Taiwanese Middle-Aged and Elderly Patients' Acceptance and Resistance Toward the Health Cloud

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Abstract. As the Taiwanese society ages, the demand for cloud services is rising, particularly among middle-aged and elderly patients, since it enables people to live independently and access health care easily. Despite cloud services great potential, there are gaps in our understanding of how patients evaluate change related to the health cloud and why they resist it. In keeping with the technology acceptance and status quo bias perspectives, this study develops an integrated model to explain middle-aged and elderly patients' intention to use and resistance to health cloud services. A field survey was conducted in Taiwan to collect data from middle-aged and elderly patients. The structural equation model was used to examine the data. The results showed that patients' resistance to use health cloud services was caused by sunk costs, inertia, and transition costs. Attitude, subjective norm, and perceived behavior control have positive and direct effects on behavioral intention to use. The results also indicate a significant negative effect in the relationship between middle-aged and elderly patients' intention and resistance to using the health cloud. Our research illustrates the importance of incorporating user resistance into technology acceptance studies in general and health technology usage studies in particular. There are grounds for a resistance model that can serve as the starting point for future studies in this relatively unexplored, yet potentially fertile, area of research.

Keywords: Health cloud · Middle-aged and elderly patients · User resistance · Technology acceptance · Status quo bias

1 Introduction

Since 1995, the National Health Insurance program has been providing comprehensive health-care coverage for the majority of Taiwan's 23 million inhabitants. The majority of patients tend to visit several hospitals throughout their lives, and "hospital shopping" has become a relatively common occurrence in Taiwan. Furthermore, due to falling birth rates and a longer average life expectancy, Taiwanese society is aging [1]. Thus,

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the accelerated growth of the middle-aged and elderly population makes health promotion and disease prevention imperative for these citizens. Given this fact, the Ministry of Health and Welfare intends to build a health platform by storing every citizen's health-care information in the health cloud. The health cloud program consists of the following: (a) a medical cloud for sharing electronic medical records across facilities in different hospitals; (b) a care cloud enabling wireless devices that allow for the monitoring of a patient's blood pressure, heart rate, and glucose level, among other functions, 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 to obtain health-related information at any time to enhance self-health management. In the future, it will be possible for patients to access these health cloud services at home without the need for hospitalization, thereby reducing the cost and emotional stress endured, and the effort invested, by middle-aged and elderly patients and their families. The health cloud services are personalized and pervasive, making them especially critical for middle-aged and elderly patients. Therefore, these patients' acceptance of, and support for, the health cloud is particularly critical in Taiwan. However, user resistance is unavoidable and may cause performance of the system to be lower than expected. User resistance demonstrates asymmetric behaviors that are typical of inhibitors because the presence of resistance hurts information system (IS) usage; however, a lack of resistance does not necessarily enhance IS usage [2]. Thus, there is a need to investigate the critical factors that stimulate technology acceptance and resistance and to examine the relationship between intention to use the health cloud and resistance against using it. From a practical standpoint, understanding why middle-aged and elderly patients resist and use the health cloud and how such resistance is manifested in their subsequent behavior can help government agencies and health-care administrators to devise appropriate intervention strategies for minimizing patient resistance and any adverse effects on health-care policy. In keeping with the technology acceptance and status quo bias perspectives, this study develops an integrated model to explain middle-aged and elderly patients' intention to use and resistance against health cloud services.

2 Background

Despite the emerging interest in the field of medical informatics and studies that have identified the application of the merits of the health cloud [3–7], only a limited understanding of middle-aged and elderly patients' behavior exists concerning the health cloud. Thus, the problem may be rooted in the absence of a generalized theory of user resistance and the lack of grounding within an established stream of research. In the next section, we attempt to develop such a research framework while grounding it in the literature related to IS acceptance and resistance.

2.1 Technology Acceptance and Resistance

When an innovative technology is implemented, users may decide to adopt or resist it based on their evaluation of the change associated with the new system [8]. In particular, health information technology (IT) has great potential to improve quality of care and patient safety [9]; however, this benefit is not always realized because many health IT efforts encounter difficulties or fail. Many of these failures and problems can be traced back to user resistance [10]. Resistance is not quite equivalent to non-usage, because non-usage may imply that potential adopters are simply unaware of a new system or are still evaluating it prior to its adoption, while resistance implies that the new system has been considered and rejected by these users [11]. 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 the implementation of a new technology. However, technology acceptance and resistance must be examined jointly within a common theoretical model because user resistance is clearly a barrier to IS usage [2]. Thus, health IT leaders and administrative leaders face the problem of how to address user resistance.

