Adoption of Accountable-eHealth Systems by Future Healthcare Professionals

An empirical research model based on the Australian context

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***Abstract*–This paper provides a first look at the acceptance of Accountable-eHealth systems, a new genre of eHealth systems, designed to manage information privacy concerns that hinder the proliferation of eHealth. The underlying concept of AeH systems is *appropriate use* of information through after-the-fact accountability for intentional misuse of information by healthcare professionals. An online questionnaire survey was utilised for data collection from three educational institutions in Queensland, Australia. A total of 23 hypothesis relating to 9 constructs were tested using a structural equation modelling technique. A total of 334 valid responses were received. The cohort consisted of medical, nursing and other health related students studying at various levels in both undergraduate and postgraduate courses. The hypothesis testing disproved 7 hypotheses. The empirical research model developed was capable of predicting 47.3% of healthcare professionals' perceived intention to use AeH systems. A validation of the model with a wider survey cohort would be useful to confirm the current findings.**

Keywords. eHealth, privacy, information accountability, consumer adoption

I. Introduction

Preservation of information privacy is an imperative requirement of eHealth systems [1]. In the healthcare setting, information privacy refers to the obligation by healthcare providers not to misuse personal information disclosed by the patients or resulting from examination of the patient to any other person or organisation without consent [2]. eHealth systems utilise electronic health records (EHR) as the main source of information, which may contain sensitive personal information about a patient that may cause negative ramifications if inappropriately disclosed. Concerns regarding these ramifications have contributed to a heightened attention on information privacy management in eHealth systems.

Whilst consumers, i.e. patients, demand better privacy preservation, healthcare professionals (HCPs) call for better access to information. Timely access to information in healthcare is of utmost importance as it enables HCPs to make fully-informed medical decisions. Access to information falls under Pfleeger's [3] third pillar of security–availability–which is concerned with ensuring that information is available to authorised users when required. Electronic information systems are often considered a double edged sword in this regard; whilst it is technologically capable of providing access to information in a time-efficient manner, they can also be the source of unnecessary delays when the underlying security policies do not accurately reflect the goals and requirements of the users.

A number of privacy management methods have been proposed in the medical informatics literature [4-6] that are predominantly preventive measures based on rigid access controls. However, systems that enforce rigid restrictions on information access may not be appropriate for eHealth systems that can be used at point-of-care. Recently however, there has been an increasing interest in information privacy management through information accountability (IA), and Accountable-eHealth (AeH) systems [7] have been proposed that rely on *appropriate use* of information through *after-the-fact* accountability. They make all uses of a patient's health information transparent and hold HCPs accountable for inappropriate uses by tracking and checking all transactions against context-aware privacy policies. Demarcation lines, instead of rigid restrictions, are used to warn HCPs when they are about to access restricted information but allow them to proceed if they professionally judge that their actions are justifiable.

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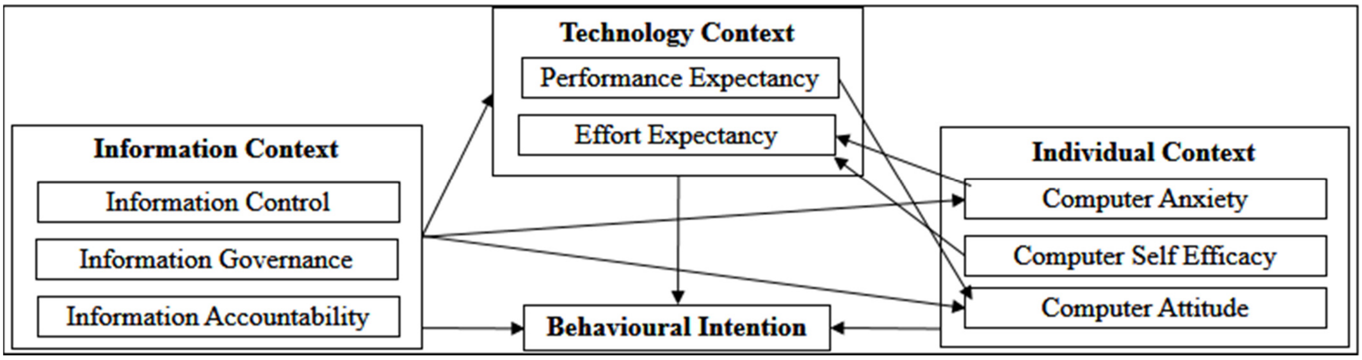

Fig 1. Hypothesised research model.

