is a commonly used sample size calculator and is available for a free download from the website <http://www.gpower.hhu.de/>. The input parameters for the G*Power sample size calculation were:

- Selected MLR—random as the statistical test. G*Power supports MLR with predictors having random or fixed value. As my research was nonexperimental, and the values of predictors were sampled from the study population, I should select the random MLR option (Fual et al., 2009):
- Selected the type of power analysis as prior to estimating the sample size before conducting the research study instead of post hoc analysis to confirm the statistical power.
- Selected the statistical tests as two tails.
- Inputted H1 p^2 as .2329682 based on the calculation as illustrated in Figure 8.
- Set H0 p^2 as zero.
- Set Type I error as .05.
- Set statistical power as .95.
- Inputted the number of predictors as 11.

As the result, the minimum sample size for this study was approximately 110. Based on the proportional stratified sampling method, the minimum number of observations for each of the four regions was equal to the total sample size (i.e., 110) multiplied by its percentage of the total population size (Stat Trek, 2014).

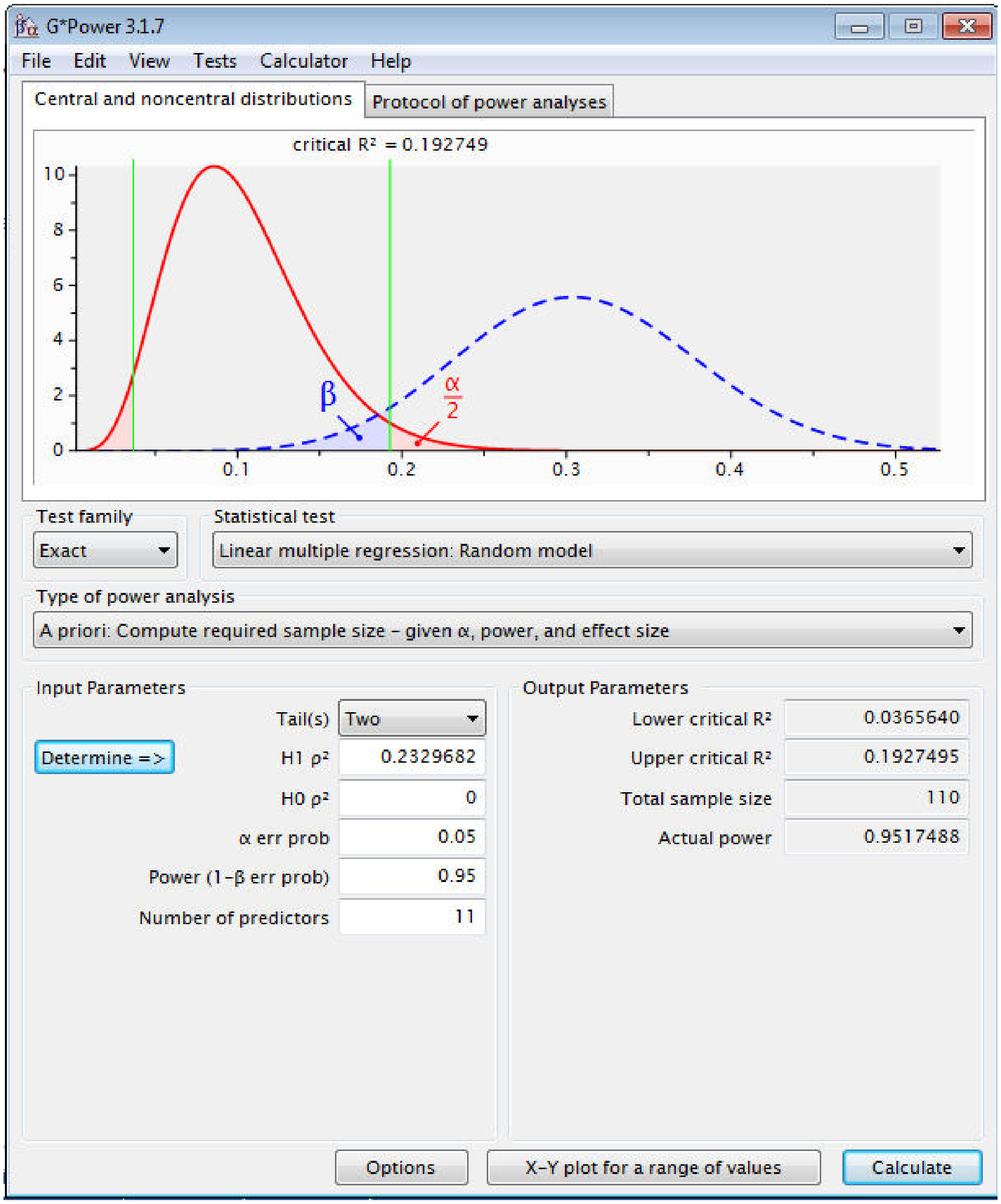


Figure 10. G*Power parameter screen. It shows the input and output parameters for sample size calculation.

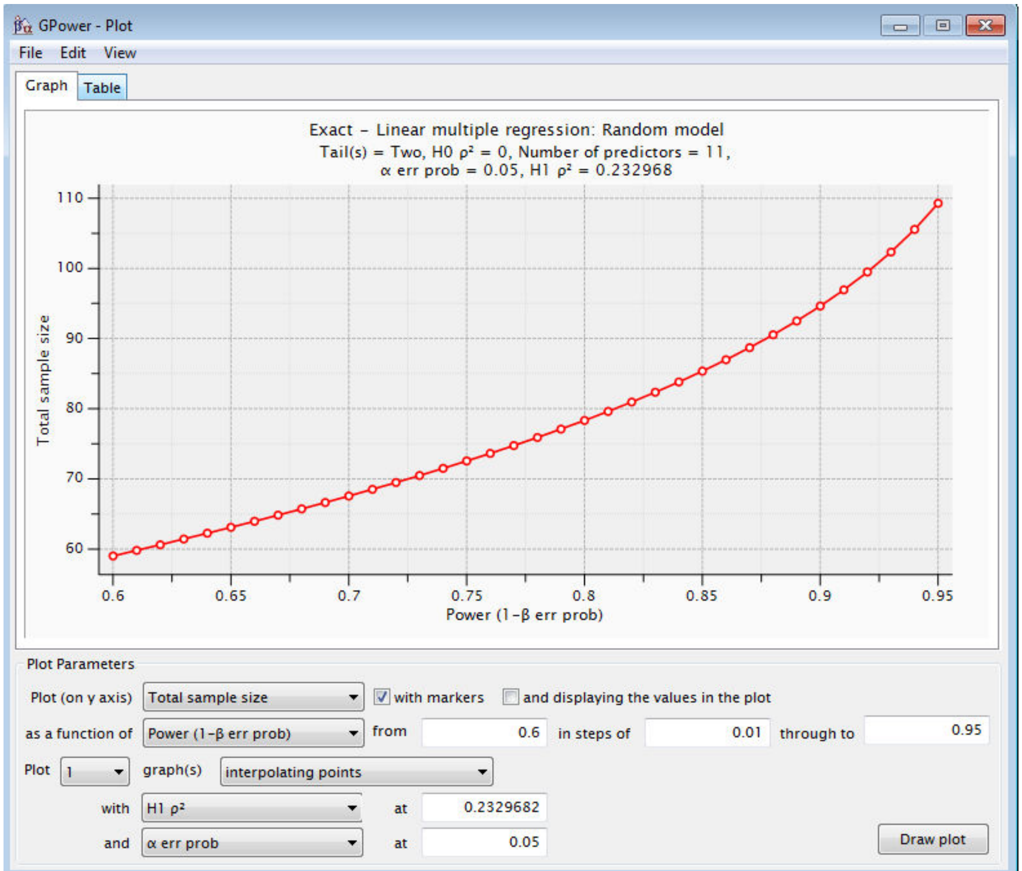


Figure 11. XY graph of sample size and statistical power. It shows the effect of sample size change on statistical power.

Procedures for Recruitment, Participation, and Data Collection

As mentioned, the planned sampling frame was the customer contact database of a software manufacturer serving most of the U.S. hospitals. I planned to extract the list of IT contacts for the U.S. hospitals from this customer contact database. Initially, I kept their contact name, position, e-mail address, phone number, and main office address in a Microsoft Excel spreadsheet. Then I added two additional columns: the first one as unique case identifier based on a randomly assigned number, and the second one as indicator of the corresponding U.S. regional value (1 = West, 2 = Midwest, 3 =

Northwest, and 4 = South). I assigned the U.S. regional value to each U.S. hospital in the list based on their state. Table 6 shows the U.S. state to region assignment. Then I sorted the edited Excel table ascendingly by the U.S. region and identifier column.

Table 6

U.S. State to U.S. Region Assignment Cross Reference

Region	State	Region	State	Region	State
West	Arizona	South	Alabama	Northeast	Connecticut
West	California	South	Arkansas	Northeast	Massachusetts
West	Colorado	South	Washington D.C.	Northeast	Maine
West	Idaho	South	Delaware	Northeast	New Hampshire
West	Montana	South	Florida	Northeast	New Jersey
West	New Mexico	South	Georgia	Northeast	New York
West	Nevada	South	Kentucky	Northeast	Pennsylvania
West	Oregon	South	Louisiana	Northeast	Rhode Island
West	Utah	South	Maryland	Northeast	Vermont
West	Washington	South	Mississippi		
West	Wyoming	South	North Carolina		
Midwest	Iowa	South	Oklahoma		
Midwest	Illinois	South	South Carolina		
Midwest	Indiana	South	Tennessee		
Midwest	Kansas	South	Texas		
Midwest	Michigan	South	Virginia		
Midwest	Minnesota	South	West Virginia		
Midwest	Missouri				

(table continues)

Region	State	Region	State	Region	State
(table continues)	North Dakota				
Midwest	Nebraska				
Midwest	Ohio				
Midwest	South Dakota				
Midwest	Wisconsin				

According to Hamilton's (2009) research, 50% of online surveys received about 26% of response rate. However, the degree of variation was high and became difficult to predict. In my research, I planned to apply this 26% response rate as my guideline to decide the required number of random invitation emails. I sent those emails to the listed hospital IT manager contacts for my online survey under each U.S. region, based on the calculated illustrated in Table 7. The invitation email clearly indicated:

- the objective of my research,
- encouragement for the survey participant,
- the incentive of receiving a full anonymous research report after completing the survey,
- the qualification for the survey participant,
- my contact for survey questions and issues, and
- the link to the online survey site.

Table 7

Minimum Sample Size and Required Survey Invitation Calculation

Region	Number of qualified hospitals (N_h)	Percentage of total population ($P_h = N_h / N$ x 100)	Minimum sample size (n_h = 110 x P_h)*	Number of required invitations for online survey ($I_h = n_h$ / 26%)**
Midwest	661	23.06%	26	98
Northeast	503	17.55%	20	75
South	1177	41.07%	46	174
West	525	18.32%	21	78
Total	2866 = N			425

Note. * 110 was the total sample size, ** 26% was the expected response rate. The calculated n_h and I_h values shown were rounded up.

The mechanic to generate the required random hospital survey invitations involved the number of contacts available for each region. Assuming for each region had N_h contacts in the prepared Excel list and I_h was the required invitations, I selected every k^{th} row in the sorted contact table within a given region, with the first one randomly selected first ($k = N_h / I_h$). The selection was a standard procedure for creating proportional random systematic sampling for each stratum.

Due to the anticipated busy schedule of hospital IT managers and the potential email reroute lead time to the appropriate hospital IT managers, a six weeks survey-taking window was included to ensure maximum return of responses. By the mid of each two weeks, emails were sent to the potential survey participants as a friendly reminder to complete an online survey. Once the survey open window expired, I transferred the collected survey data from the online survey website database into a secured laptop. The collected survey data itself did not capture any personal and hospital profile information in order to ensure full anonymity of participants.

Pilot Study

Despite the majority content of my research instrument was from Dr. Tweel's (2012) validated instrument, confirming appropriateness of my modification was still important. As part of the instrument construct validation and feasibility study, I conducted a small-scale pilot study to check the appropriateness of the survey items with the research question, the ease of understanding for all survey questions, and the logistics of the survey procedure (Teijlingen & Hundley, 2001). The participants of the pilot run included a group of five to ten subject matter expert (SME). They all had rich work experience on health care IT and understood the needs and concerns of the health care industry to adopt new technology. Besides answering the online survey questionnaire, I planned to have a 15- to 30-minute phone interview with each SME in this pilot group. The goal was to confirm the clarity of the questions, the average time to complete the survey questionnaire, and understand any hygiene factor that could be an obstruction to the participant to provide answers. As an important note, the initial result received from this pilot group was separate and did not merge with the actual final stage sampling and analysis. Essentially, I did not include the participants or use the data from the pilot study in the final study.

Instrumentation and Operationalization of Constructs

Research instrument. I used a validated research instrument, which Dr. Tweel (2012) developed, to study IT managers' cloud computing adoption for various U.S. industries. This instrument applied to the target and study population of 30,000 and 4,000 U.S. IT managers, respectively, with the sampling frame based on the contact information that Applied Computer Research maintained. In Dr. Tweel's (2012) research, he used a stratified random sampling to select sample groups from a number of U.S. industries. In total, Dr. Tweel received 221 completed sample responses that satisfied his minimum required samples of 109, with statistical power of .8 and α equal to .05. To ensure quality result, Dr. Tweel verified his survey instrument for convergent, discriminant, and construct validity. On October 13, 2013, I received Dr. Tweel's permission to use his instrument, as shown in Appendix D.

The instrument of Dr. Tweel (2012) was an online survey questionnaire to collect data for studying the correlation between the IT manager's cloud computing adoption (criterion variable) and eight predictor variables. The latter included two technological factors (relative advantage and compatibility); three organizational factors (organizational size, organizational readiness, and top management support); and three environmental factors (mimetic, coercive, and normative pressures). My core reasons for selecting this survey questionnaire as my base research instrument were as follows:

- The survey questionnaire had similar research objective in examining the relationship between IT manager's cloud computing adoption intent and several innovation influential factors.
- Its theoretical framework was also constructed according to DOI and TOE theories, except that I excluded the applied institutional theory that Dr. Tweel (2012) also applied due to my reduced research scope to exclude environmental factors.

- Dr. Tweel conducted sufficient validity and reliability tests on his survey instrument and research method. In addition, Dr. Tweel's survey instrument was also an adoption of another well-proven survey instrument, which Dr. Yoon developed in 2009, with minimal modification. Dr. Yoon's instrument, which originated for researching virtual technology adoption, has been applicable to several quantitative studies (Tweel, 2012).

Due to similarities in the theoretical framework and research design, I followed most of Dr. Tweel's data collection and analysis procedure to ensure the validity and reliability of my research. However, several major differences arose between Dr. Tweel's and my research approach. In my study, I had much narrower research scope to determine the IT manager's cloud computing adoption for U.S. hospitals only, instead of for all U.S. industries. Due to my time and resource constraint, I limited my study to technological and organizational factors, and left the study on any environmental factor for cloud computing adoption to other scholars. Under the technological factors, I intentionally inserted back complexity as one of the critical factors to examine even though Dr. Tweel claimed that complexity was not a significant factor based on his literature research. It was because, according to my literature research, several scholars found that complexity has a significant correlation with cloud computing adoption (Ekufu, 2012; Paquet, 2013; Powelson, 2012).

Under the organizational context, I altered the survey question nine in Dr. Tweel's research instrument to include survey items to study organizational structure and culture influence to cloud computing adoption intent, instead of top management support and organizational readiness. I intended to show that substituting top management support and organizational readiness by organizational structure and culture could provide a broader perspective on how organizational nature of a hospital can influence its cloud computing adoption. Furthermore, I argued that the level of top management support for innovation adoption is a reflection of certain organizational structure and culture. Similarly, the concept of organizational readiness is part of the concept of compatibility in the DOI theory, that is, if organizational readiness for a corporation is low for an innovation adoption, its perceived technological compatibility should also be low (see Appendix A for my modified survey instrument).

Operationalization. As mentioned in the study variables section, this research included three technological (relative advantage, compatibility, and complexity) and three organizational (organizational size, organizational structure, and organizational culture) predictor variables, and one criterion variable (U.S. hospital IT managers' cloud computing adoption intent). Overall, two data types of variables were included in this study—continuous and categorical. For the variables (hospital IT managers' intention for cloud adoption, relative advantage, complexity, and compatibility), their corresponding survey items were measured with a 7-point Likert scale from strongly disagree (coded as 1) to strongly agree (coded as 7). The data type for these survey items was ordinal in nature. Nevertheless, I could treat their corresponding composite variables as continuous because once I added the survey item values for the corresponding composite variable, the resulted value became interval data.

Additionally, as Simon and Goes (2013) indicated, even Likert-type scales are ordinal data but researchers can analyze with interval procedures as long as the scale item has at least five to seven ordinal categories. The argument is that with sufficient scale categories, the survey values mostly fall into a normal distribution. As Martin (2014a) explained, scholars can analyze count variables with linear models, as long as the data is not along the boundary of zero. For the independent variable (organizational size), as it always be a nonzero positive integer measured by the number of staffed patient beds in the surveyed hospitals, researchers can also treat it as continuous.

For the two independent variables (organizational structure and organizational culture), I measured and analyzed them with four organizational structures (functional, divisional, matrix, and others) and five organizational cultural styles (clan, adhocracy, hierarchy, market, and others), respectively. As they carried a predefined set of levels, these two independent variables are categorical. Before I could apply MLR analysis technique, as the standard transformation procedure, I had to either convert these two categorical variables manually into two sets of dichotomous variables via the dummy coding scheme (Stockburger, n.d.), or use the GLM method in SPSS for automated dummy variable creation (Martin, 2014b). For simplicity, I had chosen the latter approach. I explain the details under the methodology section. Table 1 in Chapter 1 shows the alignment of survey items to the study variables, calculation, and the results data type of each composite variable.

Data Analysis Plan

Similar to most other quantitative social researchers, I used a statistical software package called IBM SPSS to provide descriptive and inferential statistics for the required analyses and tests. Once I completed the data aggregation task in Microsoft Excel, the results data then loaded into the SPSS data view with each row representing a case, and column representing either case ID, demography, survey item value, or composite variable value.

To drive statistical significant conclusion, the desired confidence level must be set first (Sykes, n.d.). In my study, I set the confidence level to 95% as Field (2013) recommended. Before beginning to describe my analysis plan and statistical test procedure, the following was the recap of my research question, null hypotheses ($H0_i$), and alternative hypotheses ($H1_i$):

Does regression allow us to predict the cloud computing adoption intent of U.S. hospital IT managers (Y) as a function of the six influential adoption factors, including relative advantage (X_1), compatibility (X_2), and complexity belief of cloud computing (X_3), organizational size (X_4), organizational structure (X_5), and organizational culture (X_6)?

$H0_1$: X_1 = relative advantage is not a significant predictor of Y = Intent to adopt; mathematically, $b_1 = 0$ in the resulting regression model.

$H1_1$: X_1 = relative advantage is a significant predictor of Y = intent to adopt; mathematically, b_1 != 0 in the resulting regression model.

$H0_2$: X_2 = compatibility is not a significant predictor of Y = intent to adopt; mathematically, $b_2 = 0$ in the resulting regression model.

$H1_2$: X_2 = compatibility is a significant predictor of Y = intent to adopt; mathematically, b_2 != 0 in the resulting regression model.

$H0_3$: X_3 = complexity belief is not a significant predictor of Y = intent to adopt; mathematically, $b_3 = 0$ in the resulting regression model.

$H1_3$: X_3 = complexity belief is a significant predictor of Y = intent to adopt; mathematically, b_3 != 0 in the resulting regression model.

$H0_4$: X_4 = organizational size is not a significant predictor of Y = intent to adopt; mathematically, $b_4 = 0$ in the resulting regression model.

$H1_4$: X_4 = organizational size is a significant predictor of Y = Intent to adopt; mathematically, b_4 ! = 0 in the resulting regression model.

$H0_5$: X_5 = organizational structure is not a significant predictor of Y = intent to adopt; mathematically, $b_5 = 0$ in the resulting regression model.

$H1_5$: X_5 = organizational structure is a significant predictor of Y = intent to adopt; mathematically, b_5 != 0 in the resulting regression model.

$H0_6$: X_6 = organizational culture is not a significant predictor of Y = intent to adopt; mathematically, $b_5 = 0$ in the resulting regression model.

$H1_6$: X_6 = organizational culture is a significant predictor of Y = intent to adopt; mathematically, b_5 != 0 in the resulting regression model.

$H0_7$: The linear model $Y = b_0 + b_1X_1 + \ldots + b_6X_6$ has no significant fit; mathematically, $R(Y \mid X_1 \ldots X_6) = 0$.

$H1_7$: The linear model $Y = b_0 + b_1X_1 + \ldots + b_6X_6$ has a significant fit; mathematically, $R(Y \mid X_1 \ldots X_6) \mathrel{!}= 0$.

My data analysis began with reporting the missing data and descriptive statistics on the collected samples. It showed the mean, min, max, standard deviation, frequency, and other parametric statistics for each variable of the sample result. Then I checked the sample data linearity and identified unusual cases by using scatterplot graphs. During this stage, I eliminated some obvious outliers and performed the required data transformation to ensure linearity. As my research objective was to examine the relationship between the cloud adoption intention of the U.S. hospital IT managers (outcome variable) and the six preset adoption influential factors (predictor variables), using GLM function in SPSS was the most direct and efficient way to establish the regression model and to test the stated hypotheses.

To begin my regression analysis, first, I had to decide which of the three predictor loading methods—hierarchical, forced entry, and stepwise—I should use. Hierarchical, forced entry, and stepwise approach mean predictors are loaded in blocks, all at once, and one at a time respectively (Field, 2013; Holmes, 2011). The predictor loading priority criteria for hierarchical and stepwise method mostly bases on historical known or calculated correlation significance. Traditionally many scholars suggested to use the stepwise (either forward or backward) approach to determine the predictors should ultimately be included or excluded in their regression models (Côté et al., 2011; Holmes, 2011; Lane, n.d.; Noh et al., 2011).

