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PATIENTS' ACCEPTANCE AND RESISTANCE TOWARD THE HEALTH CLOUD: AN INTEGRATION OF TECHNOLOGY ACCEPTANCE AND STATUS QUO BIAS PERSPECTIVES

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Abstract

The latest technological trends such as health cloud provide a strong infrastructure and offer a true enabler for healthcare services over the Internet. Despite its great potential, there are gaps in our understanding of how users evaluate change related to the health cloud and decide to resist it. According to the technology acceptance and status quo bias perspectives, this study develops an integrated model to explain patients' intention to use and resistance to health cloud services. A field survey was conducted in Taiwan to collect data from patients. The structural equation model was used to examine the data. The results showed that patient resistance to use was caused by inertia, perceived value, and transition costs. Perceived usefulness (PU) and perceived ease of use (PEOU) have positive and direct effects on behavioral intention to use, and PEOU appears to have a positive direct effect on PU. The results also indicated that the relationship between intention to use and resistance to use had a significant negative effect. Our study illustrates the importance of incorporating user resistance in technology acceptance studies in general and health technology usage studies in particular, grounds for a resistance model of resistance that can serve as the starting point for future research in this relatively unexplored yet potentially fertile area of research.

Keywords: Health cloud, User resistance, Technology acceptance, Status quo bias.

1 INTRODUCTION

In recent years, software functions have moved from the individual's local hardware to a central server that operates from a remote location (Klein 2011). This centralization is called cloud computing. Cloud computing provides a facility with access to shared resources and a common infrastructure in a ubiquitous and pervasive manner, offering services on demand over the network to perform operations that meet changing needs in healthcare applications (Nur & Moon 2012). In addition, it is also providing one of the most promising opportunities to reduce technology and treatment costs within healthcare (Mathew 2013). Since 1995, the Bureau of National Health Insurance has been providing comprehensive health-care coverage for the majority of the 23 million people living in Taiwan. The majority of patients tend to visit several hospitals throughout their lives, and "hospital shopping" has become a relatively common occurrence in Taiwan. Thus, the department of health (DOH) intends to build a health platform by storing individual health information and medical records in the health cloud. Patients' health-related information on the health cloud will allow more efficient access for hospitals across Taiwan. However, for these information technology-enabled benefits to materialize, patients must first accept or adopt the health cloud, such as obtaining health information and providing healthcare from the website of the health cloud.

The information system (IS) literature has focused on technology adoption, acceptance, and use as a means of realizing the value of new technology investments (Ajzen 1985; Davis 1989; Taylor & Todd 1995; DeLone & McLean 1992, 2003). A number of preceding studies on IS usage measures have recommended some critical factors in technology acceptance. For example, Davis (1989) introduced the technology acceptance model (TAM) especially for modelling user acceptance of IS. He proposed that two beliefs (perceived usefulness and perceived ease of use) predict an individual's technology usage intention. However, user resistance is unavoidable to management and may cause performance to be lower than expected. As a result, organizations suffer defeat in new technology investment. (Norzaidi et al. 2008a). There is great resistance point in health information technology (IT) to the adoption of cloud computing due to patient information security and privacy (Mathew 2013). While some of the resistance can be explained in terms of individual or environmental factors, it must also be considered that system design and function play a role (Cenfetelli 2004). In fact, user resistance demonstrates asymmetric behaviors typical of inhibitors because the presence of resistance hurts IS usage, but lack of resistance does not necessarily enhance IS usage (Cenfetelli 2004). Thus, there is a need to investigate the critical factors that stimulate technology acceptance and resistance as well as to examine the relationship between intention to use and resistance to using the health cloud.

Prior research on IS usage has largely ignored the problem of user resistance, and prior research on user resistance has been limited. Cenfetelli's (2004) dual-factor model therefore provides a theoretical bridge to link research on IS usage and resistance to change within an integrated model (Bhattacharjee & Hikmet 2007). Cenfetelli's (2004) study was motivated by the observation that extant theories of IS usage, such as the TAM (Davis 1989), have focused almost exclusively on users' positive (enabling) perceptions related to IS usage (e.g., perceived usefulness and ease of use) while ignoring negative (inhibiting) perceptions that may hinder IS usage. Although Cenfetelli (2004) did not identify any specific inhibitor of IS usage, based on our literature review, the status quo bias perspective provides a set of useful theoretical explanations for understanding the impact of maintaining the current status or situation as inhibiting perceptions (e.g., sunk costs, regret avoidance, inertia, perceived value, transition costs, and uncertainty) of IS usage (Kim & Kankanhalli 2009).

According to Cenfetelli's (2004) dual factor model of IS usage, we propose that a user's intention to use the health cloud is based on both the traditional enablers of IS usage, such as the perceived usefulness and perceived ease of use of IS usage, as well as inhibitors such as sunk costs, regret avoidance, inertia, perceived value, transition costs, and uncertainty. From a practical standpoint, understanding why users resist and use the health cloud and how such resistance is manifested in their subsequent behavior can help governmental agencies and healthcare administrators devise appropriate intervention strategies for minimizing user resistance and their effect on the healthcare policy. Therefore, our study objectives are as follows: (a) to investigate whether resistance to use significantly affects patient behavioral intentions of use the health cloud; (b) to investigate whether

intentions of use significantly affect patient resistance to use of the health cloud; (c) to clarify which enablers are more influential on the decision to use the health cloud; and (d) to clarify which inhibitors are more influential on the decision to resist the health cloud.