When potential breaches occur, notifications will be automatically sent to consumers that direct them to the transaction in question and allow them to view further details and resolve the incident using a justification query/response mechanism. The after-the-fact approach will alleviate the concerns of both patients and HCPs, by providing an adequate level of information privacy without restricting HCPs in delivering high-quality, time-critical healthcare. Both stakeholders are likely to seek comfort from the parallels that can be drawn between AeH systems and law enforcement in the offline world [8].

Although AeH systems exhibit capabilities for the appropriate management of healthcare information, it is important to know how this new genre of eHealth systems would be accepted by eHealth stakeholders. As a first step in this direction, this paper presents a conceptual research model on the acceptance of AeH systems by future HCPs.

II. Method

The study used the survey method and employed an online questionnaire for data collection. A detailed description of the AeH system was given to the participants who were university students from three universities in Queensland, Australia outlining the specific characteristics. Participants included undergraduate and postgraduate students from medicine, nursing and various health sciences disciplines.

A. *Theoretical foundations and research model*

Underpinning the theoretical model is the Unified Theory of Acceptance and Use of Technology (UTAUT) [9], a well-established and frequently used model of technology acceptance and is also motivated by the model developed by Schaper and Pervan [10]. Their research model, also based on UTAUT and motivated by Chau et al. [11], uses three dimensions of technology acceptance: individual context, technology context and implementation context to capture the factors affecting the intention to use ICT. In our study, we adopt the individual and technology contexts and introduce an information context, which deals with aspects relating to information manipulation within AeH systems.

The individual context consists of three constructs: Computer/EHR anxiety (ANX) [12]; Computer/EHR self-efficacy (CSE) [13]; and Computer/EHR attitude (ATT) [9]. Based on prior technology acceptance research in healthcare [9-11, 14] we make 5 hypotheses relating to these three constructs (See Table V).

The technology context consists of two constructs: Performance expectancy (PE) [9] and Effort expectancy (EE) [9]. The perceptions of an individual's evaluation of technology has been found to have relevance in technology acceptance decision making in healthcare [10]. Based on related work [10, 11], we make 3 hypotheses relating to these two constructs (See Table V).

The information context is unique to our study. It consists of 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 patients' healthcare information. IC is defined as the perception of the ability for 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 against inappropriate use of information. We hypothesise 15 relationships related to these three contexts as listed in Table V.

The outcome variable in our study is behavioural intention (BI). It is defined as the measure of the strength of one's intention to perform a specific behaviour [15]. Here it represents one's intention to use an AeH system. The conceptualised research model is illustrated in Fig 1.

III. Results and Analysis

A total of 334 valid responses were received from the three participating institutions. The age of the respondents ranged from 17 years to a maximum of 58 with mean 27 (SD = 10.55). The analysis of the results from the survey was conducted using the partial least square (PLS) method of structural equation modelling (SEM). The analysis tools used were smartPLS 2.0 [16] and IBM SPSS Version 21.