Conversely, Field (2013) strongly disagreed that stepwise is the right approach to start the regression analysis. He argued that researchers could judge the predictor addition and removal by using semi partial correlation calculation of an individual predictor with the outcome value. That can be highly influenced by other predictors already entered into the regression model. With this consideration, I planned to start with the forced entry approach to load all of the six predictor variables at once because they have strong theoretical support (Rogers, 2003; Tornatzky & Fleischer, 1990) and demonstrated significant correlations with innovation adoption in other studies (Ekufu, 2012; Powelson, 2012; Ross, 2010). I put the continuous independent variables (relative advantage, compatibility, complexity, and organization size) as covariates and the categorical independent variables (organizational structure and culture) as factors in the SPSS GLM model.

For multiple regression having more than two predictor variables, the most common method to determine the best equation for the predictive model is the use of least sum of variance square methods with the measurement presented as R^2 (Holmes, 2011; Lane, n.d.). Nevertheless, it can only predict outcome variance contributed by the combined variance of predictors in the given sample. To determine the predictive power of the regression model that scholars can generalize to the target population, using adjusted R^2 is more appropriate because it includes the number of predictor variables and sample participants into consideration (Field, 2013). SPSS provides R, R^2, and adjusted R^2 value together with the estimated regression coefficient for each predictor variable as part of the GLM result output. A small delta value between R^2 and adjusted R^2 is a good indicator that the collected sample provides a good presentation to the target population (Field, 2013).

To improve the accuracy of my predictive model, I planned to rerun the GLM several times by taking a backward stepwise method to eliminate one predictive variable at a time that is most insignificant (i.e., highest *p* value). After each run, if the adjusted R^2 of the predictive model is higher than the previous one, it indicates the last model is better. At the end, the optimal predictive model would be the one with the highest adjusted R^2 and the regression coefficients of all predictor variables in the model with a significant nonzero value with $p < .05$ (Washington State University, 2007; Yale University, 1998).

After executing the initial regression, I saved the generated statistical diagnostics and conduct various statistical tests on the regression residuals (i.e., the difference between each predicted and observed value) to ensure no violation of all basic linear regression—linearity, normality, homogeneity of variance (homoscedasticity)—and independence assumptions (Field, 2013). For any violation of these assumptions, I would need to rerun the regression with GLM options turned on. As Field (2013) recommended, researchers should apply the weighted least squares regression, bootstrap data transform, and multilevel model technique to correct the violation of homogeneity of variance, normality, and independence respectively.

To accept or reject a null hypothesis, researcher needs to do significant tests. For null hypotheses $H0_1$ to $H0_6$, I used *t* statistics as the significant test method. The method is useful in determining the probability (*p* value) of getting an observed $t > 1$ (i.e., the ratio of systematic variance explainable by the model to unexplainable random errors) while the regression coefficient of its corresponding predictor variable is equal to zero. When the latter is zero, it means that the independent variable is not a significant predictor. If the probability of getting this condition is close to zero (i.e., $p < .001$), it implies the associated null hypothesis can be rejected, and the corresponding predictor variable is significant (Field, 2013; Holmes, 2011). Similarly, for the null hypothesis $H0_7$, I used F statistics as the significant test method on the entire regression model. It determines the probability (p value) of getting an observed $F > 1$ (i.e., the ratio of variance explainable by the model to unexplainable random errors) while the R value is equal to zero (i.e., $R = 0$). When that happens, it means that the regression model does not fit with the observed sample data at all. Vice versa, if the probability of getting this situation is close to zero (i.e., $p < .001$), it implies the null hypothesis $H0_7$ is not acceptable, and the presented regression model is significant (Field, 2013; Holmes, 2011).

Threats to Validity

As a measurement for any research, the result is made of true value, systematic and random errors. Reliability is a measurement of the quality of research that can produce consistent and dependable results. The test must be repeatable, and the result should be similar under the same environment setting. Validity means whether the operational definition reflects the necessary measurement to the decided concept. As a quality check, validity is helpful to determine whether the research measures the right things, and the corresponding measured results are accurate. Therefore, reliability and validity are tests for the goodness of a specific operational definition. Without these tests, we cannot assure the quality and credibility of a research (Singleton & Straits, 2005). The classification of validity threats and tests are internal, external, and construct. The following sections include a detailed explanation for the threats of my research under these three categories, the measurement method, and the potential solutions to resolve these threats.

External Validity

External validity is a measurement of the generalization power of research. When research has high external validity, it implies that its finding and conclusion could be applicable in other environments (considering the place, time, and people) with similar context (Singleton & Straits, 2005; Trochim 2001). To demonstrate the required generalization power of my study, I first had to validate all assumptions of the linear regression model as stated in the threats to construct and statistical conclusion validity section and confirm that no significant external influential factor exists, as stated in the threats to internal validity. Then I would compare the R^2 and adjusted R^2 value of the model (a cross-validation method). If the difference between these two values is small, then it indicates that the predictive power of the regression model from the sample is similar to that derived from the target population. With low shrinkage of predictive power, it means the regression model has high generalization (Field, 2013).

Internal Validity

Internal validity is a measurement for a researcher to determine the reliable evidences, to claim the stated relationship result between the independent and dependent variables, but not by other unknown external factors (Singleton & Straits, 2005; Trochim, 2001). For regression analysis, the omitted variable bias can risk the accuracy of the model as mentioned in Chapters 1 and 2. As a scholar, I need to ensure I had not omitted any important variable. That was the reason I had relied on the literature review to identify the critical predictors of the cloud computing adoption intent, according to other research studies. When the R^2 result is small, it can be a good indicator that omitted variable bias exists. As a solution, I might have to insert additional predictor variables into the model and seek for R^2 improvement.

Construct Validity

In construct validity, researcher tests the credibility of the research by applying the theoretical framework and by operationalizing the instrument and analysis plan to achieve the right measurements of the noted observations (Trochim 2001). Conclusion validity is a justification measurement for the claim of cause and effect relationship based on observations and statistical analysis. To be able to provide good prediction using MLR, researches must fulfill the basic assumptions for construct and conclusion validity (Lane, n.d.; Holmes, 2011; Sykes, n.d.) as follows:

- Linearity. The relationship between the dependent variable and each independent variable is linear.
- Normality. The errors (or called residuals) must have a normal distribution.
- Homoscedasticity. The variances of errors are the same regardless of their predicted values.
- Independence. Each sample subject is independent of other sample subjects.

When the observed data violate these assumptions, the regression coefficient estimates, the confidence intervals, and *p* values will not be reliable (Field, 2013). The following subsection contains the detection method and procedure to correct these threats.

Linearity. It implies that the relationship between the dependent and independent variables are linear, and the errors are random (Field, 2013; Holmes, 2011; Schofer, 2007). One simple way to diagnose potential linearity bias is to review the scatterplot graph of standardized residuals against standardized model predicted values (zpred vs. zresid in SPSS). When the plot result shows some forms of curve (Figure 11), it indicates the violation of linearity. To fix the issue, I had to consider applying a nonlinear transformation to the regression equation, such as log or power function, depending on which is more appropriate. Furthermore, I might have to use another predictor variable that carries a linear relationship with the criterion variable.

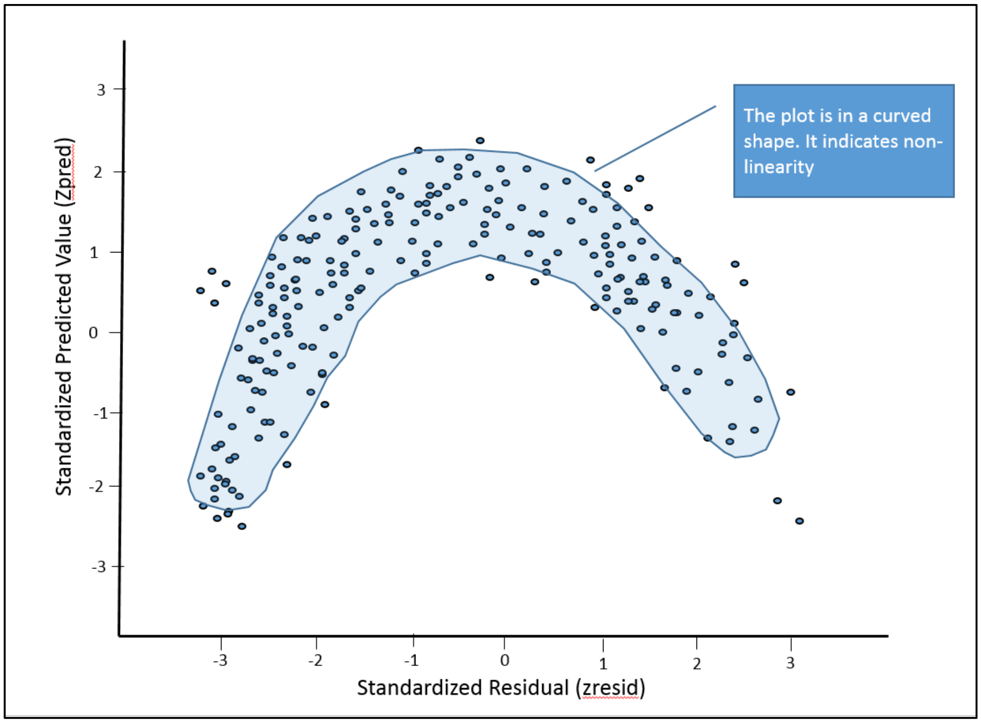


Figure 12. Scatter plot of zpred vs. zresid to check the linearity. When the plot shows a curved shape, it can be a good indicator of linearity issue.

Normality. MLR requires the normality assumption to be met. Otherwise, the coefficient and confidence intervals calculation will not be accurate. Additionally, certain significant tests rely on the assumption of normally distributed errors. One of the common contributors to nonnormality is outliers. I provided further details on the procedure to detect and eliminate outliers under the outlier section. The common normality tests include the review of histograms, *P–P* plots, and *K–S* test (Field, 2013). The review of residual histograms at different values of the predictor variable is a good spot check for normality. Figure 12 is an illustration of residual histogram that lacks normal distribution.

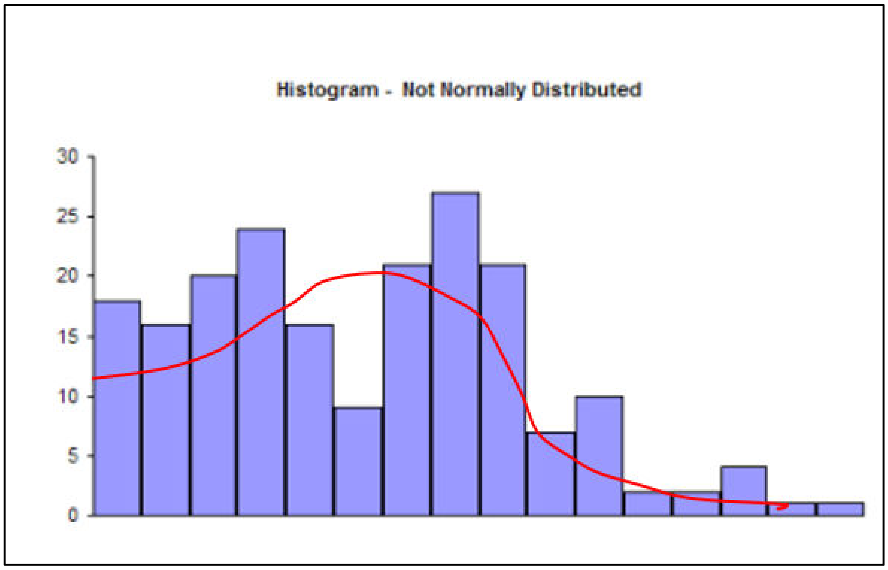


Figure 13. Histogram to check normality. It shows an example of residual histogram that does not have a normal distribution.

The *P–P* plot shows data points of the residual distribution against a normal distribution with the same mean and variance. If the residual is normally distributed, the plotted data point should be along the diagonal line. A bow-shaped pattern indicates that the residuals have excessive skewness. An S-shaped pattern indicates the residuals have excessive kurtosis (Field, 2013). Figure 13 shows the *P–P* plot of the standardized residual with good normal distribution.

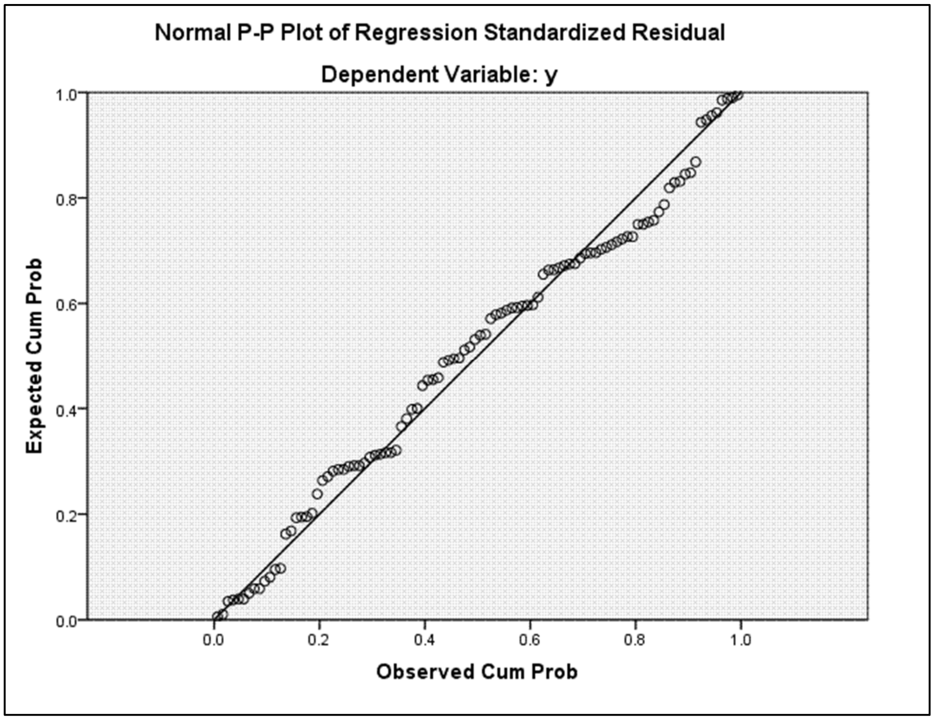


Figure 14. The normal distribution of *P–P* plot for standardized residual to check normality. It illustrates a good normal distribution for the residuals. Adopted from Research and Statistical Support by J. Starkweather. Retrieved from http://www.unt.edu/rss/class/Jon/SPSS_SC/Module9/M9_Regression/SPSS_M9_Regression2.htm. Copyright 2014 by J. Starkweather.

Similar to the concept of *P–P* plot, the *K–S* test shows the calculation of scores from the sample and compares them with the scores from a normal distribution with the same mean and standard deviation. If the test is nonsignificant (i.e., $p > .05$), it implies that the residual distribution is not significantly different from a normal distribution (Field, 2013).

Homoscedasticity. When the variance of errors is not constant at different values of the predictor variable, the coefficient estimation and confidence interval calculation is not accurate. It indicates giving too much weight to a small subset of observation data with large variance of errors. To diagnose a homoscedasticity situation, we can use a scatterplot for the criterion variable against each predictor variable (Figure 15) or a plot of the standardized predicted value against standardized residual values (Figure 14). When the data plot shows as a funnel shape, the regression model may suffer from the homoscedasticity. The solution Field (2013) recommended is to apply the weight least square regression: a function of the variance applied as weights to each case.

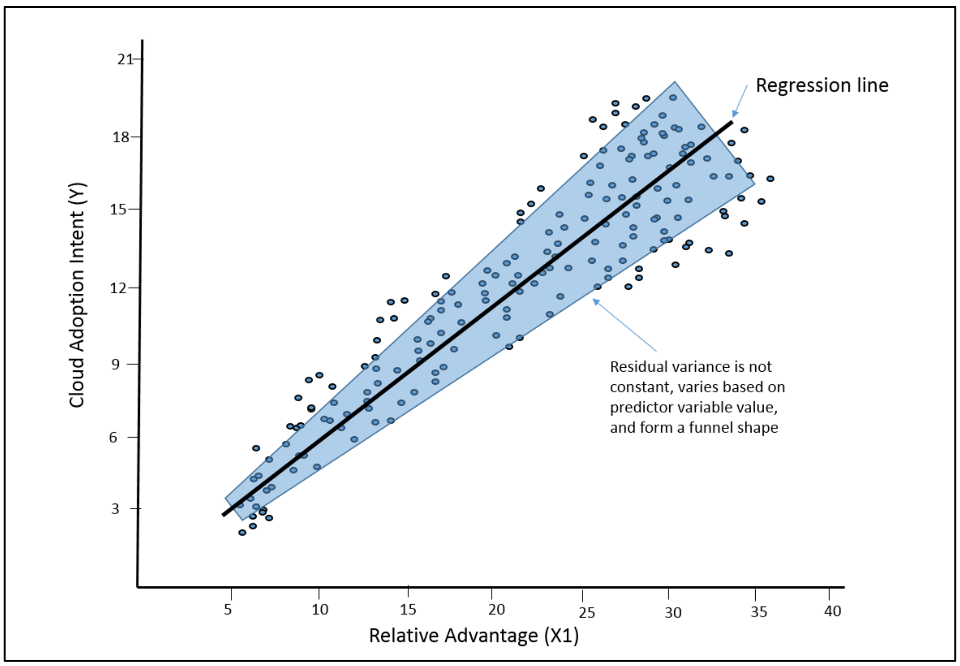


Figure 15. Scatterplot graph to check homoscedasticity. It shows the partial correlational effect of a predictor variable on the criterion variable. It shows that the residual variances increase as the predictor variable values become bigger and the overall plot forms a funnel shape.

Independence. Researchers use Durbin–Watson statistic to determine whether sample objects are independent to each other by checking whether their corresponding residuals are independent. By using this test, researchers can determine the correlation between adjacent residuals. The test result can have a value between zero and four. A value of two indicates that residuals are independent. Nevertheless, when the test value is less than one or greater than three, it illustrates the violation of the independence assumption (Field, 2013). Under that condition, researchers have to establish a multilevel model for fitting the observed sample data to the regression model. To create a multilevel model in SPSS, I would need to identify a context variable to segregate the data into different groups. In case this situation occurs, the hospital region may be a good potential context variable with the assumption that hospitals in the same geographical region have similar characteristics and preference.

Even though the four multiple regression assumptions are met, the model might still not be fitting to provide an accurate prediction if the following two situations exist, as they are influential to the correlation coefficient value of the predictor variables:

- Outliers. Some cases have extreme value compared with the others and reside far beyond the normal distribution curve. Their extreme values are highly influential to the coefficient calculation.
- Multicollinearity. Independent variables are highly correlated with other independent variables.

Outliers. An easy way to spot out significant outliers is to use a scatterplot graph for each predictor variable (Figure 16). In general, scholars recommended the method to reduce outliers by removing the observation points with a value greater than two standard deviations from the mean. However, this method has no guarantee to produce an acceptable *p* value for significant tests. With this reason, a better solution is to use influence and distance statistics. With SPSS, scholars can produce these statistics (e.g., Cook’s distance) as new variables and associate their values with each corresponding case. When the Cook's D value of a case is $> 4 / (N - k - 1)$, I might have to classify it as an outlier and exclude it from the regression, for which N is the sample size, k is the number of predictors (Schofer, 2007).

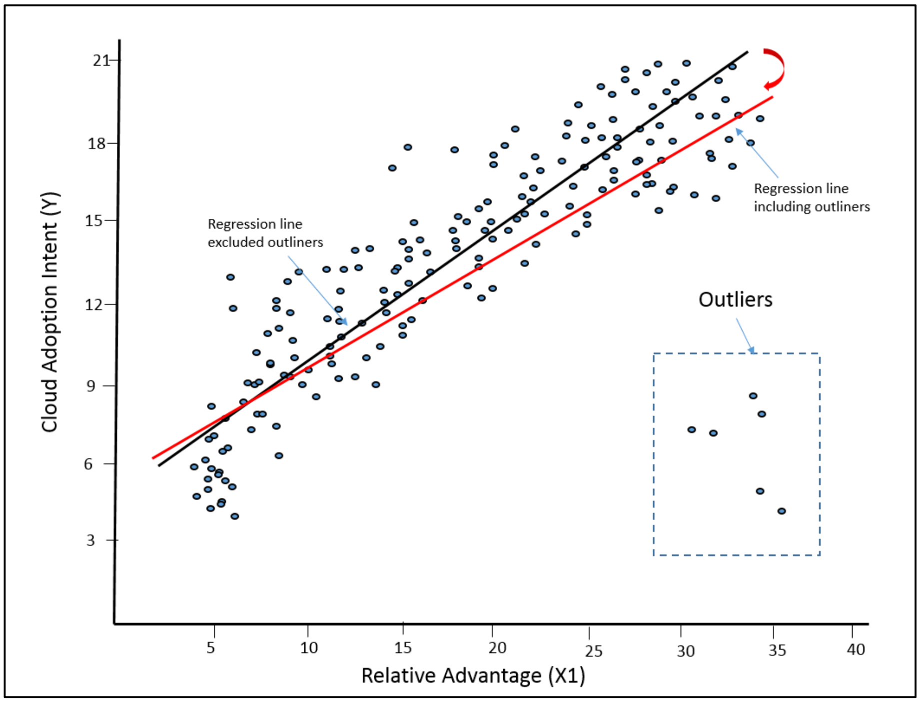


Figure 16. Scatter plot graph to detect outliers. It shows the partial correlational effect of a predictor variable on the criterion variable with or without the outliers. The black regression line shows the best fit line without the outliers while the red line shows the regression line including the outlier observations.

Multicollinearity. When the independent variables in the regression model are highly correlated, the situation is called *multicollinearity*. Once it happened, the variance that can be explained by individual independent variables is relatively small, compared with the overall variance of all independent variables explained together (Balling, 2008; Lane, n.d.). To detect a multicollinearity situation, one common approach is to review the covariance matrix generated as part of the SPSS descriptive statistic output. This matrix shows Pearson's correlation efficient, *r* between each pair of variables included in the model. When a pair of independent variables has an $r > .9$, it indicates that they are highly correlated, and the concern of multicollinearity exists. Another recommendation that Field (2013) provided to detect multicollinearity is to pay special attention to one or more of the following symptoms:

- The sign of the regression coefficient is not as expected.
- In the subsequent regression run under the stepwise model building process, the following situations occur:
    - A large change in the significance of the existing predictor variables after a new predictor becomes part of the regression model.
    - An added predictor variable becomes insignificant in the step.
    - The estimated standard deviation of the model increases significantly with the addition of a new predictor variable.

