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ACCEPTANCE OF CLOUD COMPUTING IN KLANG VALLEY'S HEALTH CARE INDUSTRY, MALAYSIA

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Abstract

In health care, cloud computing provides the opportunity for health care providers to lower the total cost of information technology investment while still maintaining compliance with health care regulations. The purpose of this study was to investigate the factors that influence the acceptance of cloud computing solutions by doctors and nurses working in hospitals across Klang Valleys, Malaysia. Quantitative research methodology utilizing the survey approach was employed. This study used an existing technology acceptance model. Multiple linear regression technique was used for data analysis. The findings indicated that perceived usefulness, attitude toward use, and perceived ease of use significantly influenced users' intention to use cloud computing solutions.

Keywords: Cloud Computing, Health care, Technological Acceptance Model (TAM), perceived values, adoption of technology, management information system, computer solutions

INTRODUCTION

Technological innovations have made information sharing a very fluid and dynamic environment. Cloud computing and mobile technologies emerge as a necessity for individuals and businesses to share information, maintain global contacts, and conduct online business transactions. The increased usage and demands have prompted enterprises and organizations, in public and private sectors, to implement these technologies as part of their business strategy.

The intention of this research was to explore health care professionals' perceptions and the degree of their acceptance of cloud computing solutions. The framework used in this research is based on the theoretical model presented by Egea and González (2011). The authors extended Davis's (1989) original technology acceptance model (TAM) with the trust and risk factors (Egea & González, 2011). Hence, the core constructs of the research model for this study include perceived usefulness, perceived ease of use, attitude toward use, institutional trust, perceived risks, and intention to use. By understanding factors that will likely cause the users to reject cloud computing solutions, such as these pre-conceived perceptions, decision-makers and implementers can better direct their efforts to minimize potential failures when deploying cloud computing solutions.

Cloud computing is a model that allows users on-demand access to resources such as servers, platforms, networks, storage, and applications in which computing resources can be rapidly provisioned and delivered over the Internet (Liu et al., 2011; Mell & Grance, 2011; Paquette et al., 2010). Cloud computing is also scalable to needs with little human interaction with cloud providers (Mell & Grance, 2011; Paquette et al., 2010). Cloud computing is comprised of cloud infrastructure, cloud platform, and cloud applications. Cloud infrastructure refers to the computational resources, network, storage, and processing which allow the user to tailor the infrastructure based on organizational needs (Paquette et al., 2010). Cloud platform is the provision of computer platforms or software stacks as a service, which allows users to deploy customized or purchased applications (Liu et al., 2011; Mell & Grance, 2011). Cloud applications are services that run on top of cloud platforms and infrastructures and are made available to the end-users (Paquette et al., 2010).Cloud applications are relatively different from the traditional applications. Traditional applications such as email applications, web applications, databases, Microsoft Office, etc. are hosted by locally-managed servers and individual desktops. Today, locally-hosted computing environments are still the main IT provisioning method used by the majority of organizations to deliver business applications to the users. In recent years, research in cloud computing related to health care has been focused mainly on the technology and the business issues related to implementation and usage.

In comparison, research on business issues related to cloud computing include security and privacy risks and legal implications such as the studies conducted by Armbrust et al. (2012), Cole-Kemp, Reddington, and Williams (2011), Gorban (2012), Klein (2011), Srinivasan (2013), Svantesson and Clarke (2010), and Umamakeswari, Vijayalakshmi, and Renugadevi (2012).

While there were many existing studies that address the advantages and the benefits of cloud computing, research on the acceptance of cloud computing remains very limited. These limited number of studies conducted on the acceptance of cloud computing have been focused on areas such as general business, government, and education; such as studies conducted by Behrend, Wiebe, London, and Johnson (2011), Cegielski, Jones-Farmer, Wu, and Hazen (2012), Chi, Yeh, and Hung (2012), and Shin (2013).

The TAM was developed specifically to predict users' acceptance of IT in which its author believed that there were determinant factors that influence the usage behaviors of the end-users (Davis, 1989; Davis, Bagozzi, & Warshaw, 1989). However, the theoretical framework that was more closely aligned with this study is the framework developed by Egea and González (2011), which the authors extended the original TAM with the trust and risk factors. The authors extended the original TAM with the risk and trust factors because these factors were believed to be relevant determinant factors that influence users' acceptance of new IT solutions (Egea & González, 2011).

Statement of the Problem

In the health care environment, cloud computing provides the opportunity for health care providers to lower the total cost of IT investment while ensuring access to the latest medical technologies and still maintaining compliance with health care regulations. Health care regulations, such as the HIPAA, require the health care providers and third party servicers to secure patients' health information in electronic format including scanned documents, email communications, or electronic printouts (Dreyzehner, 2014; Hoffman & Podgurski, 2007; Holloway & Fensholt, 2009; Keil, 2012; Lenert & Sundwall, 2012; Levy & Royne, 2009; Liginlal, Sim, Khansa, & Fearn, 2012).

Many studies were conducted to understand the implication of the law and the costs of compliance in relation to IT requirements and IT system maturity. Studies have shown that IT system maturity reduces operating costs, increases organizational performance, enables regulatory compliance, and helps businesses expand in the global market (Khoo, Harris, & Hartman, 2010; Nash, 2009; Simonsson, Johnson, & Ekstedt, 2010).

Purpose of the Study

The purpose of this study is to explore the factors that influence the degree of acceptance of cloud computing solutions by health care professionals. This is a timely and relevant study because it addresses the users' perceptions and intended usage toward cloud computing in the health care industry. The research is guided with the following null hypothesis. There is no significant relationship between the independent variables (PU, PE OU, A, ITrust, PRisk) and the dependent variable (BI), that the fit of the observed dependent variable values to those predicted by the regression equation is not better than what one would expect by chance. The null hypothesis for each individual independent variable is that adding that independent variable to the multiple regression does not improve the fit of the multiple regression equation any more than expected by chance, example, we are testing the assumptions of the regression model, that R2 for the independent variable being zero means it is not contributing to the variance of the dependent variable.

