A STUDY OF THE INTENT TO FULLY UTILIZE ELECTRONIC PERSONAL HEALTH

RECORDS IN THE CONTEXT OF PRIVACY AND TRUST

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Government initiatives called for electronic health records for each individual healthcare consumer by 2014. The purpose of the initiatives is to provide for the common exchange of clinical information between healthcare consumers, healthcare providers, third-party payers and public healthcare officials. This exchange of healthcare information will impact the healthcare industry and enable more effective and efficient application of healthcare so that there may be a decrease in medical errors, increase in access to quality of care tools, and enhancement of decision making abilities by healthcare consumers, healthcare providers and government health agencies. An electronic personal health record (ePHR) created, managed and accessed by healthcare consumers may be the answer to fulfilling the national initiative. However, since healthcare consumers potentially are in control of their own ePHR, the healthcare consumer's concern for privacy may be a barrier for the effective implementation of a nationwide network of ePHR.

A technology acceptance model, an information boundary theory model and a trust model were integrated to analyze usage intentions of healthcare consumers of ePHR. Results indicate that healthcare consumers feel there is a perceived usefulness of ePHR; however they may not see ePHR as easy to use. Results also indicate that the perceived usefulness of utilizing ePHR does not overcome the low perceived ease of use to the extent that healthcare consumers intend to utilize ePHR. In addition, healthcare consumers may not understand the different components of usage: access, management, sharing and facilitating third-party ePHR. Also, demographics, computer self-efficacy, personal innovativeness, healthcare need and healthcare literacy impact a

healthcare consumer's privacy concerns and trusting intentions in the context of ePHR and intent to utilize ePHR. Finally, this research indicates that healthcare consumers may need a better understanding of the Health Insurance and Portability and Accountability Act of 1996 (HIPAA) regulations of ePHR as well as a better understanding of the impact HIPAA has on websites that may facilitate ePHR.

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CHAPTER 1

INTRODUCTION

Overview

Everything changes. Everything is connected. Pay attention.
Jane Hirschfield

President Bush called for electronic health records for each individual healthcare

consumer by 2014. In addition, the Obama administration has promised an estimated $40 billion

for funding to aid in the establishment of the national healthcare information technology (IT)

infrastructure (Agarwal, Milch, & Van Kuiken, 2009).   The initiatives and the funds are

intended to shift our healthcare infrastructure from a silo-ridden, paper-based system to a

coordinated electronic system that works efficiently and effectively to support medical

decisions   (Agarwal et al., 2009). Furthermore, the American Recovery and Reinvestment Act

indicates that meaningful use of electronic medical records is necessary for advances in

healthcare; these advances are needed for interoperability and the nationwide compilation and

analysis of healthcare data (Wild, 2010).

The concept is that the national healthcare IT infrastructure could provide for the

common exchange of clinical information from the physician to the hospital and back and would

make the information available to healthcare consumers, third-party payers and public healthcare

organizations via secure Internet protocols (Steckler, Epstein, & Riner, 2009). Electronic health

records and the subsequent interoperability of healthcare systems are imperative to the

presidential initiatives for a national healthcare IT infrastructure. Furthermore, because the focus

of the record is the patient and because governance is in place for health consumer privacy and

control, healthcare consumers are at the center of the healthcare systems and some feel they may be the key to full integration.

Definitions

An electronic medical record (EMR) is   an electronic record of health-related information on an individual that can be created, gathered, managed and consulted by authorized clinicians and staff within one healthcare organization   (National Alliance for Health Information Technology [NAHIT], 2008). In contrast, an electronic health record (EHR) is   an electronic record of health-related information on an individual that conforms to nationally recognized interoperability standards and that can be created, managed, and consulted by authorized clinicians and staff across more than one healthcare organization   (NAHIT, 2008). The distinguishable difference between the two is the exchange of healthcare information via system interoperability. EMRs are within a healthcare facility, while EHRs can exist among many or all users of health records. The ownership of the EMR or EHR is the owner of the system either within the clinic with an EMR or within a system with an EHR. There is a documented need for a national effort to improve America's healthcare system. The use of EHRs is part of the solution (Harrison & Daly, 2009). EHR is a technology whose time has come; whether or not it can deliver on its promise, it will change healthcare profoundly (Agarwal et al., 2009).

In addition to the introduction of EMR and EHR to our national healthcare IT infrastructure, a new type of record, electronic personal health records (ePHR) are becoming a topic of discussion and interest. While the focus has been on converging paper-based records to EMR, with a goal of improving accuracy and efficiency, over time it has become clear that the record   was not just what was in the EMR of doctors and hospitals, but much of the needed

information resided with the patient (Magee, 2009). What may work better than the EMR concept is the personal health record where individuals generate and maintain information and where accessibility is given to authorized providers (Medical Experts, 2008). Although no universal definition exists, a description of ePHR is electronic applications through which individuals can access, manage and share their health information, and that of others for whom they are authorized, in a private, secure and confidential environment (Connecting for Health, 2003). Unlike the EMR or the EHR, which are owned by the health record system, the ePHR is owned by the healthcare consumer.

<div align="center">Statement of the Problem</div>

EPHR enable the healthcare consumer to electronically access, manage and share their personal health information with healthcare providers, third-party payers and public healthcare facilities or to be authorized to act for a third-party as their representative. With full interoperability, via ePHR, healthcare consumers can have better information about their healthcare status and can move easily between clinicians. In addition, payers can benefit from economic efficiencies, fewer errors, and reduced duplication. Finally, the nation as a whole can benefit from research, public healthcare reporting, bioterrorism surveillance, quality monitoring and advances in clinical trials (Braller, 2005). However, there are factors that may impact a healthcare consumer's intent to fully utilize the interoperable electronic personal health records system.

Healthcare consumers may not be comfortable with the current level of privacy and secure access to ePHR by healthcare providers, third party payers or public healthcare facilities. Therefore, they may not share information or give access to information via fully utilized and integrated personal health records. Without complete and accurate information and healthcare

consumers' consent to access and share the information, the national healthcare IT healthcare infrastructure may be inadequate and quality of care may suffer both for the healthcare consumer and for the nation as a whole. Because healthcare consumers have privacy concerns, the subsequent privacy demands could conceivably forestall benefits of networked technology (Bower, 2005).

Theoretical Foundations

The ultimate success of a new technology such as ePHR depends on patient use (DeLone & McClean, 1992). Hence, research needs to specifically enhance the understanding of healthcare consumers' intent to use. The technology acceptance model (TAM) measures behaviors related to a new technology which can identify how users will come to accept and use a new technology (Davis, Bagozzi & Warshaw, 1989). In this research, TAM was applied in the context of ePHR in order to gain a better understanding of the intentions of healthcare consumers to utilize ePHR to access, manage and share their health information. By applying TAM and analyzing the factors that contribute to the intention to use, this research focuses on understanding the antecedent relationship of TAM and the factors that may have an influence on the healthcare consumer's intent to use. Also, the advanced applicability of TAM to specific contexts such as ePHR extends the theory for specific use intentions. Based on the definition of ePHR, methods of utilization of ePHR include: access (or creation   initial access), management and sharing. In addition, the integration of privacy models through information boundary theory and trust models with the TAM model in this research extends the theory into new contexts.

Information boundary theory (IBT) was applied in order to gain a better understanding of what factors influence a healthcare consumer's intent to fully utilize ePHR. Information boundary theory posits that the motivation to reveal or withhold valued information through a

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given medium follows rules for boundary opening and boundary closure (Petronio, 1991). IBT postulates that individuals form a physical or virtual informational space around themselves with clearly defined boundaries and that this behavior results in privacy concerns (Xu, Smith, Dinev, & Hart, 2008). In addition, evidence suggests that users may hesitate to utilize an internet technology, such as ePHR due to risk concerns such as privacy.

However, trust can play a key role in overcoming privacy concerns (McKnight, Choudhury, & Kaemar, 2002). Trust may increase people's perceived privacy and therefore it is imperative to measure trust in order to fully understand reaction to privacy concerns (Joinson, Reips, Buchanan, & Schofield, 2010). In this study, ePHR intent to use was studied in the context of the antecedents of privacy concerns and trust intentions. Also, through literature review of electronic health record studies, individual healthcare consumer characteristics were identified and studied to determine the impact each of these has on the intent to utilize.

Purpose of the Study

By integrating the three models, this research examined the impact that privacy concerns and trust behaviors have on healthcare consumers' intent to fully utilize ePHR. First, the technology acceptance model was used to measure three dimensions of intent to use. Next, a research model developed by Xu et al. (2008) was used to measure privacy concerns within the information boundary theory. Finally, a trust model developed by McKnight et al. (2002) was incorporated into the final research model in order to determine the impact trust intentions have on privacy concerns and intent to utilize ePHR.

By researching and attempting to understand the antecedents of the healthcare consumer behavior through analysis of intentions, this research contributes to a better understanding of what barriers there are to adoption of ePHR and the subsequent hope to overcome these barriers.

The ultimate goal of the nationwide healthcare infrastructure is interoperability which can lead to an integrated nationwide healthcare system; integration is necessary to recognize the benefits expected. This study utilizes common theories in information technology in a new context and builds upon these existing theories to strengthen and identify contextual information for healthcare settings. Finally, this research integrates IBT with TAM in the context of ePHR in order to understand the impact privacy concerns and trust intentions may have on intent to use.

Research Questions

In order to analyze intent to utilize ePHR as well as privacy and trust as antecedents to the intent to fully utilize electronic personal health records and also to analyze the individual characteristics that represent intent to fully utilize, three research questions were addressed. In accordance with the definition of an electronic personal health record, three types of use were analyzed: access, manage and share. In addition, because sharing can be among different types of agencies, this research analyzed three contexts of sharing: healthcare providers, third-party payers and public healthcare facilities and also at the intent to use when authorized as a third-party administrator of another healthcare consumer's ePHR. Hence, the following research questions were analyzed and studied:

1. What attributes of healthcare consumers result in intent to fully utilize electronic personal health records via access to, management of and sharing of personal healthcare information with healthcare providers, third-party payers, and public healthcare facilities or as an authorized agent of a third-party's ePHR?

2. Do individual privacy concerns of healthcare consumers impact the intent to fully utilize electronic personal health records via access to, management of and sharing of personal

healthcare information with healthcare providers, third-party payers, and public

healthcare facilities or as an authorized agent of a third-party's ePHR?

3.   Does an individual's trust related behaviors impact the intent to fully utilize electronic

personal health records via access to, management of and sharing of personal healthcare

information with healthcare providers, third-party payers, and public healthcare facilities

or as an authorized agent of a third-party's ePHR?

The remainder of this dissertation is organized as follows. Chapter 2 is the literature review of the field electronic health as well as the theories used in this research. Chapter 3 explains the research methods used in this study such as the instrument design and population studied. Chapter 3 also discusses the survey administration and data analyses used to study the data. Chapter 4 gives results of the study. The data analysis results are in Chapter 5 along with the statistical results of the model and hypotheses. And finally in Chapter 6, the limitations, contributions and direction for future research are discussed.

CHAPTER 2

LITERATURE REVIEW

Overview

The premise of the promises made through the implementation of a nationwide database

of electronic health records is interoperability. The word can carry many promises, but can have

varying degrees of actual results (Amatayakul, 2009a). The use of electronic health records

(EHR) ranges from a basic electronic medical record (EMR) in a clinic, to an enterprise-wide,

comprehensive EHR in a hospital system, to a national healthcare information technology (IT)

infrastructure (Holstein, Litzinger, & Dunn, 2010). While there may be different phases of

interoperability on the horizon, ultimately full integration and interoperability is necessary for an

efficient and effective national healthcare IT infrastructure. In the absence of a national health

information exchange along with the willingness to share information, the true potential of EHR

may never be realized (Ozdemir, Barron, & Bandyopadhyay, 2011). EHRs may enable

integration across healthcare providers, third-party payers and public healthcare facilities.

Healthcare Infrastructure

Interoperability would give healthcare providers the ability to electronically exchange

and use healthcare consumers' medical information. The idea includes the ability to

communicate healthcare consumers' information to any healthcare provider or to allow a third-

party to view personal medical information. Due to the vision for integration, it is inevitable that

the use of EHR will lead to coordination with other providers. The presidential stimulus package

allows for reimbursement to providers for utilizing EHR, but the providers must show evidence

of meaningful use before the stimulus funds are released to the providers. Meaningful use

includes e-prescribing, standardized billing codes, reporting of predetermined healthcare quality

measures, and providing evidence of coordinating care with other providers (Holstein et al.,

2010). According to Healthcare Information and Management Systems Society (HIMSS), the

EHR has seven levels with Stage 7 involving fully electronic medical records. Stage 7 is where

the government initiative wants all healthcare providers to be soon, yet in Quarter1 of 2008 only

0.3% of hospitals had achieved this stage (Health Analytics, 2009).

Healthcare is becoming patient-centered. Consumers in general have high expectations

that their online applications for shopping, banking and information delivery will be personalized

and relevant (Marshall, 2009). Therefore, healthcare must move in that direction through access

to electronic personal health records. To be successful, the ePHR should have the following

qualities: accessible, secure, portable, interoperable and actionable (Marshall, 2009). And despite

the low adoption rate by physicians, consumers surveyed said that EHR were at least slightly

important in their selection of a physician and half said they would pay for it (Marshall, 2009).

In addition to the benefits of reduced medical errors, other benefits include electronic

information is easily accessible by the healthcare provider and access to an enormous amount of

medical data is at the fingertips of healthcare providers via decision support systems. The

benefits of information technology via EHRs in healthcare include organized and accessible

information which can aid in avoiding delays in care. More specifically, the key outcomes of full

integration and interoperability are (1) improved clinical outcomes; (2) more efficient clinical

care delivery; (3) prevention of medical errors; (4) lower care delivery costs; (5) increased

administrative efficiencies; (6) reduction of fraud, waste, and abuse; and (7) improved patient

experience (Sullivan, 2010). As one technology manager says, Imagine the impact on patient

safety and the reduction in adverse drug events when primary care physicians, specialists,

emergency care physicians and other care givers have access to a patient's complete medication list and past history of medical treatments at any time and at any location (Barlow, 2007).

One component of the concept of electronic health records and the integration of an IT healthcare infrastructure is the need for decision support systems. With up-to-date and complete information, the decision support system can support clinical expertise through identification of trends and patterns within an individual patient's care (Cassel, Johnston-Fleece, & Reddy, 2009). The decision support tool can enable extraordinary efficiency in sorting out a patient's symptoms while keeping the patient's past medical history in context. In addition, the availability of a complete record of past medical history can eliminate the burden of unnecessary testing or errors. However, due to the current lack of integration, patients may be the missing link to bridge the last, critical gap between EMRs and EHRs (James, 2005).

EHRs in clinical or hospital environments can increase quality of care and lower medical costs. Brigham and the General rank among the world's best hospitals and they have found that IT has cut serious medical errors by 51% and the number of overall medical errors by 81% (Symonds, 2000). A systematic review of the literature on healthcare information technology and EHR systems is the most authoritative evidence of the impact on quality of care; in this, authors conclude that there are three major benefits of quality: increased adherence to guideline-based care, enhanced surveillance and monitoring and decreased medication errors (Chaudhry et al., 2006). A study found that hospital implementation of EMR has shown a 27% decline in deaths among heart attack patients and an 88% decrease in central line bloodstream infections due to EHR systems monitoring capabilities (Magee, 2009).

Not only can EHR systems reduce medical errors, but electronic prescribing or e-prescribing as it is called, can increase accuracy and legibility of prescription orders, reduce

pharmacy callbacks, save time, allow patient selection of common prescription orders and verify

coverage and drug interaction. For example, computerized order entry is available via EHR

systems which can avoid medical errors by as much as 55% by providing current medication and

allergy information to the healthcare provider at the time of order (Symonds, 2000). Studies have

shown that electronic prescribing can prevent 95% of adverse drug events through computerized

physician order entry (Ferguson, 2003). Despite these advantages, a small percentage of

prescriptions are sent electronically (Altinkemer, De, & Ozdemir, 2006). Integration is needed

between healthcare providers and pharmacies in order for the full benefits of e-prescribing to

be realized nationwide.

In addition to improved quality of care for healthcare consumers, the nation as a whole

can benefit from a nationwide healthcare infrastructure. RAND Corporation researchers set up a

statistical model to predict the potential savings if 90% of hospitals and doctors adopt a fully-

integrated nationwide electronic health records network. The model showed a conservative

estimate of $81 billion in annual savings (Swartz, 2005). Financially, for both the healthcare

consumer and the third-party payers, the use of EHR can produce a ratio of 10:1 for financial

paybacks through assessable pharmaceutical and insurance information and subsequent issuance

of less expensive drugs.

Research shows that when there is a linkage of clinical information systems there will be

a significant reduction in medical errors (Harrison & Daly, 2009). Computerized systems are the

foundation of a national healthcare IT infrastructure which proponents say will improve quality

of care, advance medical knowledge and save the country tens of billions of dollars (M. Brown,

2009). As the government has suggested, an installed base of hospitals is necessary for the

transfer of health information (Miller & Tucker, 2009). But they go on to state that this is not

sufficient; there must be a mechanism for cooperation and coordination across hospitals for this to happen. In order for a context where minimizing transition-related errors and waste is to be maintained, there needs to be a health system that is integrated by participation of hospitals that has care settings linked by a single electronic data system; these links are essential (Cassel et al., 2009). With this, all healthcare providers will have concurrent access to accurate data and the patient would be able to see the information to ensure accuracy and also to be well informed (Cassel et al., 2009). Limited health IT integration produces medical errors resulting in poor quality of care and also frustration for the healthcare providers and healthcare consumers (Aarts & Koppel, 2009).

Despite all the benefits of EHR implementation, the deployment of EHR has had more dependencies than anticipated. For example, installing an EHR system without standardized infrastructure will be unrewarding for healthcare providers (Gleiner, 2000). Healthcare providers will incur the cost of EHR compatible systems, while healthcare consumers and third-party payers will reap the benefits. In addition to the cost, the implementation of EHR systems can be complicated and time-consuming for the healthcare providers. For example, for nearly a decade the Department of Veterans Affairs and the Department of Defense have been undertaking initiatives to exchange data between systems and create comprehensive medical records; they have faced many challenges which have led to repeated changes in focus and target completion dates (Melvin, 2007). Another factor that seems to be slowing down implementation by physicians is concerns for sharing information. Research finds that healthcare providers may not have an incentive to share patients' records electronically in the presence of provider heterogeneity and myopic consumers (Ozdemir et al., 2011).