Additionally, researchers can also apply the independent variable tolerance and variance inflation factor tests to examine the independent variables for the existence of multicollinearity (Nok et al., 2011; Radneantu, Stan, & Gabroveanu, 2011). When the average value of variance inflation factors is not much greater than one, the regression model has no sign of multicollinearity (Field, 2013). In case, the sign exists, one method to solve the collinearity issue is to take two highly correlated variables and construct them under a simple linear regression model. Once researcher determined the regression coefficient, he can substitute one correlated variable by another as to simplify the original MLR equation and fix the multicollinearity issue (Balling, 2008).

Ethical Procedures

Role of the Researcher

Unlike in qualitative research in which the scholar plays a significant role and is part of the research instrument, the researcher's role in a quantitative study is almost nonexistent by following proper ethical guidelines (Simon, 2011b). As my full disclosure, I am an IT executive and professional working for a software manufacturing company that supplies desktop, server, and cloud-based software and infrastructure worldwide. For this research, I planned to rely on my company's customer network to identify required research participants, and use its internal survey management service to collect my survey data.

This study did not impose any researcher bias in the data collection process due to a number of factors:

- I selected the study population fully based on the criteria listed in the sampling procedure.
- I utilized proportional stratified random sampling method.
- I had no direct contact with my survey respondents.
- The participant inputs were totally anonymous and voluntary.

To ensure objective data analysis, I applied all standard statistical tests for MLR to minimize any personal knowledge and experience influence to the analysis result.

Access Agreement

For this study, I followed the ethical guidelines and approval process defined by the National Institutes of Health (NIH), Office of Extramural Research, and Institutional

Review Board (IRB) of Walden University. I planned to collaborate with my company to gain access to the customer contact database for identifying potential survey participants and provide the online survey website and survey management service. For these reasons, I would have needed to obtain the letter of cooperation and data use agreement from the survey management department of my company. Finally, I conducted the research data collection and analysis work only upon the receipt of the IRB approval. The received IRB approval number was 01-14-15-0040993.

Treatment of Human Participants

The human participants in this research were IT managers of U.S. hospitals. To protect their data privacy, the survey excluded questions pertaining to personal data (e.g., name, gender, age, work experience, and academic background). The survey also excluded information about the hospital name to avoid any possible induction to locate the participant's identity. Even though at the end of the survey, the participant could supply the email address as the incentive to receive the final research report, the email address was stored separately from the collected survey data. Therefore, even the researcher is unable to associate the participant's email address with the provided survey responses.

The survey participants did not receive pressure or stress, as they were voluntary to provide their answers to the online self-administrated survey. They had the right to discontinue the survey at any time during the process. Before the online survey began, the first survey question was to ask the survey participants to review and agree on the consent for providing their data. This measure was helpful in ensuring that participants understand the intent of the survey questionnaire, the background of the research bodies, and their right on data privacy and confidentiality. In case the survey participants had any question and concern, they could contact the researcher or the research supervisor.

Treatment of Data

I planned to store the survey data in my company's survey data repository for which only authorized survey management support personnel could access. Since my research did not collect any personal and corporate profile information, no privacy and confidential information could be retrievable based on any reverse engineering scheme. Once the survey input window was closed, I transferred the raw survey data to a data encrypted and password protected laptop and stored in a password-protected Excel spreadsheet format. After I had confirmed the success in transferring raw data transfer, I would send a request to remove the original data from the online survey repository. I then aggregated and regrouped the data before loading them into SPSS for statistical data analysis. After I received my dissertation approval, I would archive and keep the raw and intermit statistical data for another five years before finally removing them, based on the IRB guidelines of Walden University.

Summary

In this chapter, I described my research design and methodology as a cross-sectional quantitative research. I picked MLR as my research analysis method to examine the relationship between the U.S. hospital IT managers' cloud adoption intent and the six technological and organizational predictor variables. The latter included relative advantage, complexity, compatibility, organizational size, organizational structure, and organizational culture. My sampling framework was planned to be the customer contact list of a software manufacturer that sold its products to most of the U.S. hospitals. My research instrument was a self-administrated online survey questionnaire that I enhanced from a validated survey research. I planned to have a minimum of 110 U.S. hospital IT managers' survey responses for my study, to analyze the collected data with SPSS GLM, to validate the required MLR assumptions, and test the research hypotheses with *F* and *t* statistics. As the result, I attempted to provide a regression model that can predict the U.S. hospital IT managers' cloud adoption intent (*Y*), based on the defined six critical factors, in the form of $Y = b_0 + b_1X_1 + b_2X_2 + \ldots b_nX_n$. In the next chapter, I reported my research results with all the statistical analysis details.

Chapter 4: Results

The purpose of this survey study was to conduct a regression analysis to examine the cloud computing adoption intent of U.S. hospital IT managers. The research question was: Does regression allow us to predict the cloud computing adoption intent of U.S. hospital IT managers as a function of six influential factors: (a) relative advantage, (b) compatibility, (c) complexity, (d) organizational size, (e) organizational structure, and (f) organizational culture? The following seven null hypotheses anchored the research question for my cloud computing adoption study:

$H0_1$: X_1 = relative advantage of cloud computing is not a significant predictor of Y = intent to adopt cloud services; mathematically, $b_1 = 0$ in the resulting regression model.

$H0_2$: X_2 = compatibility of public cloud is not a significant predictor of Y = intent to adopt cloud services; mathematically, $b_2 = 0$ in the resulting regression model.

$H0_3$: X_3 = complexity belief of public cloud is not a significant predictor of Y = intent to adopt cloud services; mathematically, $b_3 = 0$ in the resulting regression model.

$H0_4$: X_4 = organizational size is not a significant predictor of Y = intent to adopt cloud services; mathematically, $b_4 = 0$ in the resulting regression model.

$H0_5$: X_5 = organizational structure is not a significant predictor of Y = intent to adopt cloud services; mathematically, $b_5 = 0$ in the resulting regression model.

$H0_{6.}$: X_6 = organizational culture is not a significant predictor of Y = intent to adopt cloud services; mathematically, $b_6 = 0$ in the resulting regression model.

$H0_7$: The linear model $Y = b_0 + b_1X_1 + b_2X_2 + b_3X_3 + b_4X_4 + b_5X_5 + b_6X_6$ has no significant fit; mathematically, $R(Y \mid X_{1, \ldots,} X_6) = 0$.

This chapter began with a brief description of the research purpose, pilot test result, and then proceeded to the final study details including data collection outcomes, treatment and intervention fidelity, and the statistical analysis results. I provided the reliability and validity test results as graphs and statistical tables as to confirm the required assumptions for applying the categorical regression method. Finally, I provided a brief summary of my statistical findings to conclude the chapter.

Pilot Study

For my pilot study, I invited ten health care IT SMEs through my personal network, and five of them accepted the invitation. I provided my online survey with one additional open question for them to offer feedbacks on the survey clarity and recommended improvement areas. They provided several recommendations as listed below:

- Most IT executives of U.S. hospitals have different perspectives on public versus private cloud services. It was better to provide separate survey items for compatibility, complexity, and cloud adoption intents for public versus private cloud services.
- Since Q_{16} was the survey item to ask for number of staffed beds, it should be adjacent with other demographical questions at the beginning of the survey questionnaire.
- The definitions of different organizational structure types for the survey item Q_{17} was not clear, and it should provide additional clarification.

- The potential survey participants should receive the invitation emails during normal office hours as IT executives of U.S. hospitals might have limited access to their email accounts during non-office hours.
- The expected response rate could be low due to the high security and privacy concern for U.S. hospitals.

Based on the above recommendations, I restructured the originally-proposed survey items to segregate the survey questions for public versus private cloud services as shown in Table 8. Since the differences in public and private cloud services are mainly with regards to its implementation and deployment technology nature, it is reasonable to separate only the influential factors–compatibility and complexity, and the adoption intent. Table 9 shows the updated research questions and null hypotheses.

Table 8

Modified Survey Items Alignment and Value Calculation Method for Composite Variables after Pilot Study

Adoption influential factor (composite variable)	Survey item	Calculation	Data type of the final (composite) variable
X_1 = Relative advantage	Use 7-point Likert-type scale to measure from strongly disagree, disagree, neutral, agree to strongly agree with the following survey questions: Q_1 = Increase the profitability of my hospital. Q_2 = Allow your hospital to provide additional services. Q_3 = Allow for reduced operational costs. Q_4 = Allow better communication with my patients, staff, and medical partners. Q_5 = Require no up-front capital investment. Q_6 = Provide dynamic and high service availability.	$X_1 = Q_1 + Q_2 + Q_3 + Q_4 + Q_5 + Q_6$	Interval

(table continues)

Adoption influential factor (composite variable)	Survey item	Calculation	Data type of the final (composite) variable
$X_{2.1}$ = Compatibility of public cloud	Use 7-point Likert-type scale. Measuring from strongly disagree, disagree, neutral, agree to strongly agree with the following survey questions: $Q_{7.1}$ = Public cloud adoption is consistent with my hospital's beliefs and values. $Q_{8.1}$ = Attitudes towards public cloud adoption in my hospital is favorable. $Q_{9.1}$ = Public cloud adoption is compatible with my hospital's IT infrastructure. $Q_{10.1}$ = Public cloud adoption is consistent with my hospital's business strategy.	$X_{2.1} = Q_{7.1} + Q_{8.1} + Q_{9.1} + Q_{10.1}$	Interval
$X_{2.2}$ = Compatibility of private cloud	Use 7-point Likert-type scale. Measuring from strongly disagree, disagree, neutral, agree to strongly agree with the following survey questions: $Q_{7.2}$ = Private cloud adoption is consistent with my hospital's beliefs and values. $Q_{8.2}$ = Attitudes towards private cloud adoption in my hospital is favorable. $Q_{9.2}$ = Private cloud adoption is compatible with my hospital's IT infrastructure. $Q_{10.2}$ = Private cloud adoption is consistent with my hospital's business strategy.	$X_{2.2} = Q_{7.2} + Q_{8.2} + Q_{9.2} + Q_{10.2}$	Interval
$X_{3.1}$ = Complexity belief of public cloud	Use 7-point Likert-type scale. Measuring from strongly disagree, disagree, neutral, agree to strongly agree with the following survey questions: $Q_{11.1}$ = Public cloud service is cumbersome to use. $Q_{12.1}$ = Using the public cloud services requires a lot of mental efforts. $Q_{13.1}$ = Using the public cloud is often frustrating. $Q_{14.1}$ = The user interface of public cloud services is clear and understandable. $Q_{15.1}$ = Public cloud services are easy to purchase and startup.	$X_{3.1} = Q_{11.1} + Q_{12.1} + Q_{13.1} + Q_{14.1} + Q_{15.1}$	Interval
$X_{3.2}$ = Complexity belief of private cloud	Use 7-point Likert-type scale. Measuring from strongly disagree, disagree, neutral, agree to strongly agree with the following survey questions: $Q_{11.2}$ = Private cloud service is cumbersome to use.	$X_{3.2} = Q_{11.2} + Q_{12.2} + Q_{13.2} + Q_{14.2} + Q_{15.2}$	Interval

(table continues)

Adoption influential factor (composite variable)	Survey item	Calculation	Data type of the final (composite) variable
	$Q_{12.2}$ = Using private cloud services requires a lot of mental efforts. $Q_{13.2}$ = Using the private cloud services is often frustrating. $Q_{14.2}$ = The user interface of private cloud services is clear and understandable. $Q_{15.2}$ = Private cloud services are easy to purchase and startup.		
X_4 = Organizational size	It is measured by the number of staffed beds that are grouped in one to eight scale from: Q_{16}^* = 50 - 99 (= 1), 100 - 199 (= 2), 200 - 299 (= 3), 300 - 399 (= 4), 400 - 499 (= 5) and > 500 (= 6) staffed beds.	$X_4 = Q_{16}$	Interval
X_5 = Organizational structure	Use a multiple choice question to categorize into four types: Q_{17} = functional (= 1), divisional (= 2), matrix (= 3) and others (= 4).	$X_5 = Q_{17}$	Nominal
X_6 = Organizational culture	Use a multiple choice question to categorize into five types: Q_{18} = clan (= 1), adhocracy (= 2), hierarchy (= 3), market (= 4) and others (= 5).	$X_6 = Q_{18}$	Nominal
Y_1 = Public cloud adoption intent	Use 7-point Likert-type scale. Measuring from strongly disagree, disagree, neutral, agree to strongly agree with the following survey questions: $Q_{19.1}$ = Intends to adopt public cloud computing. $Q_{20.1}$ = Likely to take steps to adopt public cloud computing in the future. $Q_{21.1}$ = Likely to adopt public cloud computing in the next 12 months.	$Y_1 = Q_{19.1} + Q_{20.1} + Q_{21.1}$	Interval
Y_2 = Private cloud computing adoption intent	Use 7-point Likert-type scale. Measuring from strongly disagree, disagree, neutral, agree to strongly agree with the following survey questions: $Q_{19.2}$ = Intends to adopt private cloud services. $Q_{20.2}$ = Likely to take steps to adopt private cloud services in the future. $Q_{21.2}$ = Likely to adopt private cloud services in the next 12 months.	$Y_2 = Q_{19.2} + Q_{20.2} + Q_{21.2}$	Interval

Note: * Since I pre-screened U.S. hospitals with 50 or more staffed beds as the qualification criteria in my study, I modified the survey item Q_4 to exclude the selection options for 6-24 and 25-49 staffed beds.

Table 9

Renewed Research Questions and Hypotheses for Public and Private Cloud Adoption Analysis

Public Cloud Adoption	Private Cloud Adoption
RQ1: Does regression allow us to predict the public cloud services adoption intent of U.S. hospital IT managers as a function of six influential factors: (a) relative advantage, (b) compatibility, (c) complexity, (d) organizational size, (e) organizational structure, and (f) organizational culture?	RQ2: Does regression allow us to predict the private cloud services adoption intent of U.S. hospital IT managers as a function of six influential factors: (a) relative advantage, (b) compatibility, (c) complexity, (d) organizational size, (e) organizational structure, and (f) organizational culture?
$H0_{1.1}$: X_1 = relative advantage of cloud computing is not a significant predictor of Y_1 = intent to adopt public cloud services; mathematically, $b_{1.1} = 0$ in the resulting regression model.	$H0_{1.2}$: X_1 = relative advantage of cloud computing is not a significant predictor of Y_2 = intent to adopt private cloud services; mathematically, $b_{1.2} = 0$ in the resulting regression model.
$H0_{2.1}$: $X_{2.1}$ = compatibility of public cloud services is not a significant predictor of Y_1 = intent to adopt public cloud services; mathematically, $b_{2.1} = 0$ in the resulting regression model.	$H0_{2.2}$: $X_{2.2}$ = compatibility of private cloud services is not a significant predictor of Y_2 = intent to adopt private cloud services; mathematically, $b_{2.2} = 0$ in the resulting regression model.
$H0_{3.1}$: $X_{3.1}$ = complexity of public cloud services is not a significant predictor of Y_1 = intent to adopt public cloud services; mathematically, $b_{3.1} = 0$ in the resulting regression model.	$H0_{3.2}$: $X_{3.2}$ = complexity of private cloud services is not a significant predictor of Y_2 = intent to adopt private cloud services; mathematically, $b_{3.2} = 0$ in the resulting regression model.
$H0_{4.1}$: X_4 = organizational size is not a significant predictor of Y_1 = intent to adopt public cloud services; mathematically, $b_{4.1} = 0$ in the resulting regression model.	$H0_{4.2}$: X_4 = organizational size is not a significant predictor of Y_2 = intent to adopt private cloud services; mathematically, $b_{4.2} = 0$ in the resulting regression model.
$H0_{5.1}$: X_5 = organizational structure is not a significant predictor of Y_1 = intent to adopt public cloud services; mathematically, $b_{5.1} = 0$ in the resulting regression model.	$H0_{5.2}$: X_5 = organizational structure is not a significant predictor of Y_2 = intent to adopt private cloud services; mathematically, $b_{5.2} = 0$ in the resulting regression model.
$H0_{6.1}$: X_6 = organizational culture is not a significant predictor of Y_1 = intent to adopt public cloud services; mathematically, $b_{6.1} = 0$ in the resulting regression model.	$H0_{6.2}$: X_6 = organizational culture is not a significant predictor of Y_2 = intent to adopt private cloud services; mathematically, $b_{6.2} = 0$ in the resulting regression model.
$H0_{7.1}$: The linear model $Y_1 = b_{0.1} + b_{1.1}X_1 + b_{2.1}X_{2.1} + b_{3.1}X_{3.1} + b_{4.1}X_4 + b_{5.1}X_5 + b_{6.1}X_6$ has no significant fit; mathematically, $R(Y_1 \mid X_1, X_{2.1}, X_{3.1}, X_4, X_5, X_6) = 0$.	$H0_{7.2}$: The linear model $Y_2 = b_{0.2} + b_{1.2}X_1 + b_{2.2}X_{2.2} + b_{3.2}X_{3.2} + b_{4.2}X_4 + b_{5.2}X_5 + b_{6.2}X_6$ has no significant fit; mathematically, $R(Y_2 \mid X_1, X_{2.2}, X_{3.2}, X_4, X_5, X_6) = 0$.

Besides the improvement of the survey, with the pilot study, I was able to test out:

- the creation of online survey questionnaire,
- the robustness of the online survey site,
- the logistics of sending invitations,
- the survey result data download procedure, and
- the execution of statistical data analysis.

Nevertheless, due to insufficient data points, the statistical analysis of the pilot study would not be meaningful and thus it had not been performed.

Data Collection

The sampling plan encompassed the qualified hospitals registered in the company's customer contact database. Nevertheless, due to the company's information confidentiality policy, I was directed to use an external business profiling and contact research service (http://www.hoovers.com) subscribed by the company. From that, I was able to extract qualified hospital IT contacts together with their corresponding hospital profile information. That included the IT personnels with the managerial role who work in U.S. hospitals located in 48 continental states with 50 or more staffed beds. For each retrieved IT contact, I sent a test email that introduced my research interest and myself in order to confirm the provided email address is valid. This approach helped to exclude all invalid contacts from my sampling framework upfront. With the advice from the pilot study SMEs, I changed my expected response rate from 26% to 5%, and that tremendously increased my required survey invitations from 425 to 2200. Table 10 below provided the breakdowns of the required invitations for each U.S. region.

Table 10

Qualified Hospitals under Hoovers Sampling Framework

U.S. Region	U.S. State	Number of qualified hospitals within sampling framework	Number of qualified IT contacts with valid email address	Required Survey Invitations with expected Response Rate = 5%
Midwest		627	671	606
	IA	47	40	
	IL	106	128	
	IN	70	84	
	KS	52	50	
	MI	60	69	
	MN	41	38	
	MO	53	58	
	ND	9	11	
	NE	31	27	
	OH	88	94	
	SD	17	16	
	WI	53	56	
Northeast		413	430	388
	CT	30	50	
	MA	58	60	
	ME	18	16	
	NH	16	24	
	NJ	36	44	
	NY	140	117	
	PA	108	111	
	VT	7	8	
South		782	905	816
	AL	18	46	
	AR	24	11	
	DC	6	10	
	DE	3	0	(table continues)

U.S. Region	U.S. State	Number of qualified hospitals within sampling framework	Number of qualified IT contacts with valid email address	Required Survey Invitations with expected Response Rate = 5%
	FL	106	169	
	GA	70	96	
	KY	44	45	
	LA	54	70	
	MD	20	21	
	MS	36	34	
	NC	51	53	
	OK	40	42	
	SC	29	34	
	TN	56	60	
	TX	163	160	
	VA	33	31	
	WV	29	23	
West		365	432	390
	AZ	26	37	
	CA	153	180	
	CO	32	34	
	ID	16	20	
	MT	18	19	
	NM	13	14	
	NV	11	9	
	OR	21	30	
	UT	12	19	
	WA	48	51	
	WY	15	19	
Total		2187	2438	2200

The entire survey window was open from 5 January to 13 February, 2015. At the close of the survey window, I received 130 responses with 5 acknowledged without sufficient IT decision authority and 7 with incomplete data. That led to 118 valid survey responses with response rate of 5.4%. As the number of received responses met the minimal sample size requirement of 110, the research result should carry a significant representation for the target population. In Table 11, it shows the sample sizes for the four U.S. regions and provides a proportional comparison with the target population. Although I used a proportional stratified random sampling method, the regional sample proportions were still significantly deviated from the proportions of the target population. For South region, the received responses were less than the minimum required sample size (as shown in Table 11) by 9 (i.e., 46 – 37). It limited the ability of my research for any further statistical investigation down to the South region itself. However, the survey collected sufficient number of responses for Midwest (28), Northeast (29), and West (24) region and their percentages were in similar proportions as for the target population. Therefore, my study should still carry a reasonable representation for those three regions and the entire 48 U.S. continental states.

Table 11

Target Population and Sample Demographics by U.S. Region

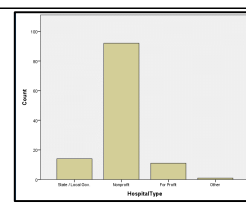
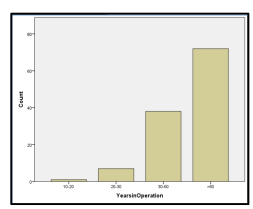
Region	Target Population*		Accessible Population**		Samples (Received Responses)	
	Frequency	%	Frequency	%	Frequency	%
Midwest	661	23.1	627	28.7	28	23.7
Northeast	503	17.6	413	18.9	29	24.6
South	1177	41.1	782	35.8	37	31.4
West	525	18.3	365	16.7	24	20.3
Total	2866	100.0	2187	100.0	118	100.0

Note. * Target population and ** accessible population data are corresponding to the data presented in Table 7 and 10.