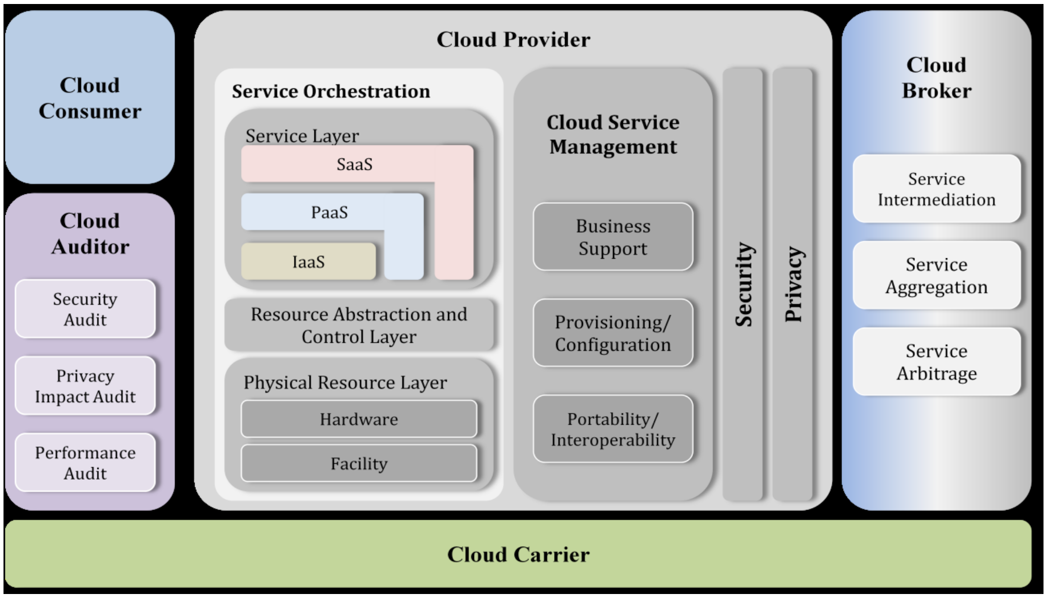
LITERATURE REVIEW

Cloud computing technology has steadily gained attention over the last few years as research and implementations have increased in public and private sectors as well as the academic arena ("Healthcare Cloud", 2012; Paquette et al., 2010; Shin, 2013). According to Marston et al. (2010), Gartner Research and AIM partners predicted that businesses will invest over $150 billion on cloud computing by 2014. Studies on global health care IT trends indicated that there has been a surge in cloud computing in the global health care IT market and it was predicted that the global health care cloud computing market revenue will increase to $5.4 billion by 2017 ("Healthcare Cloud", 2012). Moreover, studies have also shown that North America is the largest contributor to the increased value of the health care cloud computing market, which was predicted to influence the market value's increase from $1.7 billion in 2013 to $6.5 billion in 2018 ("Healthcare Cloud", 2012; "North American", 2014). Marston et al. (2010) asserted that cloud computing represents the current IT trends of efficiency, cost reductions, and business agility. These factors are beneficial in health care because IT efficiency means health care facilities can get access to the latest technologies and resource-intensive analytics capabilities at a lower IT investment costs. When the operating costs are reduced, in correlation, the health care costs to the consumers should also decrease.

Cloud computing is a model that provides users on- demand access to resources such as servers, platforms, networks, storage, and applications (Mell & Grance, 2011; Liu et al., 2011). With cloud technology, computing resources can be rapidly provisioned and delivered over the Internet to meet organizational computing demands (Mell & Grance, 2011; Paquette et al., 2010). Cloud computing services are scalable with little human interaction with the cloud providers (Mell & Grance, 2011; Paquette et al., 2010).

From this conceptual reference model, the cloud computing concept is further broken into cloud computing deployment and cloud computing service models. Cloud computing consists of four deployment models: private cloud, community cloud, public cloud, and hybrid cloud (Badger, Grance, Patt-Corner, & Voas, 2012; Liu et al., 2011; Mell & Grance, 2011).

Figure 1: Cloud computing conceptual reference model.



Source: NIST Cloud Computing Reference *Architecture*

Platform as a Service. PaaS provides IT professionals the necessary hardware and software access layers which allows for the development and deployment of applications without the need for IT professionals to invest in hardware and software development packages (Liu et al., 2011; Marston et al., 2010; Mell & Grance, 2011; Ryan & Loeffler, 2010; Srinivasan, 2013). As depicted in Figure 1, services including application development and testing and databases fall under PaaS. Several examples of PaaS include Relational Database Services by Amazon, App Engine by Google, Cloud Integration Platform by Fujitsu, Cloud Foundry by VMware, OpenShift by Red Hat, and WaveMaker by Pramati Technologies.

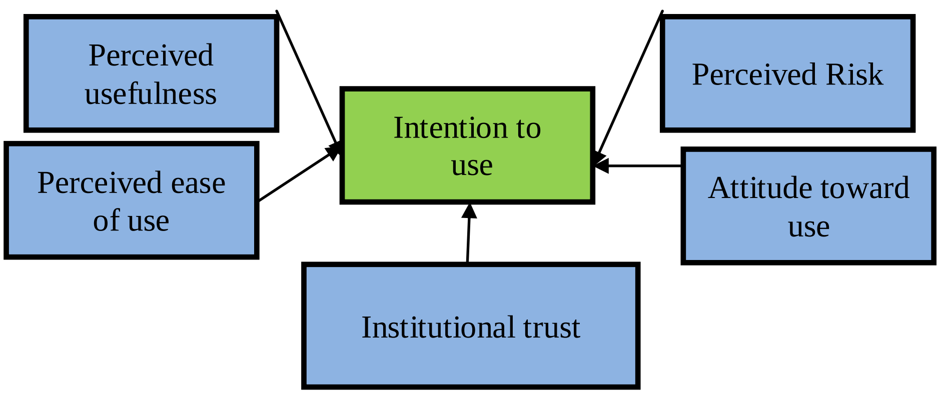
Infrastructure as a Service. As shown above, IaaS allows cloud providers to provide cloud computing capabilities, network, cloud storage, and backup and recovery to consumers (Badger et al., 2012; Liu et al., 2011;Marston et al., 2010; Mell & Grance, 201; Ryan & Loeffler, 2010; Srinivasan, 2013). Elastic Computing Cloud by Amazon, Bluelok Virtual Data Center by Bluelock, GoGrid Exchange by GoGrid, and SmartCloud Enterprise and SmartCloud+ by IBM are examples of IaaS. As the technology matures and its adoption grows, the number of cloud computing service providers has been increasing over the past several years which offer various types of cloud computing services; as the above examples indicate. It should be noted that not all cloud providers offer all three types of services. For instant, Saleforce.com and Google only offer SaaS and PaaS (Srinivasan, 2013). In addition, according to Srinivasan (2013), a 2011 study by the Ponemon Institute showed that SaaS, PaaS, and IaaS account for

55%, 11%, and 34%, respectively, of cloud computing services received from cloud providers. The increase in cloud computing usage has been clearly evident, but the question remains, how much of the increase in cloud computing usage contribute to by the health care industry?

Theoretical Framework

The underlying theoretical framework that guides this study is the original TAM conceptual framework developed by Davis (1989). However, the actual model that was used in this study is the extension of the original TAM which includes the trust and risk factors developed by Egea and González (2011). The TAM is based on the concept of users' acceptance of IT in which there are determinant factors that influence the usage behaviors of the users. In its simplest form, the original TAM conceptual model is shown below.