Not only is the IT platform for integration needed, but there are other factors that must be in place for the full-integration and benefits to occur. Healthcare providers must have EHR systems in place. However, only 4% of U.S. practices have fully functioning EHR (DesRoches, Campbell, Rao, Donelan, Ferris, & Jha, 2008). Due to the lack of EHR implementation, physician expertise is lacking. In addition, the introduction of EHR in the medical field is causing a paradigm shift in the role of physicians, nurses and other medical professionals (Cassel et al., 2009). Because of the lack of integration, there is an information gap between a clinician's access to timely and comprehensive information about a patient's medical condition and the actual time it takes to gather and record the patient's medical condition. The primary goal of the health information technology is to address the information gap (Beaton, 2008). In order for this to happen, healthcare providers must record and store a vast amount of medical information in a standardized electronic format   diagnoses, prescriptions, laboratory tests, and the like   then, this data must be made available to other clinicians and third parties through a secure, timely and useful manner (Beaton, 2008).

Healthcare IT is effective in improving quality of care, reducing costs and enhancing patient safety, but a comprehensive infrastructure is needed to make the national healthcare IT infrastructure more efficient and effective. The infrastructure should include standards for data interchange, healthcare terminologies, knowledge representation and a common format for reporting (Harrison & Daly, 2009). Without integration, fragmentation of a healthcare consumer's healthcare expense can lead to errors, duplication, lack of coordination and many other problems (Braller, 2005). Because of this lack of integration, it is estimated that $300 billion is spent on healthcare each year for treatments that are unnecessary, inappropriate, inefficient and ineffective (Bush, 2004). But without a system-wide medical informatics program

where all patient information is shared and updated, programs in place to save this money may not work (Crane & Crane, 2006).

What comes first then, the chicken or the egg; the standardized electronic medical records at clinics, the interoperable electronic health records or the national healthcare IT infrastructure? If healthcare providers adopt electronic medical record systems that are interoperable with other systems, what is the assurance that the EHR they are affiliated with will fit the standards of the national healthcare IT infrastructure? Or does the EHR grow and grow and become the national healthcare IT infrastructure. Some argue that interoperability has to precede EHR use, but others believe that once widespread use of electronic health records occurs, interoperability will naturally follow (Braller, 2005). However, there may be another solution.

<div align="center">Healthcare Consumers</div>

Putting the patient at the center of the network and giving them the ability to manage their own treatments and information may be the ultimate reason the United States healthcare system will make the transition to digital tools for healthcare (Stone, 2005). Presidential initiatives and the subsequent funding needed to bring this transition to digital tools are found in the Health Information Technology for Economic and Clinical Act (HITECH). The fundamental idea is to enable significant and measurable improvements in population health through a transformed healthcare delivery system (Dell, 2009).

With all the changes, healthcare consumers will need to take a more active role in management of their healthcare (Thielst, 2007). The digitization and integration of medical records will not only provide healthcare providers with the tools and information to provide better care, but it will also allow healthcare consumers to improve their access to their personal health information and their ability to seek help from other experts (Altinkemer et al., 2006).

Potentially, healthcare consumers can access their integrated healthcare information, diagnoses, prescriptions, billing issues and a variety of other healthcare related information through electronic personal health records (ePHR). And the government is supporting this initiative. Under the American Recovery and Reinvestment Act of 2009 (AARA), individuals have the right to receive a copy of their personal health information in an electronic format if the entity uses an EHR system (Veazie, 2009).

This is not a new concept, in addition to the HITECH initiative from the president, in 1998, Edward Wagner developed the chronic care model in which the focus was on quality of care rather than simply relying on cost reduction (Wagner, Austin, Davis, Hindmarsh, Schaefer, & Bonomi, 2001).The first component mentioned in this model is self-management support so that patients can gain the skills and confidence to maintain their own health. The other components: decision support, delivery system design, clinical information systems, organization of healthcare and community all reflect the goal of the nationwide IT healthcare infrastructure called for by both the Bush and Obama administrations.   agner's model is an empowered model where the patient feels that the illness is theirs and they have the responsibility to take care of it utilizing the tools and resources that can be made available via the personal health record (Cassel et al., 2009).

Other research also puts the healthcare consumer at the center of the healthcare IT infrastructure. One researcher offered that there may be three flavors of interoperability on the horizon: 1) completely integrated, 2) strongly interfaced with only one vendor or 3) strongly interfaced with numerous vendors contributing to a central repository (Amatayakul, 2009b). In other research the vision of personal health records is a health record bank much like the central repository mentioned previously. The idea of a healthcare record bank might work with

providers making   deposits   of healthcare information and patients maintaining the account such as they would their financial checking account (Yasnoff, 2008). The premise of this idea is that each person's medical records are scattered among all places where care has been given and the patient is in charge of   reconciling   the information and checking for accuracy and completeness. Therefore, since in this instance healthcare institutions are not responsible for ensuring complete records, the patient takes control and responsibility for maintenance of the record and is put at the center of the healthcare IT infrastructure.

Patients can have on average 11 medical charts; hospitals and healthcare providers hope to ultimately have just one record for each patient (Symonds, 2000). Sharing EMR via EHR systems enables various stakeholders to improve efficiencies by eliminating redundant treatments and tests and also by enabling patient follow-up via prescription fill notifications and healthcare monitoring systems. Studies indicate that patients adhere to the plans established by their physicians 25 to 50% of the time (Magee, 2009). This lack of adherence may not be available for physicians to see until fully-integrated healthcare records are readily available for access. This lack of adherence by patients to follow prescribed plans can lead to costly re-treatments or hospitalizations (Magee, 2009). And sometimes it is not just complete lack of adherence, but a miscommunication between the healthcare consumer and their healthcare providers. In these cases, access to records by the healthcare consumer can enable the healthcare consumer access to the plan prescribed by the healthcare provider. In addition, the healthcare provider may have access to the monitoring devices in the personal health record tools which may enable electronic notification to the healthcare provider of the patient's progress before conditions may worsen.

Often healthcare consumers move from clinic to clinic where one set of information is in one place and another set of information is in another place and there is no connection between the two. Because of the silo condition, much needed information is not readily available. For example, a patient may visit an emergency room and may have their data spread across nine different systems during one visit; these nine systems will have varying degrees of integration and communication and also will have different user interfaces, different rules, and different expectation of the users (Cantrill, 2010). With this disconnect, healthcare consumers are missing needed checkups and redundant tests are being performed (Cassel et al., 2009). Missing checkups or lacking in proactive care can lead to lower quality of healthcare. Ultimately, the patient has the most to gain from the pervasive use of electronic health records when full integration is possible.

Electronic Health Records (EHR), Electronic Medical Records (EMR) and Electronic Personal Health Records (EPHR)

At the heart of Bush and the Obama healthcare package is the initiative to raise electronic medical record adoption rates (Agarwal et al., 2009). Contrary to what most Americans believe, electronic medical records are much more than electronic copies of patient records. An EMR is an electronic record of health-related information on an individual that can be created, gathered, managed and consulted by authorized clinicians and staff within one healthcare organization (NAHIT, 2008). To understand the full functionality of EMR, developers indicate there are nine functions of an EMR: view, manage, document, share, bill, remind, comply, gather and educate (Hodge, 2002).

The reason for the presidential initiatives and the subsequent funding is found in the Health Information Technology for Economic and Clinical Act (HITECH). The fundamental

idea is to   enable significant and measurable improvements in population health through a transformed healthcare delivery system   (Dell, 2009). The federal framework introduced by the government is intended to accelerate the adoption of health information technologies. The government intends to bring these into the healthcare infrastructure through a variety of incentives and support options, including financial rewards and penalties. The hope is to interconnect clinicians through networks which will lead to improved healthcare consumer access to information, consumer-centric care, improved population health, quality of care and research (Burt & Sisk, 2005). However, the ultimate goal is not the simple creation of an EMR for each healthcare consumer; the ultimate goal is a national healthcare IT infrastructure with a network that includes comprehensive, interoperable EMR for each healthcare consumer (Beaton, 2008).

The greatest challenge is finding a way to provide and present healthcare data to a healthcare provider in a resourceful and complete fashion. One way that healthcare consumers can assume responsibility of their medical records is through ePHR. What makes the ePHR different than the EMR is that ePHR: (1) contain data from many different sources, including EMR; (2) give healthcare consumers control over their data and enable them to add their own information; (3) seamlessly connect to the workflows of multiple providers and payer systems; (4) offer secure access to data and processes; (5) cater to the needs of the family care manager and (6 allow the healthcare consumer to search for and share relevant health information (Neupert & Craig, 2009). The concept of the ePHR is now emerging and some feel may it take the place of the EMR. Currently, physician practices, hospitals, health insurers, drug companies, employers and a variety of other public, private and non-profit organizations are offering ePHR for healthcare consumer use (B. Brown, 2007a; Hoffman & Podgurski, 2009). In fact, some

EMR companies can interface with ePHR even today (Medefile Becomes , 2010; Unifi Technologies , 2010).

With full interoperability, via ePHR, healthcare consumers can have better information about their healthcare status and can move easily between clinicians. Physicians can have access to health records with ePHR as the platform which will enable access to data without the concerns of integration clinical systems (Ozdemir et al., 2011). In addition, payers can benefit from economic efficiencies, fewer errors, and reduced duplication. Finally, the nation as a whole can benefit from research, public healthcare reporting, bioterrorism surveillance, quality monitoring and advances in clinical trials (Braller, 2005). With the healthcare consumer at the center of the national healthcare IT infrastructure utilizing ePHR, it is imperative that research looks at healthcare consumers' intent to utilize this new technology. In addition, understanding the antecedents to intent to use can enable a better understanding of how to increase intent to use and subsequent actual usage of ePHR.   ith healthcare consumers' use of ePHR, the national healthcare IT infrastructure can become a reality.

<center>Technology Acceptance Model (TAM)</center>

The technology acceptance model (TAM) was developed to explain computer-usage behavior (Davis et al., 1989). The grounding for the theory is Fishbein and A zen's theory of reason action (TRA). TRA postulates that beliefs influence attitudes which influence intentions and can then guide or generate behaviors (Fishbein & Azjen, 1975). TAM then adapts the TRA model to the world of information technology as a user acceptance model. Results from studies in information technology suggest that TAM is capable of providing fairly adequate explanation of user acceptance of information technology (see Figure 1).

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Perceived Usefulness

Perceived Ease of Use

Behavioral Intention to

Actual System Use
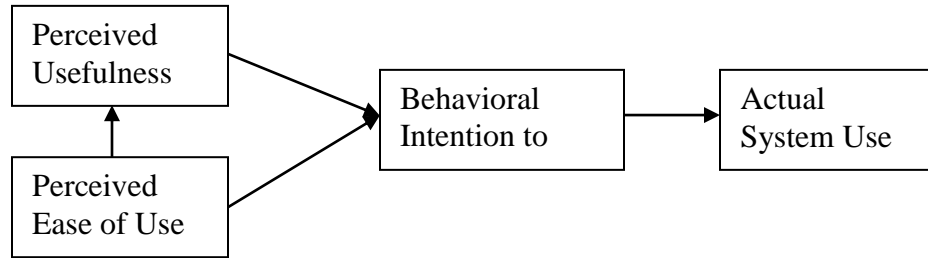
Figure 1. Technology acceptance model.

Many studies have been done on electronic health records, electronic medical records and personal health records and the user intentions of these systems. Most studies focus on physician or nurse usage; however, with the introduction of ePHR the focus is shifting to the healthcare consumer. For example, Tang, Ash, Bates, Overhage and Sands (2006) surveyed and discussed ePHR at a symposium and discovered among other things that the barriers to adoption can be categorized into three areas: economic and technical barriers, environmental barriers and individual barriers. Environmental barriers relate to the silo effects of systems of ePHR that are not integrated. The lack of EHR ubiquitous usage is the greatest barrier to integrated ePHR adoption. At the individual level, the healthcare consumer must understand the importance of maintaining and coordinating information. The researchers found that at the individual level, better evidence of efficiency and effectiveness of ePHR may be required before a healthcare consumer's intent to adopt increases (Tang et al., 2006).

Another study looked at the effects of several key antecedents to electronic health (e-health) use and applied models of acceptance from the information technology field (Wilson & Lankton, 2004). The researchers used an integrated model of TAM and a motivational model which measured intrinsic and extrinsic motivation as predictors of behavioral intention. In addition to measuring the IT acceptance models, intrinsic motivation, perceived ease of use, perceived usefulness/extrinsic motivation and behavioral intention to use e-health, there were

five antecedents used: satisfaction with medical care, healthcare knowledge, internet dependence, information-seeking preference, and healthcare need. They found that these antecedents can be used to help predict e-health acceptance.

TAM has been used in the healthcare context to study physicians and nurses. TAM was used to study physicians' acceptance of telemedicine technology and results showed that TAM was able to provide a reasonable depiction of physicians' intention to utilize technology in healthcare (Hu, Chau, Shen & Tam, 1999). These researchers were the first to apply TAM to physicians' decisions to accept telemedicine technology making this the first application of IT acceptance/adoption research to this organizational context (Hu et al., 1999). In another study, two specific types of behavioral intentions were studied in the predictive usage of personal health records: communication and patient information. Surveying 294 patients, the researchers found that usefulness and innovativeness have positive direct effects on behavioral intentions in the context of healthcare (Klein, 2007).

Theory posits that intention to carry out a behavior is a requisite condition to behavior (Fishbein & Azjen, 1975). In addition, the ultimate success of a system depends on the patient use (DeLone & McClean, 1992). Because ePHR are new to healthcare consumers, testing actual use rather than intention to use may be biased to those who already have a disposition to utilize ePHR. Since intention to carry out a behavior is requisite to the behavior and in order to avoid bias toward healthcare consumers biased toward ePHR, for this study, only intention to use ePHR will be studied. Therefore in this study, the focus is on the user intentions rather than actual behavior.

An electronic personal health record can be defined as an electronic application through which individuals can access, manage, and share their health information (Connecting for

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Health, 2004). In addition to the use of TAM in the context of healthcare, TAM has been utilized to study consumers' intent to shop online. An e-commerce usage study utilizing TAM studied four distinct ways that consumers can use or participate in e-commerce (McCloskey, 2003-2004).While many consumers use online services for shopping and to receive service and while there have been empirical studies done regarding privacy in these contexts, healthcare may pose a different set of factors. Unlike shopping, healthcare is universal and common to all people regardless of geography, race, income, gender or culture; it is the key that unlocks a nation's full productivity and potential for development (Magee, 2009).

Because there are different contexts of use possible by the healthcare consumer utilizing ePHR, the work in this research will focus on behavioral intentions at four levels as defined by ePHR and the literature review: intent to access, intent to manage, intent to share and intent to use as an authorized agent for a third-party. Klein (2007) did a similar study and focused on multiple user intentions in which two functions of use contributed toward the enhancement of patient use of patient-physician portal access. The modified measurement of intent for this will incorporate three dimensions of behavioral intent (see Figure 2).

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Perceived Ease of Use

Perceived Usefulness

Behavioral Intention to Access

Behavioral Intention to Manage

Behavioral Intention to Share

Intention to Utilize as an Authorized Agent
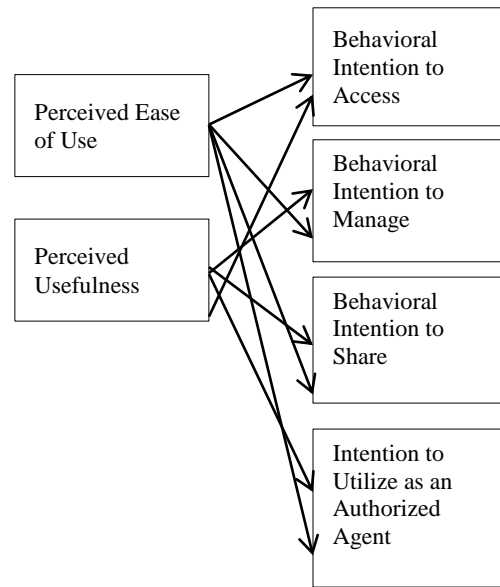
Figure 2. Modified TAM with behavioral intention to access, manage and share.

Information Boundary Theory

The definition for ePHR continues with   in a private, secure and confidential

environment.   Anderson and Agarwal (2011) were the first to study the digitization of healthcare

in the context of privacy. Their research looks at risk-as-feelings as the core conceptual

foundation and finds that emotion plays a key role and may impact the timing of consent. But the

research in this study is different than the Anderson and Agarwal (2011) study, in that the focus

is on intent to use in the context of privacy and trust and the technology is focused on ePHR.

Empirical findings suggest that privacy of healthcare information is one of the main reasons

healthcare consumers are concerned about online medicine (Willison et al., 2007).

In order to analyze the intent to use ePHR in the context of privacy, information

boundary theory (IBT) is used. IBT posits that motivation to reveal or withhold valued

information via a given medium follows rules for boundary opening and boundary closure (Petronio, 1991). IBT suggests that individuals form a physical or virtual informational space around him or her with clearly defined boundaries (Xu et al., 2008). Boundary opening and closure are dynamic, psychological processes of regulation by which people attempt to control flows of valued information to other people in their social environments (Altman, 1975, 1976; Petronio, 1991). The domain of IBT is to predict individual preferences and motivations regarding the amount and type of valuable information that the individual would be willing to reveal in a certain environment or medium such as personal health records (Stanton & Stam, 2003). In addition, there is strong evidence that privacy concern is related to both dispositional and related to the specific situation (Joinson et al., 2010).