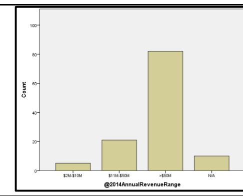
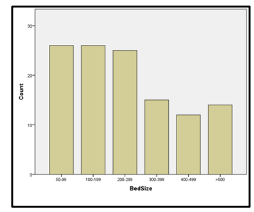
Table 12 provided demographical statistics in addition to the comparison of the target population and sample proportion by U.S. region as shown in Table 11. Additionally, Table 12 provided the data to evaluate the representation of the sample in associated with the target population by hospital type, years of operation, 2014 annual revenue, and staffed bed size. Under hospital type, the collected sample lacked of representation on Federal government hospitals and majority of the responses (78%) was from nonprofit hospitals. For years of operation, 61% of the hospitals established for more than 60 years and the resulted sample lacked representation for hospitals that were less than ten years old. For annual revenue in 2014, 69.5% of hospitals were more than \$50M. Since the demographical attributes—hospital type, years of operation, and annual revenue in 2014—were not part of dependent variables in my research, they did not affect the resulted statistical analysis. However, it had some implications for the generalization, for which I discussed further under the Evaluation of the Statistical Assumption section.

Table 12

Target Population and Sample Demographics by Other Attributes

Demographic Attribute	Target Population		Sample		Sample Histogram
	Frequency	%	Frequency	%	
Hospital Type					
1= Federal Gov.	107	3.7	0	0.0	
2= State / Local Gov.	509	17.8	14	11.9	
3= Nonprofit	1464	51.1	92	78.0	
4= For-profit	534	18.6	11	9.3	
5= Other	252	8.8	1	0.8	
Total	2866	100.0	118	100.0	
Years of Operation					
0=1-10	272	9.5	0	0.0	
1= 10-20	283	9.9	1	0.8	
2= 20-30	141	4.9	7	5.9	
3= 30-60	767	26.8	38	32.2	
4= >60	1403	49.0	72	61.0	
Total	2866	100.0	118	100.0	

(table continues)

Demographic Attribute	Target Population		Sample		Sample Histogram
	Frequency	%	Frequency	%	
Annual Revenue in 2014					
1= $2M-$10M	4	0.1	5*	4.2	
2= $11M-$50M	62	2.2	21	17.8	
3= >$50M	2758	96.2	82	69.5	
4= N/A	42	1.5	10	8.5	
Total	2866	100.0	118	100.0	
Staffed Bed Size					
1= 50-99	557	19.4	26	22.0	
2= 100-199	940	32.8	26	22.0	
3= 200-299	550	19.2	25	21.2	
4= 300-399	336	11.7	15	12.7	
5= 400-499	183	6.4	12	10.2	
6= >500	300	10.5	14	11.9	
Total	2866	100.0	118	100.0	

Note. The target population demographical statistics were retrieved and consolidated from the American Hospital Directory (AHD): www.ahd.com, American Hospital Association (AHA): www.aha.org and Hoovers: www.hoovers.com. ** The frequency for hospitals with 2014 annual revenue between $2M and $10M in the received response was higher than the demographic statistics provided by AHD for 2014.

Treatment and/or Intervention Fidelity

Firstly, I selected the survey candidates with the stratified proportional sampling method as described in Chapter 3. Then I sent professionally designed survey invitation emails (as shown in Appendix E) by using my Walden University email address with the online survey access link to the 2200 identified survey candidates. As mentioned by Dr. Tweel (2012), using university provided email account to send survey invitations could provide better confidence to the email recipients that the email is not a spam. In the first week of my survey window, I sent out about 500 invitations on each workday.

I used a U.K. based survey service company (http://www.kwiksurveys.com) that provided the online survey design, data collection, and basic data analysis capability. To ensure I could offer my research summary report to all survey participants as an acknowledgement for their support, I redirected the survey participants to my custom designed *thank you page* after they completed the survey, to provide their email addresses. Therefore, I avoided any association of my collected survey data with the participants' email addresses and ensured their responses are anonymous. Furthermore, this procedure prevented me from sending reminders to people who had already taken the survey. The response rate of my first round of invitation was very low. It was only about 1% (i.e., 22 responses) after two weeks. As part of my observation, I received no response on Monday and most responses came on Friday. The responses seem only came on the same day as requested, i.e., no response received on the dates that I did not send the survey invitation requests. To increase my response rate, I began to send out the survey request reminders in the third week of my survey window from Tuesday to Friday, but not Monday. In addition, I enhanced my invitation email with a stronger emphasis on the value of my research. The response rate had significantly raised. By the end of the fifth week, I totally received 86 responses and that triggered me to send out the second reminder as my final attempt to collect the minimal required sample responses. Finally, I received 130 responses at the end of my six weeks survey window. Besides the minor adjustment on my survey invitation logistics and using reminder approach to encourage survey participation, I did not have any adverse event of intervention.

Study Results

For the statistical analysis, I used the IBM SPSS Statistics version 21. It provided the required statistical capabilities, such as descriptive and inferential statistics, charting, and general linear modeling. My analysis consisted of two parts. In the first part, I examined the descriptive statistics and evaluated the reliability and validity of survey items used to determine the values of the composite variables. To confirm no violation of assumptions for GLM, I performed various graphical plots and statistical tests for linearity, normality, homoscedasticity, independence, and the absence of multicollinearity. In the second part, I assessed the contribution and significance of the six independent variables—relative advantage, compatibility, complexity, organizational size, organizational structure, and organizational culture—in relationship with the dependent variable—U.S. hospital IT managers' intent to adoption public and private cloud services—by using SPSS GLM method.

As described in Chapter 3, attitude type survey items—Q_1 to Q_{15} were ordinal data based on the Likert scale of 1 (strongly disagree) to 7 (strongly agree). Since the survey items Q_{11}, Q_{12}, and Q_{13} were phrased in an opposite way, the response scores had to be reversed by subtracting the answer from 8 (i.e. 8 – response value). This procedure safeguarded the responses of all survey items Q_{11} to Q_{15} were following the same direction of altitude scoring. This prevented the scores of negative phrased survey items counterbalancing out the score of the positive phrased survey items in the same group when they were summed together to produce the value for the corresponding composite variable, i.e., complexity behalf.

As mentioned in the Pilot Study section, the survey items for the composite independent variables—compatibility and complexity and the composite dependent variable—U.S. hospital IT managers' intent for cloud computing adoption were splitted into two groups—public and private cloud services. Therefore, I reported out my analysis results separately for public and private cloud adoption with the dependent and independent variables as listed in Table 13.

Table 13

Renewed Dependent and Independent Variable Lists after Segregating the U.S. Hospital IT Managers' Adoption Intent by Public versus Private Cloud Services

Public Cloud Services	Private Cloud Services
Dependent Composite Variable	
Y_1= Public cloud services adoption intent of U.S. hospital IT managers	Y_2= Private cloud services adoption intent of U.S. hospital IT managers
Independent Composite Variables	
X_1 = Relative advantage	X_1 = Relative advantage
$X_{2.1}$= Compatibility of public cloud	$X_{2.2}$= Compatibility of private cloud
$X_{3.1}$= Complexity of public cloud	$X_{3.2}$= Complexity of private cloud
X_4= Organizational size	X_4= Organizational size
X_5= Organizational structure	X_5= Organizational structure
X_6= Organizational culture	X_6= Organizational culture

Note. X_1, X_4, X_5, and X_6 remained as the same independent variables for both public and private cloud services adoption study.

Descriptive Statistics

To report out the descriptive statistics, I used the minimum, maximum, mean, standard deviation, and variance of the received responses calculated by SPSS on all survey items as shown in Table 14. For the seven composite variables, I also produced similar statistics together with skewness measurement as shown in Table 15 after applying the summation formula as explained in **Table 8**. The key observations provided by the descriptive statistics of the survey items included that no respondent:

- Strongly disagreed cloud computing services allowing their hospitals to provide additional services (Q_2).

- Strongly disagreed cloud computing services allowing better communication with patients, staff, and medical partners for their hospitals (Q_4).
- Strongly agreed public cloud computing services being consistent with their hospitals' beliefs and values (Q_7).
- Strongly agreed public cloud computing services are providing clear and understandable user interface (Q_{14}).
- Strongly agreed public cloud computing services being easy to purchase and startup.
- Strongly agreed private cloud computing services being cumbersome to use.

Table 14

Descriptive Statistics for the Survey Items

	N	Min.	Max.	Mean	Std. Deviation	Variance
Q_1 = Increase profit	118	1	7	4.45	1.647	2.711
Q_2 = Additional services	118	2	7	5.09	1.396	1.949
Q_3 = Reduce cost	118	1	7	4.91	1.664	2.769
Q_4 = Better Communication	118	2	7	5.03	1.320	1.742
Q_5 = No upfront investment	118	1	7	4.20	1.767	3.121
Q_6 = High flexibility and availability	118	1	7	5.20	1.488	2.215
Public cloud services						
$Q_{7.1}$ = Consistent with belief and value	118	1	6	3.91	1.268	1.607
$Q_{8.1}$ = Favorable attitude	118	1	7	3.76	1.363	1.858
$Q_{9.1}$ = compatible with existing infra.	118	1	7	4.18	1.534	2.353
$Q_{10.1}$ = Consistent with business strategy	118	1	7	4.06	1.348	1.817
Private cloud services						
$Q_{7.2}$ = Consistent with belief and value	118	1	7	4.73	1.344	1.806
$Q_{8.2}$ = Favorable attitude	118	1	7	4.67	1.415	2.001

(table continues)

	N	Min.	Max.	Mean	Std. Deviation	Variance
$Q_{9.2}$ = compatible with existing infra.	118	1	7	4.98	1.267	1.607
$Q_{10.2}$ = Consistent with business strategy	118	1	7	4.58	1.464	2.144
<u>Public cloud services</u>						
$Q_{11.1}$ = Cumbersome to use	118	1	7	3.69	1.195	1.427
$Q_{12.1}$ = Require a lot of mental efforts	118	1	7	3.84	1.408	1.982
$Q_{13.1}$ = Frustrated to use	118	1	7	3.99	1.544	2.385
$Q_{11.1r}$ = Not cumbersome to use	118	1	7	4.30	1.179	1.390
$Q_{12.1r}$ = Not require a lot of mental efforts	118	1	7	4.14	1.385	1.919
$Q_{13.1r}$ = Not frustrated to use	118	1	7	4.01	1.544	2.385
$Q_{14.1}$ = User interface is understandable	118	1	6	4.37	1.123	1.261
$Q_{15.1}$ = Easy to purchase and startup	118	1	6	3.95	1.358	1.844
<u>Private cloud services</u>						
$Q_{11.2}$ = Cumbersome to use	118	1	6	3.55	1.251	1.566
$Q_{12.2}$ = Require a lot of mental efforts	118	1	7	3.67	1.314	1.727
$Q_{13.3}$ = Frustrated to use	118	1	7	3.88	1.492	2.225
$Q_{11.2r}$ = Not cumbersome to use	118	2	7	4.45	1.251	1.566
$Q_{12.2r}$ = Not require a lot of mental efforts	118	1	7	4.33	1.314	1.727
$Q_{13.2r}$ = Not frustrated to use	118	1	7	4.12	1.492	2.225
$Q_{14.2}$ = User interface is understandable	118	1	7	3.92	1.141	1.302
$Q_{15.2}$ = Easy to purchase and startup	118	1	7	3.85	1.506	2.267
Q_{16} = Organizational size	118	1	6	3.00	1.643	2.701
Q_{17} = Organizational structure	118	1	4	2.17	1.081	1.168
Q_{18} = Organizational culture	118	1	5	2.90	1.297	1.682
<u>Public cloud services</u>						
$Q_{19.1}$ = Intends to adopt	118	1	7	4.19	1.543	2.380
$Q_{20.1}$ = Take steps to adopt	118	1	7	4.13	1.566	2.454
$Q_{21.1}$ = Adopt in next 12 months	118	1	7	3.65	1.549	2.400
<u>Private cloud services</u>						
$Q_{19.2}$ = Intends to adopt	118	1	7	4.81	1.157	1.338
$Q_{20.2}$ = Take steps to adopt	118	1	7	4.79	1.211	1.468

(table continues)

	N	Min.	Max.	Mean	Std. Deviation	Variance
$Q_{21.2}$ = Adopt in next 12 months	118	1	7	4.21	1.332	1.775

Note. $Q_{11.1r}$, $Q_{12.1r}$, $Q_{13.1r}$, $Q_{11.2r}$, $Q_{12.2r}$, and $Q_{13.2r}$ were the transformed survey items.They reversed the attitude of the answers from the negative to the positive tone for their corresponding survey items $Q_{11.1}$, $Q_{12.1}$ $Q_{13.1}$, $Q_{11.2}$, $Q_{12.2,}$ and $Q_{13.2}$ respectively.

To determine whether the sample data corresponding to each variable were normally distributed, the z-score value for skewness (i.e., skewness value divided by standard error of skewness) should be within the range of -1.96 and +1.96 (Doane & Seward, 2011). Based on the skewness values shown in Table 15, I concluded that all composite variables were within the required range to assume their data points were normally distributed, except for organizational size (X_4). It had the z-score skewness value of 2.161 that exceeded the upper boundary of 1.96 by 0.201 slightly. The normal curve of the histogram charts in Table 16 also revealed this fact. Since data were mostly within the suggested criteria of normality, no data transformation was required.

Table 15

Descriptive Statistics for the Composite Variables

	N	Min.	Max.	Mean	Std. Deviation	Variance	Skewness
X_1 = Relative advantage	118	10	42	28.88	6.592	43.456	.211
<u>Public cloud services</u>							
$X_{2.1}$ = Compatibility	118	4	27	15.85	4.689	21.983	.063
$X_{3.1}$ = Complexity	118	6	33	21.17	5.493	30.178	.180
<u>Private cloud services</u>							
$X_{2.2}$ = Compatibility	118	4	28	18.96	5.105	26.058	.412

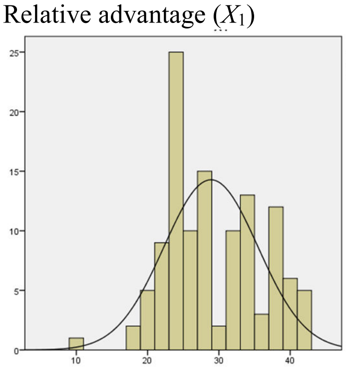
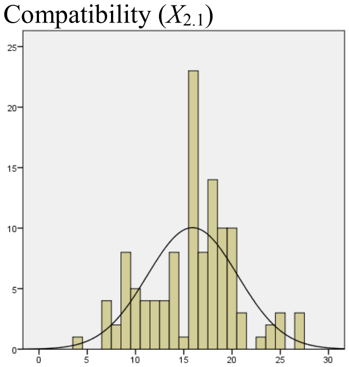
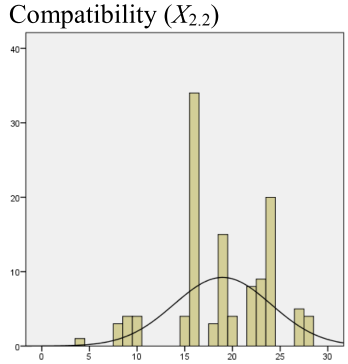
(table continues)

	N	Min.	Max.	Mean	Std. Deviation	Variance	Skewness
$X_{3.2}$ = Complexity	118	8	30	20.67	5.099	26.001	.039
X_4 = Organizational size	118	1	6	3.00	1.643	2.701	.482
X_5 = Organizational structure	118	1	4	2.17	1.081	1.168	.358
X_6 = Organizational culture	118	1	5	2.90	1.297	1.682	.025
Y_1 = Adoption intent for public cloud services	118	3	21	11.91	4.342	18.854	.284
Y_2 = Adoption intent for private cloud services	118	3	21	13.82	3.327	11.071	.330

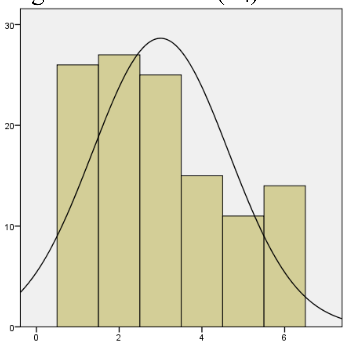
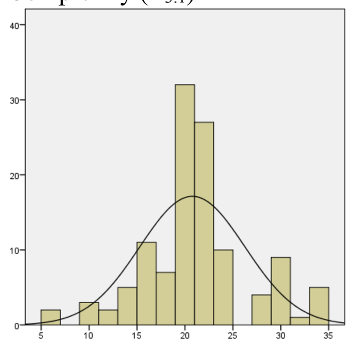
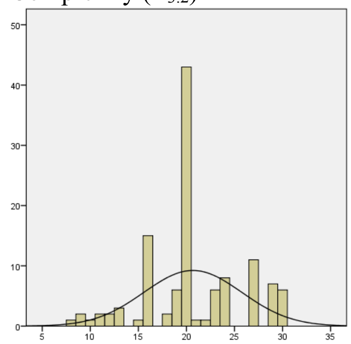
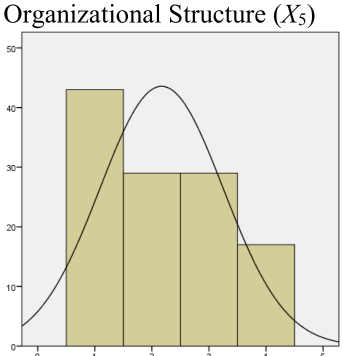
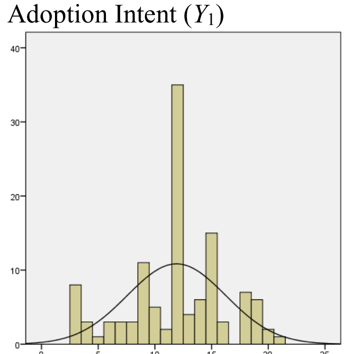
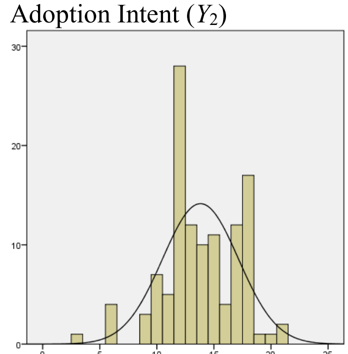
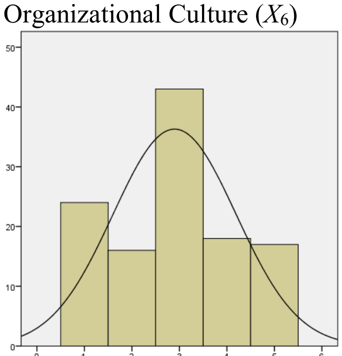
Note. Since composite variables—X_4, X_5, and X_6—had a single survey item, their descriptive statistics were equivalent to Q_{16}, Q_{17}, and Q_{18} shown in 14 respectively. The standard error of skewness for all composite variables was .223.

Table 16

Histograms with Normal Curve for Composite Variables

Common Composite Variable	Composite Variable for Public Cloud Services	Composite Variable for Private Cloud Services
Relative advantage (X_1) 	Compatibility ($X_{2.1}$) 	Compatibility ($X_{2.2}$) 

(table continues)

Common Composite Variable	Composite Variable for Public Cloud Services	Composite Variable for Private Cloud Services
Organizational size (X_4) 	Complexity ($X_{3.1}$) 	Complexity ($X_{3.2}$) 
Organizational Structure (X_5) 	Adoption Intent (Y_1) 	Adoption Intent (Y_2) 
Organizational Culture (X_6) 		

Note. The normal curve of the composite independent variable (X_4) is slightly asymmetric.

Evaluation of Statistical Assumption

As a generalization precaution, since the sample in my research did not have any representation for U.S. hospitals that is federal government owned and within one to ten years of operation, I could not assume my statistical analysis results can generalize to those specific U.S. hospitals.

Survey instrument reliability and validity assessment. As described in Chapter 3, I used a survey instrument with its reliability and validity confirmed in Dr. Tweel's (2012) research. However, as I changed some of the survey items, it was necessary to check for its reliability and validity again. Cronbach's Alpha is the most common measure of scale reliability. By comparing the alpha value of a construct with the corresponding alpha value of if-item-deleted, I could determine whether the construct is a reliable measurement in the survey instrument. As a general guideline, the overall alpha of a reliable construct should have a value higher than 0.7 (Field, 2013). For a survey item with a higher alpha value of if-item-deleted than the overall alpha value, it indicated that the construct should be more reliable after the researcher drops that survey item from the survey. In Table 17, it illustrates that all the constructs have alpha values higher than 0.7. It confirmed that the survey instrument had acceptable reliability. Nevertheless, Q_5 and $Q_{14.2}$ might need attentions as they had a much higher alpha value of if-item-deleted than for the overall construct (by .061 and .067 respectively).

Table 17

Reliability Statistics for the Constructs and Corresponding Survey Items

Construct	N of Items	Cronbach's Alpha	Corresponding Survey Items	Cronbach's Alpha if Item Deleted
X_1 = Relative advantage	5	.798	.	
			Q_1 = Increase profit	.730
			Q_2 = Additional services	.718
			Q_3 = Reduce cost	.737
			Q_4 = Better Communication	.775

(table continues)

Construct	N of Items	Cronbach's Alpha	Corresponding Survey Items	Cronbach's Alpha if Item Deleted
			Q_5 = No upfront investment	.859
			Q_6 = High flexibility and availability	.758
$X_{2.1}$ = Compatibility of public cloud services	4	.870	.	
			$Q_{7.1}$ = Consistent with belief and value	.825
			$Q_{8.1}$ = Favorable attitude	.797
			$Q_{9.1}$ = compatible with existing infra.	.918
			$Q_{10.1}$ = Consistent with business strategy	.788
$X_{3.1}$ = Complexity of public cloud services	5	.886	.	
			$Q_{11.1r}$ = Not cumbersome to use	.832
			$Q_{12.1r}$ = Not require a lot of mental efforts	.841
			$Q_{13.1r}$ = Not Frustrated to use	.856
			$Q_{14.1}$ = User interface is understandable	.887
			$Q_{15.1}$ = Easy to purchase and startup	.881
$X_{2.2}$ = Compatibility of private cloud services	4	.947		
			$Q_{7.2}$ = Consistent with belief and value	.905
			$Q_{8.2}$ = Favorable attitude	.944
			$Q_{9.2}$ = compatible with existing infra.	.951
			$Q_{10.2}$ = Consistent with business strategy	.916
$X_{3.2}$ = Complexity of private cloud services	5	.813	.	
			$Q_{11.2}$ = Cumbersome to use	.708
			$Q_{12.2}$ = Require a lot of mental efforts	.732
			$Q_{13.3}$ = Frustrated to use	.726
			$Q_{14.2}$ = User interface is understandable	.880
			$Q_{15.2}$ = Easy to purchase and startup	.791
Y_1 = Adoption intent of public cloud services	3	.933		
			$Q_{19.1}$ = Intends to adopt	.900
			$Q_{20.1}$ = Take steps to adopt	.834
			$Q_{21.1}$ = Adopt in next 12 months	.966
Y_2 = Adoption intent of private cloud services	3	.867		
			$Q_{19.2}$ = Intends to adopt	.760
			$Q_{20.2}$ = Take steps to adopt	.757
			$Q_{21.2}$ = Adopt in next 12 months	.921

By further investigating their inter-item correlation matrices as shown in Table 17 and Table 18, Q_5 and $Q_{14.2}$ also show low and negative correlation with other survey items under the same construct. This finding supported the argument if I dropped both Q_5

and $Q_{14.2}$ from their corresponding construct—X_1 and $X_{3.2}$, the reliability of the survey instrument might increase. However, since Dr. Tweel's validated survey instrument consisted of two survey items, I kept them in my result analysis and expected future research with larger sample size can provide better confirmation.