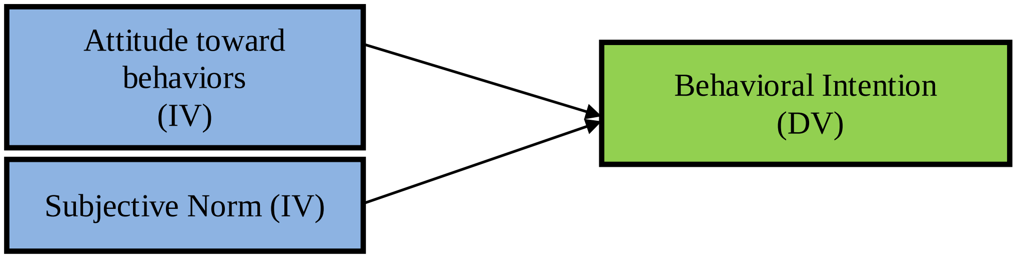
Figure 2: Conceptual model of users' acceptance of cloud computing solutions



Using this original TAM, Egea and González (2011) extended it with the risk and trust factors because these factors were believed to be relevant determinant factors that influence users' acceptance of new IT implementation. The investigation of the trust and risk factors in relation to individual's behaviors has been explored in other academic literature including Chi et al. (2012), Mayer et al. (1995), McKnight and Chervany (2002), McKnight et al. (2002) and Yarbough and Smith (2007). Therefore, Egea and González's (2011) proposed model increases the relevancy of prediction of acceptance of new IT implementations. The original TAM, Egea and González's (2011) framework, and the similarity of the constructs will be discussed in the literature review chapter.

Based on Egea and González's (2011) theoretical framework, the conceptual model used in this study is presented above.

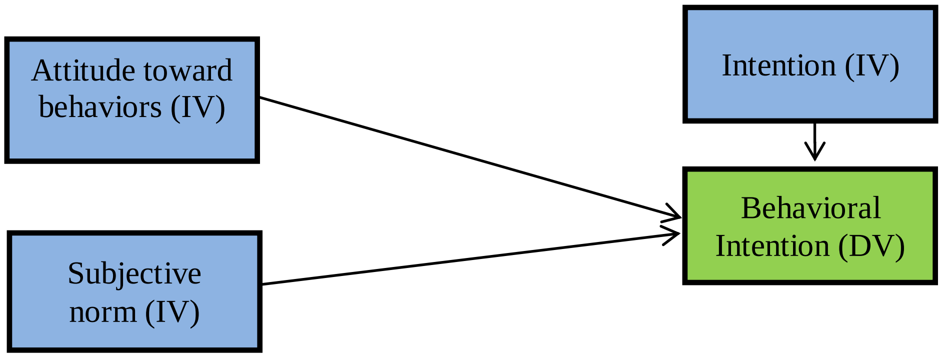
Figure 3: A simple conceptual model of TRA



The TRA was proposed by Fishbein and Ajzen (1975) and further developed by the authors in 1980. According to Chuttur (2009), TRA encompasses four foundational areas including behaviors, intentions, beliefs, and attitudes. The conceptual TRA framework includes attitude toward behaviors and subjective norm as independent constructs that have direct relationship with behavioral intentions (Davis et al., 1989; Chuttur, 2009. The TRA was aimed to predict only those behaviours that individuals have control of (Langdridge,Sheeran, Connolly, 2007). According to Davis et al. (1989) and Chuttur (2009), TRA suggests that a person's behavioural intentions are based on the subjective norm associated with the behaviour and attitude toward behaviour.To derive TPB, Ajzen (1991) added the perceived behavioural control construct to the TRA conceptual model which already has two independent variables (attitude toward behaviours and subjective norms) relating to behavioural intentions. Figure 3 shows a conceptual diagram similar to that of TRA with perceived behavioural control added. According to Langdridge et al. (2007), perceived behavioural control was added to account for behaviours that were not entirely under an individual's control. Essentially, with attitude and subjective norm being equal, as perceived control behaviour increase, an individual's intention to perform behaviour will also increase.

Regrettably, in many of the circumstances, control or behaviour intention is not quite easy to measure just before noting some actions. Some elements could be unintended or otherwise expected. Because of that, TPB advises the dimension of perceived behaviour control to be determined as the person's belief associated with how simple or hard the performance of the behavior is most likely to be (Ajzen & Madden, 1986). TPA introduces two possible versions of the model. One assumes that the impact of perceived behavior control is moderated by intent. The second one presumes a direct relationship between perceived behavioral control and actual user habits.

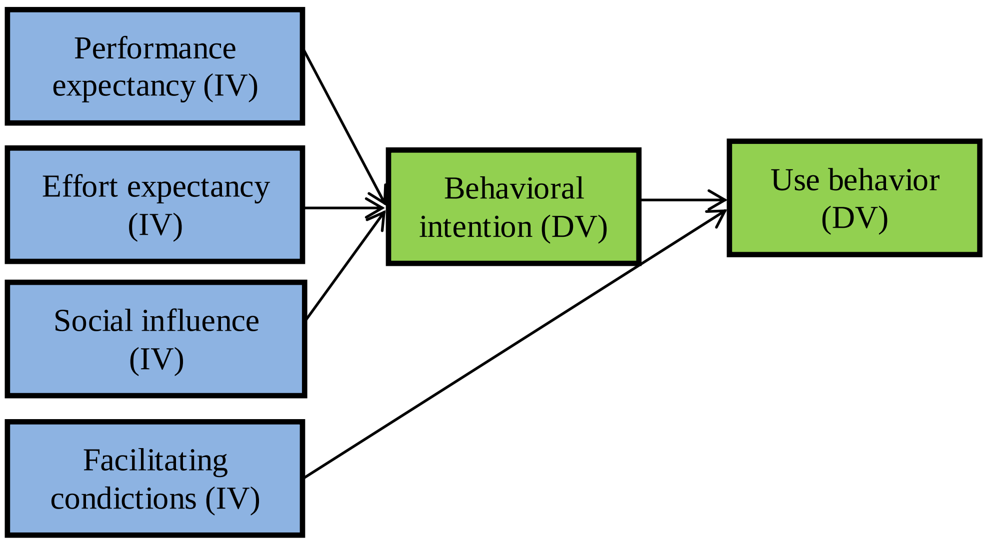
Figure 4: A simple conceptual model of TPB



Perceived behavioral control is defined as the belief of an individual's control over a behavior (Ajzen, 1991). The concept of perceived behavioral control comes from the self-efficacy theory discussed by Bandura (1997). Self-efficacy is defined as one's perception of how easy or difficult it would be to perform a behavior (Chuttur, 2009; Godin & Kok, 1996; Kraft, Rise, Sutton, & Røysamb, 2005). Godin and Kok (1996) also noted that "expectancy of success can also be viewed as a measure of perceived behavioral control. According to Kraft et al. (2005), perceived behavioral control reflects internal (skills, knowledge, etc.) and external (resource availability, others' cooperation, etc.) perceptions of an individual. In essence, an individual's abilities and preconceived notions affect his or her perception in how well he or she can perform a given task.