Several privacy studies have used IBT as the guiding theory for their research (Xu et al., 2008; Stanton & Stam, 2003; Zakaria, Stanton & Stam, 2003; Dinev & Hart, 2006; Anderson & Agarwal, 2011). These studies have focused on transactions in e-commerce, social networking, financial and healthcare sites as well as in studies of organizational privacy in regard to email. The concept of utilizing IBT in the information privacy context is that first individuals construct a personal information space and then the boundary of this space depends on the nature of the information and the individual's own personality and environmental characteristics. Then when a request is made for information disclosure, the individual initiates a calculus process whereby the risks are evaluated, control is estimated and based on the outcome of the calculus, and the individual makes a decision whether or not the disclosure is acceptable or unacceptable (Xu et al., 2008). Based on IBT, Xu et al. (2008) then developed a model to measure privacy concerns based on the concepts of the information boundary theory which will be used in this study (see Figure 3).
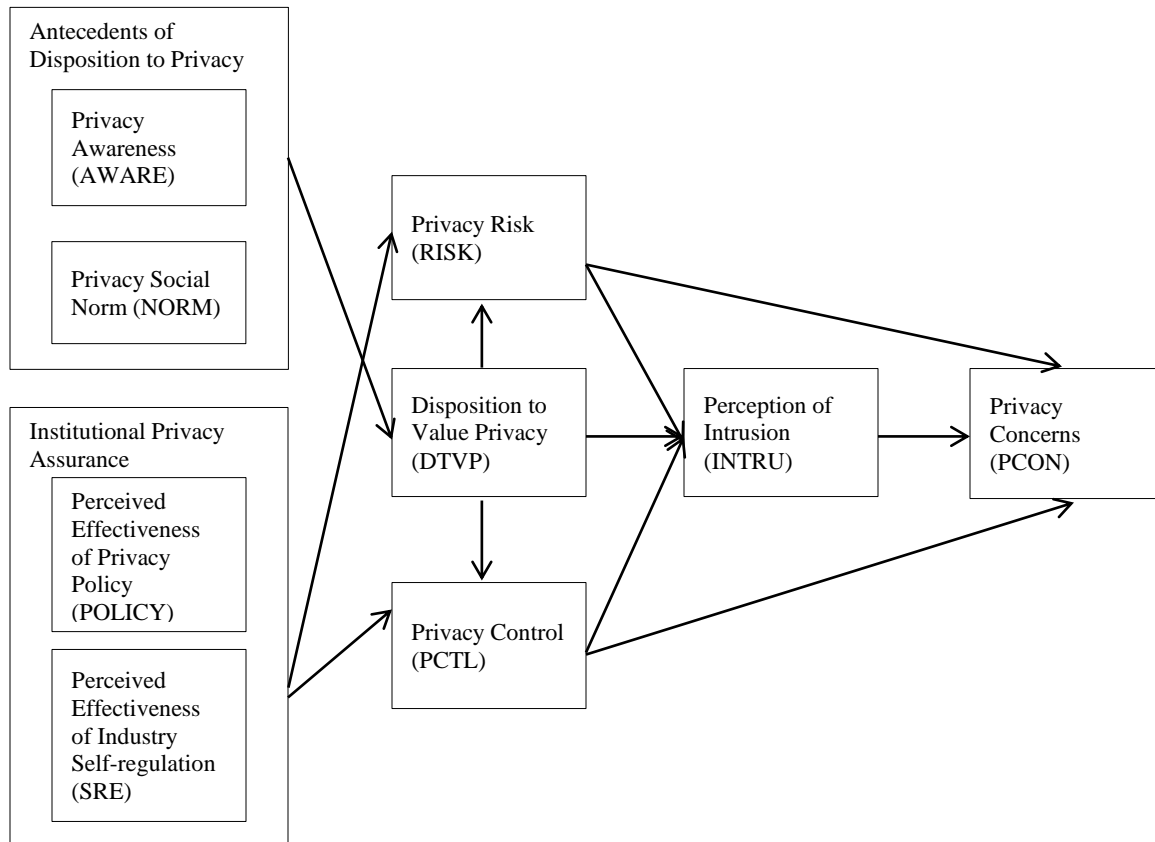
Figure 3. Information boundary theory measuring privacy concerns.

Trust

Like boundaries in privacy, there are boundaries in trust. Altman (1975) described self-boundary and dyadic boundary openings and closings dependent upon such factors as trust in the disclosure target. Studies on trust and privacy and the intent to use online services show that there is a link between privacy concern, trust and self-disclosure (Malhotra, Kim & Agarwal, 2004; Chellappa & Sin, 2005; Metzger, 2004b). In light of varying results, Joinson et al. (2010)

studied trust and privacy both as moderated and mediated relationships. They found a strong

moderator relationship between privacy and trust on personal disclosure. Others studies found

that trust is unrelated to privacy concerns (Bansal, Zahedi, & Gefen, 2010). However, these

studies were done on students which may have had a negative impact on the study.

Not only must the healthcare consumer trust the physician for healthcare needs, but in

this new environment, the healthcare consumer must trust the technology of the healthcare

provider and the system supporting the healthcare provider to protect their confidential health

information data. In e-commerce studies, evidence suggests that consumers may hesitate to

transact electronically because of trust   the uncertainty about a vendor's behavior or the risk of

having information stolen (McKnight et al., 2002). In addition, human-computer interaction

studies show that privacy and trust interact at a situational level (Joinson et al., 2010). Trust can

play a key role in overcoming perceptions of risk and insecurity and therefore trust may make

healthcare consumers comfortable enough to access, manage and share their personal health

information. In order to study the impact trust has on privacy concerns and subsequent intent to

use ePHR, this study will utilize the McKnight et al. (2002) model of trust (see Figure 4).
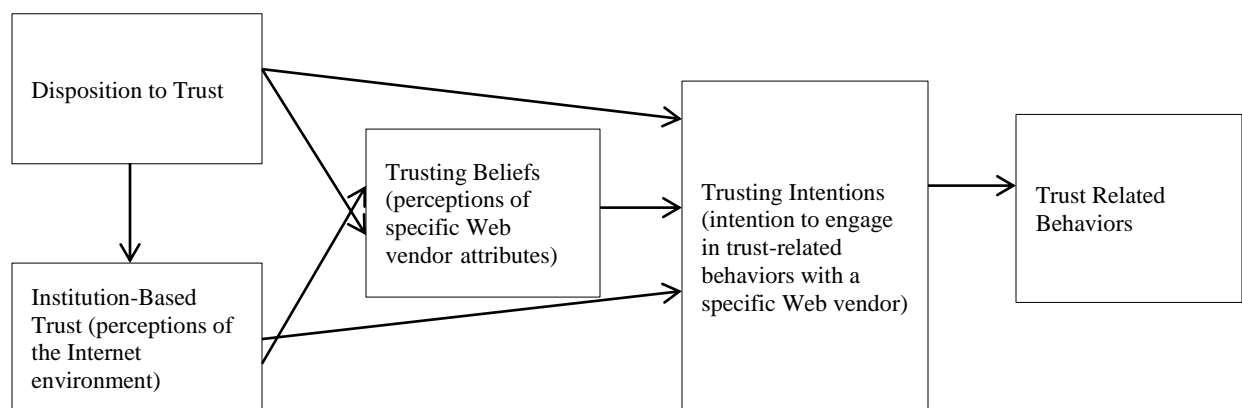
Figure 4. Web trust model.

Proposed Model and Hypotheses

Privacy, security and confidentiality concerns are all important antecedents to understanding user intent and should be investigated further (Tang et al., 2006). Privacy concerns enable the understanding of whether or not an individual will open the boundaries to their information and share with others. On the other hand, privacy risks may be too great for the individual to share. Healthcare consumers must weigh the risks and the benefits and depending upon their privacy concerns, may or may not share their healthcare information via electronic personal health record systems (Xu et al., 2008). Therefore it is important that research investigates the impact of antecedents on a healthcare consumer's intent to fully utilize ePHR. In order to investigate, TAM, IBT and McKnight et al.'s (2002) trust model were integrated along with individual characteristics found in the literature that may have an impact on intent to use.

The main purpose of this study is to integrate models of intent to use, privacy, trust and healthcare consumers characteristics in the context of electronic personal health records. Therefore, the conceptual model was tested and the relationships in the following conceptual model were assessed for statistical significance (see Figure 5).

Healthcare Consumer Characteristics

Computer Self-Efficacy

Personal Innovativeness

Health Literacy

Health Conditions

Demographics

Age

Income

Education level

Gender

Privacy Model

Antecedents of Disposition to Privacy

Privacy Awareness

Privacy Social Norm

Institutional Privacy Assurance

Perceived Effectiveness of Privacy Policy

Perceived Effectiveness of Industry Self-regulation

Privacy Risk (RISK)

Disposition to Value Privacy (DTVP)

Perception of Intrusion (INTRU)

Privacy Control (PCTL)

Trust Model

Disposition to Trust

Institution-Based Trust

Trusting Beliefs

Trusting Intentions

Contextual Factors

Privacy Concerns

Trust Related Behaviors

Modified Technology Acceptance Model

(Excludes actual usage

Includes four levels of usage)

Perceived Usefulness

Perceived Ease of Use

Behavioral Intention - Access

Behavioral Intention - Manage

Behavioral Intention Share

-Healthcare Providers

-Third Party payers

-Public Healthcare Organization

Behavioral Intention to Facilitate Third-Party ePHR

Figure 5. Proposed research model.

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Information systems research and practice would benefit from developing a greater theoretical understanding of healthcare information technology usage. There is pressure to mandate technology use in healthcare and rightly so (Hennington & Janz, 2007). Usage can decrease medical errors and increase patient safety as well as reduce healthcare costs. In addition, government mandates and financial incentives are in place to reward the mandated usage and penalties for non-compliance. There have been calls for research in IS theory in the healthcare domain and those calls have been answered via adoption and usage studies of physicians, nurses, radiologists and paramedics. Satisfaction and behavior intention studies have been done (Anderson & Agarwal, 2011; Simon, Evans, Benjamin, Delano, & Bates, 2009) and Hennington and Janz (2007) studied actual usage by nurses.

Hennington and Janz (2007) utilized Venkatesh, Morris, David and David (2003) unified theory of acceptance and use of technology (UTAUT) model as a starting point to help construct a theoretical model for a study in the usage of nurses' experiences with electronic medical records. The researchers also performed an exploratory study by conducting interviews with nurses and using the UTAUT questionnaire as a starting point for the questions. This led to new questions based on words and phrases gathered at the nurses' interviews. Ilie, Van Slyke, Parikh and Courtney (2009) studied electronic medical record usage in the context of physicians and focused on the system accessibility construct. More specifically, the researchers looked at physical accessibility (access to a computer) and logical accessibility (multiple logins) in relation to perceived usefulness and perceived ease of use. They found that inaccessibility impacts the acceptance of

complex IT in healthcare (Ilie et al., 2009). Like this research, due to the small percentage of actual users of e-health technologies, they focused on the factors that affected the beliefs rather than focusing on the actual usage.

What is missing is the behavior intention of healthcare consumers to utilize ePHR in the context of privacy and trust in a healthcare environment. The usage of ePHR is not mandated, but the benefits and risks have been widely publicized in order for healthcare consumers to make this decision. It is also clear that their voluntary usage of electronic personal health records is necessary to fully integrate the nationwide infrastructure. In order for healthcare consumer medical information to travel from a physician to a physician in a useful format, either both physicians' systems must be capable of locating patient records, authenticating users, securely sending and receiving data, and speaking in a common clinical language (Beaton, 2008), or there must be a mediator between the two such as the personal health record.

In order to better understand a healthcare consumer's intent to use ePHR in the context of privacy and trust, the antecedents to intent to use must be measured and analyzed. TAM identifies perceived usefulness and perceived ease of use as fundamental determinants of user acceptance (Davis et al., 1989). Since the study of actual usage of ePHR is limited due to the small percentage of healthcare consumers utilizing ePHR, intent to use is sufficient for this study. A person's performance of a specified behavior is determined by his or her behavioral intention (Azjen & Fishbein, 1980). Therefore, in this study, the research will focus on the constructs identified in TAM as perceived usefulness, perceived ease of use and behavioral intention.

Electronic personal health records will enable healthcare consumers to organize

their private health information, provide for effective communication with healthcare

providers, use remote patient-monitoring tools, respond quickly to warning symptoms

and more effectively manage chronic diseases from anywhere in the world (Thielst,

2007). An ePHR can be provider-owned software, patient-owned software or a portable,

interoperable digital file. EPHRs are designed to help healthcare consumers' record, store

and transmit medical information to any healthcare provider, as well as for use for online

health risk assessments and wellness program planning (B. Brown, 2007b). EPHR

technology has the potential to transform how every American keeps records and how

every healthcare provider accesses and uses it (Abrahamsen, 2007). There is a great need

for ePHR that are portable and retrievable to expedite care and minimize errors

(Abrahamsen, 2007). With the disconnect between healthcare providers, patients without

access to ePHR have no one that is responsible for coordinating the care between small

practices and their specialists, community resources and long term care providers (Cassel

et al., 2009).

Angst and Agarwal (2009) studied EMR and whether or not people can be

persuaded even before they used a technology if value-based arguments are understood

by them. Their research focused on whether or not the privacy concerns of healthcare

consumers can hinder the adoption of EHR systems and if so, can the people be

persuaded to accept the technology? Even though patients do not directly use EHRs in a

healthcare organization, they can form attitudes and beliefs about the concept of

participating, so they need to be comfortable with the idea of others using it before they

will opt-in to the idea of integration in the future. They found that argument framing, issues involvement, and concern for information privacy are all important influences on individuals' attitudes toward the use of EHRs and will subsequently influence the likelihood that the individual will opt-in to making health-related data available in a digital artifact. This study contributes to the knowledge base of EHR research by demonstrating the effects of giving the healthcare consumer the concept of control over their electronic personal health record and thereby giving them transparency into their personal healthcare related electronic data.

It is the responsibility of the healthcare consumer to initially access an ePHR that has been made available by a healthcare provider or for a healthcare consumer to create their own ePHR utilizing such systems as Google Health. While EMR and EHR systems provide healthcare providers the tools to keep electronic records and potentially share electronic records, the concept of the electronic personal health record is dependent upon healthcare consumers' intent to actually use it.

Individual hospitals can experience positive returns when other local hospitals have adopted electronic records (Miller & Tucker, 2009). But the slow adoption of EMRs by hospitals and clinics could hinder the government's goal of a national healthcare IT infrastructure. Therefore, future efforts should recognize the trade-offs between technology and privacy so that hospitals and clinics can experience greater adoption and use of EHR and ePHR combinations in order to offer access to ePHR for healthcare consumers. The platforms for ePHR may be the incentive for the middleware for interoperable systems and also enable physicians, third-party payers and public

healthcare organizations the ability to subsidize in building their own EHR systems (Ozdemir et al., 2011). These goals are only made possible if the healthcare consumer has the intent to utilize the ePHR as they become available. The challenge is to limit inappropriate access but to make legitimate data access convenient and easy (Cantrill, 2010).

The Privacy Rights and Oversight for Electronic and Commercial Transactions Act of 2006 (PROTECT Act) was introduced so that consumers, including healthcare consumers, could have a say in how companies buy, sell and market private data (Lynch-Afryl, 2006). Included in this act is a privacy bill whereby the consumer has the right to know and correct information that is kept about them. In addition, Health Information Portability and Accountability Act (HIPAA) regulations require a reporting of any unlawful disclosures of identifiable health information, a private right to sue and seek damages and the right of immediate notification when a security breach occurs (Lynch-Afryl, 2006).

Patients must take the initiative to manage or review their ePHR for many reasons. For example, fields have default values and may appear as   complete   when in fact the healthcare consumer has not addressed the question. In addition, the ePHR may contain numerous inputs from physicians, hospitals, third-party payers, etc. and the healthcare consumer must take responsibility for reviewing these for accuracy and completeness.   hen participants in a study were given a paper copy of a physician's record on their medical history, 10% found incorrect information in their records (Powell, Fitton, & Fitton, 2006).With complete disclosure of up-to-date, accurate information via

personal health records, clinics can have better access to patient information, improve

capabilities of identifying patients with recalled medications or provide information of

new treatments for their particular conditions as well as simpler prescribing   combined,

these provide greater patient satisfaction (Ewing & Cusick, 2004).

The United States healthcare network is fragmented into silos of care delivery by

different sources of information such as third-party payers, specialists, clinics, hospitals,

employers, etc. As research has shown, the missing connections between these

healthcare providers can lead to medical errors of many sorts (Cassel et al., 2009). For the

network benefits to be seen by the healthcare providers and the patients' privacy to be

protected there are two contingencies: 1) whether patients are willing to reveal health

information and have this information transferred electronically and 2) whether there are

other healthcare providers with whom it is possible to exchange health information

(Miller & Tucker, 2009).

Integration means a greater magnitude of linkages among EHR. With this greater

amount of linkages, personal medical information accessibility increases. As possibilities

of accessibility increase, health consumers' risk of loss of medical data increases.

However,   the next iteration of the   ationwide Health Information Network (NHIN)

should give people the capability to decide how they view, store and control access to

their own information. A person could say how that information flows to specific entities

or completely block the flow of information , says Dr. Robert Kolodner, National

coordinator for Health Information Technology (Ferris, 2006). In addition, the Health and

Human Services and its Office of the National Coordinator for Health IT have made

substantial progress in five major areas associated with the nationwide healthcare infrastructure goals. These five areas relate to the tools and the subsequent concerns of implementing these tools on a nationwide basis by the year 2014. The activities include: 1) advancing use of electronic health records, 2) establishing interoperability standards, 3) developing prototypes of nationwide healthcare networks, 4) addressing privacy and security issues associated with nationwide exchange of healthcare information and 5) integrating public health systems into a national network (U.S. General Accounting Office, 2006). In addition, the Certification Commission for Health Information Technology (CCHIT) was authorized to assess EMRs in three respects: functionality, security and interoperability (Beaton, 2008). As these assessments suggest, while EHR is a key component to future healthcare delivery, the crucial key to our nation's advancement in healthcare is connectivity and interoperability of the electronic health record systems via functionality based on security (Sullivan, 2010).

Despite the advantages of sharing health information, 8 out of 10 Americans are concerned about identity theft or fraud and therefore may not be willing to share the much needed information required for a personal health record to be effective (Krane, 2007). The prospects of storing data electronically question standards of security and if such concerns are not addressed, healthcare consumers will hesitate to share their personal health information (Raghupathi & Tan, 2002). Disclosure of sensitive information by patients such as emotional problems, sexually transmitted diseases, substance abuse, and genetic predispositions to diseases could cause embarrassment and can even affect insurability, child custody cases and employment continuance or

opportunities (Cannoy & Salam, 2010). For example, the size of your waistline may limit

employment opportunities, may affect your banking transactions, political ambitions and

worse (Etzioni, 2000). Shared medical information can have other negative impacts on

healthcare consumers, such as situations where individuals can lose healthcare coverage

or lose employment when personal medical information is made available. Employees

with a genetic predisposition to inherited diseases can be denied health insurance

coverage even though they had no symptoms (Etzioni, 2000).

And once online, these linkages can create opportunities for health information to

be linked with other, non-health data sets of interested parties, such as credit report

agencies, employers, private investigators, lawyers or others who may have a non-

beneficial interest in an individual's health or lifestyle (Etzioni, 2000). Therefore, most

consumers are uncomfortable with their health plan sharing health information with a

hospital, a specialist or their primary care doctor because they are concerned that others

not noted may see the information or that the information may travel via the Internet and

may be subject to lack of security and thereby breach of privacy (Border, 2006).

Studies show that 29% of Americans withhold information from their physicians

due to privacy concern (Poll: Many , 2011). In another survey, participants were given a

paper copy of a physician's record on their medical history. f those surveyed, 16%

identified information they would not share. Of the information in the medical record,

participants indicated that issues related to pregnancy, contraception, sexual health and

mental health would not be shared (Powell et al., 2006).

Patient-centered care is a transparency issue where critical information sharing is essential between the patient, payer and provider (Barlow, 2010b). When patients are informed, they can make better decisions regarding their options. Likewise, physicians should have full disclosure from the patient in order for the full spectra of options to be available. For example, a patient may have defined limits on types of treatment and allowable charges for those treatments as deemed by the insurance company. The healthcare consumer should be aware of those and the subsequent consequences and benefits when making decisions based on physician recommendations and payer guidelines. But without complete information from the healthcare consumer, the provider may not have access to all information needed to define and explain the limits and allowed treatments and charges.