Table 18

Inter-item Correlation Matrix for the Construct Relative Advantage

	Q_1	Q_2	Q_3	Q_4	Q_5	Q_6
Q_1	1.000					
Q_2	.722	1.000				
Q_3	.808	.648	1.000			
Q_4	.426	.541	.472	1.000		
Q_5	.106	.325	-.040	.056	1.000	
Q_6	.412	.456	.536	.449	.293	1.000

Note. Q_5 has a low correlation with Q_1 and Q_4, marginal correlation with Q_2, and negative correlation with Q_3.

Table 19

Inter-item Correlation Matrix for the Construct Complexity of the Private Cloud Model

	$Q_{11.2r}$	$Q_{12.2r}$	$Q_{13.2r}$	$Q_{14.2}$	$Q_{15.2}$
$Q_{11.2r}$	1.000				
$Q_{12.2r}$	.928	1.000			
$Q_{13.2r}$	.823	.839	1.000		
$Q_{14.2}$	.102	-.017	.091	1.000	
$Q_{15.2}$	.527	.419	.457	.366	1.000

Note. $Q_{14.2}$ has a low correlation with $Q_{11.2r}$ and $Q_{13.2r}$ and negative correlation with $Q_{12.2r}$.

To test the construct validity of the survey instrument, I did a principal components analysis (PCA) to determine whether the six identified independent variables were principal components for my research. As a rule of thumb, minimal ten observations per variable are required. That means I needed 70 observations for my study. As I received 118 responses, it exceeded this basic requirement for PCA. I conducted two PCAs with one for public cloud services adoption and another for private cloud services adoption. First, I checked whether the KMO value was higher than .6. If so, the null hypothesis that the correlation matrix is an identity matrix can be rejected (Bartlett's test of sphericity) and confirm the presented PCA values are relevant (Field, 2013). From the correlation matrix, I noticed that no correlation among independent variables was higher than .9 as the indicator that each dependent variable was essential components of the survey instrument. Finally, by checking the extraction value in the communalities table, I could determine whether the principal components could explain a good proportion of each variable's variance (i.e., > .3). When the included variables in the PCA could satisfy all these criteria, they could then represent as principal components (UCLA, 2015).

For public cloud services adoption, the PCA showed the KMO value of .619 that exceeded the cutoff point of .6. In

Table **20**—correlation matrix, it indicated no high correlation among independent variables (i.e., no correlation value was higher than .8). In addition, in Table 21, no extraction value was less than .3. Therefore, the construct validity of the survey instrument for public cloud services adoption was sufficient.

Table 20

Correlation Matrix of Composite Variables for the Public Cloud Model

	X_1	$X_{2.1}$	$X_{3.1}$	X_4	X_5	X_6	Y_1
X_1	1.000						
$X_{2.1}$	.362	1.000					
$X_{3.1}$	.188	.309	1.000				
X_4	.384	.075	.002	1.000			
X_5	-.328	-.042	-.129	.091	1.000		
X_6	-.069	-.094	-.115	.309	.445	1.000	
Y_1	.484	.527	.289	.450	.018	.061	1.000

Note. There is no strong correlation between dependent variables. The correlation between the independent variables—X_5 and X_6 and dependent variable Y_1 are low.

Table 21

Communalities of Composite Variables for the Public Cloud Model

	Initial	Extraction
X_1	1.000	.759
$X_{2.1}$	1.000	.678
$X_{3.1}$	1.000	.583
X_4	1.000	.777
X_5	1.000	.802
X_6	1.000	.693
Y_1	1.000	.751

Note. Extraction Method: PCA.

For private cloud services adoption, the PCA showed the KMO value of .630 that exceeded the cutoff point of .6. In Table 22—correlation matrix, it indicated no high correlation among independent variables. In addition, in Table 23, all extraction values were higher than .3. Therefore, the construct validity of the survey instrument for private cloud services adoption was also sufficient.

Table 22

Correlation Matrix of Composite Variables for the Private Cloud Model

	X_1	$X_{2.2}$	$X_{3.2}$	X_4	X_5	X_6	Y_2
X_1	1.000						
$X_{2.2}$	.369	1.000					
$X_{3.2}$	.340	.577	1.000				
X_4	.384	.030	.107	1.000			
X_5	-.328	-.177	-.146	.091	1.000		
X_6	-.069	-.122	-.103	.309	.445	1.000	
Y_2	.439	.780	.514	.131	-.270	.022	1.000

Note. There was no strong correlation between dependent variables. The correlation between the independent variable X_6 and dependent variable Y_2 was low.

Table 23

Communalities of Composite Variables for the Private Cloud Model

	Initial	Extraction
X_1	1.000	.768
$X_{2.2}$	1.000	.849
$X_{3.2}$	1.000	.614
X_4	1.000	.821
X_5	1.000	.764
X_6	1.000	.743
Y_2	1.000	.798

Note. Extraction Method: PCA

Statistical assumptions validation for GLM. As discussed in Chapter 3, I must verify the sample data that they met the linear regression assumptions for construct and conclusion validity. Otherwise, the presented statistical results could be misleading. These assumptions included linearity, normality, homogeneity of variance (homoscedasticity), independence, and multicollinearity.

To test linearity and homoscedasticity of my two categorical regression models—public and private cloud services adoption, I used the scatterplot graphs of standardized model predicted values against standardized residual values (zpred vs zresid) as shown in Figure 17. Since they did not indicate any specific curve and funnel shape, my sample data satisfied the GLM assumptions that the six independent (or called predictor) variables had linear relationships with the dependent variable, and residual variances were constant at different levels of the predictor variables.

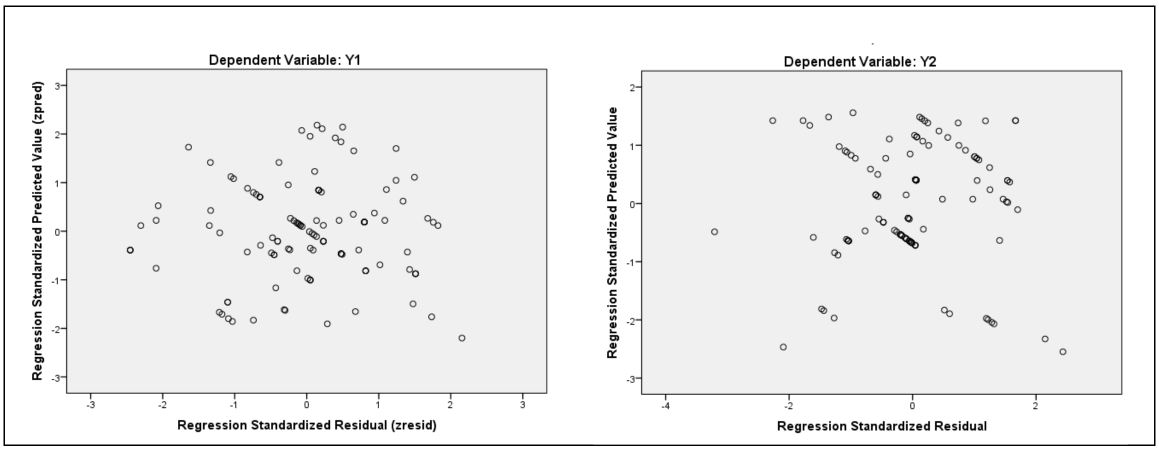


Figure 17. Scatterplot of zpred vs. zresid for the regression models of public and private cloud services adoption. It shows no specific pattern as an indicator that the models satisfy linearity and homoscedasticity assumption.

To test the normality of the two regression models, I used both the residual histogram and *P-P* plot techniques. In Figure 18, it shows the normal curves of the two models as in symmetric bell shape. In Figure 19, as the degree of the actual residual values of the two cloud models coinciding with the respective lines of expected values, the assumption of residual normality was satisfied. Nevertheless, under the private cloud adoption model, a minor kurtosis of the sample data was detected as a slight S-shaped pattern presented in the plot. Most likely, from the diagram, the normality of the private cloud services adoption model could be improved by excluding the outliers carrying residual values from -4 to -8 range.

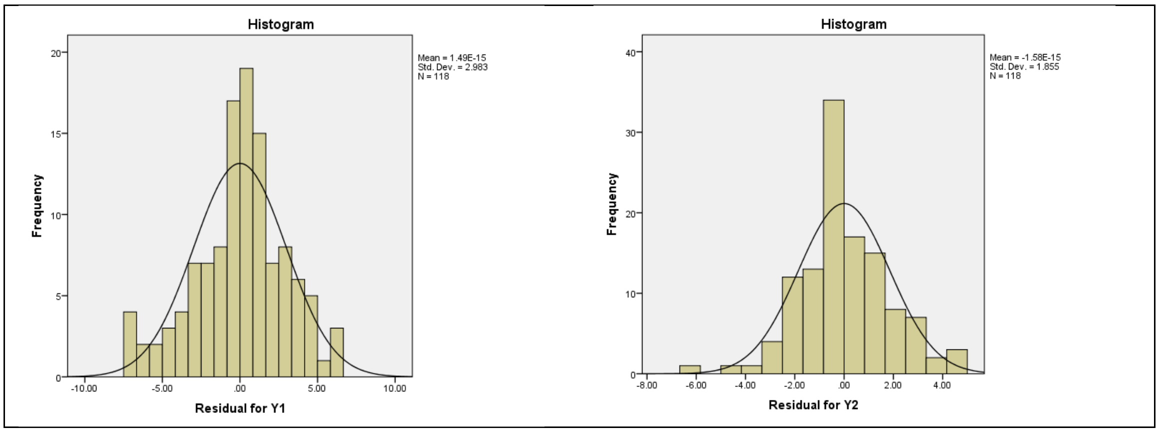


Figure 18. Residual histogram for the regression models of public and private cloud services adoption. As the normal curves were symmetric, it justified the assumption of normality for the models.

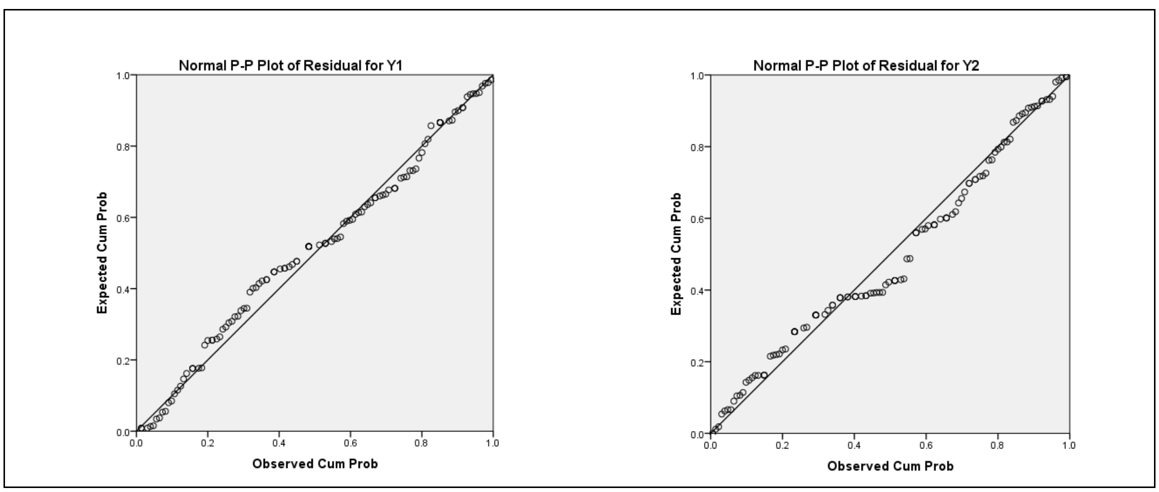


Figure 19. P-P Plot of Residual for the regression models of public and private cloud services adoption. Since the actual residual values coincided closely with the expected value, the normality assumption of the models was met.

To test the assumption of the residual independence, I used Durbin-Watson statistic. As explained by Field (2013), the test provides a value between zero to four. If the residuals are independent with each other, the test value should be close to two.

Whenever it is less than 1 or greater than 3, the independence assumption is questionable. In my sample data, the Durbin-Watson test provided a value of 2.060 and 1.975 for the public and private cloud services adoption model respectively. Since these values were close to two, I could then assume the residual independence.

To confirm the absence of multicollinearity (i.e., the independent variables do not highly correlate with each other), I could simply examine the coefficient values of the independent variables in the correlation matrices as shown in

Table **20** and Table 22. Since none of the pairs has coefficient value was greater than 0.8, I could then assume no multicollinearity existed. Another way to detect multicollinearity is to use variance inflation factor (VIF) analysis. With VIF value greater than 5, it is an evidence of multicollinearity (Annmaria's Blog, 2015). Table 24 shows the VIF values calculated for the public and private cloud regression models. Since the VIF values were from 1.128 to 1.620 that was substantially lower than 5, I could assume that it was no multicollinearity concern in my models.

Table 24

Collinearity Statistics of the Categorical Regression Models

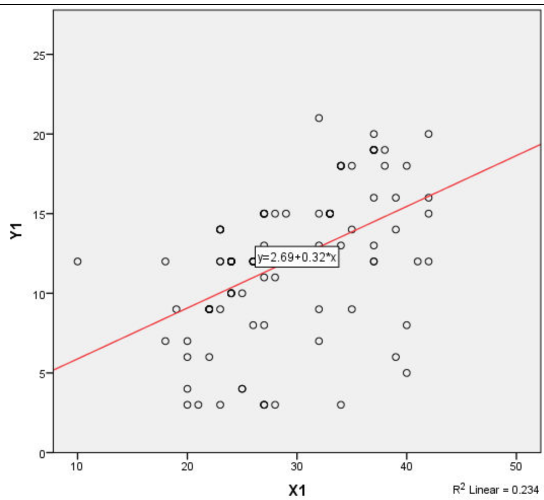
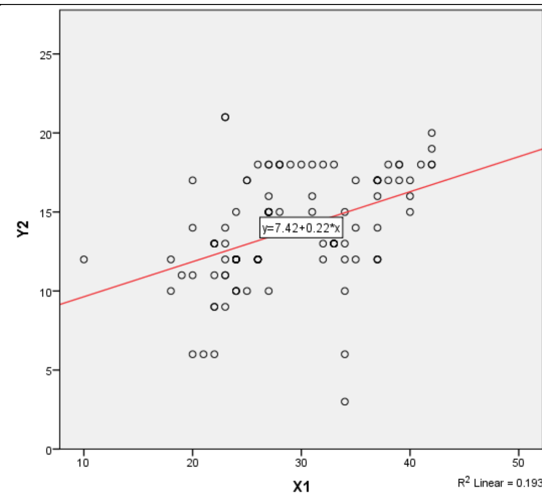
Public Cloud Services			Private Cloud Services		
Independent Variables	Tolerance	VIF	Independent Variables	Tolerance	VIF
X_1 = Relative advantage	.617	1.620	X_1 = Relative advantage	.622	1.608
$X_{2.1}$ = Compatibility	.787	1.271	$X_{2.2}$ = Compatibility	.621	1.611
$X_{3.1}$ = Complexity	.886	1.128	$X_{3.2}$ = Complexity	.644	1.552
X_4 = Organizational size	.728	1.374	X_4 = Organizational size	.721	1.386
X_5 = Organizational structure	.688	1.453	X_5 = Organizational structure	.705	1.418
X_6 = Organizational culture	.719	1.392	X_6 = Organizational culture	.723	1.383
Y_1 = Adoption intent of public cloud services			Y_2 = Adoption intent of private cloud services		

Statistical Analysis Findings

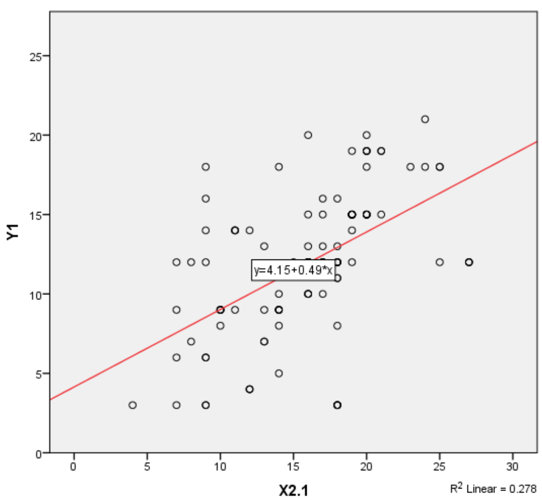
Besides the confirmation of the GLM assumptions, it is important to identify critical outliers and exclude them before the final reporting on the statistical findings. Otherwise, the outliers can significantly distort the results. As described in Chapter 3, researchers use two common methods to identify outliers. The first method is to examine the scatterplot graphs for each independent variable against the dependent variable as shown in Table 25.

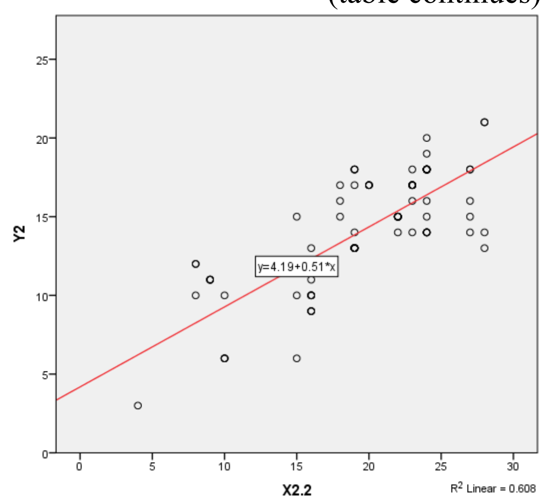
Table 25

Scatterplot Graphs of the Regression Models before Outliers Exclusion

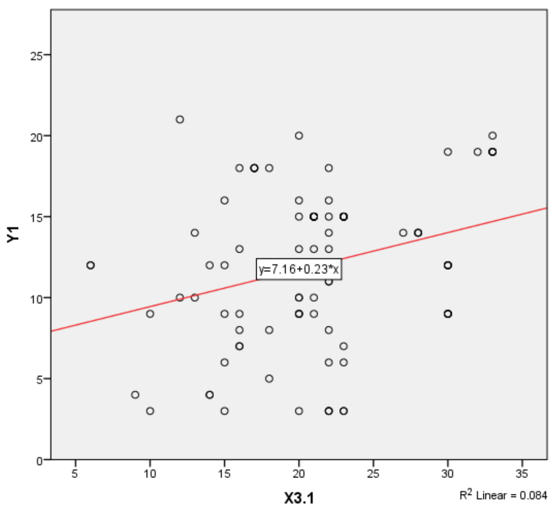
Public Cloud Services Adoption	Private Cloud Services Adoption
	

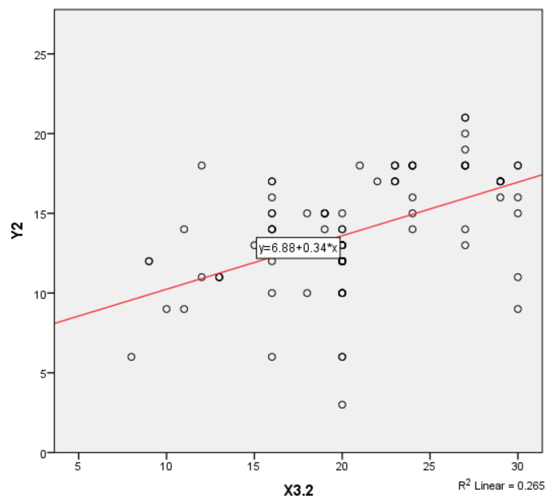
(table continues)