There have been many studies that used TPB to explain behaviors in various topics. According to Godin and Kok (1996), there were 56 health care related studies that investigate the efficiency of TPB in predicting behavioral intentions in topic areas including automotive, eating, clinical and screening, oral hygiene, exercising, HIV/AIDS, and addiction. Across those studies, empirical evidence indicated that the average variance in behaviors was 34% (Godin & Kok, 1996). Armitage and Conner (2001) further confirmed this finding by stating that as of 1997, 185 studies showed that TPB accounts for up to 37% of variance in behaviors. To further verify TPB's effectiveness, Kraft et al. (2005) applied TPB to examine exercise and recycling behaviors of college undergraduate students; perceived behavioral control, in each, had nine indicators. The authors found that, when based on all nine items in each perceived behavioral control variable, exercise and recycling has Cronbach's alphas of .83 and .89, respectively (Kraft et al., 2005).

Figure 5. A simple conceptual model of UTAUT



Venkatesh, Morris, Davis, and Davis (2003) developed the UTAUT based on eight models of technology acceptance, including their prior technology acceptance extension work. The theory was more specific to information systems, where it is used to explain the intentions and behaviors of users. Gefen, Straub, and Boudreau (2000) and Venkatesh et al. (2003) stated that an individual's perception of the effort required to learn and use a new technology will influence the individual's intention and usage behavior toward that technology. Therefore, if the required effort to learn and use a new technology is much greater than expected, then the likelihood of acceptance of the new technology will decrease.

The eight models that were used to derive UTAUT include the TRA, TPB, TAM, social cognitive theory, diffusion of innovation theory, motivational theory, model of personal computer use, and a combined of TPB/TAM (Venkatesh et al., 2003; Sun, Wang, Gou, & Peng, 2013). From these models, four main constructs were derived including performance expectancy, effort expectancy, social influence, and facilitating conditions as predictors of behavioral intention and usage behavior (Sandberg & Wahlberg, 2006; Sun et al., 2013). Venkatesh et al. (2003) and Park, Yang, and Lehto (2007) posited that voluntariness of use, gender, age, and experience are key moderators between the four main constructs and behavioral intention. Venkatesh et al (2003) provided the following definitions for the constructs.

(a) Performance expectancy is defined as user's perception of how technology will help with their job performance.

(b) Effort expectancy is defined as user's perception of the effort required to use the technology.

(c) Social influence is defined as the degree of an individual's perception of how others believe the individual should use the new technology. This variable is similar to the subjective norm in TRA and TPB.

d) Facilitating conditions is defined as user's perception of technology support provided by the IT infrastructure and the organization.

The TAM is considered one of the most influential models in technology research that has been continuously studied and modified. One modified version of the TAM is the TAM 2, which included five additional constructs that was believed to directly affect perceived usefulness including subjective norm, image, job relevance, output quality, and result demonstrability (Venkatesh & Davis, 2000). In this model, the authors also added experience and voluntariness as moderating factors between subjective norm and perceived usefulness (Venkatesh & Davis, 2000). Follow-on to the TAM 2, the TAM 3 was developed. In TAM 3, factors that directly affect perceived ease of use were added including computer self-efficacy, perceptions of external control, computer anxiety, computer playfulness, perceived enjoyment, and objective usability (Venkatesh & Bala, 2008). The authors posited that TAM 3 has a complete set of factors that influence users' acceptance and adoption of new IT (Venkatesh & Bala, 2008). Lastly, another modification of the TAM resulted in the UTAUT, which has been previously discussed.

The well-known and well-researched TAM proved its popularity, but the TAM has also received much criticism since its publication. Bagozzi (2007) and Burton-Jones and Straub (2006) stated that the TAM does not relate system usage to the accomplishment of users' goals and objectives. In addition, since subjective norm was not included in the TAM, social factors (social process and social consequences) and emotional influence were not addressed (Bagozzi, 2007; Venkatesh & Morris, 2000). Benbasat and Barki (2007) further stated that research using the TAM lacks focus on the important factors of IT artifact design and evaluation. Thus, the authors posited that research that employed the TAM does not provide many important consequences of IT acceptance and adoption (Benbasat & Barki, 2007).

METHODOLOGY

Research Design

A data collection service provider, SurveyMonkey, was used in this study. A data collection service provider was used because the provider has wider access to the population; in this case, doctors and nurses among Malaysian. Participants for this study were randomly selected from the population of doctors and nurses working in hospitals in Klang Valley which were invited through blast emails. The sample size for the actual study was calculated using the

GPower 3.1.7 software based on the number of IVs (predictors). This method is consistent with Vogt's (2007) recommendation of using the number of predictors to determine the appropriate sample size. This calculation resulted in a minimum sample size of 138 participants for the actual study. Since the instrument was given to a different population than the population Egea and González (2011) has used, a pilot study was conducted prior to the actual study. Based on recommendations from Hertzog (2008), Julious (2005), Lancaster, Dodd, and Williamson (2004), and Sim and Lewis (2012), a minimum sample size of 30 was estimated for the pilot study.

The data for pilot and actual studies was collected via an online survey administered by SurveyMonkey. The survey instrument was administered once to randomly selected participants during pilot and actual studies. The first page of the survey required participants to complete the Informed Consent form in which non- agreement with the consent form terminates participation. Collected data was partially cleaned to remove monolithic responses before the raw dataset was exported to SPSS format, downloaded, and stored encrypted on local computer for further analysis.

Sample of Population

The population of interest for this study consists of the doctors and nurses working in Klang Valley's hospitals. This population was chosen because doctors and nurses are a subset of the most critical users who utilize health care IT systems daily when seeing patients or conducting medical research. Moreover, they are more likely to have stronger influence on management's decision to adopt new IT. The sampling frame for this study was all doctors and nurses working in hospitals in Klang Valley who have been invited through emails. The sampling criteria include male and female doctors and nurses working in public or private hospitals regardless of age, experience, or IT training and knowledge. Other health care related professionals such as health care IT professionals, health care clerks, and health care administrators were excluded from the selection. The minimum sample size estimated for the actual study was 140. This means that SurveyMonkey was contracted to deliver a minimum of 140 completed survey responses. As described previously, the GPower 3.1.7 software program was used to calculate the sample size. The sample size of 140 was a rounded up from 138, which was calculated using the default parameters for liner multiple regression statistical test with five predictors. Prior to the actual study, a pilot study was conducted in which SurveyMonkey was contracted to deliver a minimum of 30 completed survey responses. Participants for the pilot study were kept separated from those selected for the actual study.