2.2 Theory of Planned Behavior

Among social cognition theories, the theory of reasoned action (TRA) [12] and the theory of planned behavior (TPB) [13] have been tested across a variety of populations, behaviors, and contexts. The TRA suggests that a person's behavior is determined by his or her intention to perform the behavior and that this intention is consequently a function of the person's attitude and his or her subjective norm toward that behavior [12]. Although the TRA has been evaluated and supported in numerous contexts, it offers a weak explanation of the essence of behavior. Ajzen [13] asserted that the TPB eliminated the TRA's limitations regarding managing behavior over which people have incomplete volitional control. Ajzen [13] showed that attitude and subjective norm determine a person's intention to use, and he further proposed that the person's perceived behavioral control (PBC) reflects the degree to which he or she feels that successfully engaging in that behavior is completely under his or her control. Behavioral intention (BI) measures the strength of a person's willingness to exert effort when performing certain behavioral activities. Attitude (A) explains the assessment of a favorable behavior for the person, which directly influences the strength of that behavior, as well as the beliefs regarding the anticipated outcome. Subjective norm (SN) expresses the perceived social pressure of a person who intends to perform a behavior, and it is related to normative beliefs regarding the expectations of other people. PBC is composed of human beliefs concerning capability and the controllability of performing the behavior. There are several examples of using the TPB to explain patients' behavior, and a number of studies have applied the TPB to guideline implementations [14–16]. TPB has focused on users' enabling perceptions related to IS usage [2]. Thus, we propose that middle-aged and elderly patients' intention to use a new IS, such as the health cloud, is based on three enablers of IS usage: their attitude, SN, and PBC of IS usage.

2.3 The Status Quo Bias Theory

Status quo bias (SQB) theory aims to explain people's preference for maintaining their current status or situation [17]. 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 [18]. Samuelson and Zeckhauser [17] separated SQB explanations into three main categories: (a) psychological commitment stemming from misperceived value costs, (b) cognitive misperceptions in the presence of inertia, and (c) rational decision making in the presence of transition costs. 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, and desiring to maintain a feeling of being in control [18, 19]. SQB may also be the result of cognitive misperceptions due to inertia. Polites and Kankanhalli [19] defined inertia in an IS context as user attachment to, and persistence in using, an incumbent IS even if there are better alternatives or incentives to change. Thus, an individual's inertia contributes to cognitive misperceptions of loss aversion. From the rational decision-making viewpoint, transition costs are the costs incurred in adapting to the new situation. In the IS context, the SQB theory is relevant because it can provide theoretically driven explanations of new IS-related change evaluation and the reasons for user resistance. Thus, the SQB perspective provides a set of useful theoretical explanations for understanding the impact of maintaining their current status as inhibitors (e.g., sunk costs, inertia, and transition costs).

3 Research Model

Based on the preceding discussion, we propose that middle-aged and elderly patients' intention to use the health cloud is based on two opposing forces: enabling and inhibiting perceptions. In regard to enabling perceptions, we propose that patients' intention to use the health cloud is based on the traditional enablers of IS usage: their attitude, SN, and PBC of IS usage [13]. In regard to the inhibiting perceptions, in keeping with the SQB perspective, we extended the causes of user resistance to include sunk costs, inertia, and transition costs into three inhibitors to improve their explanatory power and arrive at 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 health-care process. If such change is of a sufficiently significant magnitude, given the natural human proclivity to oppose change, many middle-aged and elderly patients will tend to resist the health cloud, resulting in lower intention to use. Thus, we also examine the relationship between intention to use and resistance to use. Figure 1 is a diagram of the proposed research model, which details the various dimensions and the development of the theoretical arguments.