2 BACKGROUND

Despite emerging interest in the field of medical informatics and studies that have identified the application of the merits of the health cloud (Coles-Kemp et al. 2011; Piette et al. 2011; Kim & Kim 2012; Botts et al. 2012; Nur & Moon 2012; Mathew 2013; Jaswanth et al. 2013; Kaur & Chana 2014)) and security and privacy issues associated with the health cloud (Klein 2011; Shini et al. 2012; AbuKhouza et al. 2012; Thilakanathan et al. 2013), only a limited understanding of patient behavior exists concerning the health cloud. In addition, despite the importance of understanding and managing user resistance for the success of a new technology implementation (Joshi 1991; Kim & Kankanhalli 2009), few studies have proposed theoretical explanations of user acceptance and resistance. Thus, current of the problem may have been the lack of a generalized theory of user resistance and its lack of grounding within an established stream of research. In the next section, we attempt to build such a research framework while grounding it in the IS acceptance and resistance to change literatures.

2.1 Health cloud

Most healthcare IT infrastructure needs a massive upgrade to capture and share information easily and to make healthcare organizations more intelligent and to manage the data. Cloud computing provides computation, software, data access, and storage services that do not require users' knowledge of the physical location and configuration of the system that delivers the services (Mathew, 2013). Hospitals in Taiwan usually employ their own medical staff and do not allow physicians practicing in community clinics to practice medicine at their hospitals. Therefore, patient care at a clinic is disconnected once the patient is referred to a hospital by a community physician for further care at the hospital and vice versa when the patient is referred back to the clinic after the completion of care at the hospital unless the patient makes a copy of his or her medical records and brings it to the care provider offline. Thus, the department of health (DOH) intends to build a health cloud by storing individual personal health information and medical records in the health cloud. The cloud platform will facilitate the management of personal digital medical records and cut waste resulting from overlapping medical treatment. The content of the health cloud program is as follows: (a) a medical cloud for sharing electronic medical records (EMR) across facilities in different hospitals; (b) a care cloud so that wireless patient monitoring devices can allow for the monitoring of blood pressure, heart rate, and glucose, to name a few, and enable a patient's health data to be transmitted between different locations; and (c) a wellness cloud that uses open data and cloud platforms to encourage value-added service providers to develop various innovative applications, thereby allowing people at any time to obtain health-related information to enhance self-health management. Based on the health cloud program, the DOH last year began work on a medical cloud, creating a cloud platform for the exchange of EMRs and selecting the Fuxing Township in Taoyuan County for its pilot program. Considering the relative underdevelopment of Fuxing's computer and medical systems, it was a bold choice for the program. The transmission of EMRs over the Internet and the sharing of that data via the cloud are turning out to be crucial to providing better care in remote areas. In the coming years, the DOH will build a care cloud and a wellness cloud to enhance the vision of national health management. In the future, anyone who registers a personal account will be able to access the platform to store, manage, and share personal health information through a cloud platform. Therefore, patients' acceptance of and support for the health cloud is particularly critical in Taiwan, where healthcare provider rivalry and the fee-for-service third-party payment system pose additional obstacles to health cloud implementation.

2.2 Technology Acceptance and Resistance

When an innovative technology is implemented, users may decide to adopt or to resist it based on the evaluation of the change associated with the new system (Joshi 2005). Health IT has great potential to

improve quality of care and patient safety (Weeger et al. 2011), but this benefit is not always being realized because many health IT efforts encounter difficulty or fail. Many of these failures and problems can be traced back to user resistance (Bartos et al. 2011). Resistance is not quite equivalent to non-usage because non-usage may imply that potential adopters are simply unaware of a new technology or are still evaluating the technology prior to its adoption, while resistance implies that the technology has been considered and rejected by these users (Bhattacharjee & Hikmet 2007). Resistance is often marked by open hostility toward the change agents or covert behaviors to stall or undermine change, while non-usage does not generally engender such outcomes. Accordingly, this study defines user resistance as the opposition of users to the change associated with a new technology implementation. However, technology acceptance and resistance must be examined jointly within a common theoretical model because user resistance is clearly a barrier to IS usage (Cenfetelli 2004). Thus, health IT leaders and administrative leaders face the problem of what to do about user resistance.

2.3 Dual factor theory

Herzberg et al.'s (1966) dual factor theory suggests that humans have two different sets of needs and that the different elements of the work situation satisfy or frustrate these needs. Their findings supported their belief that job satisfaction was basically determined by one set of factors and job dissatisfaction basically by a different set of factors. Herzberg et al. refer to these factors as motivation factors. These are related to the job itself and the results that the performance of the job causes. The factors found to affect job dissatisfaction included a reward system, salary, and interpersonal relations and working conditions. These factors, which Herzberg et al. calls hygiene factors, are related to the environment of the job. However, when one is satisfied, these factors do not motivate or cause satisfaction; they only prevent dissatisfaction. Several studies using the dual factor theory have been adapted to better suit the specific context studied. In the education context, the motivation factors were translated into faculty performance variables (e.g., understanding, professional, and helpful) and classes (course scheduling and projects). Hygiene factors were constituted by advising staff (e.g., accessible, reliable, helpful, and responsive) (Deshields et al. 2005). The principal findings of this study also supported Herzberg's dual factor theory. Another adapted version of the dual factor theory was employed in Lewicki et al.'s (1998) study of determinants of consumer trust and distrust. Here again, consumer trust and distrust are not opposites of one another but instead have unique characteristics that differ by more than just an opposing valence, thus making them separable, although closely related, constructs.

