Consumer Acceptance of Accountable-eHealth Systems

Randike GAJANAYAKE[a,1], Renato IANNELLA[b] and Tony SAHAMA[a]
[a] *Science and Engineering Faculty, Queensland University of Technology (QUT), Brisbane, Australia*
[b] *Semantic Identity, Brisbane, Australia*

Abstract. In this paper, we present the results of a survey conducted to measure the attitudes of the consumers of eHealth towards Accountable-eHealth systems which are designed for information privacy management. A research model is developed that can identify the factors contributing to system acceptance and is validated using quantitative data from 187 completed survey responses from university students studying non-health related courses at a university in Queensland, Australia. The research model is validated using structural equation modelling and can be used to identify how specific characteristics of Accountable-eHealth systems would affect their overall acceptance by future eHealth consumers.

Keywords. eHealth, privacy, information accountability, consumer adoption

Introduction

Accountable-eHealth (AeH) systems [1] are designed to tackle the information privacy conundrum in eHealth. Their goal is to deviate from the restrictive information models where rigid barriers are put in place for the protection of information privacy to a more open and accountable model that promotes *appropriate–use* of information. The AeH model builds an environment where healthcare professionals (HCP) access information deemed necessary for healthcare delivery but are held accountable for inappropriate use, thus, providing an incentive for consumers, i.e. patients, to alleviate concerns of privacy violations and disincentives for HCPs to misuse information, which are delivered through the presence of transparency and accountability (i.e. penalties).

Although AeH systems are technologically feasible [1], their adoption by future stakeholders is unclear. The understanding of factors that influence technology acceptance is essential for its successful adoption [2]. Although increasing HCPs' eHealth adoption is a critical aspects in itself, low consumer adoption rates can also be attributed as a critical impediment to eHealth [3]. Although there is ample evidence and concerns pertaining to the technological perspective of information privacy in eHealth [4], there are only a few studies conducted in regards to consumer adoption [5-7]. It is therefore important to measure the attitudes of the consumers towards eHealth systems and system characteristics which directly affects system acceptance once implemented. Consumers may see an increased opportunity to use eHealth systems because they empower consumers to

[1] Corresponding Author: Dr. Randike Gajanayake, QUT. Email: randike.gajanayake@gmail.com

participate in information sharing and decision making, which enables them to be more in control and contribute to quality care delivery [6].

This paper takes a first look at the factor contributing to the acceptance of AeH systems by eHealth consumers and presents and empirical research model. The primary goals of this paper is to validate the research model that tests the factors influencing the acceptance of AeH systems.

1. Method

The method of research was a quantitative online questionnaire survey. The questions included in the questionnaire were either adopted from previous technology acceptance research [8] or have been developed specifically for this study. All participants were students studying in non-health related undergraduate and postgraduate courses at a university in Queensland, Australia. The analysis of the data was done using the partial least squares (PLS) method. The analysis tool used was smartPLS 2.0 [9].

1.1. Theoretical foundations and research model

The hypotheses for this research study were based on technology acceptance research in general and in the healthcare domain focusing on the consumers' acceptance of technology. The hypotheses are related to the structural relationships amongst the model constructs. The theoretical model was based on the Unified Theory of Acceptance and Use of Technology (UTAUT) [8]. Motivated by Schaper and Pervan [10], we use three contexts to identify research constructs that influence the acceptance of AeH systems: individual; information privacy; and information (see Figure 1).

The individual context consists of three constructs; Computer/EHR Self-Efficacy (CSE), Computer/EHR Anxiety (ANX) and Computer/EHR Attitude (ATT). These constructs are drawn directly from UTAUT [8] and contextualised to fit our study. Previous studies that tested consumer acceptance of health ICT acceptance have seen that a person's feelings, perceptions, or beliefs about technology can affect their perceived acceptance of that technology [11]. Considering the findings from previous studies [6, 12-18], we make 8 hypotheses from this context as seen on Table 1. The information privacy context consists of two constructs: Privacy Concerns (PC) and Third Party Trust (TPT). Information privacy related technology acceptance studies are mostly based on the big five personality traits [18-20]. But these studies were primarily focused on domains such as corporate use of personal information [21]. Information privacy research in the healthcare domain, however, focuses on issues such as information sharing, information access and use and information control [21]. Therefore here, we adopt similar construct items to measure the privacy concerns of individuals. We make 9 hypotheses in relation to this context (see Table 1).

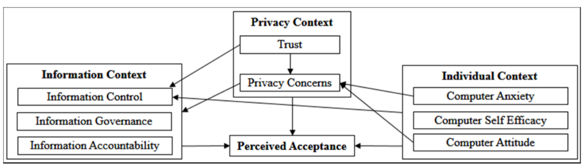

Figure 1. Hypothesised research model

The information context is unique to our study, which contains three constructs: Information Control (IC), Information Governance (IG) and Information Accountability (IA), which capture the characteristics of AeH systems. We define IG as the perception that usage rules must be enforced on how HCPs' use a patient's healthcare information. IC is defined as the perception of the ability of the owner or subject of the information to control their healthcare information–a measure used to increase confidence and trust in eHealth systems [4]. IA is defines as the perception that accountability measures must be put in place for inappropriate use of information. We hypothesise 3 relationships related these three constructs as listed in Table 1.