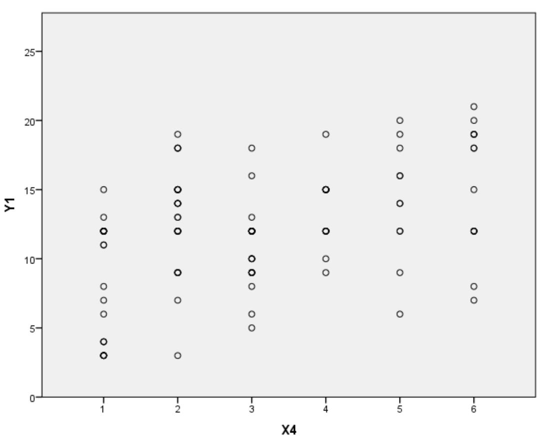


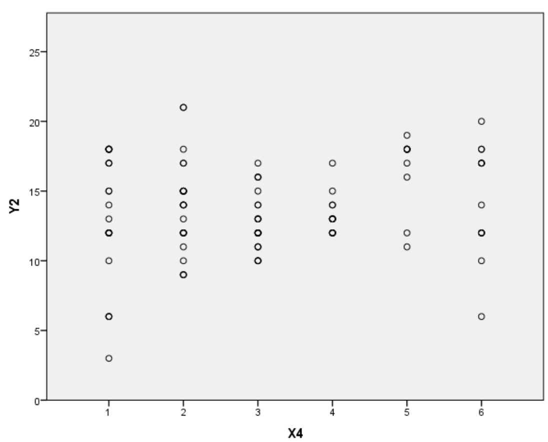


Public Cloud Services Adoption	Private Cloud Services Adoption









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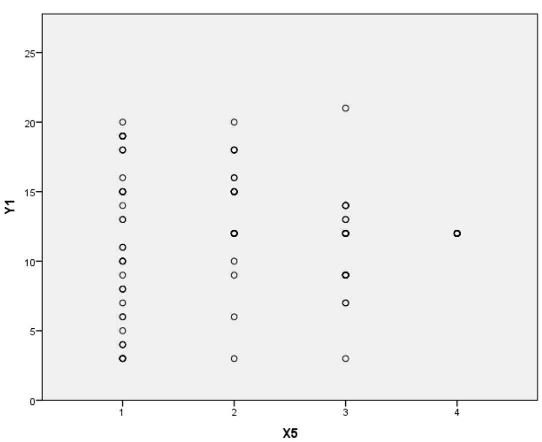
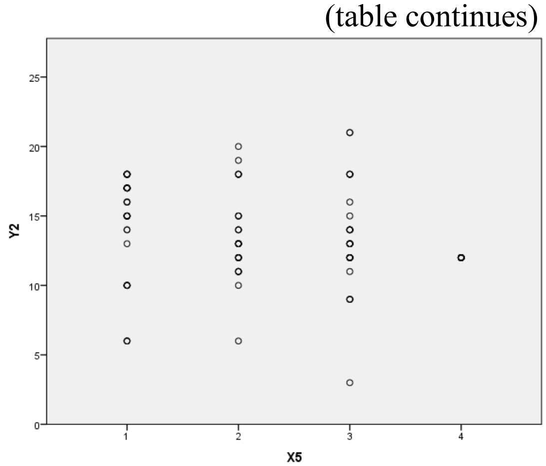
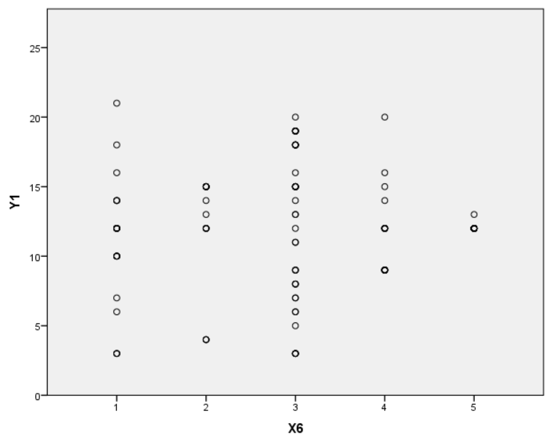
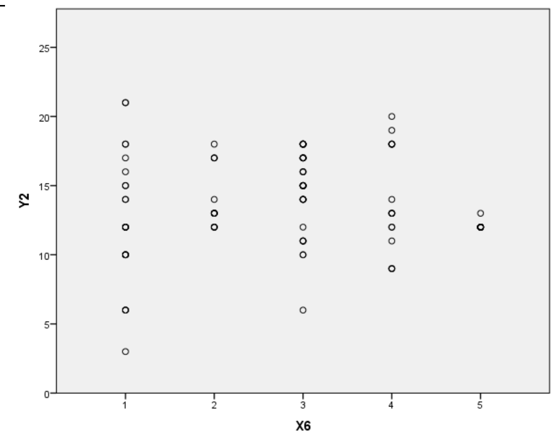




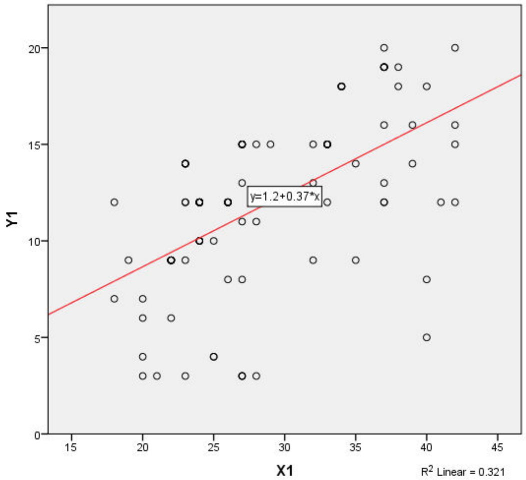
Public Cloud Services Adoption	Private Cloud Services Adoption
	

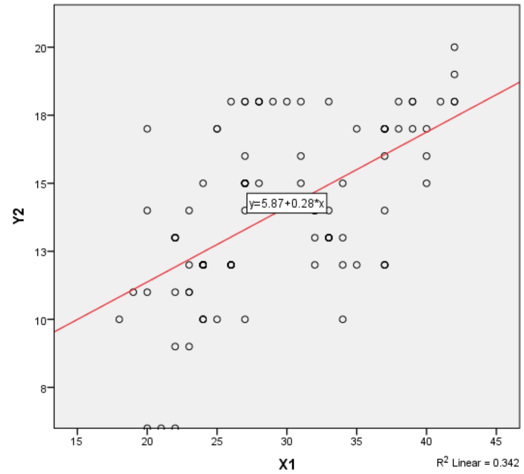
The second method is to use Cook's distance to determine whether a case is an outlier. Cook's distance is a better solution to guarantee an acceptable *p*-value for significant tests (Schofer, 2007). As mentioned in Chapter 3, when a case with Cook's distance > 4 / (N - k -1), where N is the sample size, k is the number of predictors; it is classified as outlier and should be excluded. Since my sample size was 118, and the number of predictors was 11, that meant my regression analysis should exclude any case with Cook's distance is greater than .0377. As the result, nine and ten cases were removed from the public and private cloud adoption model respectively. Table 26 shows the scatterplot graphs of each independent variable against the dependent variable for the public and private cloud services adoption model after I excluded the identified outliers. Readers can notice that the intercept and the slope of the regression lines had changed after the outliers were removed.

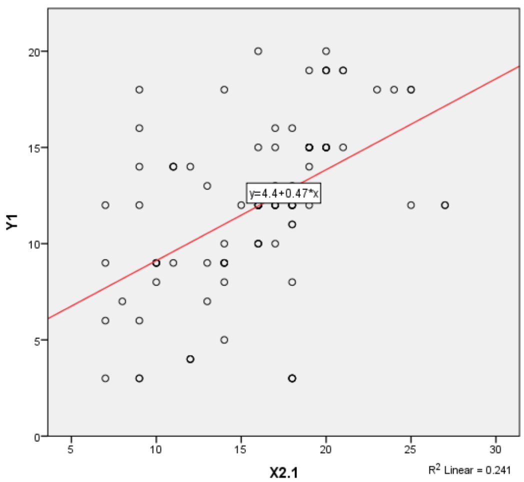
Table 26

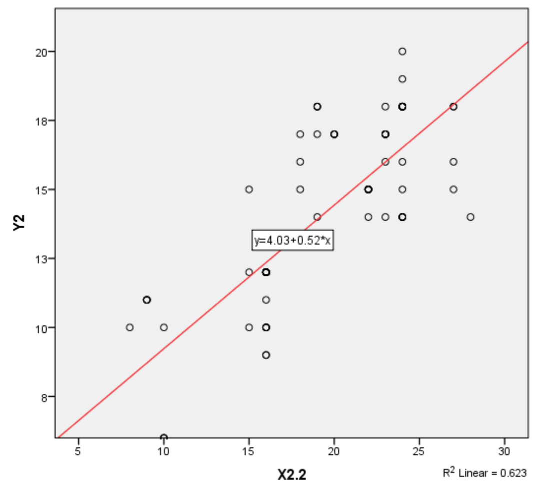
Scatterplot Graphs of the Regression after Outliers Exclusion

Public Cloud Services Adoption	Private Cloud Services Adoption

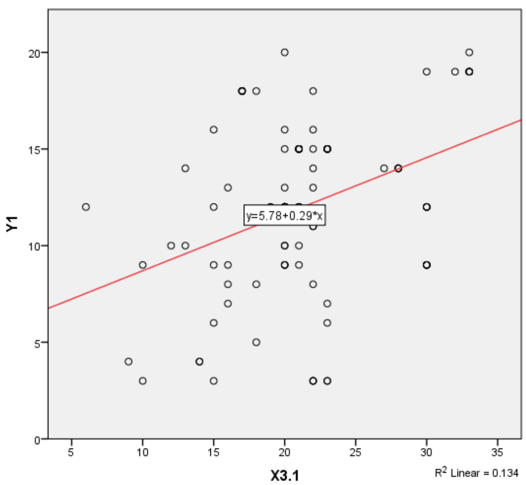
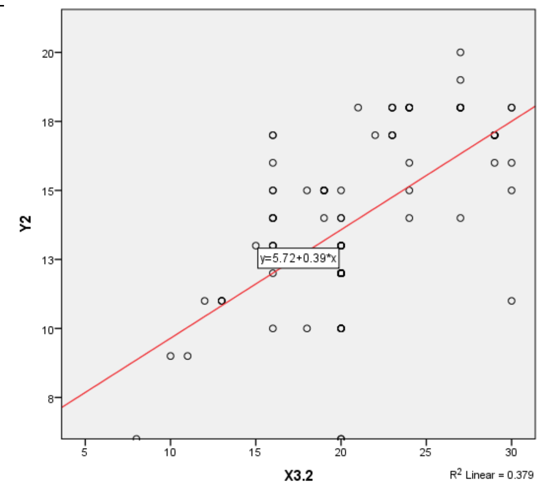
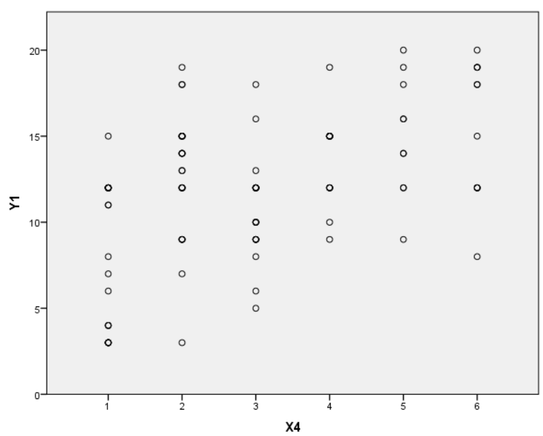
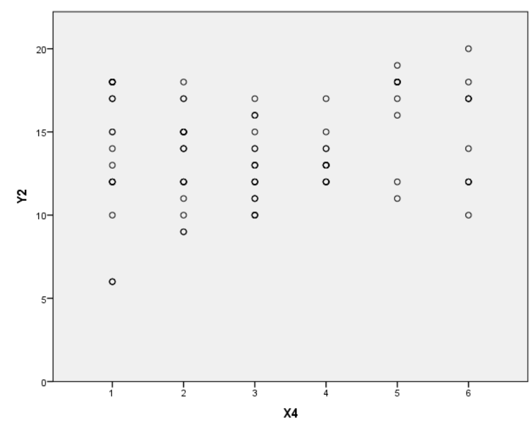
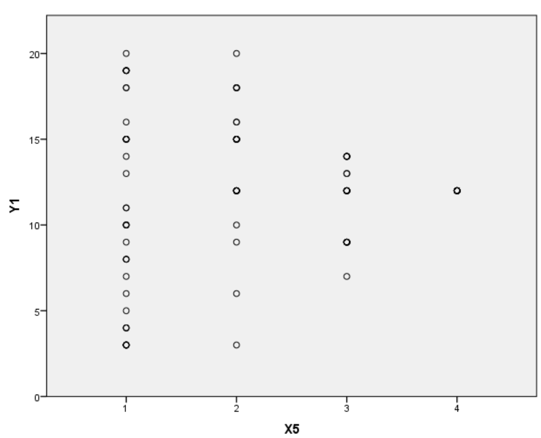
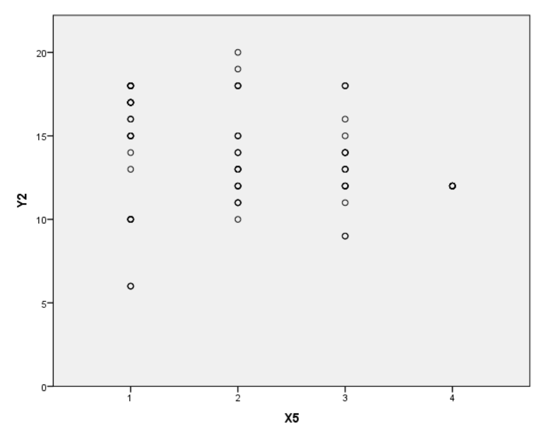






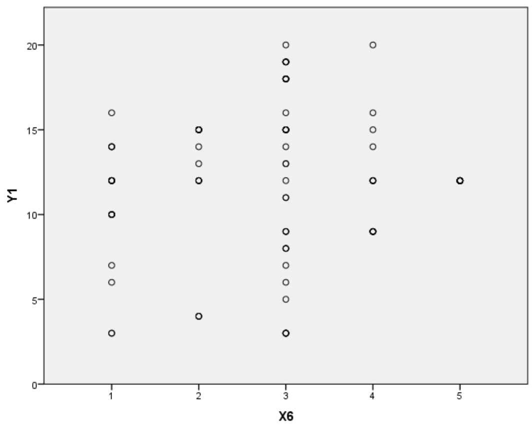


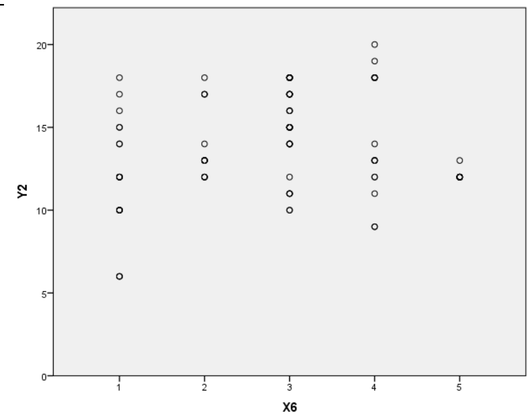
(table continues)

Public Cloud Services Adoption	Private Cloud Services Adoption
	
	
	

(table continues)

Public Cloud Services Adoption	Private Cloud Services Adoption





To address the research questions and test their corresponding research hypotheses as stated in Table 9, I conducted the GLM analysis separately for public and private cloud services adoption. The results are illustrated in Table 27 and Table **28** respectively.

Table 27

Statistical Analysis Results of the Public Cloud Regression Model (N =109, Dependent Variable = Y_1*)*

	B	SE_B	t	Sig.	Partial η^2	95% Confidence Interval
Constant	-3.889	1.589	-2.448	.016	.058	(-7.042, -.736)
X_1 = Relative Advantage	.238	.058	4.108	.000	.147	(.123, .353)
$X_{2.1}$ = Compatibility	.174	.075	2.333	.022	.053	(.026, .323)
$X_{3.1}$ = Complexity	.249	.059	4.203	.000	.153	(.131, .366)
X_4 = Organizational Size	.774	.212	3.645	.000	.119	(.353, 1.196)
X_5 = Organizational Structure = functional = 1	-5.086	1.331	-3.822	.000	.130	(-7.727, -2.445)
X_5 = Organizational Structure = divisional = 2	-2.227	1.163	-1.915	.058	.036	(-4.534, .081)
X_5 = Organizational Structure = matrix = 3	-2.951	1.149	-2.568	.012	.063	(-5.232, -.671)
X_5 = Organizational Structure = others = 4	0[a]					
X_6 = Organizational Culture = clan = 1	2.478	1.046	2.369	.020	.054	(.402, 4.553)
X_6 = Organizational Culture = adhocracy = 2	1.508	1.030	1.464	.146	.021	(-.536, 3.551)
X_6 = Organizational Culture = hierarchy = 3	2.976	.990	3.006	.003	.084	(1.011, 4.940)
X_6 = Organizational Culture = market = 4	0[a]					
X_6 = Organizational Culture = others = 5	0[a]					

Note. a. This parameter is set to zero because it is redundant. R^2 = .621, Adjusted R^2 = .583, $F(10, 98) = 16.077$, $p < 0.001$.

Table 28

Statistical Analysis Results of the Private Cloud Regression Model (N =108, Dependent Variable = Y_2)

	B	SE_B	t	p	Partial η^2	95% Confidence Interval
Constant	1.855	.789	2.350	.021	.054	(.288, 3.422)
X_1 = Relative Advantage	.102	.029	3.478	.001	.112	(.044, .160)
$X_{2.2}$ = Compatibility	.368	.045	8.248	.000	.415	(.279, .456)
$X_{3.2}$ = Complexity	.118	.043	2.772	.007	.074	(.033, .202)
X_4 = Organizational Size	-.170	.106	-1.611	.110	.026	(-.380, .039)
X_5 = Organizational Structure = functional = 1	.307	1.078	.284	.777	.001	(-1.834, 2.447)
X_5 = Organizational Structure = divisional = 2	.264	1.093	.241	.810	.001	(-1.906, 2.434)
X_5 = Organizational Structure = matrix = 3	-1.182	1.102	-1.073	.286	.012	(-3.369, 1.005)
X_5 = Organizational Structure = others = 4	0[a]					
X_6 = Organizational Culture = clan = 1	-1.286	1.079	-1.192	.236	.015	(-3.429, .856)
X_6 = Organizational Culture = adhocracy = 2	.074	1.086	.068	.946	.000	(-2.081, 2.229)
X_6 = Organizational Culture = hierarchy = 3	.831	1.056	.787	.433	.006	(-1.264, 2.926)
X_6 = Organizational Culture = market = 4	.833	1.055	.789	.432	.006	(-1.262, 2.928)
X_6 = Organizational Culture = others = 5	0[a]					

Note. a. This parameter is set to zero because it is redundant. R^2 = .807, Adjusted R^2 = .785, $F(11, 96) = 36.567$, $p < 0.001$.

The followings are the restatement of the research questions, hypotheses, and the result of the statistical findings.

Public cloud services adoption analysis.

RQ1: Does regression allow us to predict the public cloud services adoption intent of U.S. hospital IT managers as a function of six influential factors: (a) relative advantage, (b) compatibility, (c) complexity, (d) organizational size, (e) organizational structure, and (f) organizational culture?

$H0_{1.1}$: X_1 = relative advantage of cloud computing is not a significant predictor of Y_1 = intent to adopt public cloud services; mathematically, $b_{1.1} = 0$ in the resulting regression model.

From Table 27, the null hypothesis $H0_{1.1}$ was rejected, $t(97) = 4.108$, $p < .001$, partial $\eta^2 = .147$. Therefore, X_1 = relative advantage was a significant predictor of Y_1 = intent to adopt public cloud services; mathematically, $b_{1.1} = .238$ in the resulting regression model. As the effect size measurement with partial eta square (η^2), X_1 = relative advantage could explain 14.7% of the variance that other variables could not explain.

$H0_{2.1}$: $X_{2.1}$ = compatibility of public cloud is not a significant predictor of Y_1 = intent to adopt public cloud services; mathematically, $b_{2.1} = 0$ in the resulting regression model.

From Table 27, the null hypothesis $H0_{2.1}$ was rejected, $t(97) = 2.333$, $p < .05$, partial $\eta^2 = .053$. Therefore, $X_{2.1}$ = compatibility was a significant predictor of Y_1 = intent to adopt public cloud services; mathematically, $b_{2.1} = .174$ in the resulting regression model. As the effect size measurement, $X_{2.1}$ = compatibility could explain 5.3% of variance that other variables could not explain.

$H0_{3.1}$: $X_{3.1}$ = complexity belief of public cloud is not a significant predictor of Y_1 = intent to adopt public cloud services; mathematically, $b_{3.1} = 0$ in the resulting regression model.

From Table 27, the null hypothesis $H0_{3.1}$ was rejected, $t(97) = 4.203$, $p < .001$, partial $\eta^2 = .153$. Therefore, $X_{3.1}$ = complexity belief was a significant predictor of Y_1 = intent to adopt public cloud services; mathematically, $b_{3.1} = .249$ in the resulting regression model. As the effect size measurement, $X_{3.1}$ = complexity belief could explain 15.3% of variance that other variables could not explain.

$H0_{4.1}$: X_4 = organizational size is not a significant predictor of Y_1 = intent to adopt public cloud services; mathematically, $b_{4.1} = 0$ in the resulting regression model.

From Table 27, the null hypothesis $H0_{4.1}$ was rejected, $t(97) = 3.645$, $p < .001$, partial $\eta^2 = .119$. Therefore, X_4 = organizational size was a significant predictor of Y_1 = intent to adopt public cloud services; mathematically, $b_{4.1} = .774$ in the resulting regression model. As the effect size measurement, X_4 = organizational size could explain 11.9% of variance that other variables could not explain.

$H0_{5.1}$: X_5 = organizational structure is not a significant predictor of Y_1 = intent to adopt public cloud services; mathematically, $b_{5.1} = 0$ in the resulting regression model.

From Table 27, the null hypothesis $H0_{5.1}$ was rejected when organizational structure is functional (i.e., = 1), $t(97) = 3.822$, $p < .001$, partial $\eta^2 = .130$; and matrix (i.e., = 3), $t(97) = 2.568$, $p < .05$, partial $\eta^2 = .063$. Therefore, X_5 = organizational structure was a significant predictor of Y_1 = intent to adopt public cloud services when it was functional or matrix; mathematically, $b_{5.1} = -5.086$ and $= -2.951$ respectively in the resulting regression model. As the effect size measurement, X_5 = organizational structure could explain 13% and 6.3% of variance that other variables could not explain when it is functional and matrix respectively.

$H0_{6.1}$: X_6 = organizational culture is not a significant predictor of Y_1 = intent to adopt public cloud services; mathematically, $b_{6.1} = 0$ in the resulting regression model.

From Table 27, the null hypothesis $\mathrm{H}0_{6.1}$ was rejected when organizational culture is clan (i.e., = 1), $t(97) = 2.369$, $p < .05$, partial $\eta^2 = .054$; and hierarchy (i.e., = 3), $t(97) = 3.006$, $p < .001$, partial $\eta^2 = .084$. Therefore, X_6 = organizational culture was a significant predictor of Y_1 = intent to adopt public cloud services when it was clan or hierarchy; mathematically, $b_{6.1} = 2.478$ and $= 2.976$ respectively in the resulting regression model. As the effect size measurement, X_6 = organizational culture could explain 5.4% and 8.4% of variance that other variables could not explain when it was clan and hierarchy respectively.

$H0_{7.1}$: The linear model $Y_1 = b_{0.1} + b_{1.1}X_1 + b_{2.1}X_{2.1} + b_{3.1}X_{3.1} + b_{4.1}X_4 + b_{5.1}X_5 + b_{6.1}X_6$ has no significant fit; mathematically, $R(Y_1 \mid X_1, X_{2.1}, X_{3.1}, X_4, X_5, X_6) = 0$.