Standard of care   is a legal term used to reflect what a physician should generally accept as proper steps to ensure proper care for a patient (Berner, 2008). In fact, there may be ethical and legal obligations when a healthcare provider does not utilize all information that can potentially benefit the patient. Physicians have a need for complete health information related to the patient to ensure proper treatment. If the patient does not disclose this information, then physicians do not have an obligation to use it. Because EMRs are based on decision support systems, the input into the visit can affect the diagnosis, treatment, and subsequent follow-up as well as suggested preventive and wellness maintenance issues. Physicians need the whole story to determine what treatment is best. Studies have shown that the EMR-generated reminders based on

healthcare consumers' data have been found to positively affect physician behavior and care processes (Pestotnik, Classen, Evan, & Burke, 1996).

The interoperability of electronic health record systems provides access to medical records throughout healthcare consumers' medical history. Without this, healthcare providers must depend on healthcare consumers' memory for relevant information. In addition, when requesting past medical histories from healthcare consumers, healthcare providers must depend upon healthcare consumers' full disclosure of relevant information. Compounding this problem is the possibility that healthcare consumers may not know what information is relevant to their situation.

Concerns regarding incomplete patient data come from not only the lack of integration by clinicians, but the lack of a complete and accurate electronic medical record of the patient. For example, if a health consumer visits a clinic and the clinician has access to an integrated EHR, the clinician may make the assumption that the EHR is complete. The health consumer in response may state that the EHR is complete due to the interoperability of the healthcare providers. But if the patient has not given explicit access to all healthcare information, the clinician may order a test or prescribe a prescription that is unnecessary or dangerous. Patients often believe that using computers to record their medical information and share that information can be accomplished without jeopardizing their rights (Amatayakul, 2008).

But there is another view of the integration of healthcare providers and healthcare consumers' access to that information. Some physicians fear information transparency and are therefore seeking to understand the importance of sharing information and the

impact of sharing this information with those who are sometimes competitors (Thielst, 2007). Healthcare providers fear that sharing all medical information may open up a plethora of misunderstandings. Some physicians are concerned about how patients will react to reading blunt observations like morbidly obese in their file (Brooks & Grotz, 2010). However, there are others that feel that sharing records will strengthen relationships and encourage patient participation (Denton, 2001). A survey of 1,400 physicians done in 2004 revealed that the two emerging trends in healthcare are: demand for online patient-physician communication and use of secure connectivity and messaging among physicians, labs, hospitals and pharmacies (DeShazo, Fessenden, & Schock, 2005). Health consumerism is growing due to the changing healthcare environment. There is a call for transparency by healthcare consumers for pricing and quality (Davis & Adams, 2007). Not only are healthcare consumers looking to transparency in their own records, they are looking for transparency in their healthcare providers via pillars of excellence such as patient safety; clinical quality; financial results; employee, physician and patient satisfactions and community citizenship (Davis & Adams, 2007).

Healthcare providers will be required to ensure privacy and security for confidential healthcare information through operating policies and procedures and appropriate technologies that satisfy the HIPAA privacy and security rules. In addition, healthcare providers will be required to provide transparency and consumer choice about what health information is shared, with whom and for what purpose (Office of the National Coordinator for Health Information Technology, 2009). During the period of

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2011-2015, one of the measurable outcomes to be monitored is to determine if meaningful use and subsequent financial incentives are applicable for healthcare providers. Another is that the patients are provided by the healthcare providers, upon request, a timely accounting of disclosures for treatment, payment and healthcare operations (United States Department of Health & Human Services, 2003). HIPAA also allows healthcare consumers the right to allow or disallow access to personal health information and also requires transparency for the healthcare consumer.

Electronic personal health records integrated with EHR systems can provide healthcare consumers access to lab results, medication history, information on allergies and some of the physicians' diagnoses. Through integration with ePHR portals healthcare providers are enabled the tools to comply with many of the meaningful use regulations (Brooks & Grotz, 2010). Some believe that the real value of electronic records does not come in the collection of data, but in the secondary use of the data via sharing among payers, providers, pharmaceutical companies and others throughout the system (Veronneau, 2009). This secondary use of data is collected through EMRs, ePHR, insurance claims, clinical-trial information, billing information and other sources.

In addition, if the physician can link to the ePHR, then the physician can easily monitor vital signs across time, receiving alerts when intervention might avoid illnesses and emergency room visits (Beaton, 2008). The ePHR can also enable communication between healthcare consumers and their medical providers. Patients can use secure email to ask about symptoms or medications and to make appointments. Personal health records

will enable patients to contribute to their medical records through remote monitoring of patients (Glaser, Markell, & Stone, 2010).

The clinical administrative staff will also derive benefits from improved document management with more timely and simultaneous access to patient records (Cottrell, 2005). One study noted that up to 81% of physicians could not find the information they needed to treat a patient during a visit (Stone, 2005). EHRs can provide electronic prescription, lab, and x-ray correspondence. In addition, EMRs can facilitate storage of digital radiology which enables shared and simultaneous image sharing and also telemedicine which allows for specialists' opinions without patient travel (Symonds, 2000). A nationally interoperable healthcare system would allow healthcare providers, healthcare consumers and third-party payers to document and efficiently share through the use of technology, but it will require standardized formats, security regulations, unanimous support and a large financial investment (Thompson & Brailer, 2004).

Hospitals can derive network benefits from EMRs when they can electronically exchange patient information with other healthcare providers and third-party payers due to the speed and increased reliability of the exchange (Miller & Tucker, 2009). The exchange can also be profitable; hospitals can lose money when duplicate tests are run with or without knowledge of the previous testing. According to Miller and Tucker (2009) this can lead to network effects where the benefits of one hospital are dependent upon the other hospitals and clinics' adoption rate.   ne study found that in outpatient settings, 13% of needed information was not available (Smith, 2005). Timely and efficient access to patients' comprehensive medical information continues to be one of

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the largest challenges in our healthcare system (Boerner, 2004). This represents two of the major problems of healthcare that electronic systems can address: fragmentation of information and the lack of accessible information (Berner, 2008). Through ePHR, patients will have the ability to give healthcare providers all information needed to enable efficient and effective care. Most healthcare consumers generally lack the information needed about costs and quality to make informed decisions about their care (Hillestad et al., 2005).

The difficulty and mortality associated with caring for healthcare consumers without adequate health records is well documented (National Research Council, 2000; Audit Commission, 2001). The problem with treating healthcare consumers with inadequate health records is that it leads to incomplete medical records which can eopardize a patient's safety (Amatayakul, 2008).

Clinicians cite that in addition to high costs, there are other implementation concerns of fully integrated EHR. Some of these include misinterpretation due to incomplete or inaccurate data entry, meaningful interoperability is almost non-existent and implementation to reach enterprise-wise functionality is expected to take more than a decade (Stead & Lin, 2009). These concerns lead physicians to believe that EHRs may actually take away from patient care and diverts attention away from the patient (Hartzband & Groopman, 2008). In 2005, only 20% of U.S. hospitals and a small percentage of doctors' offices had paperless records. Even the small percentages that are used are not easily transferred into other systems (Swartz, 2005). Historically, there has

been little appreciation for an overall system, but current technology now enables the possibility of fully integrated healthcare (Cantrill, 2010).

Surveys show that patients believe the government should have a role in making rules for privacy and confidentiality of online health information, but only 3% felt that doctors should have complete access to their medical record (Ferris, 2006). On the other hand, some studies show that consumers trust healthcare providers and doctors more than the government 4 to 54 (Americans Trust , 2009). A survey was conducted on consumers' perceptions of electronic personal health records in 200 . Among the findings for attitudes of consumers, the following were most noted: high perception of value, high interest, privacy concerns, questions about healthcare provider privacy practices, concern that utilization remains low, too many variations of vendors and availability of a wide variety of effective enforcement (Connecting for Health, 2008).

However, physicians may be reluctant to tie directly to each other due to barriers related to competition and negotiation in other areas of their business. The potential effects of healthcare consumers withholding information is based on the presumption that interconnectedness and interoperability are in place via EHR systems. This study is not based on predictions, but on the premise of what could happen if healthcare consumers choose to withhold information.

Harris Interactive surveyed individuals to determine levels of privacy beliefs. In 2001, privacy fundamentalists were at 34%, privacy pragmatists were 58% and privacy unconcerned 20% (Westin, 2001). In decision making, individuals are rational economic agents who go about deciding how to protect or divulge their personal information.

Multiple factors can affect individual decisions with respect to privacy, incomplete

information, bounded rationality and systematic deviations from rationality (Acquisti &

Grossklags, 2005). The incomplete information factor can affect privacy decisions

because of externalities. These externalities happen when third parties share personal

information about an individual and these transactions may affect the individual without

his or her involvement in the transaction (Varian, 1997). The incomplete information

factor relates to information asymmetries or how the information will be used (Acquisti

& Grossklags, 2005).

EMR have the potential to improve billing performance and the collection and

enhancement of cash flow (Jones & Kessler, 2010). Payers stand to gain the most from

the greater reliance on IT and the nationwide healthcare infrastructure (Agarwal et al.,

2009). The combined information and access will enable payers to make better decisions

on reimbursements for diagnoses, pharmaceuticals and medical devices. The healthcare

industry must move forward to a patient-specific   bill of materials   (Barlow, 2010a). In

addition, the healthcare provider can improve the efficiency and effectiveness to create,

consume and change data at the front-end registration process in an effort to improve the

revenue cycle (Glaser et al., 2010). Physicians need to be able to see what the options are

and select options that allow the best value for each patient. The modern software

provides for clinical decision support to enable choosing the proper code to include all

services provided as well as to document and choose to defend against challenges from

the insurers (Callan & DeShazo, 2007). Currently, approximately 90% of practices have

computer-based billing and 80% of practices' that are using EHR are integrated with

billing systems (Gans, Kralewski, Hammons, & Dowd, 2005).

Due to the magnitude and infiltration of technology in the healthcare arena, most

hardware vendors, software vendors and medical practices have limited themselves to the

patient billing and financial arena of hospital or clinical information systems (Cantrill,

2010). During 2001-2003, information technology was more frequently used for billing

patients than for maintaining medical records (Burt & Hing, 2005). Therefore medical

informatics currently has had a limited impact on the day-to-day patient care (Cantrill,

2010). But consider this: in 2003, the most-wired facilities process from 21 to 40% of

their claims electronically and receive an electronic funds transfer on 1 to 20% of their e-

claims; less-wired hospitals process only 1 to 20% of their claims on the web or receive

electronic payments (Coile, 2003). The benefits of an ePHR and the network of users that

can be developed for the benefit of the healthcare consumer are great. Privacy may be

voluntarily sacrificed when benefits are perceived to be greater than the cost (Laric, Pitta,

& Katsanis, 2009). This can be true with third party payers for smooth and easy

payments. For example, if a patient visits a clinic and they have met their $1,000

deductible for the year at another healthcare provider then this fact should be taken into

consideration by the treating facility. Without sufficient proof, the clinic may charge a

fee. Without seamless integration, one claim may be processed before the other and the

patient may be charged their deductible multiple times. It is not uncommon to hear

healthcare consumers complain about the confusion of the third-party payment process

due to electronic flow of inaccurate or insufficient information.

In addition to linkages to traditional healthcare providers, the ePHR can open up connections to local centers for aging, faith-based organizations and community centers (Cassel et al., 2009). The healthcare market can take advantage of advertising and online services to not only increase revenue, but likely improve patient service. For example, one professional gives nine strategies for healthcare providers to utilize the web for business (Coile, 2003). Of these, several could be integrated with ePHR. Advertising based on personalization, customer information and referrals, online shopping for health-related products and services, internet pharmacies, health insurance sales, online health advice, telemedicine and customer service are all components of healthcare that could potentially be provided via ePHR.

Employers have also found that interconnected EHRs can enable preventive measures for their employees which aid in decreased health insurance premiums may and also aid in research endeavors. Medical plan data can be useful for evaluating interventions and impacts of wellness or managed care plan design features (Henderson, 1995). Even though the employer can capture some data, access to the employee's ePHR with integrated information from all healthcare providers can enable even more informed studies which can be made available to the public.

The benefits of giving access to third parties can also come with costs. As more access is gained to ePHR through transmission and copies of information, the potential for errors or leakages will likely increase (Laric et al., 2009). In their study, Laric et al. (2009) exhibit the numerous global pathways of the healthcare system and explain how the threats to the privacy of information increase exponentially.

Another way that third-parties can benefit from access to medical information is through collecting, analyzing and disseminating information about chronic diseases. This data comes from insurers, physicians, hospitals, pharmacies and labs (Boyens, Krishnan, & Padman, 2004). Beyond the immediate uses for healthcare data, there is a broad range of uses for which the information can be aggregated and used. This data resource could be a national treasure, but it is trapped on paper and in systems that are not integrated (Garrett, 2010). HIPAA prevents healthcare institutions from sharing personally identifiable patient information without informed consent from the patient, but if unidentifiable information can be shared and if there is no reasonable basis to believe that the information can be identified to an individual, then the information can be used without the patient's consent (Agrawai, Grandison, Johnson, & Kiernan, 2007). As part of good citizenship, the American people can voluntarily submit de-identified health information to a nationally coordinated Clinical Effectiveness Research (Magee, 2009). These research facilities and database sources will enable healthcare consumers to be co-contributors for improved health in America. Healthcare information can be de-identified, aggregated, analyzed and presented in a format for improving healthcare outcomes, reducing medical errors, predicting health trends and demonstrating comparative value of drugs and treatments (Veronneau, 2009).

In addition, the Health information Technology for Economic and Clinical Health Act of 2009 (HITECH) extends the provisions beyond covered entities such as hospitals to include all business associates. There are now criminal penalties and civil monetary penalties in place and there are compliance officers in place to review security and

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privacy compliance (Withrow, 2010). However, privacy should be balanced with our public responsibility to support national priorities   public healthcare, research, quality care and fight against healthcare fraud and abuse (Van der Goes Jr., 1999).

The government has enacted new legislation to address patient privacy concerns as a result of the exchange of health information over an electronic network. For one, the Act will require business associates to comply with many of the HIPAA rules and standards heretofore only required of covered entities   (Maffeo, 2009). Next, notification of any individual whose protected health information has been accessed or disclosed due to a breach in privacy or security will now be the responsibility of the covered entity   (Maffeo, 2009). And finally,   the Act establishes new requirements for the accounting of protected health information disclosures in electronic health records (Maffeo, 2009). In addition, there will be civil monetary penalties for the violation of these laws. These government enacted laws seem effective, but some fear that government control is simply not enough.

One purpose of the presidential stimulus was to provide a platform for sharing information among public healthcare agencies and private care providers so that public healthcare quality increases. In order to facilitate the information sharing among public healthcare agencies, the Certification Commission for Health Information Technology (CCHIT) was given the charge of developing national certification standards for functionality, interoperability, and data security of health IT (NAHIT, 2008).

Likewise, the governmental EHR incentives fall under the Health Information Technology for Economic and Clinical Health act (HITECH). Under this act, the key

goals for EHR include a) improving quality, safety and efficiency, b) engaging patients and their families, c) improving care coordination, d) improving population and public healthcare and e) ensuring privacy and security protections (Brooks & Grotz, 2010).

A study conducted by researchers concluded that increased efforts to protect the privacy of health data will hamper the adoption of EHR systems and subsequently that states with strong regulations for safeguarding the privacy of medical records are often the slowest in EHR adoption (Vijayan, 2009). This study concluded that the privacy laws in the state made it more difficult and more expensive for the hospitals and clinics to comply with the laws that enable the exchange and transfer of information. In addition, Miller and Tucker (2009) found that there is a trade-off between rapid implementation of EMR technology and strong healthcare privacy laws. Again, this study cites that privacy laws get in the way of the exchange of information.

When patient informed consent to gain access to medical records is required, participation is lower and the time involved is greater; low participation is problematic since it compromises the ability to generalize from the results (McCarthy, Shatin, Drinkard, Kleinman, & Gardner, 1999). Also, timely intervention with public healthcare authorizes is slowed down due to the process of receiving patient permission. There is concern when this information is released for study that the privacy of the individual is invaded. In order to ensure that the patient's privacy is protected, often the medical information is unidentified before it is released to heterogeneous databases. Studies have shown that a privacy mediator with query rewriting can ensure access and eliminate

identifying features of the data. This is just one way to enable sharing of data without embarrassing consequences to healthcare consumers.

De-identified data is the basis for anonymous research. But, healthcare consumers may not be fully aware of the risks associated with the links between different pieces of personal data and how powerful those links can be (Acquisti & Grossklags, 2005). For example, Imagine that somebody does not know you but knows your date of birth, sex, and zip code. What do you think the probability is that this person can uniquely identify you based on those data   About 69% answered that the probability was 50% or less and 45.5% believe the probability to be less than 25%. According to Carnegie Mellon University research,   of the US population may be identified with a five-digit zip code, birth date and sex.   (Acquisti & Grossklags, 2005). Someone with access to the complete claims file of an organization can identify recipients of a particular test and cross-link with other information and find a unique medical record identifier; it will be necessary to maintain oversight over access to and the uses of de-identified information (Platt, 2007).

There is a national need for rapid learning from evaluation studies and clinical trials. Through input from EMRs, researchers are developing large-scale, physiology-based simulation models (Eddy, 2007). In the past, researchers have been limited to longitudinal studies, large sample sizes, disruption of current practices, narrowness, generalizability and high costs. Now, with access to unidentifiable medical information via EMRs, research can build simulation models that can answer hundreds of medical questions. One model, called Archimedes, consists of thousands of virtual people with

virtual psychologies, virtual diseases and virtual behavior. The virtual situations are drawn from real people in the EMR system and draw the people's medical situation, demographics, physician examination results, behavior, family history, medical conditions, biological variables, medical history, symptoms, current medications and so forth to calculate hidden chronic damage that the specific factors imply and how different treatments result (Eddy, 2007). Access to EMR data will make models such as Archimedes more accurate and more powerful, but it is important that the data is complete. The main limitation at this point is the quality of data   or more likely the quality of the EMR or the ePHR. The linkage from complete ePHR to such models could open up promising new ways to improve the quality and efficiency of medical care (Eddy, 2007).

However, with privacy laws in place, researchers believe that patients may be more willing to candidly share their health information and risk factors or undergo testing (Miller & Tucker, 2009). Westin (2001) surveyed healthcare consumers and found that 69% are very concerned that an EMR system could lead to more sharing without patient knowledge and 65% felt that it was more likely that others would not disclose sensitive but necessary information for fear that it would be computerized and therefore digitally sharable.

In addition to improved personal care via integrated EHR, health consumers can benefit from quickly delivered geographically targeted warnings about outbreaks of infectious diseases, food poisoning or bioterrorist attacks (Scanlon, 2009). Also, interconnected EHRs can generate electronic data on health outcomes and cost of care

which leads to efficiently allocated resources and cost-effective treatments (Certificate Commission for Health Information Technology, 2008). Part of the transparency will be access to integrated knowledge from healthcare research centers. For better or worse, Americans will soon have access to positive and negative results at the time of completion of medical research efficacy and effectiveness studies of new products and health devices (Magee, 2009).