TABLE I. ITEM LOADINGS, INTERNAL COMPOSITE RELIABILITIES AND AVERAGE VARIANCE EXTRACTED

Construct	Indicators	Loading	AVE	Composite Reliability
Computer/EHR self-efficacy	CSE1	0.8975	0.6227	0.7635
	CSE2	0.6632		
Computer/EHR anxiety	ANX1	0.8003	0.5904	0.8516
	ANX2	0.8064		
	ANX3	0.6822		
	ANX4	0.778		
Computer/EHR attitude	ATT1	0.8511	0.5653	0.8651
	ATT2	0.6907		
	ATT3	0.7032		
	ATT4	0.636		
	ATT5	0.8521		
Performance expectancy	PE1	0.8445	0.6414	0.8767
	PE2	0.848		
	PE3	0.7001		
	PE4	0.802		
Effort expectancy	EE1	0.7385	0.6610	0.8535
	EE2	0.8424		
	EE3	0.8532		
Information governance	IG1	0.7643	0.5371	0.8219
	IG2	0.7827		
	IG3	0.7358		
	IG4	0.6402		
Information control	IC2	0.6025	0.5424	0.7742
	IC3	0.6473		
Information accountability	IA1	0.8244	0.5030	0.7808
	IA2	0.6534		
	IA3	0.463		
	IA4	0.7773		
Behavioural intention	BI1	0.6685	0.6507	0.7841
	BI2	0.9244		

TABLE II. PREDICTIVE PROPERTIES OF THE MODEL

Construct	R^2 Value
Computer/EHR attitude (ATT)	0.630
Computer/EHR anxiety (ANX)	0.069
Effort expectancy (EE)	0.378
Performance Expectancy (PE)	0.069
Behavioural intention (BI)	0.473

A. *Assessment of the measurement model*

The first step towards testing the hypotheses was the assessment of the measurement model, i.e. the questionnaire items. To that end, the construct reliability of the model was determined using individual item reliability, composite reliability and the average variance extracted (AVE) (see Tables I). Discriminant and convergent validity, which are determinants of construct validity, were determined using the correlations of the constructs (see Table III) and cross loading of constructs (see Table IV). Individual item reliability is considered significant if the item loadings are greater than 0.3 [17]. The determinant for internal consistency of the measurement model was the composite reliability of the constructs, which is considered significant if it is greater than 0.707 [17]. A value greater than 0.5 for AVE meant that each construct was capable of capturing an acceptable level of variance from its indicators relative to measurement error [18]. Discriminant validity is used to measure the difference of a construct to other constructs used in the model. Convergent validity is used to determine the convergence of the items used to measure a construct. It shows how they associate with each other to reflect the construct they are designed to measure [19]. In PLS, correlations of the constructs and cross loading of constructs are used to determine the discriminant and convergence validity. As seen in Table III, the square root of AVE of each construct is greater than the correlation of other constructs (with the exception of the relationship between ATT and PE), which gives an accurate measure of the correlation of constructs in the measurement model. The cross loadings seen in Table IV shows that the loadings of each of the items on the corresponding constructs are significantly greater than with other constructs.

The measurement model was successfully validated following the removal of one questionnaire item which did not adequately reflect the measured construct.

B. *Assessment of the structural model*

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 between the models' constructs. The predictive power of the model was established by performing PLS analysis and producing the R^2 values for each of the dependent variables (see Table II).

The results revealed that the model was able to explain 47.3% of the BI, thus quantifying the acceptance of AeH systems. The predictive power of our model is at a highly satisfactory level in technology acceptance research. The model was also able to predict 63.0% of variance in ATT, 37.8% of variance in EE, and 6.9% of that in PE and ANX.

To establish the relationship of the model's constructs, the path coefficients and t-values for each of the structural paths were calculated. Twenty three of the 24 hypotheses are tested. A bootstrapping resampling technique was used to calculate the t-values, which are summarised in Table V together with the results of the PLS analysis.

TABLE III. CORRELATION OF CONSTRUCTS AND SQUARE ROOT OF AVE

	CSE	ANX	ATT	PE	EE	IG	IC	IA	BI
CSE	**0.789**								
ANX	-0.326	**0.768**							
ATT	0.372	-0.569	**0.751**						
PE	0.335	-0.480	~~0.792~~	**0.801**					
EE	0.410	-0.564	0.557	0.498	**0.813**				
IG	0.310	-0.224	0.306	0.333	0.280	**0.732**			
IC	0.003	0.106	-0.072	-0.04	-0.059	0.222	**0.736**		
IA	0.163	-0.199	0.169	0.167	0.133	0.520	0.288	**0.709**	
BI	0.310	-0.415	0.610	0.666	0.388	0.259	-0.092	0.126	**0.806**