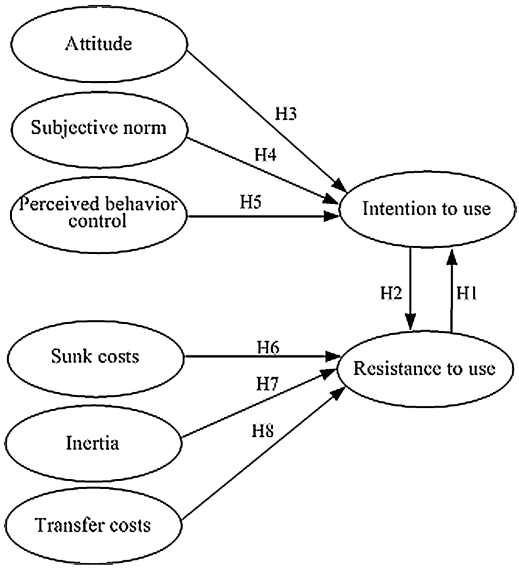

Fig. 1. Research framework

Norzaidi et al. [20] proposed an examination of the relationship between user resistance and usage. When usage is mandatory, the patients who initially refused to use the health cloud may finally do so because they have no alternative way to accomplish their health-care tasks. Moreover, there are circumstances in which patients may use the system voluntarily, but they will stop using it after a while. Another factor that is likely to cause user resistance to the health cloud is a prior negative experience. Previous studies have provided support for the negative effect of resistance on IS usage [11, 21]. Thus, we suggest the following hypotheses:

H1. Middle-aged and elderly patients' resistance to use is negatively related to their intention to use the health cloud.

H2. Middle-aged and elderly patients' intention to use is negatively related to their resistance to use the health cloud.

According to the TPB model, attitude influences behavioral intentions, and this relationship has received substantial empirical support [13]. People who form positive attitudes toward the health cloud have a stronger intention to adopt it; therefore, they are more likely to employ it. Prior studies on users' acceptance of health IT have also supported the attitude–BI correlation [22, 23]. Thus, we propose the following hypothesis on the relationship between attitude and intention to use:

H3. Attitude is positively related to the intention to use the health cloud.

SN is the extent to which a person feels that other people want him or her to perform a behavior [13]. The more people perceive that others think that they should engage in a behavior, the greater their motivation to comply. Prior studies

have shown that the SN perceived by a person has a substantial effect on his or her BI [22, 23]. Therefore, we propose the following hypothesis:

H4. SN is positively related to the intention to use the health cloud.

PBC describes a person's perceptions of the availability of knowledge, resources, and the opportunities necessary for using an IS [13]. A person has a higher level of PBC if he or she has adequate access to resources that facilitate a specific behavior; thus, PBC has a positive influence on that person's BI. Accordingly, a patient has a greater intention to use the health cloud if he or she possesses adequate resources. Accordingly, we propose the following hypothesis:

H5. PBC is positively related to the intention to use the health cloud.

According to the SQB perspective, sunk costs may lead to resistance to use because users do not want to forgo their past investment in the status quo [18]. The greater the investment in the status quo alternative, the more strongly it will be retained [17]. Thus, we suggest the following hypothesis:

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

Users persist in using an incumbent system either because this is what they have always done or because it may be too stressful or emotionally taxing to change [19]. Therefore, we suggest the following hypothesis:

H7. Inertia has a positive effect on resistance to use.

As the transient expenses and permanent losses increase, users are more likely to be resistant to the implementation of the new technology because they are motivated to cut their losses [24]. Hence, we propose the following hypothesis:

H8. Transition costs have a positive effect on resistance to use.

4 Research Method

4.1 Questionnaire Development

The construct measures shown in Fig. 1 were all adopted from previous studies and were rated using a 7-point Likert scale; the anchors ranged from "strongly agree" to "strongly disagree." Although previous studies have validated the questionnaire items, we conducted pretests by requesting several health-care professionals and information management professors to evaluate each item. To ensure validity and reliability, we conducted a pilot test with a sample that was representative of the actual respondents. We conducted structural equation modeling using partial least squares (PLS) estimations for the data analysis because the PLS method requires a minimal sample size and has few residual distribution requirements for model validation [25].

4.2 Sample and Data Collection

The target participants were middle-aged and elderly patients in Taiwan. Three medical institutions were successfully contacted to secure their collaboration. A total of 150 questionnaires were distributed through an administrator of the hospital, and 110 questionnaires were returned. We collected questionnaires from one medical center, one regional hospital, and one local hospital; after discarding five incomplete questionnaires, 105 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 the last three days). We found no significant difference between the two respondent groups based on the sample attributes (e.g., gender and age).