Integration can also provide the government access to our personal life-style as well as our health information. Some feel that if Big Brother wants to monitor health records via a national healthcare IT infrastructure, it may mean the end of all privacy as we know it. One way the government is considering controlling healthcare data is through the issuance of patient identification numbers. If patient identification numbers are issued or social security numbers used, the government will have in its possession the ability to deny basic services, including daycare, school, college, access to hospital emergency rooms, health insurance, driver's license, etc. to those who do not conform to government health policies (Schlafly, 1998). While this may seem extreme, the reality of personal health records complete integration with the national healthcare IT infrastructure opens doors to these types of situations.

Archimedes is a new tool in clinical research which enables predicting potential problems and identifying new treatments and approaches that can improve care. EHRs contain actual data on healthcare consumers in readily accessible format. Therefore, the raw data is the information about real people and real health experiences while the interventions and deaths and injuries from failed interventions happen to virtual, not real

people (Lumpkin, 2007). The great challenge is privacy or the unintentional release of individually identifiable information. Firm privacy policies must be in place before models such as Archimedes can be fully operational.

America's population is aging. As the population ages, people find themselves facing more illness and more serious medical conditions. The current healthcare environment is changing due to, among other things, aging (Davis & Adams, 2007). Some feel that as medical conditions worsen, the privacy of health information becomes less important than when they are healthy (Merrill, 2009). In this study, the researchers set out to find patients' attitudes toward technology in healthcare and for the most part found that patients are very comfortable with the idea of computers playing a central role in their healthcare.

In addition to the healthcare consumer having access to their own data, the ePHR also enables families of elderly patients to stay informed and in touch through access to an ePHR. Under the American Recovery and Reinvestment Act of 2009 (AARA), individuals have the right to receive a copy of their personal health information in an electronic format or to designate a third party to be the recipient if the entity uses an EMR system (Veazie, 2009).

Our society is aging due to lifestyles, socio economic status, education and other characteristics of a civilized society (Cassel et al., 2009). The aging society will not only result in rising healthcare costs, but also a need for a system to facilitate the care of the again society. When an elderly person is in a retirement center and is admitted for care, physicians need immediate access to up-to-date medical information. If the family is

involved in the care of the elderly, they will need to have access and permission to update and view the patient's records so that in their absence proper care can be given.

Studies show that in 25% of American homes, a nonprofessional, family caregiver works without pay and without support to manage frail parents, grandparents, immature children or grandchildren (Magee, 2009). These caregivers can be at a disadvantage because they may lack adequate information to make decisions. In addition, doctors, nurses and hospitals agree that there needs to be a partnership for mutual decision making in caregiver situations. What they are lacking is a healthcare information support system. This healthcare support system may not only provide access to adequate information for the caregiver, but can also relieve some of the burden of the caregiver by an electronic monitoring system to remind the elderly to bathe, take medicine, increase fluids, exercise or even to simply call (Magee, 2009).

Perceived usefulness is the degree to which a person believes that using a particular system would enhance his or her ob performance (F. Davis., 1989). When a system is high in perceived usefulness the user or healthcare consumer in this instance will perceive that the system is easier to use than another and is therefore more likely to be accepted. A very small percentage of healthcare consumers are currently utilizing ePHR and do not have sufficient user experience to compare. By defining ePHR and making the healthcare consumer aware of the benefits and risks involved, this research will discover the healthcare consumer's perceived usefulness of an ePHR in a healthcare setting; the impact privacy concerns and trust-related behavior have on perceived usefulness and the subsequent impact on intent to fully utilize the system.

Hu1: Perceived usefulness positively impacts a healthcare consumer's intent to access an electronic personal health record.

Hu2: Perceived usefulness positively impacts a healthcare consumer's intent to manage an electronic personal health record.

Hu3: Perceived usefulness positively impacts a healthcare consumer's intent to share via an electronic personal health record with a healthcare provider.

Hu4: Perceived usefulness positively impacts a healthcare consumer's intent to share via an electronic personal health record with a third-party payer.

Hu5: Perceived usefulness positively impacts a healthcare consumer's intent to share via an electronic personal health record with a public healthcare organization.

Hu6: Perceived usefulness positively impacts a healthcare consumer's intent to facilitate an electronic personal health record as an authorized agent of a third-party.

Perceived ease of use is the degree to which a person believes that using a particular system would be free of effort (F. Davis, 1989). The claim is that an application perceived to be easier to use than another is more likely to be accepted. The other use for electronic personal health records is to not have integration and not be able to have a repository for medical records that is accessible by the healthcare consumer, healthcare providers, third-party payers and the public healthcare facilities. On the other hand, the ePHR is electronic and there may be technology barriers in place that prevent the healthcare consumer from seeing the perceived ease of use. However, the

convenience of having a one-stop shop for medical information may overcome the technology and privacy fears.

Patients are frequently angered by being asked to complete a blank form on medications and problems at each visit (Jones, 2008). Electronic health cards could be one answer, but even though supermarkets nationwide can accept debit and credit cards, healthcare providers still rely on paper and pencil and often ask patients the same questions asked at previous visits or at previous healthcare providers. In a non-urgent situation this can lead to wasted time, inaccuracy, incomplete information and medical errors; in an urgent situation, this can lead to death (Musgrove, 2006). Therefore:

Hu7: Perceived ease of use positively impacts a healthcare consumer's perceived usefulness.

Hu8: Perceived ease of use positively impacts a healthcare consumer's intent to access an electronic personal health record.

Hu9: Perceived ease of use positively impacts a healthcare consumer's intent to manage an electronic personal health record.

Hu10: Perceived ease of use positively impacts a healthcare consumer's intent to share via an electronic personal health record with a healthcare provider.

Hu11: Perceived ease of use positively impacts a healthcare consumer's intent to share via an electronic personal health record with a third-party payer.

Hu12: Perceived ease of use positively impacts a healthcare consumer's intent to share via an electronic personal health record with a public healthcare organization.

Hu13: Perceived ease of use positively impacts a healthcare consumer's intent to

facilitate an electronic personal health record as an authorized agent of a third-

party.

One of the major challenges with ePHR implementation is the ethical dilemma of

privacy issues. Despite the fast-moving market demands for EMR systems and integrated

EHR via the national healthcare IT infrastructure, the contentious issue of how the more

aggressive use of EHR and subsequently the integration with ePHR will affect healthcare

consumers' privacy is left unanswered (Agarwal et al., 2009). Healthcare leaders are

trying to understand ways to ensure privacy and security of patients and to comply with

HIPAA. It is interesting that even though our personal health information is sacred and

privacy is paramount, other industries that deal with very sensitive information, like

banks, have figured out the interoperability issues along with privacy and security

standards (Sullivan, 2010).

For a successful implementation of the nationwide healthcare IT infrastructure

and personal health records as the main component of this infrastructure to become

reality, to enable healthcare consumer's input, confidentiality, patient privacy and control

over records must be realized (Magee, 2009). In order to encourage healthcare consumer

input, HIPAA has provided governance for the healthcare data. The information that

flows directly from the EMR of a HIPAA-covered entity is personal health information

(PHI) and is therefore subject to HIPAA privacy and security rules.

A brief summary of the privacy rules follows:

1) Privacy and security rules must be followed by all covered entities , which includes healthcare providers,

2) Personal health information may only be used or disclosed to authorized persons   those authorized by the individual or those required or permitted by the privacy rule,

3) The only required disclosures are to U.S. Department of Health and Human services,

4) Permitted uses and disclosures may be made to the individual, for treatment, payment, and healthcare operations, when the individual has been given the opportunity to agree or object (Gallagher, 2004).

HIPAA provides for certain privacy and security protections in order to encourage efficiencies through healthcare IT (Withrow, 2010). HIPAA has put into place administrative, physical and technical safeguards in order to provide healthcare consumers with sufficient protection. For example, one solution is to install Active Enforcement (AE) as a middleware solution between the enterprise applications and the database to ensure that the patient preferences and applicable laws guide the access and disclosure of health information (Agrawai et al., 2007). The two stages, policy and preference, enable the healthcare provider and the patient respectively to define and indicate access and disclosure of their personal information. These regulations have been put into place in order to provide assurance to healthcare consumers that their healthcare information remains private. Since privacy concerns are the main obstacle to utilization of ePHR it is vitally important to understand not only how the privacy concerns impact

the full utilization of ePHR, but also to understand the constructs that make up the privacy concerns.

The model used in this study to understand privacy concerns of healthcare consumers and the impact they have on intent to utilize ePHR is derived from IBT through research done to integrate privacy concerns (Xu et al., 2008). The model was developed and then tested in four contexts: e-commerce, social networking, finance and healthcare. The model was able to account for 37% - 59% of the variance in privacy concerns across different usage context, with 59% being the highest in the context of healthcare. The model has shown sufficient explanatory power to make the interpretation of the path coefficients meaningful (Xu et al., 2008).Therefore, this model is used in order to understand the impact that privacy concerns have on a healthcare consumer's intent to utilize ePHR and to gain a systematic understanding how privacy concerns are formed.

Prior research of privacy has focused on understanding what motivates individuals to disclose personal information and likewise what inhibits them from disclosing (Xu et al., 2008). In the contextual factors of this study, the research will focus on how privacy concerns are formed in order to gain a better understanding of the impact these privacy concerns may have on a healthcare consumer's intent to use ePHR. Privacy concerns, in this model, are defined as concerns about possible loss of privacy as a result of information disclosure to healthcare providers, third-party payers and public healthcare facilities (Xu et al., 2008).

The threat from privacy concerns comes from uniqueness of identifiers, convergence of huge databases, lack of control and governmental initiatives dealing with the issue (Elgarah & Falaleeva, 2005). Studies in e-commerce have found that privacy concerns negatively affect intent to use websited while perceived usefulness can positively impact the intent to use websites (Dinev & Hart, 2006). Because privacy concerns have a negative impact, it is expected that this negative impact will carry forward to impact perceived usefulness. As a result and based on TAM theory and IBT theory, in this study, privacy concerns are expected to decrease perceived usefulness of ePHR.

> Hp1: Privacy concerns negatively impact a healthcare consumer's perceived usefulness of an electronic personal health record.
>
> Hp2: Privacy concerns negatively impact a healthcare consumer's perceived ease of use of an electronic personal health record.
>
> Hp3: Privacy concerns negatively impact a healthcare consumer's intent to access an electronic personal health record.
>
> Hp4: Privacy concerns negatively impact a healthcare consumer's intent to share an electronic personal health record.
>
> Hp5: Privacy concerns negatively impact a healthcare consumer's intent to share an electronic personal health record with a healthcare provider.
>
> Hp6: Privacy concerns negatively impact a healthcare consumer's intent to share an electronic personal health record with a third-party payer.

Hp7: Privacy concerns negatively impact a healthcare consumer's intent to access an electronic personal health record with a public healthcare organization.

Hp : Privacy concerns negatively impact a healthcare consumer's intent to facilitate an electronic personal health record as an authorized agent of a third-party.

Privacy intrusion can be defined as invasive acts that disturb one's tranquility or solitude and also involves the unwanted general incursion of another's presence or activities (Solove, 2006). While intrusion by definition invades, Xu et al. (2008) argue that privacy intrusion is not always seen as harmful penetration of personal space. Among the examples given when, sensitive medical information is requested to select the best medical treatment may be an invasion into personal space boundaries that may not be perceived as a harmful intrusion.

People value their information privacy and yet they will surrender it at the drop of a hat. People resolve this by noting that as long as those they reveal information to do not use the information to harm them, they are content to reveal the details to strangers when they derive benefits (Posner, 2007). As Posner put it, the analogy is to a person who has never missed a plane in his life because he contrives always to arrive at the airport eight hours before the scheduled department time. Therefore, in the healthcare context of ePHR, perception of intrusion is a different construct than privacy concerns, but is an important predictor to privacy concerns:

Hp9: Perception of intrusion positively impacts a healthcare consumer's privacy concerns.

Disclosure renders people vulnerable because the private information becomes available to others (Petronio, 1991). Because others now have access to the information healthcare consumers may deem private, this disclosure of information now brings some degree of risk (Metzger, 2004a). Privacy risk in this context is defined as the expectation of losses associated with the disclosure of personal information in ePHR (McKnight et al., 2002). Perceived risk and cost are important factors in a patient's desire to protect the privacy of his or her health information (Dowling & Staelin, 1994). In general, medical privacy is positive for healthcare consumers, but may not always allow for quick implementation and access of EMR systems (Brooks & Grotz, 2010). In addition, to the risk of disclosing information, there is also the risk of a lower quality of treatment if private information is not given or if the patient does not give access to a full medical record history. Therefore, the healthcare consumer must weigh the risks involved and make a decision.

Risk and uncertainties are also components of the incomplete information privacy decision factor and all are complex, multifaceted and context-specific (Acquisti & Grossklags, 2005). However, like any technology intervention, one needs to balance the benefits of utilizing personal health records with the potential risks to the patient (Berner, 2008). There can be two costs of the privacy of medical information: social cost and economic cost (Schwartz, 1997). Misuse of medical information can impact employment opportunities, social acceptance and individual relationships which can all affect the quality of life and individuals may want this kept confidential (Rice, 2003). In addition to medical treatment information, electronic personal health records can contain

background information including lifestyle information like smoking or alcohol consumption, sedentary lifestyle, obesity, domestic relationships, involvement in high-risk activities and family medical history (Laric et al., 2009).

If all of this information is online in a medical record, with the proper access, it can be obtained at the touch of a button (Fridell, 2004). Disclosures of sensitive information could cause negative consequences outside of the purpose of a clinical visit. For example, emotional problems, sexually transmitted diseases, substance abuse and genetic predispositions to disease may be health conditions that consumers would be reluctant to share when they do not see the need for the clinician to know in order to diagnose the current condition. The fear of giving this information is that the disclosure to the clinician could go into a database and then through integration, others would see the information and this could cause embarrassment, affect insurability, child custody cases and employment (Cannoy & Salam, 2010). Therefore, the perceived privacy risk that a healthcare consumer has calculated may impact the healthcare consumer's perception of intrusion.

Hp10: Privacy risk positively impacts a healthcare consumer's perception of intrusion.

In addition to privacy risk having an impact on perception of intrusion, Xu et al. (2008) argue that there is a negative relationship between risk perception and privacy concerns. They draw on theory of reasoned action (TRA) and view privacy risk as a negative antecedent belief which affects a person's attitude toward a behavior, in this

case privacy concerns (Azjen, 1991). Studies in e-commerce have shown this negative relationship between perceived risk and privacy concerns (Dinev & Hart, 2006).

Despite most people's inability to comprehend those who are willing to invest significant amounts of resources to hack into another's identity, hackers exist nonetheless and are waiting to tap into personal health information (Perry, 2008). The national healthcare IT infrastructure offers a robust system full of information that would enable hackers to access millions of records through multiple points and multiple systems (Perry, 2008). Some feel that privacy of medical records is impossible. Albeit this claim is dated, one physician states that with the electronic format and access to files that reside in an online databank accessible by insurance clerks, medical staff, researchers, health-policy analysts, employers, blackmail market, hackers, elderly fraud, etc., privacy is not possible and therefore the risk is too great for the healthcare records to maintain acceptable privacy standards (Greenberg, 1999). Subsequently, due to the fear of losing information, the perceived privacy risk due to possible unlawful access to vulnerable healthcare information may impact healthcare consumers' perception of privacy concerns.

Hp11: Privacy risk positively impacts a healthcare consumer's privacy concerns.

Control can be positioned as a key factor in shaping privacy. In the Xu et al. (2008) model, perceived control over disclosure and subsequent use of personal information was viewed as a contrary factor that is weighed against privacy concerns. This was based this on the empirical evidence that reveals control as one of the key factors and provides the greatest degree of explanation for privacy concern (Phelps,

Nowak & Ferrell, 2000; Sheehan & Hoy, 2000; Xu, 2007). HIPAA provides healthcare

consumers with the opportunity to control their healthcare information via privacy policy

disclosure where healthcare consumers can be informed about their choices regarding

how the collected information is used, protected and how the information can be updated

or corrected (Xu et al., 2008). Therefore, even though HIPAA provides for these

assurances, when the healthcare consumer has the perception of control of their

healthcare information, the privacy concerns of the healthcare consumer may be less.

Hp12: Privacy control negatively impacts a healthcare consumer's privacy

concerns.

Prior literature has shown that individuals who perceived they had control over

the use of the information disclosed experienced less perception of privacy intrusion

(Fusilier & Hoyer, 1980). Privacy intrusion questions are asked in the negative form

meaning that if they strongly agree, they expect privacy intrusion. Therefore:

Hp13: Privacy control negatively impacts a healthcare consumer's perception of

intrusion.

Disposition to value privacy is the extent to which a person displays a

willingness to preserve his or her private space or to disallow disclosure of personal

information to others across a broad spectrum of situations and persons (Xu et al.,

2008). In IBT theory, personal characteristics have been shown to determine boundary

opening/closure rules (McKnight et al., 2002). Many factors can affect individuals when

making privacy decisions, including personal attitudes, knowledge of risks and

protection, trust in other parties, faith in the ability to protect information and monetary

considerations (Acquisti & Grossklags, 2005). Xu et al. (2008) posit in their research that disposition to value privacy directly impacts perception of intrusion and indirectly impacts privacy concerns. However, their model tested on students in the healthcare context did not show statistical significance in this relationship. Despite previous research results, in this research, the path will be tested again on healthcare consumers in a healthcare environment in order to determine if the path is statistically significant in this new environment.

Hp14: Disposition to value privacy positively impacts a healthcare consumer's perception of intrusion.

Xu et al. (2008) showed in their research that individuals with the disposition to value privacy will perceive higher risk.

Hp15: Disposition to value privacy positively impacts a healthcare consumer's perception of privacy risks.

Xu et al. (2008) failed to show statistical significance in the relationship between disposition to value privacy and perceived privacy control. However, this research will test the relationship in the context of healthcare on real healthcare consumers to determine if there may be statistical significance in this environment.

Hp16: Disposition to value privacy negatively impacts a healthcare consumer's privacy control.

The privacy model also indicates that there are two antecedents to disposition to value privacy: privacy awareness and privacy social norms. Privacy awareness is healthcare consumers' knowledge of privacy practices and policies, how the disclosed

information is used and awareness of how private space can be preserved. This awareness is enhanced by the HIPAA laws which require healthcare providers to give this information to the healthcare consumer and require the healthcare consumer to read and sign that they have read and understood the privacy practices. Despite the governance behind electronic health records, healthcare consumers must understand not only how the technology works, but also the capabilities and limitation of the technologies (Thielst, 2007). Part of understanding the technology of ePHR is the understanding and awareness of how the ePHR vendor can protect the privacy of the healthcare consumer. In the Xu et al. (2008) model privacy awareness was viewed as an antecedent to personal disposition to value privacy based on IBT. Therefore:

Hp17: Privacy awareness positively impacts a healthcare consumer's disposition to value privacy.