TABLE IV. CROSS LOADING OF CONSTRUCTS

Indicators	CSE	ANX	ATT	PE	EE	IG	IC	IA	BI
CSE1	**0.897**	-0.319	0.306	0.267	0.392	0.276	0.016	0.091	0.230
CSE2	**0.663**	-0.170	0.2956	0.28	0.231	0.2087	-0.021	0.2009	0.2876
ANX1	-0.321	**0.800**	-0.616	-0.594	-0.504	-0.322	-0.006	-0.273	-0.449
ANX2	-0.260	**0.806**	-0.412	-0.338	-0.383	-0.122	0.0959	-0.100	-0.329
ANX3	-0.134	**0.682**	-0.284	-0.165	-0.331	-0.074	0.1436	-0.071	-0.190
ANX4	-0.240	**0.778**	-0.352	-0.261	-0.475	-0.099	0.1409	-0.11	-0.242
ATT1	0.1773	-0.400	**0.6360**	0.3743	0.2955	0.1401	-0.095	0.0745	0.3559
ATT2	0.2913	-0.422	**0.8521**	0.7816	0.4677	0.2914	-0.045	0.1677	0.5758
ATT3	0.3095	-0.366	**0.7032**	0.5000	0.4558	0.1629	-0.047	0.1189	0.4119
ATT4	0.3574	-0.494	**0.8511**	0.7019	0.5743	0.3068	-0.003	0.1499	0.4938
ATT5	0.2442	-0.478	**0.6907**	0.5145	0.2511	0.2021	-0.114	0.1002	0.4145
PE1	0.2702	-0.383	0.6513	**0.8445**	0.4078	0.2478	-0.021	0.1215	0.556
PE2	0.2135	-0.352	0.614	**0.8480**	0.3825	0.2395	-0.017	0.1181	0.5347
PE3	0.2913	-0.388	0.6763	**0.8020**	0.4355	0.2331	0.0002	0.0817	0.5662
PE4	0.2966	-0.412	0.5899	**0.7001**	0.3634	0.3515	-0.112	0.2198	0.4695
EE1	0.3276	-0.439	0.4340	0.3908	**0.8424**	0.2092	-0.041	0.0654	0.2396
EE2	0.356	-0.418	0.4691	0.4306	**0.8532**	0.2165	0.006	0.0844	0.3259
EE3	0.3121	-0.504	0.4479	0.3866	**0.7385**	0.2506	-0.101	0.163	0.364
IG1	0.2516	-0.180	0.1884	0.1962	0.2069	**0.7643**	0.1685	0.4264	0.2122
IG2	0.235	-0.191	0.2343	0.289	0.1935	**0.7827**	0.1494	0.3864	0.1912
IG3	0.1508	-0.175	0.0987	0.1168	0.1206	**0.7358**	0.2486	0.5281	0.1161
UR4	0.2335	-0.118	0.3022	0.3008	0.2533	**0.6402**	0.1231	0.2558	0.204
IC2	0.0400	0.0698	0.0156	0.0223	-0.024	0.1107	**0.6025**	0.1973	0.0012
IC3	0.0422	0.0451	-0.030	-0.011	0.0338	0.0905	**0.6473**	0.2144	-0.068
IA1	0.164	-0.175	0.1749	0.1414	0.132	0.4985	0.1868	**0.8244**	0.1267
IA2	0.0856	-0.100	0.0829	0.1264	0.0674	0.2907	0.3124	**0.6534**	0.0523
IA3	-0.017	-0.011	-0.009	0.0310	-0.026	0.2861	0.3599	**0.4630**	-0.021
IA4	0.1087	-0.166	0.1109	0.1156	0.0934	0.352	0.1887	**0.7773**	0.0948
BI1	0.2631	-0.160	0.3014	0.3463	0.2166	0.2012	-0.075	0.1157	**0.6685**
BI2	0.2581	-0.444	0.6187	0.6667	0.3809	0.2259	-0.078	0.1004	**0.9244**