The dual factor theory has also been applied context adapted in studies of the IS usage. For example, Cenfetelli (2004) contended that, while IS adoption is best predicted by enablers, IS rejection tends to be best predicted by inhibitors. Enablers are those external beliefs (e.g., perceived usefulness and ease of use) regarding the design and functionality of an IS that either encourage or discourage usage, depending on valence. Cenfetelli (2004) defined inhibitors as hygiene factors that discourage IS usage when present but do not necessarily favor usage when absent. This asymmetric effect implies that inhibitors are not quite the opposite of enablers but are qualitatively distinct constructs that are independent of but may coexist with enablers. Inhibiting perceptions can be further distinguished from enabling perceptions by having differing antecedents and consequent effects. However, Cenfetelli's (2004) model did not mention any specific inhibitor of IS usage, resistance to use fits the classic definition of an inhibitor and reflects similar idealized behavior. In the medical informatics context, Bhattacharjee and Hikmet (2007) drew upon Cenfetelli's dual-factor model of IS usage to explain users' resistance to healthcare information. The principal findings of this study supported Cenfetelli's model. Thus, Cenfetelli's dual-factor model of IS usage provides a theoretical bridge that links health IS acceptance and resistance in an integrated model.

2.3.1 The Technology Acceptance model

The technology acceptance model (TAM) was introduced by Davis (1989) to explain computer usage behavior. Since then, TAM has been the most frequency cited and influential model for understanding the acceptance of IS and has received extensive empirical support. In particular, Chau and Hu (2002)

tested two models explaining behavioral intentions to adopt health IT: the theory of planned behavior (TPB; Ajzen 1985) and TAM. They found that TAM explains more variance in health IT adoption than TPB. TAM suggests that perceived usefulness (PU) and perceived ease of use (PEOU) are two salient cognitive determinants of technology acceptance because individuals want to use IS that benefit their task and do not cost them a lot of effort. PU refers to the extent to which individual believe that IS usage will enhance their job performance, while PEOU is the extent to which individuals believe that their usage will be relatively free of effort (Davis, 1989). Hence, both PU and PEOU tend to be positively related to IS usage intention. According to the dual factor perspective, TAM has focused on users' enabling perceptions related to IT usage (e.g., its perceived usefulness and ease of use) (Cenfetelli 2004; Bhattacharjee & Hikmet 2007). Thus, we propose that patients' intention to use a new IS such as a health cloud is based on both the traditional enablers of IS usage, the perceived usefulness and perceived ease of use of IS usage.

2.3.2 *The Status Quo Bias Theory*

Status quo bias (SQB) theory aims to explain people's preference for maintaining their current status or situation (Samuelson & Zeckhauser 1988). Thus, SQB theory provides a set of useful theoretical explanations for understanding the impact of incumbent system use as an inhibitor of new system acceptance (Kim & Kankanhalli, 2009). Samuelson and Zeckhauser (1988) described SQB explanations in terms of three main categories: (a) psychological commitment stemming from misperceived value costs, regret avoidance, or a drive for consistency; (b) cognitive misperceptions in the presence of inertia and perceived value; and (c) rational decision making in the presence of transition costs and uncertainty. The first SQB explanation is based on psychological commitment. Psychological commitment may be due to incorrectly factoring in sunk costs, striving for cognitive consistency in decision making, attempting to maintain one's social position, attempting to avoid regret that might result from making a bad decision, or desiring to maintain a feeling of being in control (Kim & Kankanhalli 2009; Polites & Kankanhalli 2012). SQB may also be the result of cognitive misperceptions due to loss aversion. Kahneman and Tversky (1984) showed that individuals weigh losses heavier than gains in making decisions. They label this phenomenon loss aversion. According to the loss aversion perspective, Polites and Kankanhalli (2012) defined in an IS context inertia as user attachment to and persistence in using an incumbent IS even if there are better alternatives or incentives to change. Perceived value refers to whether the benefits derived are worth the costs incurred in changing from the status quo to the new IS implementation. If the perceived value of the change is low, individuals are likely to have greater resistance to change. Thus, an individual's inertia and perceived value contribute to cognitive misperceptions of loss aversion. From the rational decision making viewpoint, two types of costs are identified: transition costs and uncertainty. Transition costs are the costs incurred in adapting to the new situation. Uncertainty, representing the psychological uncertainty or the perception of risk associated with the new alternative, can also cause status quo bias. In the IS context, the SQB theory is relevant since it can provide theoretically driven explanations of new IS-related change evaluation and the reasons for user resistance. Thus, the status quo bias perspective provides a set of useful theoretical explanations for understanding the impact of maintaining their current status as inhibitors (e.g., sunk costs, regret avoidance, inertia, perceived value, transition costs, and uncertainty).