It is theorised that the Perceived Acceptance (ACC), our dependent construct, will have a direct effect on the actual acceptance by the consumers, similar to behavioural intention in [8], since the actual acceptance of the designed AeH system cannot be tested as part of this research study.

Table 1. Research hypotheses and path coefficients from PLS analysis

Hypothesis	Path	t-Values	Path Coefficient
H1 – CSE will have a direct positive effect on consumers' perception on IC	CSE → IC	3.299	0.229**
H2 – CSE will have a direct effect on consumers' perceived ACC	CSE →ACC	2.268	0.125*
H3 – ANX will have a direct positive effect on consumers' perceived PC	ANX →PC	2.601	0.176**
H4 – ANX will have a direct negative effect on perceived ACC	ANX →ACC	3.339	-0.228**
H5 – ANX will have a direct negative effect on IC	ANX →IC	1.149	0.092
H6 – ATT will have a direct negative effect on consumers' perceived PC	ATT → PC	4.919	-0.361***
H7 – ATT will have a direct positive effect on consumers' perceived ACC	ATT →ACC	9.595	0.544***
H8 – ATT will have a direct positive effect on IC	ATT →IC	3.421	0.298**
H9 – PC will have a direct positive effect on consumers' perception of IG	PC →IG	4.566	0.476***
H10 – PC will have a direct positive effect on consumers' perception of IC	PC →IC	4.959	0.393***
H11 – PC will have a direct positive effect on consumers' perception of IA	PC →IA	3.863	0.302**
H12 – PC will have a direct negative effect on consumers' perceived ACC	PC →ACC	1.972	-0.131*
H13 – TPT will have a direct negative effect on consumers' perceived PC	TPT →PC	4.189	-0.276***
H14 – TPT will have a direct negative effect on consumers' perception on IG	TPT →IG	1.065	0.150
H15 – TPT will have a direct negative effect on consumers' perception on IC	TPT →IC	4.133	-0.288***
H16 – TPT will have a direct negative effect on consumers' perception on IA	TPT →IA	0.076	0.007
H17 – TPT will have a direct negative effect on consumers' perceived ACC	TPT →ACC	2.299	0.111*
H18 – IG will have a direct positive effect on consumers' perceived ACC	IG →ACC	0.532	0.023
H19 – IC will have a direct positive effect on consumers' perceived ACC	IC →ACC	2.020	0.108*
H20 – IA will have a direct positive effect on consumers' perceived ACC	IA →ACC	1.305	-0.061

Notes: *$p < 0.05$, **$p < 0.01$, ***$p < 0.001$

2. Results and Analysis

A total of 186 valid responses were received. The age of the respondents ranged from a minimum of 17 to a maximum of 65 with a mean of 27 (SD = 10.1).

2.1. Assessment of the measurement

The first step in testing the hypotheses was the assessment of the measurement model, which involves determining the construct reliability and discriminant and convergent validity of the model. This was done by, first, calculating the individual item loadings, which were greater than the acceptable level of 0.3; composite reliabilities, which were greater than the required threshold of 0.707; and the average variances extracted (AVE) for all constructs, which were greater than the required 0.5 threshold. Second, discriminant and convergent validity were determined using the correlations of the constructs and cross loading of constructs, which were less than the square root of the AVE and greater than that with other constructs, respectively. The measurement model was, thus, deemed reliable.

2.2. Assessment of the structural models

The assessment of the structural model reveals the significance of the hypotheses. The process involves testing the predictive power of the model and the significance of the relationships (path model) between the models' constructs. The predictive power of the model was established by performing a PLS analysis. The R^2 values for each of the dependent variables were produces as a result.

The results revealed that the model was capable of explaining 69.8% of ACC of AeH systems, which is a highly satisfactory level in technology acceptance research. The model was also able to predict 36.1% of variance in PC, 38.6% of variance in IC, 19.4% of variance in IG and 8.9% of variance in IA. To establish the relationships between the model constructs, the path coefficients and t-values for each of the structural model paths were calculated. A bootstrapping resampling technique was used to calculate the t-values, which are summarised in Table 1 together with the results of the PLS analysis.

3. Discussion and Conclusion

The results of hypothesis testing revealed that five (H5, H14, H16, H18 and H20) of the twenty tested hypotheses were not supported. PC exhibited a significant negative effect on ACC. This indicates that if an eHealth consumer felt concerned about their privacy in the systems, they are less likely to adopt the system, thus confirming our thesis that information privacy concerns of consumers are a significant issue for eHealth systems. The results revealed that there were no positive or negative effects from the information context towards ACC except from IC, which had a significant positive effect. PC had significant positive effects on IG, IC and IA, supporting our hypotheses H9 – H11. This indicates that if an eHealth consumer is concerned about privacy, they believe that the countermeasures put in place in AeH systems are required. TPT also plays a significant role in the research model presented. The level of trust the respondents had on third parties had a significant negative effect on PC and IC, thus supporting our hypotheses H13 and H15 respectively. This indicates that privacy concerns are high when the trust levels are low and that the respondents believed that they should have the control of their own health information. Therefore, by providing the consumers the control of their information, AeH systems caters for a need that would improve system acceptance, which is supported by the evidence relating to H19 where IC shows a significant contribution to ACC. We believe that once consumers are exposed to an AeH system, IA and IG may also show positive contributing effects on ACC.