5 Research Results

The resulting 105 valid questionnaires constituted a response rate of 70 %. The majority of the questionnaire respondents were men (57 %) between the ages of 51 and 60 years (60 %). We tested the reliability and validity of the proposed model. Reliability was assessed based on a construct reliability greater than 0.8 [26]. Convergent validity was assessed based on the following three criteria: (a) item loading greater than 0.7 and statistically significant, (b) composite construct reliability (CR) greater than 0.80, and (c) average variance extracted (AVE) greater than 0.5 [27]. The discriminant validity between the constructs was assessed based on the criterion that the square root of the AVE for each construct should be greater than the corresponding correlations with all other constructs [26]. In this study, the construct reliabilities are all greater than 0.9. For the convergent validity, the item loadings are all greater than 0.7, and the AVEs range from 0.77 to 0.97. For the discriminant validity, the square root of the AVE for a construct is greater than its corresponding correlations with other constructs. Table 1 shows the descriptive statistics of the principal constructs and the correlation

Table 1. Reliability and validity of the scale

Construct	Item loading	CR	AVE	Correlation							
				AT	SN	PBC	SC	IN	TC	IU	RU
AT	.78– .94	.94	.81	**.90**							
SN	.85– .90	.90	.77	.20	**.88**						
PBC	.87– .96	.96	.85	.45	.14	**.92**					
SC	.94– .97	.96	.92	−.07	−.07	.09	**.96**				
IN	.86– .94	.94	.83	−.37	−.07	−.03	.54	**.89**			
TC	.84– .91	.92	.78	−.29	−.13	−.04	.10	.24	**.88**		
IU	.98– .99	.99	.97	.55	.30	.09	−.21	−.60	−.45	**.98**	
RU	.95– .97	.98	.93	−.51	−.07	−.22	.22	.48	.54	−.65	**.96**

Note: Leading diagonal shows the square root of AVE of each construct
Attitude (AT), Subjective norm (SN), Perceived behavior control (PBC), Sunk costs (SC), Inertia (IN), Transition costs (TC), Intention to use (IU), and Resistance to use (RU)

matrix, respectively. These results indicate acceptable reliability, convergent validity, and discriminant validity.

The testing results in the structural model are indicated in Fig. 2. In general, the statistical testing conclusions all support this research model. Intention to use in this study was jointly predicted by attitude ($\beta = 0.214$, standardized path coefficient, $p < 0.001$), SN ($\beta = 0.205$, $p < 0.001$), PBC ($\beta = 0.106$, $p < 0.001$), and resistance to use ($\beta = -0.34$, $p < 0.001$), and these variables together explained 54 % of the variance of intention to use. As a result, hypotheses 1, 3, 4, and 5 were all supported. In this study, resistance to using the health cloud was predicted by sunk costs ($\beta = 0.128$, $p < 0.001$), inertia ($\beta = 0.573$, $p < 0.001$), transfer costs ($\beta = 0.411$, $p < 0.001$), and intention to use ($\beta = -0.51$, $p < 0.001$). Together, these variables explained 53.8 % of the total variance. These findings validated hypotheses 2, 6, 7, and, 8 respectively.

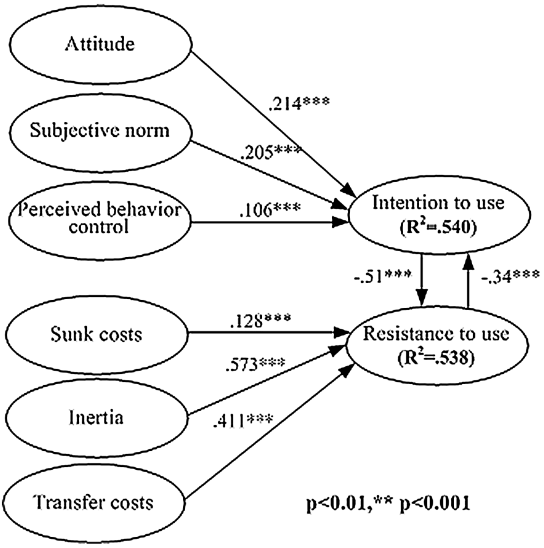

Fig. 2. Results of the structural model

6 Discussion

In this empirical study, we analyzed middle-aged and elderly patients' acceptance of and resistance to the health cloud. First, we analyzed the relationship between the three enablers (attitude, SN, and PBC) and intention to use. Second, we analyzed the three inhibitors (sunk costs, inertia, and transition costs) and resistance to use. Third, we analyzed the relationship between intention to use and resistance to use health cloud services. In the proposed models, the explained variance ($R^2 = 0.54$) appeared to be superior to the results of prior studies [1, 28] 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 middle-aged and elderly patients' 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 [11, 21]. As such, higher resistance will reduce middle-aged and elderly patients' intention to use the health cloud. Among the enablers under study, attitude is the most influential regarding the decision to use the health cloud. This implies that middle-aged and elderly patients' intention to accept the health cloud was directly influenced by their attitude toward using it. These findings are in accordance with the results of previous research [29, 30]. In other words, the effects of these enablers were significant in explaining middle-aged and elderly patients' acceptance behavior, which is in keeping with the work of Ajzen [13] (1985), who maintained that the relative importance of attitude, SN, and PBC in predicting usage intention varies across behaviors and situations.