3 RESEARCH MODEL

Based on the preceding discussion, we make use of the dual factor model of IS usage as an important theoretical foundation in the IS usage literature to integrate and add to relevant concepts from the TAM and SQB theory to explain patient acceptance and resistance prior to a health cloud implementation. Thus, we propose that patients' intention to use a new health IT such as a health cloud is based on two opposing forces: enabling and inhibiting perceptions. In the enabling perceptions, we propose that patients' intention to use a health cloud is based on both the traditional enablers of IT usage, their perceived usefulness and the ease of use of IT usage (Davis et al. 1989). In the inhibiting perceptions, following the SQB perspective, we extended the causes of user resistance to include psychological commitment (e.g., sunk costs and regret avoidance), cognitive

misperceptions (e.g., inertia and perceived value), and rational decision making (e.g., transition costs and uncertainty) into six inhibitors to provide higher explanatory power and a more precise understanding of user resistance antecedents. Similar to e-commerce, the health cloud is a platform for delivering services, and activities are performed online and processed virtually. Personal contact is absent and can raise doubts as to whether the requested information exchanges were correctly processed. Thus, the introduction of the health cloud often engenders significant changes in a patient's existing healthcare process. If such change is of a sufficiently high magnitude, given the natural human proclivity to oppose change, many patients will tend to resist the health cloud, resulting in lower intention to use. However, a review of the literature indicates that no previous studies have addressed the relationship between technology acceptance and resistance. Thus, we also examine the relationship between intention to use and resistance to use. Figure 1 shows a diagram of the proposed research model which details the various dimensions and the development of the theoretical arguments.

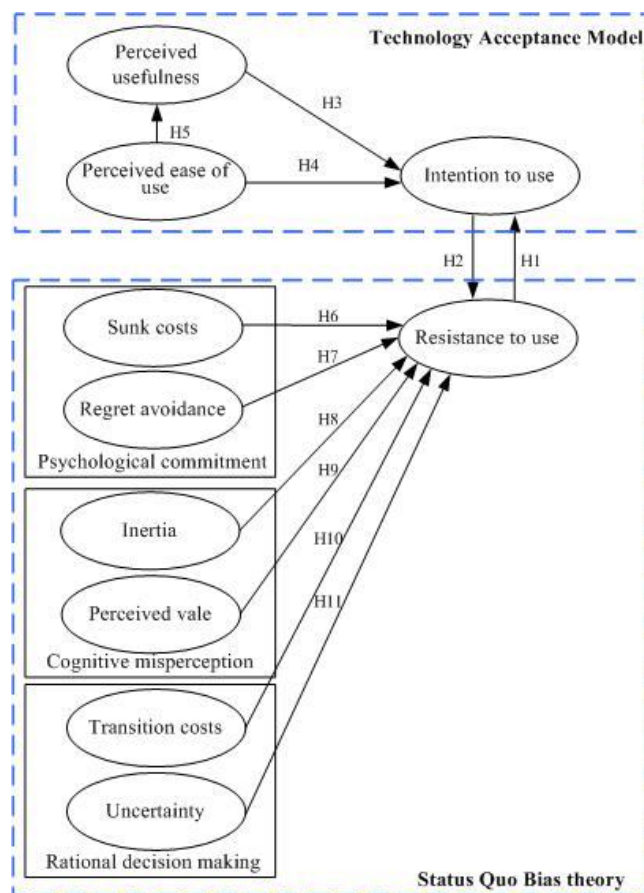


Figure 1. Research framework

Norzaidi et al. (2008a, 2008b) proposed an examination of the relationship between user resistance and usage. The introduction of a new system often engenders significant changes in a user's existing work process. When usage is mandatory, the users who first refused to use the IT may finally use it because they do not have any other alternative way to accomplish their tasks. Thus, patients are compelled to use the health cloud to complete their health care tasks since there are no other alternatives. For example, if a health task requires them to upload health data to the health cloud, they will use it to complete the task. Moreover, there are circumstances when patients may use the system voluntarily, but they will stop using it after a while. Another factor that probably causes user resistance to the health cloud is a prior bad experience. Users may feel comfortable because the health cloud could offer benefits they expect; however, if it fails to provide useful information or the system always crashes, then they may not use it. Prior studies have provided support for the negative effect of

resistance on IS usage (Poon et al., 2004; Bhattacharjee & Hikmet 2007 Poon et al., 2004; Bhattacharjee & Hikmet 2007). Thus, we suggest the following hypotheses:

H1. Patients' resistance to use is negatively related to their intention to use a health cloud.

H2. Patients' intention to use is negatively related to their resistance to use a health cloud.

TAM suggests that PU and PEOU are two salient cognitive determinants of IS acceptance because individuals want to use IS that benefits their tasks and that does not cost them a lot of effort (Davis, 1989). Hence, both PU and PEOU tend to be positively related to IS usage intention. Moreover, a new system that requires less effort and is easier to use will be perceived as more useful. Since the health cloud is one specific instance of medical informatics, the salience and effects of PU and PEOU on IS usage should also apply to the healthcare context as enablers of IS usage. Empirical support for both associations within the healthcare context was provided by Tung et al. (2008) and Yu et al. (2009), leading us to hypothesize the following:

H3. The PU of health cloud usage is positively related to the intention to use a health cloud.

H4. The PEOU of health cloud usage is positively related to the intention to use a health cloud.

H5. The PEOU of health cloud usage is positively related to the PU of health cloud usage.

According to the SQB perspective, sunk costs may lead to resistance to use because users do not want to forgo their past investment made in the status quo (Kim & Kankanhalli 2009). The greater the investment in the status quo alternative is, the more strongly it will be retained (Samuelson & Zeckhauser 1988). Thus, we suggest the following hypothesis:

H6. Sunk costs have a positive a positive effect on resistance to use.

Users find themselves in the unpleasant position of regretting the outcomes of past decisions. Such lessons of experience teach them to avoid, if possible, regrettable consequences (Samuelson & Zeckhauser 1988). As Kahneman and Tversky (1982) argued, users feel stronger regret for bad outcomes that are the consequence of new technology taken than for similar bad consequences resulting from the status quo. Hence, regret avoidance is likely to have a direct impact on resistance to use.