The constructs of the individual context also show significant effects on PC, IC and ACC. ANX shows a significant positive relationship with PC and a significant negative relationship with ACC. Therefore, if an eHealth consumer's anxiety level in relation to the system is high their privacy concerns will be high and they are less likely to accept the system. Similar arguments can be made in relation to ATT, which is reflected through H6 and H7. ATT showed a significant positive effect on IC. As seen from a supported H1, CSE also positively affects IC.

The research model presented in this paper identified several key constructs that influence the acceptance of AeH systems by eHealth consumers. However, to address the limitation of non-generalizability, a cohort of consumers with a wider age range can be used in future studies. Such studies conducted using this empirical model can give valuable insights into how consumers behave in relation to AeH systems. The results of those studies can improve implementation of AeH systems.

References

[1] Gajanayake R, Iannella T, Lane B, Sahama T. Accountable-eHealth systems: The next step forward for privacy. Electronic Journal of Health Informatics 2013.

[2] Rogers EM. Diffusion of innovations: Simon and Schuster; 1995.

[3] Barlass T. Patients reject eHealth system. The Sydney Morning Herald. 2012 August 12; Sect. IT Pro.

[4] Petkovic M, Ibraimi L. Privacy and Security in e-Health Applications. 2011. In: E-Health, Assistive Technologies and Applications for Assisted Living: Challenges and Solutions [Internet]. [23-48].

[5] Wilkowska W, Ziefle M, editors. Perception of privacy and security for acceptance of E-health technologies: Exploratory analysis for diverse user groups. Pervasive Computing Technologies for Healthcare (PervasiveHealth), 2011 5th International Conference on; 2011: IEEE.

[6] Or CKL, Karsh BT. A systematic review of patient acceptance of consumer health information technology. J Am Med Inform Assoc. 2009; 16(4):550-60.

[7] Gustafson DH, Hawkins RP, Boberg EW, McTavish F, Owens B, Wise M, et al. CHESS: 10 years of research and development in consumer health informatics for broad populations, including the underserved. Int J Med Inform. 2002; 65(3):169-77.

[8] Venkatesh V, Morris MG, Gordon BD, Davis FD. User Acceptance of Information Technology: Toward a Unified View. MIS Quarterly. 2003; 27(3):425-78.

[9] Ringle CM, Wende S, Will S. SmartPLS 2.0 (M3) Beta. 2.0 ed. Hamburg 2005.

[10] Schaper L, Pervan G. ICT and OTs: A model of information and communication technology acceptance and utilisation by occupational therapists. Int J Med Inform. 2007; 76:S212-S21.

[11] Holden RJ, Karsh BT. A theoretical model of health information technology usage behaviour with implications for patient safety. Behav Inf Technol. 2009; 28(1):21-38.

[12] Compeau D, Higgins C. Computer self-efficacy: Development of a measure and initial test. MIS Quarterly. 1995:189-211.

[13] Hsu MH, Chiu CM. Internet self-efficacy and electronic service acceptance. Decision Support Systems. 2004; 38(3):369-81.

[14] Hu PJH, Chau PYK, Sheng ORL, Tam KY. Examining the technology acceptance model using physician acceptance of telemedicine technology. Journal of Management Information Systems. 1999:91-112.

[15] Lai TY, Larson EL, Rockoff ML, Bakken S. User Acceptance of HIV TIDES—tailored interventions for management of depressive symptoms in persons living with HIV/AIDS. J Am Med Inform Assoc. 2008; 15(2):217-26.

[16] Finkelstein J, Khare R, Ansell J, editors. Feasibility and patients' acceptance of home automated telemanagement of oral anticoagulation therapy. AMIA Annual Symposium Proceedings; 2003: American Medical Informatics Association.

[17] Lober W, Zierler B, Herbaugh A, Shinstrom S, Stolyar A, Kim E, et al., editors. Barriers to the use of a personal health record by an elderly population. AMIA Annual Symposium Proceedings; 2006: American Medical Informatics Association.

[18] Korzaan ML, Boswell KT. The influence of personality traits and information privacy concerns on behavioral intentions. The Journal of Computer Information Systems. 2008; 48(4):15-24.

[19] Smith HJ, Milberg SJ, Burke SJ. Information privacy: measuring individuals' concerns about organizational practices. MIS Quarterly. 1996:167-96.

[20] Graeff TR, Harmon S. Collecting and using personal data: consumers' awareness and concerns. Journal of Consumer Marketing. 2002; 19(4):302-18.

[21] Angst CM, Agarwal R. Adoption of Electronic Health Records in the Presence of Privacy Concerns: The Elaboration Likelihood Model and Individual Persuasion. MIS Quarterly. 2009; 33(2):339-70. PubMed PMID: 38224406.