TABLE V. RESERCH HYPOTHESES AND PATH COEFFICIENTS FROM PLS ANALYSIS

Construct	Hypothesis	Path	t-Value	Path Coefficients
Computer Self Efficacy (CSE)	H1: CSE will have a direct positive effect on EE	CSE → EE	4.9404	0.2474**
	H2: CSE will not have a direct effect on BI	CSE ↛ BI	1.4122	0.0735
Anxiety (ANX)	H3: ANX will have a direct negative effect on EE	ANX → EE	8.558	-0.4853***
	H4: ANX will not have a direct effect on BI	ANX ↛ BI	1.243	-0.0681
Attitude (ATT)	H5: ATT will have a direct positive effect on BI	ATT → BI	2.0758	0.1624*
Performance Expectancy (PE)	H6: PE will have a direct positive effect on ATT	PE → ATT	30.3758	0.7691***
	H7: PE will have a direct positive effect on BI	PE → BI	7.828	0.4739***
Effort Expectancy (EE)	H8: EE will have a direct positive effect on BI	EE → BI	0.341	-0.0203
Information Governance (IG)	H9: IG will not have a direct negative effect on EE	IG ↛ EE	2.145	0.070*
	H10: IG will not have a direct negative effect on PE	IG ↛ PE	5.755	0.232**
	H11: IG will have a direct negative effect on ANX	IG → ANX	2.665	-0.153**
	H12: IG will have a direct negative effect on ATT	IG → ATT	0.006	-0.000
	H13: IG will not have a direct negative effect on BI	IG ↛ BI	0.6823	0.038
Information Control (IC)	H14: IC will not have a direct negative effect on EE	IC ↛ EE	0.736	0.041
	H15: IC will not have a direct negative effect on PE	IC ↛ PE	0.562	-0.035
	H16: IC will have a direct negative effect on ANX	IC → ANX	1.541	0.105
	H17: IC will have a direct negative effect on ATT	IC → ATT	0.751	-0.028
	H18: IC will not have a direct negative effect on BI	IC ↛ BI	1.179	-0.049
Information Accountability (IA)	H19: IA will not have a direct negative effect on EE	IA ↛ EE	0.969	-0.051
	H20: IA will not have a direct negative effect on PE	IA ↛ PE	0.823	0.057
	H21: IA will have a direct negative effect on ANX	IA → ANX	2.279	-0.146*
	H22: IA will have a direct negative effect on ATT	IA → ATT	0.997	0.046
	H23: IA will not have a direct negative effect on BI	IA ↛ BI	0.0507	-0.041

Notes: $^*p < 0.05$, $^{**}p < 0.01$, $^{***}p < 0.001$

IV. DISCUSSION

The PLS analysis revealed that seven hypotheses were not supported (H8, H9, H10, H12, H16, H17 and H22), i.e. the independent construct either had or did not have any statistically significant effect on the dependent construct, thus contradicting the initial hypothesis. By not having a significant effect on BI, EE supports previous technology acceptance research in the healthcare domain [11]. IG and IA showed significant negative effects on ANX, thus supporting hypotheses H11 and H21 respectively. This negative relationship indicates that if a respondent feels that either accountability measures or computerised information governance are suitable, their anxiety level about the system reduces and vice versa. Although IA and IG negatively affected ANX, they do not have a negative effect on BI since ANX also has no significant effect on BI, which was initially hypothesised based on UTAUT [9]. IG had significant positive effects on PE and EE. This indicates that if a respondent believes that the presence of a computerised knowledgebase that governs information usage is suitable, it would improve their perceived job performance and perceived ease of use.

Our hypotheses H13, H18 and H23 were also supported from the results, which indicate that the presence of usage rules on health information use, accountability measures and the fact that patients have control of their information do not negatively affect BI.

Two of the three hypothesised direct effects on BI were found to be statistically significant (H5 and H7) with PE (H7) having the highest direct effect. In technology acceptance research generally, ATT does not have a significant effect on BI [9]. But in the healthcare domain, ATT has been seen to have a significant effect on BI [11], thus supporting our findings.

V. Conclusion

The established research model can predict the behaviour of future HCPs in relation to the acceptance of AeH system, which fills a significant gap in the knowledge. However, the results can be further validated using a sample consisting of practicing HCPs, thus addressing the apparent limitation of using a student cohort in this study.

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