H7. Regret avoidance has a positive a positive effect on resistance to use.

Users persist in using an incumbent system either because this is what they have always done in the past or because it may be too stressful or emotionally taxing to change (Polites & Karahanna 2012). In other words, inertia will result in lowered usage intentions. Therefore, we suggest the following hypothesis:

H8. Inertia has a positive a positive effect on resistance to use.

Perceived value concerns whether the benefits derived are worth the costs incurred in changing from the status quo to the new technology implementation (Kim & Kankanhalli 2009). If the perceived value of the change is low, users are likely to have greater resistance to the implementation of the new technology. Conversely, if the perceived value is high, users are likely to have lower resistance to the implementation of the new technology. Thus, we suggest the following hypothesis:

H9. Perceived value has a negative effect on resistance to use.

Transition costs include transient expenses and permanent losses associated with the change (Kim & Kankanhalli 2009). As the transient expenses and permanent losses increase, users are more likely to be reluctant concerning the implementation of the new technology because they are motivated to cut their losses (Kahneman & Tversky 1979). Hence, transition costs are likely to have a direct impact on resistance to use.

H10. Transition costs have a positive effect on resistance to use.

Uncertainty, as perceived risk, increases the anticipation of negative outcomes, leading to an unfavorable attitude that typically results in a negative effect on a user's intention to use (Weeger et al.

2011; Benlian & Hess 2011; Polites & Kankanhalli 2012). Consequently, uncertainty increases the patients' resistance to using the system. Thus, we propose the following hypothesis:

H11. The uncertainty of health cloud usage has a negative effect on resistance to use.

4 RESEARCH METHOD

4.1 Questionnaire development

The instrument was designed to include a two-part questionnaire. The first part includes nominal scales, and the remainder includes seven-point Likert scales, ranging from *strongly agree* to *strongly disagree*. Accordingly, the first part of the questionnaire was used to collect basic information about the respondents' characteristics, including gender, age, education, occupation, and experience using cloud computing. The second part of the questionnaire was developed based on the constructs of PU, PEOU, sunk costs, regret avoidance, inertia, perceived value, transition costs, uncertainty, intention to use, and resistance to use. Table 1 presents the construct definitions and sources.

Construct	Definition	Reference
Perceived usefulness	The extent to which individuals believe that using a specific application increases his or her task performance.	Davis 1989
Perceived ease of use	The extent to which individuals believe that performing a behavior of interest is free of effort.	Davis 1989
Sunk costs	The extent to which individuals do not want to forgo their past investment made in the status quo.	Polites & Karahanna 2012
Regret avoidance	Individuals feel stronger regret for bad outcomes that are the consequence of new actions taken than for similar bad consequences resulting from inaction.	Tsiros & Mittal 2000
Inertia	The extent to which individual attitudes and preferences from past actions will tend to persist in these actions.	Polites & Karahanna 2012
Perceived value	The extent to which individuals evaluate whether the benefits derived are worth the costs incurred in changing from the status quo to the new situation.	Kim & Kankanhalli 2009
Transition costs	The extent to which individuals believe that using a specific application increases the time and effort required to adapt to a new situation.	Kim & Kankanhalli 2009
Uncertainty	The extent to which individuals perceive the risk associated with the new alternative.	Benlian & Hess 2011
Resistance to use	The extent to which individuals do not want the health cloud change healthcare.	Bhattacharjee and Hikmet (2007)
Intention to use	The extent to which patients intend to use a health cloud.	Davis 1989

Table 1. Construct of Definitions and Sources

Although the instrument had been validated by previous studies, we examined it to ensure the content validity and reliability was within acceptable range. We conducted pretests by requesting information management professors to evaluate the instruments. To ensure validity and reliability, a pilot test was conducted with samples of representative respondents. Table 2 lists construct definitions and sources. This study was conducted using SPSS10.0 and AMOS 20 as analysis tools. The data analysis method involved descriptive statistics, confirmatory factor analysis (CFA), and the structural equation model (SEM). AMOS is used because of its simplicity and technically advanced nature. More importantly, AMOS provides a more precise assessment of discriminant validity than exploratory analysis (Miles 2000). The test of the proposed model includes an estimation of two components of a casual model: the measurement and the structural models.

4.2 Sample and data collection

The target participants were patients in Taiwan. Because the resources necessary to use this system differ among hospitals, we classified the medical institutions into three categories (i.e., medical centers, regional hospitals, and local hospitals) and four locations (i.e., north, central, south, and east) to for the sampling. Twelve medical institutions were successfully contacted to secure their collaboration. A total of 600 questionnaires were distributed through an administrator of the hospital, and 461 questionnaires were returned. We collected questionnaires from four medical centers, four regional hospitals, and four local hospitals; after discarding 88 incomplete questionnaires, 443 were available for analysis. We assessed nonresponse bias by comparing early and late respondents (e.g., those who replied during the first three days and during the last three days). We found no significant difference between the two respondent groups based on the sample attributes (e.g., gender, age, and education).

5 RESEARCH RESULTS

5.1 Respondent characteristics

The resulting 443 valid responses constituted a response rate of 73.83%. The response rate is in a highly acceptable level and would be less likely to cause the problem of non-response bias. Table 1 summarizes demographics of the sample respondents.