From Table 27, the null hypothesis $H0_{7.1}$ was rejected, $R^2 = .621$, Adjusted $R^2 = .583$, $F(10, 98) = 16.077$, $p < 0.001$. The linear model $Y_1 = -3.889 + .238X_1 + .174X_{2.1} + .249X_{3.1} + .774X_4 + b_{5.1}X_5 + b_{6.1}X_6$ had a significant fit; where $b_{5.1} = -5.086$ or -2.951 if organizational structure was functional or matrix respectively, $b_{6.1} = 2.478$ or 2.976 if organizational culture was clan or hierarchy respectively. The linear model could explain 62.1% and 58.3% of the variance of the U.S. hospital IT managers' adoption intent for the public cloud services in the sample and target population respectively. Since R^2 and adjusted R^2 had only 3.8% difference, the generalization power of this public cloud services adoption model was good.

Private cloud services adoption analysis.

RQ2: Does regression allow us to predict the private cloud services adoption intent of U.S. hospital IT managers as a function of six influential factors: (a) relative advantage, (b) compatibility, (c) complexity, (d) organizational size, (e) organizational structure, and (f) organizational culture?

$H0_{1.2}$: X_1 = relative advantage of cloud computing is not a significant predictor of Y_2 = intent to adopt private cloud services; mathematically, $b_{1.2} = 0$ in the resulting regression model.

From Table 28, the null hypothesis $H0_{1.2}$ was rejected, $t(96) = 3.478$, $p < .05$, partial $\eta^2 = .112$. Therefore, X_1 = relative advantage is a significant predictor of Y_2 = intent to adopt private cloud services; mathematically, $b_{1.2} = .102$ in the resulting regression model. As the effect size measurement, X_1 = relative advantage could explain 11.2% of variance that other variables could not explain.

$H0_{2.2}$: $X_{2.2}$ = compatibility of private cloud is not a significant predictor of Y_2 = intent to adopt private cloud services; mathematically, $b_{2.2} = 0$ in the resulting regression model.

From Table 28, the null hypothesis $H0_{2.2}$ was rejected, $t(96) = 8.248$, $p < .001$, partial $\eta^2 = .415$. Therefore, $X_{2.2}$ = compatibility is a significant predictor of Y_2 = intent to adopt private cloud services; mathematically, $b_{2.2} = .368$ in the resulting regression model. As the effect size measurement, $X_{2.2}$ = compatibility could explain 41.5% of variance that other variables could not explain.

$H0_{3.2}$: $X_{3.2}$ = complexity belief of private cloud is not a significant predictor of Y_2 = intent to adopt private cloud services; mathematically, $b_{3.2} = 0$ in the resulting regression model.

From Table 28, the null hypothesis $H0_{3.2}$ was rejected, $t(96) = 2.772$, $p < .05$, partial $\eta^2 = .074$. Therefore, $X_{3.2}$ = complexity belief is a significant predictor of Y_2 = intent to adopt private cloud services; mathematically, $b_{3.2} = .118$ in the resulting regression model. As the effect size measurement, $X_{3.2}$ = complexity belief could explain 7.4% of variance that other variables could not explain.

$H0_{4.2}$: X_4 = organizational size is not a significant predictor of Y_2 = intent to adopt private cloud services; mathematically, $b_{4.2} = 0$ in the resulting regression model.

From Table 28, the null hypothesis $H0_{4.2}$ was not rejected, $t(96) = 1.611$, $p = .110$. Therefore, $X_{4.2}$ = organizational size is not a significant predictor of Y_2 = intent to adopt private cloud services; mathematically, $b_{4.2} = 0$ in the resulting regression model.

$H0_{5.2}$: X_5 = organizational structure is not a significant predictor of Y_2 = intent to adopt private cloud services; mathematically, $b_{5.2} = 0$ in the resulting regression model.

From Table 28, the null hypothesis $H0_{5.2}$ was not rejected; $t(96) = .284$, $p = .777$ when organizational structure is functional (i.e., = 1); $t(96) = .241$, $p = .810$ when organizational structure is divisional (i.e., = 2); $t(96) = -1.073$, $p = .286$ when organizational structure is matrix (i.e., = 3). Therefore, X_5 = organizational structure is not a significant predictor of Y_2 = intent to adopt private cloud services; mathematically, $b_{5.2} = 0$ in the resulting regression model.

$H0_{6.2}$: X_6 = organizational culture is not a significant predictor of Y_2=intent to adopt private cloud services; mathematically, $b_{6.2} = 0$ in the resulting regression model.

From Table 28, the null hypothesis $H0_{6.2}$ was not rejected; $t(96) = 1.192$, $p = .236$ when organizational culture is clan (i.e., = 1); $t(96) = .068$, $p = .946$ when organizational culture is adhocracy (i.e., = 2); $t(96) = .787$, $p = .433$ when organizational culture is hierarchy (i.e., = 3); $t(96) = .789$, $p = .432$ when organizational culture is market (i.e., =

4). Therefore, X_6 = organizational culture is a significant predictor of Y_2 = intent to adopt private cloud services; mathematically, $b_{6.1} = 0$ in the resulting regression model.

$H0_{7.2}$: The linear model $Y_2 = b_{0.2} + b_{1.2}X_1 + b_{2.2}X_{2.2} + b_{3.2}X_{3.2} + b_{4.2}X_4 + b_{5.2}X_5 + b_{6.2}X_6$ has no significant fit; mathematically, $R(Y_2 \mid X_1, X_{2.2}, X_{3.2}, X_4, X_5, X_6) = 0$.

From Table 28, the null hypothesis $H0_{7.2}$ was rejected, $R^2 = .807$, Adjusted $R^2 = .785$, $F(11, 96) = 36.567$, $p < 0.001$. The linear model $Y_2 = 1.855 + .102X_1 + .368X_{2.2} + .118X_{3.2}$ has a significant fit. The linear model could explain 80.7% and 78.5% of the variance of the U.S. hospital IT managers' adoption intent for the public cloud services in the sample and population respectively. Since R^2 and adjusted R^2 had only 2.2% difference, the generalization power of this private cloud services adoption model was good.

Summary

Chapter 4 began with the outcomes of the pilot study. As its result, my research on overall cloud computing adoption intent became splitting into public and private cloud services adoption intent for U.S. hospitals. It described the adjustments of the survey items in my survey instrument, research questions, and hypotheses. Then it followed by the actual data collection procedure and result. I reported out the sampling framework change from my company's customer contact database to a research corporation's business profiling and contact database (http://www.hoovers.com). I reported the demographical distribution of the 118 valid survey responses with comparison to the target population, including count by region, hospital type, years of operation, and 2014 annual revenue. Descriptive statistics and histogram charts on the survey items and computed composite variables were included to analyze the data distribution of the survey result. I tested the reliability and validity of the enhanced survey instrument with PCA. I confirmed the linearity, normality, homoscedasticity, independence, and the absence of multicollinearity of the two categorical regression models—public and private cloud service adoption—by use of various statistical tests and charting techniques. That included Durbin-Watson, VIF, KMO, correlation matrix, *P-P* plot, and scatterplots. I used Cook's distance test to identify and eliminate outliers. I conducted two SPSS GLM analyses with the dependent variable set as U.S. hospital IT managers' adoption intent for public and private cloud services. Both SPSS GLM applied organizational structure and organizational culture as fixed factors, and relative advantage, compatibility, complexity belief, and organizational size as covariates.

As the result, the analyses indicated that relative advantage, compatibility, and complexity behalf are significant predictors for U.S. hospital IT managers' adoption intent for both public and private cloud services. For public cloud services adoption, the regression model showed statistical significance regarding organization size with U.S. hospital IT managers' adoption intent, but not for private cloud services adoption. Furthermore, when organizational structure was functional and matrix and organizational culture was clan and hierarchy in the sample cases, they showed significant relationships with U.S. hospital IT managers' adoption intent under the public cloud services adoption model. However, organizational structure and organizational culture did not show any statistically significant relationship with U.S. hospital IT managers' adoption intent under the private cloud services adoption model. Both categorical regression models seemed to have significant fit with the collected sample values. They were able to explain 62.1% and 80.7% of the variance in the U.S. hospital IT managers' adoption intent under the public and private cloud adoption model. Chapter 5 provides the detailed interpretation of the findings, limitations of the study, implications, and conclusion of the research findings.

Chapter 5: Discussion, Conclusions, and Recommendations

As presented by TCS (2011), the health care industry is slow in adopting cloud computing. Particularly for U.S. hospitals, data privacy and security concerns seem to be the major barriers (Japsen, 2013). Due to the lack of scholarly research on U.S. hospitals' cloud computing adoption, the purpose of my research was to address this gap by examining the suspected influential factors affecting U.S. hospital IT managers' intent for cloud computing adoption. This research used online self-administrated survey questionnaire as the research instrument for data collection and utilized the SPSS GLM for data analysis and hypothesis testing. I used a proportional stratified random sampling method to select the participants for this study from a paid industrial contact profiling service, (http://www.hoovers.com). The survey participants included IT executives of U.S. hospitals who play a critical role in influencing technology adoption decisions and work in the qualified U.S. hospitals within the 48 U.S. continental states.

As part of the pilot study recommendation, I separated the survey questions and the result analysis for public versus private cloud services adoption. In total, I sent 2200 survey invitation emails to potential candidates together with two iterations of reminder emails to encourage participation. As the result, I received 118 valid survey responses within six weeks of my survey window.

The key findings included the significant relationships of all six influential factors with the public cloud adoption of U.S. hospitals, and the significant relationship of the three technological factors with the private cloud adoption of U.S. hospitals. The predictability of the public and private cloud adoption regression model seemed high with adjusted R^2 equal to .583 and .785 respectively.

This chapter begins with the interpretation of the findings and results in comparison with the peer-reviewed literature described in Chapter 2. Then follows the generalization and validity limitation discussion, recommendation for further research and implications for positive social change and future methodological and theoretical development. Finally, it concludes with the summary of key essence of this study.

Interpretation of Findings

As my theoretical framework, I applied DOI and TOE framework to study the influential impacts of U.S. hospital cloud adoption by the six identified critical factors under the technological and organizational context. Based on my research result summary as shown in Table 29, both the public and private cloud services adoption model explained a significant portion of the outcome variances within the sample—62% (R^2 = .621) and 81% (R^2 = .807) respectively. While all six predictor variables (technological—relative advantage, compatibility, and complexity; and organizational—size, structure, and culture) were significant for the public cloud services adoption, only the technological factors were significant for the private cloud services adoption. This finding on significance of technological factors on cloud services adoption aligned with the research result produced by Powelson (2012) and Tweel (2012). It also confirmed the DOI and TOE framework theory that the technological factors (relative advantage, compatibility, and complexity) are critical for new technology adoptions (Rogers, 2003). However, the orders of significance among these factors were quite difference. The previous researches concluded that relative advantage, compatibility, and complexity had the highest correlation with the adoption intent for cloud computing technology. Nevertheless, my research result showed that organizational factors had higher correlation than technological factors with the public cloud services adoption. It confirmed that one could not ignore the organizational factors for new technology adoptions as stated in TOE framework (Tornatzky & Fleischer, 1990). On the other hand, it disconfirmed Rogers' (2003) claim that relative advantage, compatibility, and complexity are three most significant influential factors for new technology adoptions.

I found organizational size was a significant factor with high correlation (B = .774) under the organizational context, and compatibility had lower correlation than other organizational factors (B = .174) with public cloud services adoption. Whereas, Dr. Tweel (2012) reported that organizational size had no significant relationship with the cloud adoption intent in his Arizona small business cloud adoption study. Additionally, it is important to highlight that my research result also showed that the three organizational factors had no significant relationship with the private cloud services adoption for U.S. hospitals. It disconfirmed the TOE framework that factors under organizational context are as critical as factors under technological context for new technology adoptions (Tornatzky & Fleischer, 1990). Additionally, this specific finding on the difference of influential factors for public versus private cloud services adoption brought up new curiosity on how different cloud deployment models can affect the adoption intent. It will require scholars to explore in the future.

By comparing the regression coefficient of each technological factor—relative advantage, compatibility, and complexity—between the public and private cloud services adoption model, I discovered that the proportion of the significance of these three factors were tremendously different in these two models. Under the public cloud services adoption model, relative advantage, and complexity factor explained uniquely about 15% variances (partial η^2 = .147 and .153) of the adoption intent and compatibility explained only 5% variances (partial η^2 =.053). In contrast, under the private cloud adoption model, the compatibility factor explained uniquely about 42% variances (partial η^2 = .415) of the adoption intent while relative advantage and complexity explained only 11% (partial η^2 = .112) and 7% variances (partial η^2 = .074) respectively, as shown in Table 29. This empirical phenomenon revealed that private cloud services require a tight integration with existing IT architecture of U.S. hospitals. It meant that IT decision makers of U.S. hospitals have to consider the compatibility of private cloud services seriously before their adoption. However, for public cloud services adoption, majority of U.S. hospital IT managers are mainly considering for productivity tools, like Microsoft O365 or other standalone cloud applications at the current stage. It may be the reason that compatibility with hospitals' belief and infrastructure is not a significant factor to consider for public cloud adoption of U.S. hospitals.

Beyond the different finding on the complexity factor, my research confirmed that relative advantage and complexity were the two most critical technological factors influencing public cloud services adoption. It was similar to the research results reported by other scholars (Aljabre, 2012; Armbrust et al., 2009; Campbell, 2010; Good, 2013;

Ross, 2010; Shimrat, 2013). In Ekufu's (2012) research, he also identified that perceived ease of use was a critical factor for cloud services adoption, for which perceived ease of use was the exact reverse measurement for complexity.

Table 29

Statistical Analysis Result Summary of the Regression Models

		Public Cloud Services Adoption			Private Cloud Services Adoption		
Dependent Variable		R^2	Adj. R^2	Sig.	R^2	Adj. R^2	Sig.
Adoption Intent for U.S. Hospital Managers		.621	.583	.000	.807	.785	.000
Independent Variables		B	Sig.	Partial η^2	B	Sig.	Partial η^2
Relative Advantage		.238	.000	.147	.102	.001	.112
Compatibility		.174	.022	.053	.368	.000	.415
Complexity		.249	.000	.153	.118	.007	.074
Organizational Size		.774	.000	.119			
Organizational Structure	functional	-5.086	.000	.130			
	matrix	-2.951	.012	.063			
Organizational Culture	clan	2.478	.020	.054			
	hierarchy	2.976	.003	.084			

Turning to organizational factors, based on my research results, organizational structure defined as functional and matrix had significant relationships with public cloud services adoption, but not for divisional and others. When an organization is structured functionally, it means the segregation of duty and line of authority is based on its internal business functions, like finance and sales, instead of external services or market segments. Since matrix organizational structure is a combination of functional and divisional structure, it implies that the functional element of organizational structure has influential relationship to the public cloud services adoption. From Table 29, functional and matrix organizational structure had negative regression coefficient values, -5.086 and

-2.951 respectively in the public cloud services adoption model. It implied that a hospital has less tendency to adopt public cloud services if its organization structure is either functional or matrix. One possible explanation was that functionally organized hospitals are more internal tasks focused than divisionally organized hospitals, for which are more cross-functional and care more on team collaboration. Therefore, an organization with a functional structure has less demand to take advantage of the anywhere and anytime information sharing capability of public cloud services for enhancing team collaboration. In addition, organizations with a functional structure are traditionally more risk adverse and have less willingness to accept changes, like new technology adoptions (Griffin, 2015).

As a recap on the definition of organizational culture as clan and hierarchy, clan meant that an organization focuses on organizational flexibility and internal capability while hierarchy meant that the organization focuses on stability and internal capability. From my research results, only organizational cultures as clan and hierarchy had a significant relationship with the public cloud services adoption, but not for organizational cultures as adhocracy and market. The latter two both carries external positioning as their essential cultural element. By comparing the two essential elements of these four types of organizational culture (internal capability versus external positioning), it confirmed that internal capability consideration had stronger influence than external positioning on public cloud services adoption for U.S. hospitals. This empirical phenomenon made sense as hospitals have important social responsibility to provide high quality of patient services than making profit. It meant that they normally focus more on their internal capability than external positioning. When an organization is eager to improve internal capability, it will have a higher tendency to adopt public cloud services. The main reason is to take the technological advantages of public cloud services on cost reduction, scalability, and flexibility, as stated in Chapter 2.

Another important finding from my analysis results was that organizational factors had no significant relationship with private cloud services adoption. One explanation is that the benefit and risk of private cloud services are not tremendously different from existing technologies deployed in U.S. hospitals. Therefore, regardless of what organizational size, structure, and culture, U.S. hospitals can consider adopting private cloud services when they believe they are compatible and appropriate to increase their internal capabilities.

Limitations of the Study

In general, the limitation of my study was in-line with the expected limitation stated in Chapter 1. For instance, the R^2 and adjusted R^2 were significant for both the public (.621 and .583) and private cloud services adoption model (.807 and .785). There were moderate omitted variable biases existed as the regression models could not explain only about 41.7% and 21.5% of the outcome variances based on the adjusted R^2 values. The internal reliability and validity check of my research could be limited as I newly introduced organizational structure and organizational culture as two categorical predictor variables that no other scholar did any similar cloud adoption research before. According to the feedback from the SMEs under the pilot study, the original definition of the organization structure was not clear. Although I made additional effort to provide further explanation of the definition of the organization structure in my final study, it might still be not clear enough for some survey respondents. It might have affected their responses in the survey.

In the first two weeks of the survey-taking window, the response rate was very low (only about 1%). I had to send two rounds of reminder emails to encourage survey responses. This situation might be due to the extreme workload of U.S. hospital IT managers, serious concerns for data security and privacy, or even due to public relationship policy of U.S. hospitals that limited the survey responses. Therefore, early, late, and non-response bias might exist.

The sample size was slightly below the minimal requirement of 110 after I excluded the outliers based on Cook's distance value. The ultimate number of relevant sample cases applied in the public and private cloud services adoption model are 109 and 108 respectively. Since there was slightly insufficient statistical power to represent the population, the generalization from the sample to target population was less conclusive (Koshar, 2015). Therefore, it affected the external validity. Researchers should caution to apply my research results to other types of enterprise and geographical locations as my target population was the qualified hospitals of the 48 U.S. continental states (Trochim, 2001). As the technologies, types, nature, and acceptance of the cloud services are rapidly evolving, researchers who attempt to replicate my research study in the future might get very different results. Due to this fact, the predictive validity may be limited. However, longitude statistical studies on the cloud services adoption can still provide very valuable information on how the cloud adoption intent changes over time and relates to different factors. Using abstracted influential factors recommended in the DOI and TOE theories allowed me to maintain higher reliability of my research results over time. This approach was different from other scholars' research methodology. For example, Ross (2010) used cost-effectiveness, need, reliability, and security effectiveness applied in his cloud adoption study.

Another limitation of my study was the lack of sample representation for any federal government and newly established (i.e., years of operation is between one to ten years) hospitals. Since I did not have sample data to examine IT managers' cloud adoption intent and attitudes on the six influential factors for these groups of hospitals, it would be inappropriate to draw any conclusion for them.

Recommendations

As the lack of commonly agreed definitions for organizational structure and organizational culture, using them as predictor variables for cloud adoption study might draw some levels of confusion to the survey participants. In the future academic research, scholars may try to consider using multiple Likert scale survey items to construct the composite predictor variables for organizational structure and organizational culture, instead of using categorical variables as in my study. The statistical analysis procedure and interpretation of the result will then be simpler as traditional MLR procedures can be used, without the need to use dummy coding or GLM. It can also avoid the concern of the interactive effect of the categorical variables. That may affect the result of the regression model depending on the sequence of the independent variables entering into the model (Stockburger, n.d.). Furthermore, using multiple survey items to create a composite variable will have the advantage to provide a more reliable survey instrument. Researchers can conduct reliability test with Cronbach's alpha statistics for continuous variables but cannot measure reliability of a categorical variable value precisely.

Since my research was a new academic study for the cloud services adoption of U.S. hospitals, there was a lack of any previous baseline statistics and findings for reference. Therefore, more future quantitative and qualitative research on the similar topic can help to create a better understanding of the critical factors that affect cloud services adoption for U.S. hospitals. As my sample size was marginally acceptable, I would recommend future quantitative research studies to increase their sample size to at least 200 and include the types of hospitals missed in my research. With sufficient sample size, it will avoid the situation of insufficient sample cases after researchers removed outliers. Although using an external business profiling and contact service provided an easy way to access the required IT contacts of U.S. hospitals, it did not provide the credibility to convince potential respondents to accept my survey invitations. That perhaps was the reason for my low response rate. One of my pilot study SMEs suggested collaborating with some Healthcare IT associations for survey research. With the support to send the survey invitations to their association members, researchers can expect a higher response rate.

Due to time and resource constraints, I excluded environmental factors in my research. Given about 41.7% and 21.5% of outcome variances could not be explained in my public and private cloud services adoption models, including environmental factors in future research studies may explore other critical factors. That may contribute to creating a better predictive regression model for cloud services adoption of U.S. hospitals.

Another recommendation for future research is to conduct case studies for U.S. hospitals to analyze qualitatively on how different influential factors can affect their adoption intent for different types of cloud services. Finally, in order to provide a better global generalization for my research findings, it requires other scholars to conduct similar research studies with my survey instrument and method. Those results will help to confirm or disconfirm my result findings for hospitals in other countries. This kind of longitude quantitative studies can provide the trending perspectives on the changes of the influential factor effect over time with cloud services adoption.

Implications

With better awareness on the degree of influence of the six identified critical factors on cloud services adoption for U.S. hospitals, IT managers can develop their strategies and deployment roadmaps for cloud services adoption with higher confidence on the expected value and resistance. Furthermore, the cloud services providers can allocate the right level of resources and set proper priority to enhance their cloud service capacities. That will then accelerate the services adoption through improved values and reduced barriers. In certain areas, it also helps the cloud services providers to create effective public awareness and training to help addressing the low cloud adoption situation for U.S. hospitals.