As noted earlier, SurveyMonkey data collection service was used to recruit participants and collect the data. Therefore, the sampling procedure followed the procedures employed by SurveyMonkey to randomly select participants based on the inclusion and exclusion criteria as described above. While the researcher created the web-based survey, the SurveyMonkey project manager launched the survey to collect the data, and thus, there was no interaction between the researcher and the participants. The data type for this study is interval data. The Likert-type variables are linear combinations of responses to the corresponding Likert questions; i.e. the average response to the Likert-type questions for any given observation or survey response associated with that Likert variable is computed. In this study, the Central Limit Theorem is invoked which states that the mean of a sufficiently large number (more than 30) of iterates of independent random variables, each with a well-defined mean and a well-defined variance, will be approximately normally distributed (Field, 2009).

Instrumentation/Measures

Using the original TAM model developed by Davis (1989), Egea and González (2011) extended it with the risk and trust factors. The variables from the existing instrument survey include perceived usefulness, perceived ease of use, attitude toward use, intention to use, institutional trust, perceived risk, and information integrity. The trust and risk factors were added to the original TAM because these factors were believed to be relevant determinant factors which influence users' acceptance of new IT implementation (Egea & González, 2011). The investigation of trust and risk factors in relation to individual's behaviors has been explored in other academic literature including Mayer et al. (1995), McKnight et al. (2002), and Yarbough and Smith (2007). Therefore, Egea and González's (2011) proposed theory increases the relevancy of prediction of IT acceptance. In terms of instrument's reliability and validity, according to Egea and González (2011), the results were as follows:

The constructs used in this research were a subset of the constructs in the extended TAM for health care developed by Egea and González (2011). Adapted from the extended TAM, the model used in this study has six constructs which include five predictors (IVs) and an outcome variable (DV). The five IVs include perceived usefulness, perceived ease of use, attitude toward use, perceived risk, institutional trust, which was assumed to have direct relationship with the intention to use (DV).

Data Analysis

The TAM model has been used in its original or extended forms in over 500 studies of health care technology implementations. In these studies, parametric and non- parametric tests have been used to determine the relationship and strength between the variables in a specified model. For example, Egea and González (2011) used Structural Equation Modeling and Confirmatory Factor Analysis to test the hypotheses and provide the psychometric properties for the instrument. Descriptive statistics provides an insight into the characteristics of the data (Vogt, 2007). Thus, for descriptive statistics, the raw data was explored to determine its completeness and to provide a summary of the data's characteristics. The research question in this study is intended to explore the relationship between several IVs (predictors) and the outcome variable. According to Field (2009), "regression analysis is a way of predicting an outcome variable from one… or several predictor variables" Vogt (2007) and Field (2009) also mentioned that interval data can be analyzed using parametric (linear regression analysis) procedures.

EMPIRICAL RESULTS AND DISCUSSION

Table 1: Frequency Distribution of Gender and Professional Work Title

	Female		Male	
	Frequency	Percentage	Frequency	Percentage
Medical Doctors	16	8.89%	12	6.67%
Registed Nurse	136	75.56%	9	5.00%
Nurse Practioner	7	3.89%	0	0.00%

Note. N=180

Table above provides the central tendency of the data for the six variables in this study. The small standard deviation (relative to the mean) means that the data is grouped close together resulting in a pointy distribution (Field, 2009). The small standard error of mean relative to the sample mean, as shown in Table 1 , indicated that the "sample is likely to be an accurate reflection of the population" (Field, 2009). On the average, approximately 58.4% (combined average percentage of SA and A for PU) of participants believed cloud computing solutions would be useful in their job. Similar observation is true for PEOU with the average of 53.8% of participants believed that cloud computing is easy to use. In addition, approximately 73.9% of participants (combined average percentage of SA and A for BI) intended to use cloud

computing if they have access to it. About 66.30% of participants displayed positive attitude toward cloud computing solutions and 58.4% of participants have confidence in cloud computing solutions in terms of its functions and benefits; due to reverse-worded of A2 and ITrust2, percentages of D and SD were used to calculate the average percentage. Finally, approximately 61% of participants perceived cloud computing solutions to be categorized as a low risk technology in the health care environment (percentages of D and SD of PRisk were used in calculation). Standard regression analysis and multiple linear regression analysis were used to address the omnibus research question and its corresponding hypotheses. An alpha level of $p < .05$ with a confidence level of 95% is assumed for this study.

To test the first set of hypotheses (H01 and HA1), standard regression analysis was conducted for individual IV and the DV. Detailed results are presented in below table. For PU, A, PEOU, and PRisk, the results showed that the relationship between the each IV and the DV is statistically significant ($p < .001$) and that the fit of the observed DV value to those predicted by the regression equation is better than what one would expect by chance. Therefore, for PU, A, PEOU, and PRisk, the null hypothesis (H01) is rejected and the alternate hypothesis (HA1) is accepted. However, the results also showed that while there was a relationship between ITrust and BI, that relationship is not significant ($p > .001$) and that the fit of the observed DV value to those predicted by the regression equation is not better than what one would expect by chance. Thus, for ITrust, the null hypothesis (H01) is not rejected.

To test the second set of hypotheses (H02 and HA2), a hierarchical multiple linear regression analysis was performed with the first block include one IV and each subsequence block has an additional IV added, thus increasing the number of IV for each block by one. That is, block one includes PU. Block two includes PU and A. Block three includes PU, A, and PEOU. Block four includes PU, A, PEOU, and PRisk. Block five includes PU, A, PEOU, PRisk, and ITrust. Detailed results for the multiple regression analysis are presented belows table too. For PU, A, PEOU, and PRisk, the results showed that adding an individual IV to the multiple regression model does improve the fit of the regression equation; i.e. R2 for each IV is different from zero. Therefore, for PU, A, PEOU, and PRisk, the null hypothesis (H02) is rejected and the alternate hypothesis (HA2) is accepted. However, the results showed that ITrust makes zero contribution to the prediction of BI, and thus does not improve the fit of the regression equation; i.e. R2 equal to zero. Hence, for ITrust, the null hypothesis (H02) is not rejected.

Table 2: Regression Analysis for Perceived Usefulness (PU)

	B	SE B	β	t	Sig.
(Constant)	0.557	0.13		4.295	.000
PU	0.692	0.091	0.716	13.699	.000

Note. R2 = .513; adjusted R2 = .510; F(1, 178) = 187.671, p < .001.