Respondent characteristics	Item	Frequency	Percent (%)
Gender	Male	184	41.53
	Female	259	58.47
Age	21-30	117	26.41
	31-40	95	21.44
	41-50	89	20.09
	51-60	82	18.51
	>61	60	13.54
Education	Secondary School or Less	221	49.89
	College/university	189	42.66
	Master/PhD	33	7.45
Employee type	Industry	210	47.40
	Public service	93	20.99
	Students	60	13.54
	Others	80	18.06
Categorization of respondents	Non-experienced users	166	37.47
	Experienced users	277	62.53
Years using cloud computing for experienced users	<1 year	80	28.88
	1-2 years	62	22.38
	2-3 years	32	11.55
	>3 years	103	37.18

Table 1. Respondent demographics

5.2 Scale validation

Initially, a pre-test was conducted for the scale. The translation, wording, structure, and content of the scale were carefully examined by selected practitioners and academicians in this field. Their comments were taken into consideration when updating the scale to guarantee initial reliability and validity. Furthermore, CFA with AMOS software was used for scale validation, as described below. First, a measurement model was assessed for model fit. The literature suggested that, for a goodness of model fit, chi-square/degrees of freedom (χ^2/df) should be less than 5 (Bentler 1989), both tucker-lewis index (TLI) and comparative fit index (CFI) should be greater than 0.9, and root mean square error (RMSE) should be less than 0.10 (Henry & Stone 1994). Next, convergent validity was assessed

by three criteria: item loading (λ) with a minimum of 0.7, composite reliability (CR) with a minimum of 0.8, and average variance extracted (AVE) for a construct larger than 0.5 (Fornell & Larcker 1981). Discriminant validity was assessed by the measure that the square root of AVE for a construct should be larger than its correlations with other constructs. The testing results indicate a goodness of model fit for the measurement model with χ^2/df (786.16/389 = 2.02), TLI (0.96), CFI (0.97), and RMSE (0.05). Regarding reliability, all composite construct reliabilities are above 0.8. For convergent validity, factor loadings are all above 0.7, composite construct reliabilities range from 0.70 to 0.94, and AVEs range from 0.54 to 0.86. For discriminant validity, the square root of AVE for a construct is above its correlations with other constructs. These results indicate reliability, convergent validity, and discriminant validity in an acceptable level, as reported in Table 2. Multiple regression analysis was conducted to assess the effects of eight predictor variables on the intention to use and resistance to use. None of the variance inflation factors (VIFs) were greater than 5, which indicated that a serious multicollinearity problem did not occur (Hair et al. 1992; Henseler & Fassott 2005).

Construct	Item loading	C R	AVE	Correlation													
				PU	PEOU	SC	RA	IN	PV	TC	UN	US	RU				
PU	.70- .91	.90	.68	.82													
PEOU	.81- .95	.94	.80	.60	.89												
SC	.88- .94	.84	.72	-.13	-.02	.85											
RA	.79- .91	.79	.65	-.10	-.33	.01	.81										
IN	.61- .93	.82	.54	-.06	-.02	.28	.15	.73									
PV	.82- .91	.85	.65	.34	.24	-.14	-.02	-.40	.81								
TC	.79- .85	.70	.54	-.20	-.17	.18	.14	.46	-.52	.73							
UN	.79- .86	.79	.56	-.01	-.10	.09	.51	.22	-.32	.43	.75						
US	.92- .96	.94	.86	.63	.48	-.22	-.08	-.10	.40	-.32	-.06	.93					
RU	.87- .94	.93	.77	-.36	-.28	.09	.03	.38	-.63	.53	.22	-.44	.88				

Note: Leading diagonal shows the square root of AVE of each construct
 Perceived usefulness (PU), Perceived ease of use (PEOU), Sunk costs (SC), Regret avoidance (RA), Inertia (IN), Perceived value (PV), Transition costs (TC), Uncertainty (UN), Intention to use (US), Resistance to use (RU)

Table 2. Reliability and validity of the scale

5.3 Analysis of the structural equation model

The causal structure of the proposed theoretical framework was examined using the structural model. The first step is to examine the model fit of the structural model. The second is to find path coefficients for the hypothesized relationships and coefficients of determination (R^2) for the endogenous variables. Finally, the forming indicators are presented for the major constructs with weight scores. All measuring indices report a goodness of model fit with χ^2/df (894.822/404=2.21), TLI (0.95), CFI (0.96), and RMSE (0.05). The testing results in the structural model are indicated in Figure 2. In general, the statistical testing conclusions partially support this research model. Intention to use in this study was jointly predicted by PU ($\beta=0.58$, standardized path coefficient, $p<0.001$), PEOU ($\beta=0.18$, $p<0.01$), and resistance to use ($\beta= -0.25$, $p<0.001$), and these variables together explained 50% of the variance of intention to use. As a result, hypotheses 1, 3, and 4 were all supported. PEOU ($\beta=0.69$, $p<0.001$) significantly influenced PU while explaining 36% of the total variance in PU. Accordingly, hypothesis 5 was supported. Resistance to using a health cloud in this study was predicted by inertia ($\beta=0.17$, $p<0.01$), perceived value ($\beta= -0.44$, $p<0.001$), transition costs ($\beta=0.18$, $p<0.05$), and intention to use ($\beta= -0.26$, $p<0.001$). Together, these variables explained 50% of the total variance. These findings validated hypotheses 8, 9, 10, and 2, respectively. Furthermore, sunk costs ($\beta=0.06$, $p>0.05$), regret avoidance ($\beta=0.02$, $p>0.05$), and uncertainty ($\beta=0.02$, $p>0.05$) did not significantly affect resistance to using a health cloud. Hence, hypotheses 6, 7, and 11 were not supported.