As was privacy awareness, privacy social norm can be seen as a sub-construct of a healthcare consumer's disposition to value privacy. Privacy social norm is based on the construct in the IBT which posits that perception of space is also associated with the notion of privacy (Laufer & Wolfe, 1977). Therefore, Xu et al. (2008) show that the social norm about privacy determines an individual's disposition to value privacy. Cultural issues and trends may also expedite healthcare consumers' intent to use ePHR system (Tang et al., 2006). Greater awareness and greater availability of ePHR may increase intent to use. Therefore, the perceived social norm of the environment surrounding the healthcare consumer may have an impact on their disposition to value privacy in the healthcare context.

Hp18: Privacy social norm positively impacts a healthcare consumer's disposition

to value privacy.

In the privacy model proposed and tested by Xu et al. (2008) institutional privacy

awareness represents the environmental factors that influence information boundary

management decisions. Institutional privacy awareness is more specifically defined as the

interventions that a particular company makes to ensure consumers that efforts have been

devoted to protect personal information (McKnight et al., 2002). The model more

precisely looks at two types of interventions: company privacy policy and industry self-

regulation.

Privacy concerns have increased due to the introduction of electronic medical

records. Previously, healthcare consumers may have disclosed private information to

sundry recipients and could still retain a great deal of privacy. But with the digitization of

data, information is recorded indefinitely at little cost, information is held by numerous

merchants, the information can be readily pooled and then an assembling of all the

recorded information concerning an individual is in a single file and can be easily

retrieved and searched (Posner, 2007). Even though EHRs improve the way records are

kept and reviewed and have the potential to make huge advances in patient healthcare,

the records can also make the healthcare consumer more vulnerable. With paper records,

control is easier due to the central location of the medical record. With the electronic

format of medical records, electronic copies are easily moved and transferred to other

locations. Therefore, the perceived effectiveness of the privacy policy of an organization,

whether it be a healthcare provider, a third-party payer or the government, may have a

positive impact on healthcare consumers' perception of the privacy control of the organization and the subsequent privacy risk involved.

Fear of identity theft tops the list of why individuals have privacy concerns regarding a nationwide medical record system (Electronic Medical , 200). Due to the sensitive nature of healthcare data, fraudsters may set their sights on healthcare providers in order to gain access to healthcare information. Identify theft can change a person's perspective on privacy and security. About 69% of people surveyed had heard of someone's medical records being lost or stolen and of those, 7% believe that their medical records may have been lost or stolen (Krane, 2008). But there is a distinction between medical identity theft and other types of identity theft such as financial identity theft. Medical identity theft occurs when a patient's identifying information is used to misappropriate or obtain medical services or goods (Dixon, 2006). The hallmark of medical identity theft is the falsification of a patient's medical record with information from the perpetrator of the crime (Dixon, 2006). Medical identify theft is on the rise due to the high cost of healthcare; according to the FDC, medical identity theft grew 197% from 2001 to 2005 (Long, 2010; Identity Theft 911, n.d.). Therefore, with the public awareness of medical identity theft, it is even more important that healthcare consumers are made aware of the privacy practices in place by the electronic health record vendor.

Medical identity theft hits people at a vulnerable point in their life when they are seeking medical treatment (Identity Theft 911, n.d.). In addition to seeking medical treatment by using another's identity, harm can come to individuals when healthcare providers base decisions on falsified medical records unknown to the healthcare

consumer. Physicians must be aware of the security risks and be proactive in protecting medical records. Lafferty (2007) offers three specific suggestions for clinicians: (1) executive management team should be fully aware of patient information security, (2) risk assessment should be done within an organization for HIPAA compliance and (3) creation and implementation of effective policies and procedures should be in place.

Privacy is the obligation of the authorized persons using personal health information to keep the information secret. Security is the procedures set in place to prevent unauthorized persons from accessing personal health information (Withrow, 2010). Privacy advocates argue that stringent security procedures and privacy protocols, including patient consent, must be part of the EHR system (Crane & Crane, 2006). Yet, studies show that there is a lack of knowledge by individuals regarding their knowledge about technological or legal forms or privacy protection (Acquisti & Grossklags, 2005). The President's Information Technology Advisory Council (PITAC) stresses that secure, private, interoperable, electronic healthcare information exchange is critical for the nationwide IT infrastructure in healthcare to fulfill the promise of reduced medical errors, higher quality of care and lower costs (Agrawai et al., 2007). While security is not sufficient for privacy, for certain individuals with simplified mental models, these may be synonyms (Acquisti & Grossklags, 2005). For instance, researchers found that when respondents commented on secure transactions, they believed that their transactions were private, as well.

Healthcare consumers should understand that their medical information is protected via security measures of all parties who have access to their information.

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Security measures such as anti-virus, firewalls, intrusion detection, some level of encryption, employee communication and awareness training and consumer education should all be in place (Clarke, Flaherty, Hollis, & Tomallo, 2009). In addition, consumers should be aware of the security policies and should be assured that they are in place and are being monitored. There are many threats to data: malicious insiders, remote access of data, firewall configurations, VPN vulnerabilities and attacks, bot-nets that steal data, key loggers that steal passwords, intrusion prevention that blocks attacks, encryption options to mask the data and adequate policies to ensure level of enforcement if privacy is violated (Clarke et al., 2009). Electronic data is vulnerable to improper disclosure through hacking, laptop theft, inadvertent disclosure or deliberate leaks; once it is accessed, it can be rapidly distributed worldwide (Hoffman & Podgurski, 2009). Commonly violated security breaches come from information access management and access control. The two most commonly violated privacy breaches are from impermissible uses and disclosure of protected health information (Withrow, 2010). Even though technology can play a key role in protecting information, because there is the human factor, there will always be a need for policies, procedures and staff to play a direct role in security (Cannoy & Salam, 2010). HIPAA has provided the policies and procedures required, but if healthcare employees and subsequent business associates do not comply, there will be privacy and security risk of healthcare information. Studies have been done to determine what factors affect the behavior of employees of healthcare providers in relation to the protection of patient healthcare information (Cannoy & Salam, 2010). This study found that deeper levels of policy compliance are found in

organizations where there are employees with high propensity for compliance beliefs and

organizations that have high managerial level of intervention through training, meetings,

policy implementations and enforcement.

Healthcare consumers can be proactive in protecting personal health information

by playing a key role in understanding disclosures and consent for sharing information.

Fortunately for healthcare consumers, while the EMR is owned by the healthcare

institution collecting the information, the patient has the unconditional right to be

informed of the data-handling practices (Health Insurance Portability and Accountability

Act, 1996). Privacy policy disclosure is the tool where healthcare consumers can be

informed about their choices regarding how the collected information is used, protected

and how the information can be updated or corrected (Xu et al., 2008). HIPAA provides

healthcare providers the incentive to effectively communicate the privacy policies and

therefore feel that this increased communication will enhance healthcare consumers'

perception of privacy control of the institution. Research has shown that when the

presence of a privacy policy is clear, perception of confidence and procedural fairness is

exemplified in the organization handling the information (Culnan & Armstrong, 1999).

Privacy protection for individuals and assurance that security measures are in place can

provide healthcare consumers with the needed information for them to more likely report

accurate medical information (Miller & Tucker, 2009). Privacy protection, awareness and

assurance of privacy protection can have a positive impact on healthcare consumers'

perception of privacy control and privacy risk.

Hp19: Perceived effectiveness of privacy policy positively impacts a healthcare

consumer's perception of privacy control.

Hp20: Perceived effectiveness of privacy policy negatively impacts a healthcare

consumer's privacy risk.

Some researchers believe that government intervention is necessary for effective

use of electronic health records to overcome the barriers to adoption (Holstein et al.,

2010). National strategies would help reduce redundancies, confusion and wasted effort

with all the EMR systems competing for business as well as the lack of standards and

interoperability (Aarts & Koppel, 2009). Americans expect and assume that medical

records privacy is a primary and well-defended right in our society (Van der Goes Jr.,

1999). While HIPAA has regulations in place, the priority of HIPAA is standardization

for integration, not privacy. In fact, the change in healthcare has caused a paradigm shift

in the way healthcare records are handled which may have left the legal framework for

medical record privacy protection obsolete (Van der Goes Jr., 1999).

While private sector e-commerce businesses can boast such privacy seals as

Online Privacy Alliance or TRUSTe, the healthcare industry can truthfully boast the

industry-regulated HIPAA compliance rules. When healthcare organizations clearly

explain their compliance with HIPAA and when the healthcare consumer understands the

governmental backing and regulations behind HIPAA, it should foster healthcare

consumers' feelings of control over their personal healthcare information as well as a

reduced risk of sharing their personal healthcare information (Xu et al., 2008).

Furthermore, in studying these factors, researchers have found that the current public

debate regarding privacy seems anchored in two prominent positions: either a consumer should be granted the right to manage their own privacy trade-offs or the government should step in to protect the consumer (Acquisti & Grossklags, 2005).

There is also great concern that the government privacy laws enacted by the presidential initiatives will require hospitals and clinics to implement costly filters and access controls in order to comply. The customization will be costly and will contribute to the slow adoption rate, especially in states with stringent privacy requirements (Vijayan, 2009). An empirical study done by Miller and Tucker (2009) found that state privacy regulation restricting hospital release of health information reduces EMR adoption by more than 24%. The study suggests that this is due to network externalities. These network externalities derive from the apparent reduction that privacy laws have on the network effect of EMRs (Miller & Tucker, 2009).

Another issue is the privacy paradox in which most civil libertarians and many other privacy advocates point the finger at the government as the enemy of privacy while at the same time these very same privacy advocates are calling on the government for new legislation to stop massive and encompassing privacy violations (Etzioni, 2000). There are societal, technological, legal and moral justifications for Congress to enact clear, robust legislation governing the use of identifiably medical information. The changes in delivery of care and the changes in collection, use and sharing of health information drive the need for change in how the law obtains access to and uses citizens' health records. Boundaries, security, consumer control and accountability must be

weighed against public responsibility in order for privacy rights in regard to healthcare to work (Van der Goes Jr., 1999).

If the healthcare industry provides a platform for integration and interoperability of healthcare records but does not provide assurance to healthcare consumers that their information is protected, then the initiative will be in jeopardy (Cannoy & Salam, 2010). Government intervention may be necessary to achieve the goal of a national healthcare IT infrastructure. Holstein et al. (2010) identified four determinants of the need for government intervention and the first is the need for national standards to ensure interoperability, data security and privacy. The other three determinants were economies of scale, externalities and network effects. National standards need to be in place so that EHR systems are able to effectively share with other providers and public healthcare agencies. But the real problem arrives due to the data security and privacy concerns. If the government cannot ensure security and privacy of data, then healthcare consumers' fear of privacy control and privacy risk may result in a reluctance to share sufficient healthcare data for interoperability and complete healthcare IT infrastructure. Therefore:

Hp21: Perceived effectiveness of industry self-regulation positively impacts a healthcare consumer's perception of privacy control.

Hp22: Perceived effectiveness of industry self-regulation positively impacts a healthcare consumer's perception of privacy risk.

Healthcare consumers' greatest concerns are the security, privacy and confidentiality of their personal health information. This may be the Achilles' heel to realizing most of the claimed benefits of EHRs (Goldschmidt, 2005). Not only does

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electronic storage open the door for vulnerability, but government access is now sanctioned and the possibilities for abuse are virtually limitless. Ultimately, (healthcare) consumers must trust that the system is working for, rather than against, them (Goldschmidt, 2005). Trust can enable a healthcare consumer to overcome perceptions of risk. When a healthcare consumer trusts, they may be more likely to have intentions to utilize an ePHR.

In order to gain a better understanding of the antecedents of trust related behaviors, the research will utilize a trust model developed specifically to understand trust-related behavior in an e-commerce setting. Albeit healthcare and e-commerce are different contexts, this model was developed as a multidimensional and multidisciplinary model in e-commerce. This model includes four high-level constructs which integrate prior research in e-commerce transactions (McKnight et al., 2002). By investigating multiple constructs, this research plans to adapt the model to the healthcare context. To develop the model, the research integrated the McKnight et al. (2002) model into the Theory of Reasoned Action (TRA) research in that beliefs lead to attitudes and attitudes to intents. Following Davis et al. (1989) a parsimonious model was used which left attitudes out of the model due to empirical testing, Mc night et al.'s (2002) model posits that trusting beliefs lead to trusting behaviors such as decreased privacy concerns and intent to utilize ePHR.

Trust related behaviors are actions that demonstrate dependence on a web vendor that make one vulnerable to the vendor or increase one's risk (Mayer, Davis, & Schoorman, 1995). In e-commerce, trust-related behaviors include sharing personal

information, making a purchase or acting on information provided by a Web site (McKnight et al., 2002). While the McKnight et al. (2002) study did not measure trust-related behaviors in its research, it did call for future research to not only measure this construct but to also measure how trust related behaviors lead to trusting intentions such as intent to utilize an ePHR.

Privacy concern is negatively associated with trusting beliefs; the lower the trusting beliefs, the higher the privacy concerns (Joinson et al., 2010; Eastlick, Lotz & Schofield, 2010; Kim 2008). In addition, willingness to provide personal information depends on a risk analysis whereas higher risk assessment lowers trust and hence the willingness to disclose information (Dinev & Hart, 2006). In this study, trusting behaviors was not measured, but the relationships between trusting intentions and privacy concerns, perceived usefulness, perceived ease of use and intent to utilize ePHR were viewed as trusting behaviors. Trusting intentions means that the truster is securely willing to depend, or intends to depend on the trustee (McKnight et al, 2002).

Ht1: Trusting intentions negatively impact a healthcare consumer's privacy concerns.

Ht2: Trusting intentions positively impact a healthcare consumer's perceived usefulness of an electronic personal health record.

Ht : Trusting intentions positively impact a healthcare consumer's perceived ease of use of an electronic personal health record.

Ht4: Trusting intentions positively impact a healthcare consumer's intent to access an electronic personal health record.

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Ht5: Trusting intentions positively impact a healthcare consumer's intent to

manage an electronic personal health record.

Ht6: Trusting intentions positively impact a healthcare consumer's intent to share

an electronic personal health record with a healthcare provider.

Ht7: Trusting intentions positively impact a healthcare consumer's intent to share

an electronic personal health record with a third-party payer.

Ht8: Trusting intentions positively impact a healthcare consumer's intent to share

an electronic personal health record with a public healthcare organization.

Ht9: Trusting intentions positively impact a healthcare consumer's intent to

facilitate an electronic personal health record as an authorized agent of a third-

party.

Willingness to depend and subjective probability of depending are two different

sub-constructs of trusting intentions. Trusting beliefs means that the trustee has

attributes that are beneficial to the truster (McKnight et al., 2002). In this context, the

trustee is the healthcare provider, third-party payers or the public healthcare organizations

while the truster is the healthcare consumer. McKnight et al. (2002) broke the trusting

beliefs model down into three types based on the literature: competence, benevolence,

and integrity.

Ht10: Trusting beliefs positively impact a healthcare consumer's trusting intentions.

Disposition to trust is the extent to which a person displays a tendency to be

willing to depend on others across a broad spectrum of situations and persons

(McKnight et al., 2002). In this model, disposition to trust is broken down into two sub

constructs: faith in humanity and trusting stance. Faith in humanity is about attributes of

others in general while trusting stance is a personal approach to dealing with others

(McKnight et al., 2002).

Ht11: Disposition to trust positively impacts a healthcare consumer's institution

based trust.

Ht12: Disposition to trust positively impacts a healthcare consumer's trusting

beliefs.

Ht13: Disposition to trust positively impacts a healthcare consumer's trusting

intentions.

Institution-based trust is   the belief that the needed structural conditions are

present to enhance the probability of achieving a successful outcome in an endeavor like

e-commerce   (McKnight et al., 2002). Institution-based trust is broken down into two sub

constructs: structural assurance and situational normality. Structural assurance relates to

the procedures in place in the environment while situational normality deals with the

order of the environment.

Ht14: Institution-based trust in healthcare providers positively impacts a

healthcare consumer's trusting beliefs.

Ht15: Institution-based trust in healthcare providers positively impacts a

healthcare consumer's trusting intentions.

After review of the literature on EMR, EHR and ePHR, as well as review of

TAM, TRA, IBT, trust models and privacy concerns, several patient-centered factors

were identified to have a potential effect on the acceptance and subsequent intent to use

personal health records. Healthcare consumer's characteristics can play a key role in the

relationships between privacy, trust and intent to use in healthcare settings (Bansal, et al.,

2010). For example, among other things, there are three compelling reasons for patients

to want access to their personal health records: patients with chronic illnesses or

unexpected health events, the availability of internet-enabled computers and the HIPAA

regulations right to access medical information for the patient (Denton, 2001).

Characteristics like these may play a role in impacting the privacy concerns and trust

intentions that lead to intent to use ePHR. Every patient is unique and it is impossible to

judge which information a patient may perceive as sensitive and potentially harmful.

HIPAA provides for this via a statement in the December 28, 2000, Federal Registry,

  The level of sensitivity varies not only with the type of information, but also with the

individual and the particular situation faced by the individual.   (U.S. General Accounting

Office, 2000).

Computer self-efficacy is defined as an individual's ability to use technology to

accomplish a given task (Compeau, 1995). Computer self-efficacy has been shown to be

a predictor of personal innovativeness, perceived ease of use and perceived usefulness

(Taylor & Todd, 1995; Agarwal & Karahanna, 2000; Venkatesh et al., 2003). Subsequent

research has shown that computer self-efficacy can extend to acceptance and use of an

information technology (Venkatesh & Davis, 2000). Since ePHR are based on the use of

technology to access, manage and share health information, a healthcare consumer's

ability to use technology should impact their intent to utilize ePHR.

Personal innovativeness has also been shown to be an important construct in understanding individual acceptance of technology innovations (Agarwal & Prasad, 1998). Personal innovativeness can be defined as the willingness of an individual to try out any new information technology. Therefore, since ePHR technology is relatively new and prior research supports personal innovativeness as an important predictor of perceived ease of use, perceived usefulness and behavioral intentions, this study will study the impact personal innovativeness has on the research model.

In addition to computer efficacy, health literacy and knowledge or health information competence may be an antecedent to effective use of personal health records. In order for the ePHR to be useful, patients must understand and be presented with data and tools that enable them to understand and act upon the information in ePHR (Tang et al., 2006). Health self-efficacy is the healthcare consumer's perception of self-efficacy specific to health-related situations (Gustafon et al., 2005). Research has shown that health information competence has been found to be an antecedent to usage of an e-health system (Gustafon et al., 2005). Health self-efficacy and participation in healthcare were measured by a research team identifying the usage of a system for e-health for low-income cancer patients (Gustafon et al., 2005). Health information competence was found to have statistical significance in this study while health self-efficacy and participation in healthcare were not found to be statistically significant. Therefore individuals may be more likely to utilize ePHR when they have a confidence in their ability to understand the health information contained in ePHR.