The regression analysis for PU is shown above. There was a significant relationship between PU and BI, Pearson r = .716, p (one-tailed) < .001. The result indicated that PU (t(178) = 3.801, p < .001) is a significant contributor of BI. R2 (.513) shows that PU accounts for 51.3% of variation in BI. Moreover, the difference between R2 and adjusted R2 (.510) is only .003; as shown in Table 2. This means that if the model is derived from the population, it would account for 0.3% less variance in BI. The regression analysis for A is shown in Table below. There was a significant relationship between A and BI, Pearson r = .694, p (one-tailed) < .001. The result indicated that A (t(178) = 12.857, p < .001) is a significant contributor of BI. R2 (.482) shows that A accounts for 48.2% of variation in BI. Moreover, the difference between R2 and adjusted R2 (.479) is only .003; as shown below. This means that if the model is derived from the population, it would account for 0.3% less variance in BI.

Table 3: Regression Analysis for Attitude Toward Use (A)

	B	SE B	β	T	Sig.
(Constant)	-1.221	.272		-4.482	.000
	1.248	..097	.69	12.857	.000

Note. R2 = .482; adjusted R2 = .479; F(1, 178) = 165.304, p < .001.

Table 4: Regression Analysis for Perceived Ease of Use (PEOU)

	B	SE B	β	t	Sig.
(Constant)	.390	.165		2.370	.019
PEOU	.736	.063	.658	11.662	.000

Note. R2 = .433; adjusted R2 = .430; F(1, 198) = 136.012, p < .001.

The regression analysis for PEOU is shown above. There was a significant relationship between PEOU and BI, Pearson r = .658, p (one-tailed) < .001. The result indicated that PEOU (t(178) = 12.857, p < .001) is a significant contributor of BI. R2 (.433) shows that PEOU accounts for 43.3% of variation in BI. Moreover, the difference between R2 and adjusted R2 (.430) is only .003; as shown in Table 3. This means that if the model is derived from the population, it would account for 0.3% less variance in BI.The regression analysis for PRisk is shown in Table 4. There was a significant relationship between PRisk and BI, Pearson r = -.554, p (one-tailed) < .001. The result indicated that PRisk (t(178) = -8.877, p < .001) is a significant contributor of BI. R2 (.307) shows that PRisk accounts for 30.7% of variation in BI. Moreover, the difference between R2 and adjusted R2 (.303) is only .004; as shown in Table 4. This means that if the model is derived from the population, it would account for 0.4% less variance in BI.

Table 5: Regression Analysis for Perceived Risk (PRisk)

	B	SE B	B	t	Sig.
(Constant)	4.493	.260		17.303	.000
PRisk	-.638	.072	-.554	-8.877	.000

Note. R2 = .307; adjusted R2 = .303; F(1, 178) = 78.802, p < .001.

Table 6: Regression Analysis for Institutional Trust (ITrust)

	B	SE B	β	t	Sig.
(Constant)	1.624	.416		3.901	.000
ITrust	.211	.143	.110	1.479	.141

Note. R2 = .012; adjusted R2 = .007; F(1, 178) = 2.188, p > .001.

The regression analysis for ITrust is shown above. There was a relationship between ITrust and BI but the relationship was not significant, Pearson r = .110, p (one- tailed) > .001. The result indicated that ITrust (t(178) = 1.479, p > .001) is not a significant contributor of BI. R2 (.012) shows that ITrust accounts for 1.2% of variation in BI. Moreover, the difference between R2 and adjusted R2 (.007) is only .005.This means that if the model is derived from the population, it would account for 0.5% les variance in BI. For PU, A, PEOU, and PRisk, the results showed that the relationship between each IV and the DV is statistically significant and that the fit of the observed DV value to those predicted by the regression equation is better than what one would expect by chance. Therefore, the null hypothesis (H01) for PU, A, PEOU, and PRisk is rejected and the alternate hypothesis (HA1) is accepted. However, for ITrust, the results showed that the relationship between ITrust and BI is not statistically significant and that the fit of the observed DV value to those predicted by the regression equation is not better than what one would expect by chance. Hence, the null hypothesis (H01) for ITrust is not rejected.

As mentioned earlier, to test the second hypothesis, a hierarchical regression analysis was performed. The regression coefficients for each step (block) of the five- block regression model are provided below. The multiple regression model summary is shown below too. In the final model, Model 4, the resulting R2 (.658) shows that PU, A, PEOU, and PRisk account for 65.8% of variation in BI. Additionally, the difference between adjusted R2 (.650) and R2 is .005. This means that if the model is derived from the population, it would account for 0.5% less variance in the BI.

Table 7: Regression Analysis - a Hierarchical Regression Model

	B	SE B	β
Step 1			
(Constant)	.557	.130	
PU	.692	.051	.716
Step 2			
(Constant)	-.837	.243	
PU	.446	.059	.462
A	.719	.110	.400
Step 3			
(Constant)	-1.130	.240	
PU	.253	.071	.262
A	.707	.105	.393
PEOU	.318	.072	.284
Step 4			
(Constant)	-.302	.426	
PU	.238	.071	0.246
A	.658	.105	0.366
PEOU	.266	.075	0.237
PRisk	-.149	.064	-0.129
Step 5			
(Constant)	-0.360	.443	
PU	.234	.071	.242
A	.654	.106	.364
PEOU	.261	.075	.233
PRisk	-.16	.067	-.139
ITrust	.046	.091	.024

Note. Dependent Variable: BI

Table 8: Multiple Regression Analysis – Model Summary

Measure	Frequency (N=180)					Percentage				
	SA	A	N	D	SD	SA	A	N	D	SD
PU										
PU1	22	77	60	18	3	12.50%	42.80%	33.30%	10%	1.70%
PU2	24	69	56	25	6	13.30%	38.30%	31.10%	13.90%	3.30%
PU3	27	76	55	17	5	15%	42.20%	30.60%	9.40%	2.80%
PU4	30	95	41	10	4	16.70%	52.80%	22.80%	5.60%	2.20%
PEOU										
PEOU1	17	86	60	13	4	9.40%	47.80%	33.30%	7.20%	2.20%
PEOU2	16	82	52	28	2	8.90%	45.60%	28.90%	15.60%	1.10%
PEOU3	15	73	71	18	3	8.30%	40.60%	39.40%	10%	3%
PEOU4	16	84	66	10	4	8.90%	46.70%	36.70%	5.60%	2.20%
A										
A1	26	90	47	13	4	14.40%	50%	26.10%	7.20%	2.20%
A2	3	13	45	100	19	1.70%	7.20%	25%	55.60%	10.60%
A3	22	101	40	13	4	12.20%	56.10%	22.20%	7.20%	2.20%

Table 8….