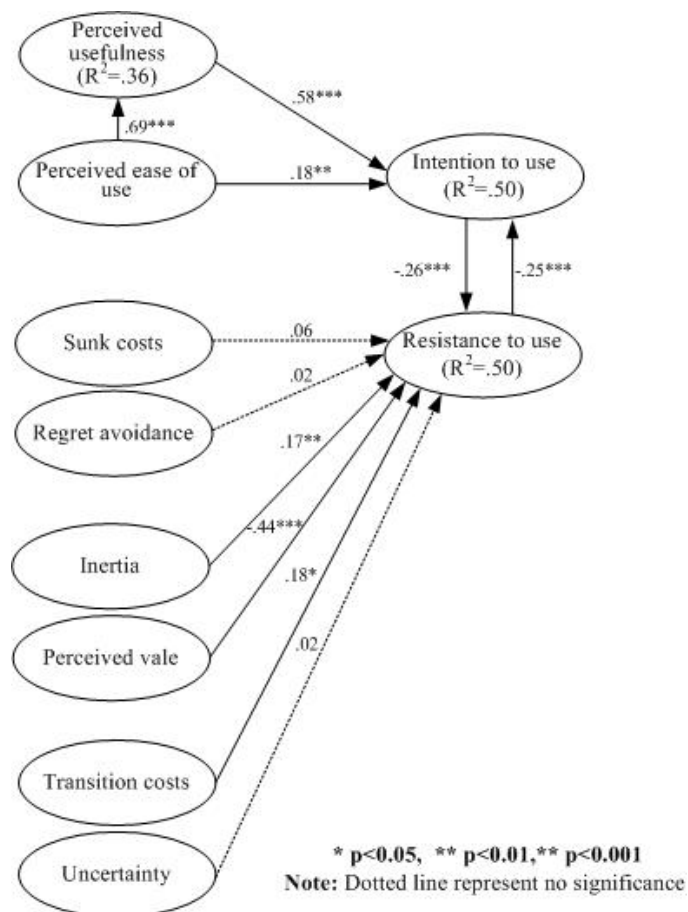


Figure 2. Results of the structural model

6 DISCUSSION

In this empirical study, we analyzed patients' acceptance of and resistance to a health cloud. First, we analyzed the relationship between the two enablers (PU and PEOU) and intention to use. Second, we analyzed the six inhibitors (sunk costs, regret avoidance, inertia, perceived value, transition costs, and uncertainty) and resistance to use. Third, we analyzed the relationship between intention to use and resistance to use of health cloud services. In the proposed models, the explained variance ($R^2 = 0.50$) appeared to be superior to the results of prior studies (Chau & Hu 2002; Bhattacharjee & Hikmet 2007; Yu et al. 2009) in explaining user intention or resistance to use the health IT. This implies that the proposed model could be a robust research model for predicting patient intention to use similar health IT.

Our study confirmed that the relationship between intention to use and resistance to use had a significant negative effect. This result coincided with the findings of previous studies on health IT adoption (Poon et al. 2004; Bhattacharjee & Hikmet 2007). As such, higher user resistance will reduce a patient's intention to use a health cloud. Among the enablers under study, PU is more influential on the decision to use a health cloud. Further, we found that the variables of PU and PEOU have positive and direct effects on behavioral intention to use, and PEOU appears to have a positive direct effect on PU. As a result, the level of PEOU had significant indirect effects on the intention to use a health cloud, suggesting the important mediating effects of PU and intention to use. These findings are in accordance with the previous findings (Tung et al. 2008; Yu et al. 2009). In other words, the effects of these enablers were significant in explaining patients' acceptance behavior by conforming to the work of Davis (1989), who maintained that the relative importance of PU and PEOU in predicting usage intention varies across behaviors and situations. PU is the greatest predictor of intention to use a health cloud. The results show that the easier patients feel it is to use a health cloud is, more useful they feel the health cloud is. PU, in turn, has a positive effect on the intention to

use a health cloud. Thus, a health cloud should be designed and developed to deliver value to them. The usefulness can be enhanced by providing enhanced healthcare services without increasing the complexity of the healthcare process.

Among the inhibitors under study, our study confirmed that patient resistance to use was caused by inertia, perceived value, and transition costs. Perceived value is more influential on the decision to resist use of a health cloud. This result coincided with the findings of previous studies on IS adoption (Polites & Kankanhalli 2012). The study found that the perceived value of a change reduces user resistance to new IS. These results are consistent with those of previous research (Joshi 1991; Kim & Kankanhalli 2009) indicating that changes where the costs exceed the benefits (e.g., there is low perceived value) are likely to be resisted. Inertia has a direct positive effect on user resistance to healthcare, meaning that higher inertia results in higher resistance to using the health cloud. Further, perceived transition costs increase user resistance to using a health cloud. These findings are in accordance with previous findings (Kim & Kankanhalli 2009). As a result, the findings regarding transition costs can perhaps be explained by the SQB perspective. Transition costs represent rational decision making on the part of the individual. This rationalization of the costs of transition from the incumbent system can, even in the absence of a known alternative, lead to resistance. However, sunk costs, regret avoidance, and uncertainty did not significantly affect usage intention. As Polites and Kankanhalli's (2012) suggested, although the SQB perspective represents a comprehensive set of theoretical explanations that account for status quo bias, not all explanations are present in a specific context. In particular, patient usage behavior has certain differences from typical user behavior, including the following factors: (a) healthcare is not only a type of service but also a lifesaving mechanism by the health cloud services; (b) Health cloud is not a simple activity, but a socioeconomic interactive process between health care organizations and the environment in which they operate. Patients are generally not responsible for selecting a software system; rather, the DOH and a hospital's IT department would typically make such decisions and patients are simply required to health care with the system provided to them. The concerns of patients about the adequate functioning of an IS application (e.g., healthcare management) are likely to inhibit the diffusion of information, such as in health cloud. Therefore, sunk costs, regret avoidance, and uncertainty do not influence patient resistance to using a health cloud.