As described in Interpretation of Findings section, organizational structure as functional and matrix had significant negative relationships with the public cloud services adoption. It implied that hospitals with traditional functional line of authority are more redundant to adopt public cloud services. As a logical explanation, those hospitals are more conservative in nature and unwilling to adjust to service focus like hospitals organized divisionally. Therefore, they are more resistance to new technology adoptions.

When the organizational culture of a hospital is clan or hierarchy, it meant that they have higher focus on internal capability than external market positioning. From the regression analysis result, it showed significant positive relationship with the public cloud services adoption. It provided the implication that hospitals carry these organizational cultures would be more favor to adopt public cloud services. One explanation was that the IT managers of those hospitals are more eager to improve IT capability by adopting new technologies.

The discovery of significant difference for factors influencing public versus private cloud services adoption intent for U.S. hospitals implied cloud services providers should consider taking different approaches and priorities to drive different types of cloud services adoption. For example, promoting the high-security nature of private cloud services to hospitals with serious data security and privacy concerns can help shifting the mindset on cloud services and realize some of their benefits. It can be a stepping-stone for future broader cloud services adoption.

In the Interpretation of Findings section, I reported that the predictive power of the three technological factors for private cloud services adoption was quite high (adjusted $R^2 = .785$). Nevertheless, for public cloud service adoption, the three organizational factors were the main influencers instead of technological factors.

Therefore, it implied that cloud services providers might need to customize their cloud services selling approach for hospitals with different organizational size, structure, and culture. For small cloud services providers that do not have sufficient sales resources, it may be better to focus on developing and selling the private cloud services for U.S. hospitals. It is because they can have a higher confidence in their return on investment based on their technological capabilities and features as those are the key drivers for adoption.

As an important positive social change implication, with higher and faster cloud services adoption for U.S. hospitals, its main benefit in reducing IT investment, scalable pay-as-you-go cost structure, high service reliability, and anywhere and anytime information accessibility can reflect quickly on better quality and lower cost services for patients. In a long run, when patients' medical and health data can be securely kept in and accessible through the cloud environment, the overall health care service efficiency improvement via patient information sharing among health care providers can tremendously accelerate.

Under theoretical framework, I confirmed that the technological and organizational factors extracted from DOI and TOE theories were significant to predict the public cloud services adoption for U.S. hospitals. It aligned with other scholars' cloud adoption research for different industries and countries (Hailu, 2012; Tweel, 2012; Ross, 2010). However, the organizational factors under the TOE framework did not seem applicable to the private cloud services adoption, as my research result showed no significance for the organizational factors in the private cloud adoption model. This finding was novel, as I could not identify any other scholar reported similar finding before. However, to confirm this empirical phenomenon, I encourage scholars to conduct additional studies in the future to explore further the relationships between cloud services deployment models and influential factors.

Conclusions

The objective of my research study was to examine the predictive power of six critical factors influencing the cloud computing adoption intention for U.S. hospitals, as described in DOI and TOE framework. As the conclusion, I completed my study with validated survey instrument and comprehensive statistical analysis with confirmed validity and reliability. The outcomes of my research were two good predictive models for cloud services adoption intent for U.S. hospitals—one for public cloud services and another for private cloud services. Based on the adjusted R^2 values, these two regression models could explain a high proportion of the outcome variances—58.3% and 78.5% respectively.

Under the public cloud adoption model, I confirmed that the three technological (relative advantage, compatibility, and complexity) and the three organizational factors (organizational size, organizational structure, and organizational culture) were statistically significant in predicting the U.S. hospital IT managers' adoption intent. All six factors had a positive correlation with the adoption intent, except for functional and matrix organizational structure having negative correlation. The finding of positive relationships between the technological factors and cloud adoption intent aligned with previous research studies on cloud computing adoption under different research settings, such as industries and countries (Aljabre, 2012; Armbrust et al., 2009; Campbell, 2010; Good, 2013; Ross, 2010; Shimrat, 2013). Nevertheless, it was an important discovery that U.S. hospitals having functional or matrix organizational structure and clan or hierarchy organizational culture had significantly negative and positive influence respectively to the public cloud services adoption. It is noteworthy to mention that U.S. hospitals with functional organizational structure had the highest absolute regression coefficient (5.086) with public cloud services adoption intent while compatibility factor had the lowest absolute regression coefficient (.176). In addition, the organizational factors had overall higher absolute regression coefficient than technological factors under the public cloud adoption model for U.S. hospitals. It implied organizational factors carrying more weight than technological factors influencing U.S. hospital IT managers on adopting public cloud services. It might tie back to the importance of the subjective norm impacts on the cloud adoption as concluded by Ross (2012).

Under the private cloud adoption model, the statistical result confirmed that only the three technological factors had significantly correlation with the adoption intent and showed no significant influence from all three organizational factors. One potential explanation for this phenomenon was that private cloud service nature does not carry any attribute limiting organization with certain size, structure or culture to adopt.

These findings provided the hospital IT managers and cloud services providers the insights to decide their strategies and roadmaps on how to accelerate their cloud services adoption by influencing these six identified factors to a favorable direction. As a positive social change, by accelerating the cloud services adoption, hospitals should be able to realize the financial and technological benefit of cloud services. Ultimately, it will be beneficial to the patients by having a much higher quality and lower cost health care services.

With the limitation of my sample size, I recommend scholars who plan to adopt or extend my research in the future to utilize a bigger sample size. Furthermore, adding environmental factors into my regression models may improve further the models' predictive power on cloud services adoption intent for U.S. hospitals.

Finally, my research study filled the academic research gap in the current limited understanding of the influential factors for the cloud services adoption of U.S. hospitals. It provided additional insights on the influential power of organizational structure and organizational culture on the public cloud services adoption and difference on influential factors for U.S. hospitals' public and private cloud services adoption.

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Appendix A: U.S. Hospitals' Cloud Computing Adoption Survey Instrument

Cloud Computing Adoption Survey for U.S. Hospitals - Consent

WALDEN UNIVERSITY

Purpose. You are invited to participate in a research study being conducted for a dissertation at Walden University. The purpose of this study is to examine the relationship between the technological and organizational factors and the intention for IT managers of U.S. hospitals to adopt cloud computing. It will take about 10 to 15 minutes to complete and there is no deception in this study. I am interested in your opinions about cloud computing adoption.
Participation Requirements. Participants for this study are expected to (a) have some expertise pertaining to the IT activities and operations, (b) play a role in influencing the adoption decision process and (c) work in a U.S. hospital.
Research Personnel. The following people are involved in this research project and may be contacted at any time:
Terence Lee (Researcher-Primary contact) - terence.lee@waldenu.edu
Dr. Christos Makrigeorgis (Dissertation Chair) - christos.makrigeorgis@waldenu.edu
Potential Risk / Discomfort. There is no known or anticipated risk in this study. However, you can choose not to answer any question that makes you uncomfortable.
Potential Benefits. If desired, you could receive a summary of the investigation finding upon completion of the research. The results will have scientific interest that may eventually have benefits for people who contemplate adopting cloud computing. No incentive for participation is offered.
Anonymity/Confidentiality. The data collected in this study are confidential. To ensure the anonymity of the respondents, this survey tool is utilized to provide anonymous response collection. All data is collected and coded such that your email are not associated with them. In addition, the coded data are made available only to the researcher associated with this project.
Withdrawal. Participation in this study is voluntary and can withdraw at any time. You may also skip questions on the questionnaire if you do not want to answer them. I am happy to answer any question that may arise about the study. Please direct your questions or comments to: Terence Lee, via email at: terence.lee@waldenu.edu. If you have any question concerning your rights as participants, you would contact the Walden Research Participant Advocate (phone: 1-612-312-1210 or email: irb@waldenu.edu).

1) To authorize participation in this survey, please consent to the above anonymity/confidentiality terms, please select "I agree" below to proceed with the survey. *Please keep/print a copy of this consent page for your future reference.	
I agree	
I do not agree	

2) For the purpose of this survey, the participant is expected to have IT knowledge, play a critical role in influencing technology adoption decisions and work in an U.S. hospital. Please indicate whether you meet this profile.	
Yes	
No	

Cloud Computing Adoption Survey for U.S. Hospitals - P.1

The following questions are related to the nature and characteristics of your hospital.

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3) What is the state your hospital located in?	
AL - Alabama	
AR - Arkansas	
AZ - Arizona	
CA - California	
CO - Colorado	
CT - Connecticut	
DC - Washington DC	
DE - Delaware	
FL - Florida	
GA - Georgia	
GU - Guam	
IA - Iowa	
ID - Idaho	
IL - Illinois	
IN - Indiana	
KS - Kansas	
KY - Kentucky	

LA - Louisiana	
MA - Massachusetts	
MD - Maryland	
ME - Maine	
MI - Michigan	
MN - Minnesota	
MO - Missouri	
MS - Mississippi	
MT - Montana	
NC - North Carolina	
ND - North Dakota	
NE - Nebraska	
NH - New Hampshire	
NJ - New Jersey	
NM - New Mexico	
NV - Nevada	
NY - New York	
OH - Ohio	
OK - Oklahoma	
OR - Oregon	
PA - Pennsylvania	
RI - Rhode Island	
SC - South Carolina	
SD - South Dakota	
TN - Tennessee	
TX - Texas	
UT - Utah	
VA - Virginia	
VT - Vermont	

WA - Washington	
WI - Wisconsin	
WV - West Virginia	
WY - Wyoming	

4) What type of hospital is yours belonging to?	
Federal Government	
State / Local Government	
Nonprofit	
For Profit	
Other (Please Specify)	

5) How many years has your hospital been in operation?	
1-5	
5-10	
10-20	
20-30	
30-60	
>60	

6) What is your hospital's annual revenue range of last year?	
$2-10 Million	
$11-50 Million	
>$50 Million	
N/A	

7) Approximately how many staffed beds does your hospital currently have?	
50-99	
100-199	
200-299	

300-399	
400-499	
> 500	

Cloud Computing Adoption Survey for U.S. Hospitals - P.2

The following questions are related to the technological factors of cloud computing adoption.

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8) Information technology can be used for a number of objectives. To what extent is cloud computing adoption important for the fulfillment of the following objectives in your hospital?

	Strongly Disagree	Disagree	Slightly Disagree	Neutral	Slightly Agree	Agree	Strongly Agree
Increase the profitability of your hospital.							
Allow your hospital to provide additional services.							
Allow for reduced operational costs.							
Allow better communication with my patients, staff, and medical partners.							
Require no up-front capital investment.							
Provide dynamic and high service availability.							

9) Please indicate how much you agree or disagree with each of the following statements based on a scale ranging from strongly disagree to strongly agree.

	Strongly Disagree	Disagree	Slightly Disagree	Neutral	Slightly Agree	Agree	Strongly Agree

Public cloud adoption is consistent with your hospital's belief and value.							
Attitudes towards public cloud adoption in your hospital is favorable.							
Public cloud adoption is compatible with your hospital's IT infrastructure.							
Public cloud adoption is consistent with your hospital's business strategy.							
Public cloud service is cumbersome to use.							
Using public cloud services requires a lot of mental efforts.							
Using public cloud services are often frustrating.							
The user interface of public cloud services is clear and understandable.							
Public cloud services are easy to purchase and startup.							

10) Please indicate how much you agree or disagree with each of the following statements based on a scale ranging from strongly disagree to strongly agree.

	Strongly Disagree	Disagree	Slightly Disagree	Neutral	Slightly Agree	Agree	Strongly Agree
Private cloud adoption is consistent with your hospital's belief and value.							
Attitudes towards private cloud adoption							

in your hospital is favorable.							
Private cloud adoption is compatible with your hospital's IT infrastructure.							
Private cloud adoption is consistent with your hospital's business strategy.							
Private cloud service is cumbersome to use.							
Using private cloud services requires a lot of mental efforts.							
Using private cloud services are often frustrating.							
The user interface of private cloud services is clear and understandable.							
Private cloud services are easy to purchase and startup.							

Cloud Computing Adoption Survey for U.S. Hospitals - P.3

The following questions are related to the organizational factors of cloud computing adoption.

11) What is your hospital's primary organizational structure? *It means the hierarchical arrangement of lines of authority of an organization in this survey.	
Functional - Employee's reporting channel is organized by their functional responsibilities and tasks.	
Divisional - Employee's reporting channel is organized by product / service types.	
Matrix - It is a combination of functional and divisional structure.	
Other (Please Specify)	

12) What is the most perceived organizational culture of your hospital?	
Clan - have an internal and organic focus on value creation and performance criteria. Emphasize on internal collaboration.	
Adhocracy - have an external and organic focus on value creation and performance criteria. Emphasize on product/service creativity.	
Hierarchy - have an internal and control focus on value creation and performance criteria. Emphasize on internal control.	
Market - have an external and control focus on value creation and performance criteria. Emphasize on external competition.	
Other (Please Specify)	

Cloud Computing Adoption Survey for U.S. Hospitals - P.4

The following questions are related to your current cloud computing adoption status and future plan.

WALDEN UNIVERSITY

13) Please indicate how much you agree or disagree with each of the following statements based on a scale ranging from strongly disagree to strongly agree.

	Strongly Disagree	Disagree	Slightly Disagree	Neutral	Slightly Agree	Agree	Strongly Agree
Intends to adopt public cloud computing.							
Likely to take steps to adopt public cloud computing in the future.							
Likely to adopt public cloud computing in the next 12 months.							

14) Please indicate how much you agree or disagree with each of the following statements based on a scale ranging from strongly disagree to strongly agree.

	Strongly Disagree	Disagree	Slightly Disagree	Neutral	Slightly Agree	Agree	Strongly Agree
Intends to adopt private cloud computing.							
Likely to take steps to adopt private cloud computing in the future.							
Likely to adopt private cloud computing in the next 12 months.							

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Request for Usage Permission

2 messages

Terence Lee <terence.lee@waldenu.edu> Sun, Nov 9, 2014 at 3:21 PM
To: permissions@oreilly.com

Hi Permission Department,

My name is Terence Lee. I am a PhD student at Walden University School of Management. I am currently conducting my Dissertation research on cloud computing technology adoption in U.S. hospital. In my research, I discussed various cloud service models.

I would very much like to get your permission to utilize the diagram "Cloud Service Models" on p.17 of the book "Cloud Security and Privacy: An Enterprise Perspective of Risks and Compliance (Theory in Practice). ISBN: 1449379516, 9781449379513.

Thanks for your prompt response.

Best Regards,
Terence Lee
Student Id: A00040993
Tel: 928-863-6123

Teri Finn <teri@oreilly.com> Mon, Nov 10, 2014 at 2:44 PM
To: Terence Lee <terence.lee@waldenu.edu>

Hi Terence,

Thank you for your inquiry. O'Reilly Media is happy to grant you permission to include the diagram referenced in your Dissertation. We ask that you provide proper attribution to the book.

Best regards,

Teri Finn
O'Reilly Media, Inc.
[Quoted text hidden]

Request for Usage Permission
2 messages

Terence Lee <terence.lee@waldenu.edu> Sun, Nov 9, 2014 at 12:59 PM
To: Jonathan.Starkweather@unt.edu

Dear Jon Starkweather,

My name is Terence Lee. I am a PhD student at Walden University

School of Management. I am currently conducting my Dissertation research

on cloud computing technology adoption in U.S. hospital. In my research, I discussed

the multiple linear regression method to identify and validate the predictive model for cloud computing adoption.

I would very much like to get your permission to utilize the normal P-P plot of regression standard residual diagram illustrated in your online course web page:

http://www.unt.edu/rss/class/Jon/SPSS_SC/Module9/M9_Regression/SPSS_M9_Regression2.htm

Thank you for your prompt response.

Best Regards,

Terence Lee

BSc (Hong Kong, China), MSc (Coventry, UK).

Starkweather, Jonathan <Jonathan.Starkweather@unt.edu> Mon, Nov 10, 2014 at 5:30 AM
To: Terence Lee <terence.lee@waldenu.edu>

Terence,

Those webpages are for anyone to use. I'd be pleased if you simply cite me using any generic format you like.

Best regards,

S I M O N & S C H U S T E R

1230 Avenue of the Americas
New York, NY 10020
212-698-7262 • Fax: 212-698-7284
E-Mail: edith.golub@simonandschuster.com

Edith Golub
Permissions Department

November 17, 2014

Terence Lee
22348 ne 18th Street
Sammamish, WA 98074
Terence.lee@waldenu.edu

Re: DISSERTATION

Dear Terence Lee:

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Sincerely,

Edith Golub

Edith Golub
Permissions Manager

Appendix C: IRB Approval Letter

Gmail by Google

Terence Lee <terence.lee@waldenu.edu>

IRB Materials Approved - Terence Lee
1 message

IRB <IRB@waldenu.edu> Wed, Jan 14, 2015 at 3:20 PM
To: Terence Lee <terence.lee@waldenu.edu>
Cc: Christos Makrigeorgis <christos.makrigeorgis@waldenu.edu>, IRB <IRB@waldenu.edu>

Dear Mr. Lee,

This email is to notify you that the Institutional Review Board (IRB) has approved your application for the study entitled, "Regression Analysis of Cloud Computing for U.S. Hospitals."

Your approval # is 01-14-15-0040993. You will need to reference this number in your dissertation and in any future funding or publication submissions. Also attached to this e-mail is the IRB approved consent form. Please note, if this is already in an on-line format, you will need to update that consent document to include the IRB approval number and expiration date.

Your IRB approval expires on January 13, 2016. One month before this expiration date, you will be sent a Continuing Review Form, which must be submitted if you wish to collect data beyond the approval expiration date.

Your IRB approval is contingent upon your adherence to the exact procedures described in the final version of the IRB application document that has been submitted as of this date. This includes maintaining your current status with the university. Your IRB approval is only valid while you are an actively enrolled student at Walden University. If you need to take a leave of absence or are otherwise unable to remain actively enrolled, your IRB approval is suspended. Absolutely NO participant recruitment or data collection may occur while a student is not actively enrolled.

If you need to make any changes to your research staff or procedures, you must obtain IRB approval by submitting the IRB Request for Change in Procedures Form. You will receive confirmation with a status update of the request within 1 week of submitting the change request form and are not permitted to implement changes prior to receiving approval. Please note that Walden University does not accept responsibility or liability for research activities conducted without the IRB's approval, and the University will not accept or grant credit for student work that fails to comply with the policies and procedures related to ethical standards in research.

When you submitted your IRB application, you made a commitment to communicate both discrete adverse events and general problems to the IRB within 1 week of their occurrence/realization. Failure to do so may result in invalidation of data, loss of academic credit, and/or loss of legal protections otherwise available to the researcher.

Both the Adverse Event Reporting form and Request for Change in Procedures form can be obtained at the IRB section of the Walden website: http://academicguides.waldenu.edu/researchcenter/orec

Researchers are expected to keep detailed records of their research activities (i.e., participant log sheets, completed consent forms, etc.) for the same period of time they retain the original data. If, in the future, you require copies of the originally submitted IRB materials, you may request them from Institutional Review Board.

Both students and faculty are invited to provide feedback on this IRB experience at the link below:

http://www.surveymonkey.com/s.aspx?sm=qHBJzkJMUx43pZegKlmdiQ_3d_3d

Sincerely,

Libby Munson

Research Ethics Support Specialist

Office of Research Ethics and Compliance

Email: irb@waldenu.edu

Fax: 626-605-0472

Phone: 612-312-1283

Office address for Walden University:

100 Washington Avenue South, Suite 900

Minneapolis, MN 55401

Information about the Walden University Institutional Review Board, including instructions for application, may be found at this link: http://academicguides.waldenu.edu/researchcenter/orec

Lee Consent Form.pdf
145K

Appendix D: Dr. Tweel's Approval Email

Subject:	Re: Permission for use of your survey questionnaire
From:	Terence Lee (rhk499@yahoo.com)
To:	drtweel@gmail.com;
Date:	Sunday, October 13, 2013 8:17 PM

Hi Dr. Tweel,

Thanks a lot. By the way, I forgot to mention that your dissertation is very well written and provided a lot of insights to me. After my dissertation has been approved, I shall send you a copy.

Best Regards,
Terence
Cell: (928)863-6123

On Sunday, October 13, 2013 7:16 PM, dr Tweel <drtweel@gmail.com> wrote:
Hello Terence,
Sure you have my permission. Good luck in your dissertation.
p.s. it would be nice if you could email a copy of your dissertation after you publish it.
Regards
Dr. Tweel
On Oct 13, 2013 9:48 PM, "Terence Lee" <rhk499@yahoo.com> wrote:

> Dear Dr. Tweel,
>
> I am currently pursuing my PhD study and working on my PhD dissertation. My research interest is also related to cloud computing adoption, but with the focus on corporations under health care industry. I would like to study some factors which have excluded from your research, such as organization culture, organization structure and external support infrastructure (like legal compliance), on their influence to cloud computing adoption. Also whether the intent of adoption varies based on different cloud service models, such as IaaS, SaaS and PaaS.
>
> I would like get your permission to use your research survey instrument in the research paper named "Examining the relationship between technological, organizational and environmental factors and cloud computing adoption".
>
> If you are the copyright owner and it is okay for you, please grant your permission by relying to this email. Thanks a lot for your support.
>
> Best Regards,
> Terence
> P.S. I got your email address from your dissertation listed above.

Appendix E: Survey Invitation Letter

WALDEN UNIVERSITY
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Ph.D. Research Survey of Cloud Computing Adoption for U.S. Hospitals

Dear Sir / Madam,

My name is Terence Lee and is a Ph.D student at Walden University. Currently, I am conducting research to identify influential factors that will affect the cloud computing adoption intent for U.S. hospitals.

Due to your IT professional position in a qualified U.S. hospital, you have been identified as a key person to be a participant ("respondent") in my survey process. Below is a link to the online survey:

http://kwiksurveys.com/s.asp?sid=vytu82c1f9l1gfg482692

I shall keep your response completely confidential. The survey is web-based. The participant's name, email and IP address will not be attached to any results, and to ensure your anonymity we will not report any results that have less than three respondents. The survey is user-friendly, and you should be able to complete it within 10 minutes or less.

I appreciate your willingness to participate and value your feedback. My hope is this survey can help persons like you to understand better the drivers and barriers to cloud computing adoption. With better cloud computing services and adoption plan, scholars and industry experts expect the business agility and cost structure for U.S. hospitals will be tremendously improved.

If you have any questions, please feel free to contact me at Terence.lee@waldenu.edu.

Thank you for your participation. As to thank you, I shall provide my research result summary to you via email after my dissertation have been finished.