ITrust										
ITrust1	19	97	44	16	4	10.60%	53.90%	24.40%	8.90%	2.20%
ITrust2	6	28	52	80	14	3.30%	15.60%	28.90%	44.40%	7.80%
PRisk										
PRisk1	9	42	47	72	10	5%	23.30%	26.10%	40%	5.60%
PRisk2	1	12	45	99	23	0.60%	6.70%	25%	55%	12.80%
PRisk3	2	18	43	97	20	1.10%	10%	23.90%	53.90%	11.10%
PRisk4	2	22	38	97	21	1.10%	12.20%	21.10%	53.90%	11.70%
BI	24	109	30	15	2	13.30%	60.60%	16.70%	8.30%	1.10%

Note. SA = *Strongly Agree*; A = *Agree*; N = *Neutral*; D = *Disagree*; and SD = *Strongly Disagree*

In more detail, the results showed that in Model 1, PU accounts for 51.3% of variation in BI. When A was added, Model 2 accounts for 60.8% of variation in BI, and thus, A accounts for 9.5% of variation in BI. Model 3 shows R2 increased to .647 when PEOU was added, which means that PEOU accounts for 3.9% of variation in BI. Hence, Model 3, with all three predictors, accounts for 64.7% of variation in BI. When PRisk was added to Model 4, the cumulative model accounts for 65.8% of variation in BI, which means PRisk accounts for 1.1% of variance in BI. However, in Model 5, when ITrust was added, R2 remains the same as it was in Model 4. This clearly showed that ITrust makes no contribution to the prediction of BI.

Table 9: ANOVA Analysis – Assessing Model Fit

ANOVAa

Model		Sum of squares	*df*	Mean Square	F	Sig.
1	Regression	62.716	1	62.716	187.671	.000b
	Residual	59.484	178	0.334		
	Total	122.2	179			
2	Regression	74.327	2	37.163	137.403	.000c
	Residual	47.873	177	0.27		
	Total	122.2	179			
3	Regression	79.081	3	26.36	107.596	.000d
	Residual	43.119	176	0.245		
	Total	122.2	179			
4	Regression	80.39	4	20.097	84.119	.000e
	Residual	41.81	175	0.239		
	Total	122.2	179			
5	Regression	80.45	5	16.09	67.057	.000f
	Residual	41.75	174	.240		
	Total	122.2	179			

Note. a. Dependent Variable: BI

b. Predictors: (Constant), PU c. Predictors: (Constant), PU, A

d. Predictors: (Constant), PU, A, PEOU e. Predictors: (Constant), PU, A, PEOU, PRisk

f. Predictors: (Constant), PU, A, PEOU, PRisk, ITrust

For Model 1, the F-ratio is 187.671 which is significant ($p < .001$). For Model 2, the F-ratio is 137.403 and is also significant ($p < .001$). For Model 3, the F-ratio is 107.596 and is significant ($p < .001$). Further, when adding PRisk and ITrust to Model 4 and 5, respectively, the F-ratios of 84.119 and 67.057 which are significant ($p < .001$). For PU, A, PEOU, and PRisk, since adding an individual IV to the multiple regression model does improve the fit of the regression equation; i.e. R2 for each predictor is different from zero. Therefore, the null hypothesis (H02) for PU, A, PEOU, and PRisk is rejected and the alternate hypothesis (HA2) is accepted. However, when adding ITrust to the multiple regression model, it does not improve the fit of the regression equation; i.e. R2 for ITrust is zero. Therefore, for ITrust the null hypothesis (H02) is not rejected.

Figure 6: Histogram of residual distribution.

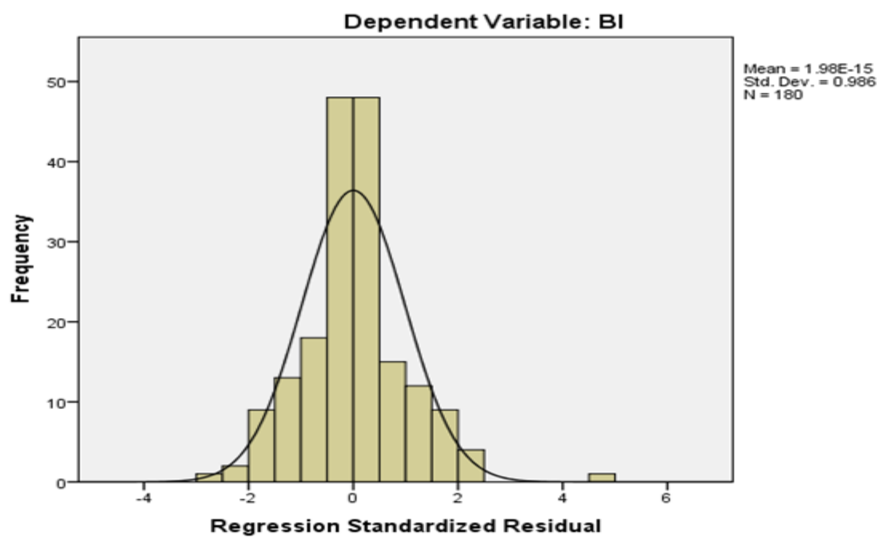


Figure 7: P-P plot of residual distribution

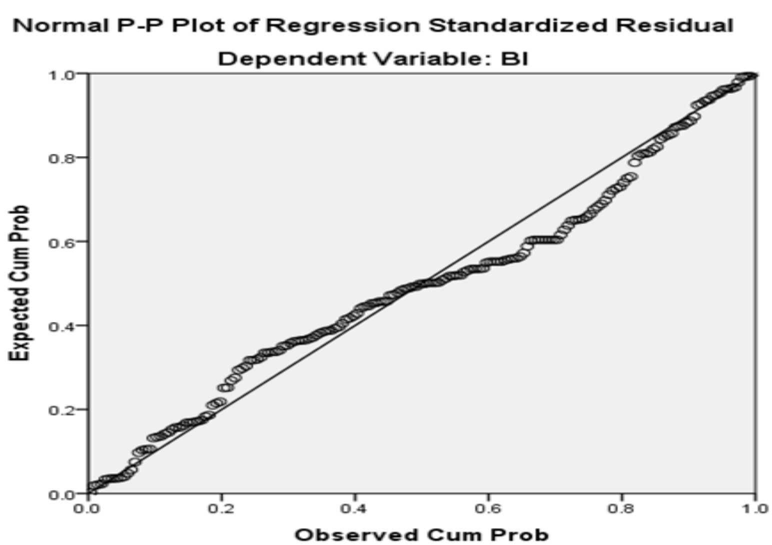
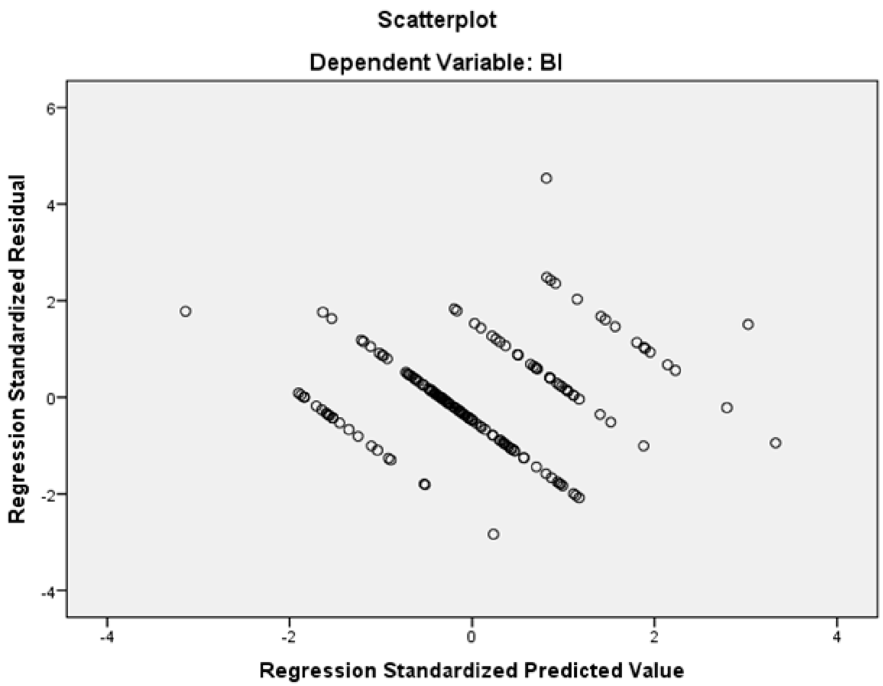