In managing disease, providers ranked access to EMR at 84% and information in the EMR at 77% as two of the top three resources needed. Results are presented in terms of the percentage of respondents who rated the importance of resources as "great" or "significant." The third resource ranked was communication with physicians at 88% (Kash, Gamm, Bolin, & Peck, 2005). Individuals with chronic or life-threatening illnesses and the need to manage their diseases may engage and attempt to understand their health condition and therefore have a higher intent to utilize ePHR system. Therefore, users who may benefit the most from ePHR and may subsequently be more intent to utilize ePHR system may be the patients with complicated chronic conditions and those with needs for extensive care or treatment (Steinbrook, 2008; Bansal et al., 2010). Researchers discovered that patients with greater healthcare needs foresee increased usage to access ePHR (Klein, 2007). In addition, access and availability of EHR information can be especially useful for patients with chronic illnesses who see specialists and want to give access to the new specialists (Miller & Tucker, 2009). In one study, more than half the growth in healthcare spending between 1987 and 2000 came from chronic conditions (Thorpe, Florence, & Joski, 2004).

One huge perceived benefit of personal health records is the ability of chronic care patients to organize, communicate, use remote patient-monitoring tools, respond to warnings and manage this from anywhere in the world (Thielst, 2007). Communication between healthcare consumers and providers can be facilitated via integrated healthcare records (Kash et al., 2005). Treatment of healthcare consumers with chronic illness or disease is aided by the use of EMR. Disease management prevention can identify people

with potential or active chronic disease, target services to them, monitor their condition, attempt to modify their behavior and adjust their therapy (Hillestad et al., 2005).

In addition to benefits and subsequent intent to utilize technology for healthcare, there is a strong correlation between health conditions and privacy concerns (Krane, 2007). Among individuals who feel that their health is only fair or poor, significantly more have concerns about the confidentiality and security of their health information. In a study done by Laric et al. (2009) they found that in the United States and Canada the mean responses for concerns for privacy rose from lower levels for the more everyday ailments to higher levels for the more severe, sensitive or contagious conditions. The rising cost of healthcare is related to use of specialists and the intensity of medical care per person (Anderson, Reinhardt, Hussey, & Petrsyan, 2003). Tremendous costs are related to small, but significant number of people who have enormous healthcare needs (Cassel et al., 2009). For this reason, those who hold to privacy the strongest may be the very ones who can benefit the most from full disclosure.

In 1999 a survey was done to determine computer, internet, email use and use of computers to seek health information sorted by age and also demographics such as, income, education and race (Brodie, Flournoy, Altman, Beldnon, Benson, & Rosenbaum, 2000). In addition, questions were asked to determine the type and frequency of computer usage and then the kinds of internet usage, in particular the use of the internet to gather health information. The survey focused on individuals under 60 years of age due to the preliminary analysis determining that Americans over 60 differ greatly from younger adults in computer usage and availability. The survey found that despite older Americans

being the biggest users of healthcare, the current computer revolution is not reaching their age group. Race showed statistical differences between lower-income blacks and whites in ownership of computers. This survey concluded that in order for all citizens to benefit from health information, there may be a role for government to ensure access for more Americans (Brodie et al., 2000).

In addition, in 2009, Laric et al. specifically studied privacy concerns of consumers in the area of healthcare services and looked at the consumers' search, choice and consumption of medical services. Their study focused on privacy levels of different types of medical treatment and medical procedures and the dependent variables. They found no statistical relationships between most of the medical conditions and a patient's concern for privacy with gender, race, insurance and age. However, in some of the medical conditions and procedures females were more concerned with privacy, older subjects were more concerned with privacy and minorities were more concerned with privacy with everyday procedures. The population is aging. Studies show that healthcare providers feel that the increasing need for healthcare services due to an aging population is one of the top two business issues that would have the most impact in the coming years (Garets & Horowitz, 2008). The other was patient satisfaction. Therefore, it is important to understand the impact demographics will have on the healthcare consumer's intent to utilize ePHR.

CHAPTER 3

METHODS

Overview

This chapter outlines the research methods used in testing the hypotheses

presented in chapter 2. In addition, the data collection and analysis along with the

instrument development are discussed. Reliability and validity issues are addressed and

discussed. This chapter consists of the following sections: population and sample, unit of

analysis, instrument design and development, survey administration and data analysis

strategies.

Population and Sample

While many technology acceptance model (TAM) studies in e-health survey

students for convenience purposes, this study surveyed actual healthcare consumers in a

healthcare setting (Bansal et al., 2010). A portion of the survey participants were actual

healthcare consumers visiting one of two urgent care clinics in Oklahoma or Texas.

Urgent care clinics (UCC) are one of the fastest growing segments of the healthcare

industry. Because UCC operate as emergency, no-appointment-required clinics, they may

not have a patient base and therefore may not have complete electronic health record

(EHR) on patients seeking care. The reasons healthcare consumers visit urgent care

clinics vary as do the demographics of the healthcare consumers. Therefore, by focusing

on the healthcare consumers in an actual urgent care clinic, the study attempts to gain a

broad and diverse set of individual characteristics. Because a sample of the survey

respondents were actual healthcare consumers seeking treatment and not students or

participants selected for this study, these results will be a better representation of the general public thereby enabling external validity of the results. Some survey participants were students; however, those students were requested to fill out the questionnaire only if they had visited an UCC in the past as a patient.

One reason that urgent care clinics are the focus of the study is that the structure of the typical urgent care clinic is that of a smaller, more rural, non-system affiliated clinic. These types of clinics may be the bottleneck to the proposed nationwide healthcare network due to the economic barriers of implementation of new technology. Therefore, utilization of electronic personal health records (ePHR) by healthcare consumers may potentially enable these small, rural, non-system affiliated clinics the opportunity to network via healthcare consumers' ePHR. Other studies have shown that healthcare quality and cost savings will be seen through increased use of health information technology (IT). Many of these studies are at advanced academic medical centers and integrated delivery systems which do not represent the mainstream U.S. medical care, the small, rural, non-affiliated clinics (Parente & McCullough, 2009). However research on advanced and integrated systems does provide important information which can be used to study the smaller, rural clinics. Researchers at advanced and integrated systems studied Medicare patients nationwide and found that electronic medical records (EMR) were the only health IT application to have a clear and statistically significant effect on patient safety (Parente & McCullough, 2009). However, other studies show that a significant predictor of EMR adoption is negatively related to smaller, more rural, non-system affiliated hospitals and clinics; more specifically, this is a result of the barriers of cost,

concerns regarding information security and physician resistance (Kazley & Ozcan, 2007).

Group size does matter; studies show that the larger the group, the higher the EMR penetration level (Versel, 2004). Contrarily, 81% of physicians rank clinical benefits of EHR as most important above financial factors (Barlow, 2007). Therefore, physicians, even in rural areas, realize the impact EHR can make on healthcare. Although healthcare issues are similar whether rural or urban, they are magnified for rural healthcare providers (Dickinson, 2006). The majority of care in our country is provided by small practices (Cassel et al., 2009). Patients see these small practices as more personal, but these small practices can suffer from the disadvantage of care coordination, access and efficiency unless the patient has a complete and updated record that is easily accessible by the small practice. The two UCC in this study are operated by less than five physicians/owners at each location.

Since the barriers to adoption of EHR are the focus of this study, utilizing UCC as the focus provides an environment where the healthcare consumer can see a great need for ePHR adoption. Not only does the U.S. lag behind other countries in the development of a national healthcare IT structure, but there are also issues with a negative correlation between adoption of EMR and physician group size and the size of the practice as well as locations in rural or underserved communities (Holstein et al., 2010). In the United States, fragmented small-practice models represent more than 75% of the patient visits (Landon & Normand, 2008). In addition, 75% of the nation's physicians work in offices of 10 or fewer doctors (Lohr, 2009). About one third of physicians still practice in solo

and two-physician practices (Liebhaber & Grossman, 2007). As a result of the economies of scale and the high cost of EHR systems, the adoption rate is higher among integrated health plans of hospitals, physicians and laboratories than small, rural, non-affiliated clinics (Holstein et al., 2010).

High acquisition cost and maintenance cost are the biggest deterrents of adoption (Goldstein, 2009; Brooks & Grotz, 2010). American healthcare providers in small practices have little reason to adopt. One physician said,   hen a physician invests in EMR, 89% of the benefit goes to someone else.   uite often, small medical group practices buy an EHR technology that meets internal needs but lacks interoperability (Kralewski, Dowd, Zink, & Gans, 2010). One option is for small physician groups or clinics to utilize an EHR system through a shared health IT facility on a subscription basis (Holstein et al., 2010). Another option is the electronic personal health record via integration and patient-centered focus. A research study was done at a chain of urgent care clinics to try to understand the influx of patient walk-ins and the subsequent struggle to balance trading partners such as specialists, hospitals, and insurers who may or may not be integrated via electronic health records (Thompson, 2008). The chain launched an EMR system and found that internal operations became more efficient and effective through sharing among the clinics in the chain and also via electronic prescription order entry and lab order entry. EPHR could enable the sharing of information among clinics, pharmacies and labs.

In order for the government stimulus packages to work, the funds should be targeted toward healthcare providers who may not benefit from the economies of scale

and externalities inherent in the purchase, maintenance and use of the EHR systems (Holstein et al., 2010). These smaller practice groups must be given financial incentives based on their conditional use of a certified EHR system which ensures communication, data security and privacy (Holstein et al., 2010). This is necessary to provide the platform for health consumers to provide sufficient access to complete information and further the intent to utilize ePHR.

Unit of Analysis

The unit of analysis was the individual healthcare consumer visiting the UCC or those who have visited an UCC in the past. The survey was given to healthcare consumers upon checking into the UCC or given via an email or Facebook request. The healthcare consumers were given a general definition of ePHR and upon agreement they understood the definition and components of ePHR, they were then asked to provide demographic information as well as answer survey questions related to privacy, trust and intent to utilize ePHR. In the UCC, receptionists at each location were educated on answering general questions regarding the surveys.

The goal of using the healthcare consumers as the individual unit of analysis was to assess the individual characteristics that led to the privacy, trust and intent to use concerns of healthcare consumers in general. The goal of using the UCC as the environment of the study or to ask the healthcare consumer if they had visited an UCC, is to place the individual in the context of actual healthcare in a setting where ePHR would be very beneficial.

Instrument Design and Development

This study combined three models: privacy, trust and technology acceptance to produce the final research model. The survey instrument was developed by combining items from the three surveys related to these models. Wording was adapted to fit the context of this study and items that were not applicable were removed. In addition, demographics and other control variables identified in the literature review: computer self-efficacy, personal innovativeness, healthcare need and healthcare knowledge, were obtained via the survey instrument. The new instrument was presented to a group of information technology professionals as well as a group of healthcare consumers. Based on feedback from both groups, wording was changed in order to provide a better explanation of the question and to avoid confusion by the survey respondents.

Davis et al. (1989) developed the technology acceptance model in order to better understand individuals' intentions to use a system with intention to use serving as a mediator of actual system use. With ePHR being a new technology, there are few actual users of ePHR and therefore the actual usage construct was omitted from this study. In the Davis et al. (1989) study, perceived usefulness and perceived ease of use determine an individual's intent to use a technology.

In 2003, Venkatesh et al. formulated a unified model that integrates elements across the user acceptance literature. This study adopts survey questions and measures adapted in 2003, by Venkatesh et al. from the 1989, Davis et al. study. As with the Klein (2007) TAM study of patient intention to use, this study adopts a previously developed four- item measure of perceived usefulness and perceived ease of use (Davis et al., 1989)

and three-item measure of behavioral intention (Venkatesh et al., 2003). Based on these studies, this research model identified four types of usage based on the definition of the ePHR and created a modified TAM instrument by incorporating the different types of usage.

The different types of use as defined by research were developed into the survey in order to capture differences in types of use: access or create, manage, share with healthcare providers, share with third-party payers, share with public healthcare facilities or use as an authorized representative for a third-party. Overall, 18 questions were asked in order to measure the different contexts of intent to use. The modified survey questions are as shown in Table 1.

Table 1

Instrument for Modified Technology Acceptance Model

Construct	Items	Types of use*
Intent to Use	1. I intend to (use*) an ePHR for healthcare related tasks in the future.	-Access or create -Manage -Share with healthcare providers -Share with third-party payers -Share with public healthcare facilities -Use as an authorized representative for a third-party
	2. For future healthcare related tasks, I would (use*) an ePHR.	-Access or create -Manage -Share with healthcare providers -Share with third-party payers -Share with public healthcare facilities -Use as an authorized representative for a third-party
	3. I intend to (use*) an ePHR for healthcare related tasks in the future.	-Access or create -Manage -Share with healthcare providers -Share with third-party payers -Share with public healthcare facilities -Use as an authorized representative for a third-party
Construct	**Items**	
Perceived Ease of Use	1. My interaction with ePHR will be clear and understandable.	
	2. I believe it would be easy to get ePHR to do what I want it to do.	
	3. Overall, I believe ePHR will be easy to use.	
	4. Learning to use ePHR will be easy for me.	
Perceived Usefulness	1. Using ePHR would make it easier to handle healthcare related tasks.	
	2. Using ePHR would help me to accomplish healthcare related tasks I do.	
	3. Using ePHR would improve the quality of healthcare related tasks I do.	
	4. Using ePHR would enhance my effectiveness in my healthcare related tasks.	

The focus of this study is incorporating privacy and trust as predictors of behavioral intention to utilize ePHR. To measure personal privacy beliefs, this study developed and validated a survey based on information boundary theory (IBT). IBT presents an integrative model that suggests that individual privacy concerns form because of the individual's disposition to privacy or situational cues that enable one person to assess the consequences of information disclosure (Xu et al, 2008). The many dimensions of privacy presented in the Xu et al. (2008) study suggest that privacy is a multi-dimensional construct made up of nine different construct. The privacy study survey questions were adapted to the context of ePHR and are presented in Table 2.

Table 2

Instrument for Privacy Measurements

Construct	Items
Privacy Concerns	1. It bothers me when websites ask for too much information.
	2. I am concerned that websites are collecting too much personal information about me.
	3. I am concerned that unauthorized people may access my personal information.
	4. I am concerned about submitting information to websites.
Privacy Intrusion	1. I feel that as a result of my using ePHR websites, others know about me more than I am comfortable with.

Construct	Items
	2. I believe that as a result of my using ePHR websites, the information about me that I consider private is now more readily available to others than I would want to.
	3. I feel that as a result of my using ePHR websites, the information about me is out there that, if used, will invade my privacy.
	4. I feel that as a result of my using ePHR websites, my privacy has been invaded by the others that collect all the data about me.
Privacy Risks	1. In general, it would be risky to give personal information to ePHR websites.
	2. There would be high potential for privacy loss associated with giving personal information to ePHR websites.
	3. Personal information could be inappropriately used by ePHR websites.
	4. Providing ePHR websites with my personal information would involve many unexpected problems.
Privacy Control	1. I believe I have control over who can get access to my personal information collected by ePHR websites.
	2. I think I have control over what personal information is released by these ePHR websites.
	3. I believe I have control over how personal information is used by these ePHR websites.

Construct	Items
	4. I believe I can control my personal information provided to these ePHR websites.
Perceived Effectiveness of Privacy Policy	1. I feel confident that ePHR websites' privacy statements reflect their commitments to protect my personal information.
	2. With their privacy statements, I believe that my personal information will be kept private and confidential by websites that collect personal health information.
	3. I believe that websites that collect personal health information privacy statements are an effective way to demonstrate their commitments to privacy.
Perceived Effectiveness of Privacy Seal	1. I believe that privacy seals from third-party approval programs or HIPAA governance will impose sanctions (penalties) for online companies' noncompliance with its privacy policy.
	2. Third-party privacy seal of approval programs or HIPAA compliance will stand by me if my personal information is misused during and after transactions with online companies.
	3. I am confident that privacy seal of approval programs or HIPAA compliance are able to address violation of the information I provided to online companies.
Disposition to Value Privacy	1. Compared to other people, I am more sensitive about the way online companies handle my personal health information.

Construct	Items
	2. To me, it is the most important thing to keep my online privacy.
	3. Compared to others, I tend to be more concerned about threats to my personal privacy.
Awareness to Privacy	1. I am aware of the privacy issues and practices in our society.
	2. I follow the news and developments about the privacy issues and privacy violations.
	3. I keep myself updated about privacy issues and the solutions that companies and the government employ to ensure our privacy.
Social Norm	1. People who influence my behavior think that keeping personal information private is very important.
	2. My friends believe I should care about my privacy.
	3. People who are important to me think I should be careful when revealing personal information online.

To measure trust between patient and physician and patient and clinic operations, measurements will be taken from validated scales developed by McKnight et al. (2002) in regard to developing and validating trust measures. The trust dimensions analyzed in this study use validated measures for a multidisciplinary, multidimensional model of trust in e-commerce. The trust model uses four high-level constructs which are further delineated

into 16 sub constructs. This study adapts the survey questions to the context of

healthcare and ePHR and focuses on the high-level constructs. The survey questions are

presented in Table 3.

Table 3

Instrument for Trust Model

Construct	Items
Disposition to Trust	1. In general, people really do care about the well-being of others.
	2. In general, most folks keep their promises.
	3. I believe that most professional people do a very good job at their work.
	4. I usually trust people until they give me some reason not to trust them.
Institution-Based Trust	1. I feel good about how things go when I do purchasing or other activities on the Internet.
	2. I feel that most Internet vendors would act in a customer's best interest.
	3. I am comfortable relying on Internet vendors to meet their obligations.
	4. In general, most Internet vendors are competent at serving their customers.
	5. The Internet has enough safeguards to make me feel comfortable using it to transact personal business.

Construct	Items
Trusting Beliefs	1. I believe that an authorized user of my ePHR would act in my best interest.
	2. An authorized user of my ePHR would be trustful in dealings with me.
	3. An authorized user of my ePHR would be competent and effective in providing performing their duties.
Trusting Intentions	1. When an important healthcare issue or problem arises, I would feel comfortable depending on the information provided to me by an authorized user of my ePHR.
	2. If I had a challenging healthcare condition, I would want to use an authorized user of my ePHR.
	3. I would not hesitate to use the information an authorized user of my ePHR supplied me.
	4. Suppose you wanted specific healthcare information and you could consult an authorized user of your ePHR via the Internet free of charge. For this service, please answer: In this situation, I would not hesitate to share my name, address and social security number.
	5. Suppose you wanted specific healthcare information and you could consult an authorized user of your ePHR via the Internet for a fee. For this service, please answer: In this situation, I would not hesitate to share my name, address and social security number.