Among the inhibitors under analysis, our study confirmed that middle-aged and elderly patients' resistance to use was caused by sunk costs, inertia, and transition costs. Inertia has a direct positive effect on user resistance to health care, meaning that higher inertia results in higher resistance to using the health cloud. This result coincided with the findings of previous studies on IS adoption [19]. In the absence of inertia, it is possible that a habitual patient of an incumbent system may readily recognize the advantages of switching to the health cloud and may form genuine intentions to do so. High perceptions of sunk costs have a direct positive effect on user resistance to health care, meaning that higher sunk costs lead to user resistance because people do not want to forgo their past investment in the traditional (face-to-face) health-care services. One possibility is that patients had either a formal or abstract awareness of the sunk cost effect, and once alerted to the past investment of resources, they consciously or subconsciously attempted to circumvent this bias and make a treatment decision based solely on the available clinical evidence. Further, perceived transition costs increase patients' resistance to using the health cloud. These findings are in accordance with previous findings [18]. This rationalization of the costs of transition from the incumbent system can, even in the absence of a known alternative, lead to resistance. Thus, the SQB perspective represents a comprehensive set of theoretical explanations that account for status quo bias, and these explanations are present in a health-care context.

This study has several implications for, and makes numerous contributions to, other research. A primary contribution is that technology acceptance and resistance theories are combined to examine how users assess overall change related to a new health IT. By making use of TPB 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 the user resistance literature. Hence, we provide theoretical insights for researchers that may assist in encouraging middle-aged and elderly 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 attitude, SN, and PBC are critical factors for facilitating intention to use the system. While the role of inhibitors (e.g., sunk costs, inertia, and transition costs) is important, the driving forces would have a positive effect on the middle-aged and elderly patients' resistance to using the health cloud. This finding could interest and encourage researchers who are

developing an IS acceptance and resistance model. Future research should aim to identify additional incumbent system constructs and theorize on the interplay between incumbent system and new system cognition and behaviors. 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 [18, 19]. As an extension of previous research, this study has demonstrated how SQB theory can be applied in health IT research to explain middle-aged and elderly patients' 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 the differences in study results.

The results of this study offer suggestions to management regarding how to alleviate user resistance in health cloud implementation. First, the results of the study show that attitude, SN, and PBC have a significant influence on usage intention. Thus, the health cloud should be designed in a more user-friendly manner that is consistent with current needs. Middle-aged and elderly patients who are able to use the health cloud with ease, as well those who can retrieve health-care 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 the following: (a) creating an environment that ensures middle-aged and elderly patients have a positive attitude toward the system; and (b) developing a system that meets the subjective norms of patients, and; and (c) 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 sunk costs, inertia, and transition costs by enhancing middle-aged and elderly patients' favorable opinions toward new IS-related change. Third, management should aim to increase the perceived value of change to reduce middle-aged and elderly patients' resistance. To increase the perceived value of using the health cloud, the advantages should be emphasized from the viewpoints of middle-aged and elderly patients. The benefits, therefore, need to be communicated clearly to middle-aged and elderly patients before the health cloud implementation. Furthermore, most health IT designs tend to focus on system considerations, such as new functionalities and connectivity, rather than on user considerations, such as the system's impact on users' health-care behaviors and potential user resistance. A better understanding of users' resistance to health IT may help design better systems that are both functionally good and acceptable to their targeted user populations.

The limitations of our findings should be acknowledged. The first limitation is our choice of constructs, which was based on prior literature and our own observation of the behavior of middle-aged and elderly patients at our study site. There may be other enablers or inhibitors of health cloud usage that were not included in this study and that can be the subject of future research. Further, there may be additional predictors of resistance, beyond sunk costs, inertia, and transition costs, 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 specific population: middle-aged and elderly 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 varying information needs and different levels of computing support and abilities, could obtain different results. Future research should focus on accumulating further empirical evidence and data to overcome the limitations of this study.

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