6.1 Implications for research

This research study offers several implications and contributions for other researchers. A primary contribution is in combining technology acceptance and resistance theories to examine how users assess overall change related to a new technology. According to the dual factor perspective, by making use of technology acceptance literature (TAM) to integrate and add to relevant concepts from SQB theory, the study contributes by operationalizing and testing the developed model through a survey methodology, which has little precedence in user resistance literature. Hence, we provide theoretical insights for researchers that may assist in encouraging patients to use a new health IT. Second, enablers and inhibitors have not been clearly defined or measured in prior research. Thus, we contribute to both IS research and the dual factor theoretical perspective by explicitly conceptualizing and measuring individual-level enablers and inhibitors. Our study confirms that PU and PEOU are critical factors for facilitating intention to use the system. While the role of inhibitors (e.g., inertia, perceived value, and transition costs), the driving forces would have a positive effect on the patients' resistance to use a health cloud. This finding could interest and encourage researchers who are developing an IS acceptance and resistance model. Future research should aim at identifying additional incumbent system constructs and theorizing on the interplay between incumbent system and new system cognition and behaviors. The dual factor perspective provides a set of theoretical explanations that can be further leveraged to identify such additional constructs and relationships. This study has a third key theoretical implication in terms of SQB theory. This theory was developed for planning bias toward maintaining the status quo in human decision making and behavior. Since then, it has been applied to explain human decision making in the IS field (Kim & Kankanhalli 2009; Polites & Kankanhalli 2012). As an extension of previous research, this study has demonstrated how SQB theory can be applied in health IT research to explain patient resistance to new health IT-related

change. Thus, this reliable and valid instrument provides an effective tool for researchers to measure user behavior, as well as to explain, justify, and compare differences in study results.

6.2 Implications for Practice

The results of this study offer suggestions to management about how to alleviate user resistance in health cloud implementation. First, higher levels of perceived usefulness and ease of use encourage patients to have a more positive attitude toward the system. A health cloud should be designed in a more user-friendly manner that is consistent with current needs. Patients who are able to use the health cloud with ease, as well those who can retrieve healthcare data, are more likely to develop a positive attitude toward the system, thereby encouraging them to use the health cloud. Hospital managers should focus more on (a) creating an environment that ensures patients have a positive attitude toward the system and (b) providing adequate resources for patients who use the health cloud. Second, management should be aware of the critical effect of inhibitors on user resistance. Management can attempt to reduce inertia and transition costs by enhancing users' favorable opinions toward new IS-related change. Third, management should aim to increase the perceived value of change to reduce user resistance. To increase the perceived value, the advantages of a health cloud should be emphasized from the viewpoint of the patient. Adopting benefits, thus, need to be communicated clearly to patients before a health cloud implementation. Furthermore, most health IT designs tend to focus on system considerations, such as new functionalities and connectivity, rather than user considerations such as the system's impact on users' healthcare behaviors and potential user resistance. A better understanding of user resistance of health IT may help design better systems that are both functionally good and also acceptable to their targeted user population.

7 LIMITATIONS AND CONCLUSION

The limitations of our findings should be acknowledged. The first limitation of our study is our choice of constructs, which was based on the prior literature and our own observation of patient behavior at our study site. There may be other enablers or inhibitors of health cloud usage that were not included in this study and can be the subject of future research. Further, there may be additional predictors of resistance, beyond sunk costs, regret avoidance, inertia, perceived value, transition costs, and uncertainty, that should be examined in future research. The identification and validation of such constructs will also help advance our preliminary model of health cloud resistance. Second, the relevance of this study is confined to the health cloud behavior of a general population: patients. The findings and implications drawn from this study cannot be readily generalized to other groups, such as medical personnel. A study targeting medical personnel, who might have different information needs and different levels of computing support and abilities, could obtain different results. Future research could focus on accumulating further empirical evidence and data to overcome the limitations of this study.

This study contributes to the existing body of knowledge in terms of narrowing the research gap by examining the causal relationships between intention to use and resistance to a health cloud in Taiwan. The novelty of this study is that it provides a holistic perspective of the critical factor (e.g., enablers and inhibitors) that influences technological intention to use and resistance to use a health cloud. These findings supported our initial expectation that patients' intention to use a health cloud is predicted by both enabling (e.g., PU and PEOU) and inhibiting (e.g., inertia, perceived value, and transition costs) perceptions, although some inhibitors may be less salient to predicting resistance to use. We offered implications regarding medical practice and academic research based on our findings. We hope that this study will stimulate future interest in the health IT resistance phenomena and motivate researchers to examine in greater depth this unexplored yet potentially fertile area of research.

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