Table 10. Multicollinearity Analysis

Variable	Tolerance	VIF
PU	0.366	2.733
A	0.571	1.751
PEOU	0.439	2.278
PRisk	0.642	1.557

Figure 8: Plot of *ZRESID against *ZPRED



Based on the regression results for PRisk and ITrust as described in above, additional regression analyses were performed to include gender as another independent variable, to determine its effects on PRisk and ITrust in the prediction of the outcome. The results were interesting in that they were not consistent for ITrust. Results showed that ITrust accounts for 3.5% of variance in the outcome even though the contribution was not significant ($p < .001$). However, when ITrust was added, R2 for Model 5 remains the same as R2 for Model 4. With that said, the overall R2 of the final regression model (Model 4) has increased to .664, with gender included in the analysis.

Table 11: Multiple Regression Analysis for Gender, PRisk, and ITrust

Model	R	R^2	Adj R^2	Std.Error of the Estimate	R^2 Change	F Change	*df1*	*df2*	Sig. F Change	D-W
1	.573a	.329	.321	.68073	.329	43.352	2	177	.000	
2	.603b	.364	.353	.66456	.035	9.723	1	176	.002	2.458

Note. a. Predictors: (Constant), PRISK, Gender

b. Predictors: (Constant), PRISK, Gender, ITRUST

c. Dependent Variable: BI

Table 12: Multiple Regression Analysis for all IV Along with Gender as Another IV

Model	R	R^2	Adj R^2	Std.Error of the Estimate	R^2 Change	F Change	*df1*	*df2*	Sig. F Change	D-W
1	.721a	.520	.515	.57542	.520	96.031	2	177	.000	
2	.785b	.616	.609	.51652	.095	43.667	1	176	.000	
3	.808c	.652	.644	.49277	.037	18.380	1	175	.000	
4	.815d	.664	.654	.48594	.012	5.953	1	174	.016	
5	.815e	.664	.652	.48721	.000	.094	1	173	.759	2.407

Note. a. Predictors: (Constant), PU, Gender

b. Predictors: (Constant), PU, Gender, A

c. Predictors: (Constant), PU, Gender, A, PEOU

d. Predictors: (Constant), PU, Gender, A, PEOU, PRISK

e. Predictors: (Constant), PU, Gender, A, PEOU, PRISK, ITRUST

f. Dependent Variable: BI

CONCLUSION

To address the research problem and the research question, a quantitative approach was employed to measure users' perceptions and determine the factors that influence users' technology acceptance. This quantitative approach utilized a survey instrument based on the well-tested TAM (Davis, 1989; Davis et al., 1989; Egea & González, 2011). Pilot testing confirmed the validity and reliability of the survey instrument in the context of cloud computing solutions research related to health care in Malaysia. The actual study resulted in a total of 180 valid responses with no missing data, which was more than the expected minimum sample size of 140.Standard and multiple regression analysis techniques were used to analyze the survey data in order to address the research question and its corresponding hypotheses. The findings supported the hypotheses for four variables (PU, A, PEOU, and PRisk), indicating significant and positive relationship between PU, A, PEOU and the intention to use cloud computing solutions. In addition, the findings indicate significant but inverse relationship between perceived risk and users' intention to use cloud computing solutions. The findings also demonstrated that each predictor, except for institutional trust, contributed to the increase in the predictive power of users' acceptance of cloud computing solutions. Moreover, based on the multiple regression analysis, it is concluded that perceived usefulness and attitude toward use were shown to be the strongest determinant factors of users' acceptance of new IT solutions.

LIMITATIONS

The outcome of the study was not exactly as expected, especially with the low contribution of perceived risk to the prediction of the outcome and zero contribution of institutional trust. As mentioned in the discussion section, the findings could be affected by the inherent limitation in the study. The first limitation in this study was the exclusion of other users including laboratory technicians, physician assistants, and medical research assistants, due to time constraints. These groups of users are likely to use more IT applications (or cloud computing solutions) in their job functions, and therefore, they should have been included in this study. The second limitation was the exclusion of possible predictors that are likely to have significant influence on users' perceptions and attitude such as gender, users' IT knowledge, user knowledge and experience with cloud computing, and users' attitude toward IT security. The third limitation is the reliance on third party for data collection, due to time and budget constraints. While there were clear benefits to use a data collection service provider, some aspects of random sampling were not within the control of the researcher, which could affect the findings. For example, the findings showed that the majority of participants in this study were female. It could be that there were more female than male registrants in SurveyMonkey's proprietary database, or perhaps the random selection process or algorithm selects an unequal number of male and female respondents for the study.

RECOMMENDATION FOR FURTHER RESEARCH

First, future studies should expand the population to include laboratory technicians, medical research assistants, and physician assistants because they are also critical users of health IT systems. This inclusion should further clarify one of the factors that influence the research findings. Second, future studies should include other predictors that may have influence on users' intention to use cloud computing solutions in health care such as gender, IT education, IT experience, knowledge of health care regulations, and IT security knowledge. Third, it is always suggested that larger sample size is better because it is more representative of the population and thus, increasing the accuracy of the prediction (Field, 2009; Vogt, 2007). Therefore, future inquiries of this study, or similar research, should take into consideration to increase the minimum sample size.

Fourth, if a third party was used for data collection, it is recommended that the sampling criteria should include a specification for random sampling of an equal number of male and female participants. This might be an important factor to consider because the majority of male or female participants would likely result in gender-bias which could impact the findings due to varying perceptions on things including technology (Chinyamurindi & Louw, 2010; Gefen & Straub, 1997).

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