In order to capture the control variables and demographics noted in the research model, survey questions were adapted from similar studies. As with the Klein (2007) TAM study of patient intention, this study uses a ten-item measure of computer self-efficacy (Compeau, 1995) and a four-item measure of personal innovativeness of information technology (Agarwal & Prasad, 1998). In addition, a three-item measure of healthcare need and a two-item scale to measure health knowledge scale will be incorporated into the study (Wilson & Lankton, 2004). A binary variable captures gender while a grouped scaled captures level of income and level of education. The items used are summarized in Table 4.

Table 4

Instrument for Demographics and Control Variables

Construct	Items
Computer self-efficacy	1. I COULD COMPLETE AN EPHR USING A C MPUTER A D S FT ARE if there was no one around to tell me what to do as I go.
	2. if I had never used a package like it before.
	. if I had only the software manuals for reference.
	4. if I had seen someone else using it before trying it myself.
	5. if I could call someone for help if I got stuck.
	6. if someone else had helped me get started.
	. if I had a lot of time to complete the ob for which the software was provided.
	. if I had ust het built-in help facility for assistance.
	9. if someone showed me how to do it first.

Construct	Items
	10. if I had used similar packages before this one to do the same job.
Personal Innovativeness	1. If I heard about a new technology, such as ePHR, I would look for ways to experiment with it.
	2. Among my peers, I am usually the first to try out new information technologies.
	3. In general, I am hesitant to try out new information technologies.
	4. I like to experiment with new information technologies.
Healthcare Need	1. How many face-to-face visits to a healthcare provider have you had in the past six months?
	2. How many different physicians have you seen during the past six months?
	3. Do you have a chronic disease (such as diabetes or asthma) that requires special medical attention?
Health Literacy	1. I am very knowledgeable regarding my care for my health problems.
	2. I understand my health problems and how to care for them.
Age	18-20, 21-25, 26-30, 31-35, 36-40, 41-45, 46-50, 51-55, 56-60, or over 60
Gender	Male or Female
Level of Income	$0-25,000 $25,001-50,000 $50,001-100,000 $100,001-150,000 $Over 150,000
Level of Education	High School Some College 2-year College Degree 4-year College Degree Graduate School Degree or Higher

The research instrument was developed and based on these measurements. All

items other than age, gender, income level, education level and healthcare need were

scored on a 1-7 Likert-scale with Strongly Agree and Strongly Disagree as the two

anchors for the endpoints of the scale, and "eutral" as the anchor for the mid-point of the scale. In order to test the instrument, a pilot study was done on MBA students at a local university. The demographics of the MBA students represent the general public. In addition, the MBA students are enrolled in a technology class which studies EHR, EMR and ePHR and therefore should have a good understanding of the context of the study. The MBA students were asked to give feedback on questions and asked to provide comments related to the clarity and content of the instrument. Adjustments to the survey instrument were made based on the feedback from the MBA students.

<center>Survey Administration</center>

A paper-based survey and electronic survey were utilized in this study. Since part of the study looks at computer self-efficacy, using a computer-based survey may cause some healthcare consumers not to participate based on their lack of experience or comfort with computer use. In order to determine if computer usage had an impact on survey results, an analysis was done of the comparison of paper-based and electronic surveys. The healthcare consumers were given assurance that participation is voluntary and that all results would remain confidential. They were not asked to provide their name or their reason for visiting the UCC. Although identification arguably can be made based on demographics, this research will make no attempt to identify the participants.

For survey participants in the UCC, in order to encourage participation in the survey, the healthcare consumers were given a gold dollar coin upon completion of the survey. A note and a coin were on display for the healthcare consumers to see upon entering the clinic. In addition, the receptionists were provided an office luncheon for

their help in getting the surveys completed and collected. Since the receptionists will be responsible for passing out and collecting the surveys, the reward of the office luncheon encouraged them to be serious and diligent in collecting the surveys. Feedback from the receptionists indicated that not all healthcare consumers were interested in the gold dollar coin and more were interested in finding out about ePHR and how they could utilize those at the clinic.

One set of paper-based surveys was collected via a Rotarian luncheon where the researcher presented an informative definition and explained the different uses of ePHR and the related concerns surrounding the implementation of ePHR. There were 77 surveys were collected from the participants at the luncheon and also by the offices they represented. These participants were told only to complete the survey if they had ever visited an UCC in the past. The Rotarians did ask that research results be presented at a meeting in the future.

Other survey participants were contacted via Facebook messages. The message indicated that as a Facebook friend, the researcher needed those of them who had visited an urgent care clinic in the past to please complete the electronic survey. As with the paper-based survey, participants were told it was a voluntary survey, they could leave at any time and no identifying information was collected. The surveys were collected using Word Press and input directly into Excel by the researcher. The only identification on the surveys was the number and the IP address in which the surveys were done. By using the electronic outreach, the demographics of the survey participants was expanded to include

other geographic regions of the country. Feedback from friends of the researcher indicated that there is a great interest in learning more about using ePHR.

Finally, students were asked to complete the ePHR survey both by paper-based and electronic methods. The demographics of the students at the university in which the survey was given were comparable to those of who visited an UCC and are analyzed for comparison. In addition, the students were asked if they had ever visited an UCC before beginning the survey. Statistical methods were used to determine if there was a bias of the demographics of the students with the general population and the patients of the local UCC.

Since many healthcare consumers are not familiar with ePHR, research subjects were given the following definition of a personal health record:

The (electronic) personal health record (ePHR) is an Internet-based set of tools that allows people to **access** and **coordinate** their lifelong health information and make appropriate parts of it **available** to those who need it. PHRs offer an integrated and comprehensive view of health information, including information people generate themselves such as symptoms and medication use, information from doctors such as diagnoses and test results, and information from their pharmacies and insurance companies. Individuals access their PHRs via the Internet, using state-of-the-art **security** and **privacy** controls, at any time and from any location. Family members, doctors or school nurses can see portions of a PHR when necessary and emergency room staff can retrieve vital information from it in a crisis. People can use their PHR as a communications hub: to send

email to doctors, transfer information to specialists, receive test results and access online self-help tools. PHR connects each of us to the incredible potential of modern healthcare and gives us control over our own information (Connecting for Health, 2003).

Before beginning the survey, the participants were asked if they understood the definition well enough to continue. Otherwise, they were asked to read it again or to contact the researcher via email or phone.

<div align="center">Data Analysis Strategies</div>

The research model requires a structural technique to analyze the relationships. structural equation modeling (SEM) was used to analyze the data since this method takes on a confirmatory approach in order to test the hypotheses. SEM is particularly useful when the patterns of inter-relationships among the research constructs are specified a priori and are grounded in established theory such as in this research study (Byrne, 1998). Raw data was entered into LISREL software to estimate and evaluate the SEM model for this research as well as generate iterations, goodness-of-fit indices and standardized paths. SEM research involves two models, the measurement model and the structural model.

One of the biggest advantages of SEM is the ability to assess the construct validity of a proposed measurement theory utilizing confirmatory factor analysis (CFA) (Hair, Black, Babin, Anderson, & Tatham, 2006). The reliability and validity were assessed by confirmatory factor analysis. Construct validity tells us what portion of the total variance is accounted for by each of the constructs (Kerlinger & Lee, 2000).

Reliability is the measure of the degree to which a set of indicators of the latent

constructs is internally consistent in their measurements (Hair et al., 2006). Reliability is

necessary but not sufficient for construct validity.

There are two types of construct validity: convergence and discriminability.

Convergence means that evidence from different sources gathered in different ways all

indicate the same or similar meaning of the construct (Kerlinger & Lee, 2000).

Discriminability means that one can empirically differentiate the construct from other

constructs that may be similar, and that one can point out what is unrelated to the

construct (Kerlinger & Lee, 2000). Convergent validity was estimated using factor

loadings and average variance extracted (AVE). Factor loadings should be higher than

0.50 and ideally 0.70 or higher (Hair et al., 2006). In addition, AVE should be 0.50 or

higher on each latent construct in the model. Reliability is also an indicator or convergent

validity. High construct reliability means that internal consistency exists, and that all

measures represent the same latent construct. A good rule of thumb in research is that the

reliability estimate should be higher than 0.70 and higher than 0.60 is acceptable (Hair et

al., 2006).

Then, the structural model validity is tested using goodness-of-fit indices from the

LISREL model for empirical support of the model. Goodness-of-fit indices indicate how

well the specified model reproduces the covariance matrix among the indicator matrices

(Hair et al., 2006). The most fundamental fit index is ^{2} statistic. In addition, the

goodness-of-fit index (GFI), root means squared error of approximation (RMSEA) and

other incremental fix indices such as comparative fit index (CFI) were used to assess the fit of the structural model.

A sample size of 500 healthcare consumers to be surveyed was planned which would provide usable results for this study. There are 21 measurable constructs or free parameters estimated in this model. The common rule of 10 for SEM modeling is 10:1 for participants to latent variables which would indicate a sample size of 210 (Schreiber, Nora, Stage, Barlow, & King, 2006). While some studies in the field of management information systems (MIS) have shown that there may be better methods than the rule of ten, due to the size and nature of this study, those methods are not possible within the length and budget of this study (Westland, 2010). In addition, there is a proposed critical sample size of 200 in SEM research which is understood to provide sufficient statistical power for data analysis (Garver & Mentzer, 1999) However, due to the recent concern regarding the sample size of MIS studies utilizing SEM, every effort was made to collect a sufficient number of usable surveys (Westland, 2010). Plans were in place if sufficient data was not collected initially at the UCCs, alternative methods of collection would begin. Alternative methods included seeking participation from students, organizations and/or Facebook requests and after lower than expected involvement from clinic visitors, were implemented into the study.

CHAPTER 4

RESULTS

Survey Respondents

Based on annual averages, combined between the two clinics, approximately 100 healthcare consumers enter the two urgent care clinics (UCC) in this study each day. The UCC are open on average six days a week. A required target of 2,000 healthcare consumers entering the clinic was needed assuming a response rate of 25%, or 500 surveys. Therefore, the study was planned to run for approximately 60 working days or approximately nine weeks. The survey ran from July 15, 2011, to September 30, 2011. During this time, the two clinics combined saw an average of 58 patients per day, however it is unknown how many of these healthcare consumers were repeat patients during the time of the survey. Also, the amount of patients seen was lower than expected due to the timing of the survey. Typically the busy months for an UCC are during October through March which is the flu season; however this study ran from July to September when typically the flu and/or allergy season has not begun. The number of respondents from the clinical setting was 165. Feedback from the healthcare consumers was that they would prefer not to fill out the survey due to illness or time constraints.

Due to the lower than expected response from clinic visitors, a Facebook request was sent to all Facebook friends over 18 years of age and also was then requested that it be forwarded to other Facebook friends. Therefore, the number of Facebook users that saw the survey is unknown. However, the original request went to 91 users and 156

replied to the electronic request. The Facebook request indicated that the participant be at least 18 years old and had visited at least one UCC at least once as a patient.

A local Rotary club member requested a presentation to the members of their club on information related to electronic personal health records (ePHR). After the presentation, 77 paper-based surveys were collected from the Rotary club members and their respective office personnel. The Rotary club requested the presentation of electronic Personal Health Records and in return would fill out surveys and take surveys back to places of employment. The presentation audience was approximately 40 professionals and most took at least five surveys with them to be completed by staff in their offices giving an approximate response rate of 38.5%.

In order to get a sufficient number of surveys for statistical analysis, students at a regional, Midwestern university were requested to fill out paper surveys. The students were given 25 bonus points in their respective classes for filling out the surveys and were told to only fill one out if they had visited UCC. Opportunities for bonus points were given to those who had not visited UCC, but none requested the optional bonus points thereby indicating that all had visited UCC as a patient. Surveys were given in upper level and Master's classes in order to gather from a more diverse demographic audience and one that was more comparable to the patient base of UCC. The demographics of the university are similar to the demographics of the general population as is shown in the analysis of participants. Upon completion of the survey, 123 student surveys were collected.

In addition, through interviews and individual requests, 85 paper surveys were completed and an additional 89 electronic surveys were completed by an electronic request to members of an email address book. In total, 695 useable surveys were collected and used for statistical analysis. The demographic distribution and comparison of means is reported in order to determine if there was bias in any groups based on location of collection. An analysis of variance (ANOVA) was run to determine if location had an impact on the survey respondents replies. Results of this test are shown in Table 5 and are shown based on constructs in the model. Those constructs with p values < 0.05 indicate that there is statistical significant difference between the locations for those constructs.

Table 5

ANOVA of Location

Construct	Significance
Privacy Concerns	**0.000**
Perception of Intrusion	0.082
Privacy Risk	**0.000**
Privacy Control	0.067
Privacy Policy	**0.000**
Privacy Seal	**0.001**
Disposition to Value Privacy	0.31
Privacy Awareness	**0.001**
Privacy Social Norm	0.085

Construct	Significance
Disposition to Trust	**0.001**
Institution-Based Trust	**0.000**
Trusting Beliefs	**0.000**
Trusting Intentions	**0.000**
Perceived Usefulness	**0.000**
Perceived Ease of Use	**0.017**
Intention to Access	**0.010**
Intention to Manage	**0.004**
Intention to Share with Healthcare Providers	0.106
Intention to Share with Third-Party Payers	**0.022**
Intention to Share with Public Healthcare Organizations	0.378
Intention to Facilitate a Third-Party's ePHR	0.111

Some surveys were given electronically and some online; therefore, a statistical test, ANOVA, was conducted to determine if there was a statistical significance of the method of survey. Results of this test are shown in Table 6 and are shown based on constructs in the model. Those constructs with p values < 0.05 indicate that there is statistical significant difference between the methods of survey for those constructs.

Table 6

ANOVA of Method of Survey

Construct	Significance
Privacy Concerns	**0.000**
Perception of Intrusion	**0.049**
Privacy Risk	**0.000**
Privacy Control	**0.000**
Privacy Policy	**0.000**
Privacy Seal	**0.000**
Disposition to Value Privacy	**0.019**
Privacy Awareness	**0.000**
Privacy Social Norm	**0.002**
Disposition to Trust	**0.000**
Institution-Based Trust	**0.000**
Trusting Beliefs	**0.000**
Trusting Intentions	**0.000**
Perceived Usefulness	**0.000**
Perceived Ease of Use	**0.000**
Intention to Access	**0.000**
Intention to Manage	**0.000**
Intention to Share with Healthcare Providers	**0.001**
Intention to Share with Third-Party Payers	**0.000**

Construct	Significance
Intention to Share with Public Health Organizations	**0.000**
Intention to Facilitate a Third-Party's ePHR	**0.000**

Analysis of Survey Respondents

The demographics of the respondents were analyzed according to age, gender, income level, and education level. These were further broken down into five groups: respondents who visited the UCC, presentation participants, Facebook users including electronic requests, interviews and students. In addition, these demographics were compared to the general population and also to the demographics of the patient base at a UCC as presented in Table 7. After the analysis of the demographic variables, the control variables: personal innovativeness, computer self-efficacy, healthcare need and health literacy were analyzed and grouped for comparison and can also be seen in Table 7.

Table 7

Gender Distribution

Group	Number	Percent
General Population – Southern Oklahoma and Northern Texas counties		
Male		**48.9%**
Female		**51.2%**
UCC Patient Base		

Group	Number	Percent
Male	16,636	49.57%
Female	16,923	50.43%
Total Survey Respondents		
Male	308	44.32%
Female	387	55.68%
UCC visits		
Male	60	36.37%
Female	105	64.63%
Presentation participants		
Male	29	37.67%
Female	48	62.33%
Facebook users & electronic requests		
Male	109	44.90%
Female	136	55.10%
Interviews		
Male	43	50.59%
Female	42	49.41%
Students		
Male	65	52.85%
Female	58	47.15%

As can be seen, in every group except interviews and students, the percentage of females was slightly higher than that of males. A statistical test, ANOVA, was conducted to determine if there was a statistical significance in the difference in the responses of the survey based on gender. Results of this test are shown in Table 8 and are shown based on constructs in the model. Those constructs with p values < 0.05 indicate that there is statistical significant difference between the gender responses for those constructs. The SPSS output for mean comparison and the ANOVA can be found in Appendix A.

Table 8

ANOVA of Gender

Construct	Significance
Privacy Concerns	**0.006**
Perception of Intrusion	0.246
Privacy Risk	0.432
Privacy Control	**0.016**
Privacy Policy	**0.000**
Privacy Seal	**0.002**
Disposition to Value Privacy	0.225
Privacy Awareness	0.261
Privacy Social Norm	0.555
Disposition to Trust	**0.041**
Institution-Based Trust	**0.000**
Trusting Beliefs	**0.000**

Construct	Significance
Trusting Intentions	**0.001**
Perceived Usefulness	**0.001**
Perceived Ease of Use	0.217
Intention to Access	0.448
Intention to Manage	0.765
Intention to Share with Healthcare Providers	0.948
Intention to Share with Third-Party Payers	**0.015**
Intention to Share with Public Healthcare Organizations	0.403
Intention to Facilitate a Third-Party's ePHR	0.672

As can be expected, the student group had a larger percentage of 21-25 year olds. In comparison with the UCC demographics where 37.1% is 18-40, the total population surveyed in that age group was 64.34% most likely due to the student population. However, even the healthcare consumers in the clinics that agreed to take the surveys had a higher percentage of users 18-40, 51.5%, than the population base of the UCC. This may indicate that older adults may be more hesitant to fill out paper surveys or surveys of any kind.

Table 9

Age Distribution

Age Group	18-20	21-25	26-30	31-35	36-40	41-45	46-50	51-55	56-60	Over 60
UCC Demographics %	37.1% of patient base is 18-40					45.4% of patient base is over 40				
General Population %	54.1% of population is 18-65 in Southern Oklahoma and Northern Texas counties									15.7
Total survey respondents %	8.06	21.29	6.91	16.98	11.1	10.79	11.94	4.75	3.74	4.46
UCC - %	1.8	17	9.7	10.9	12.1	12.1	13.9	7.3	4.9	1.8
Presentation - %	6.5	3.9	1.3	23.4	13	23.4	18.2	3.9	3.9	6.5
Facebook & electronic request - %	13.1	23.3	4.1	18.4	11	8.6	8.6	5	4.5	13.1
Interviews - %	4.71	3.53	3.53	24.71	16.5	12.94	24.7	2.35	2.35	4.71
Students - %	9.8	46.3	14.6	13	4.9	4.1	3.3	3.3	1.6	9.8

A statistical test, ANOVA, was conducted to determine if there was a statistical significance in the difference in the responses of the survey based on age. Results of this test are shown in Table 10 and are shown based on constructs in the model. Those constructs with p values < 0.05 indicate that there is statistical significant difference between the ages for those constructs. The SPSS output for Mean comparison and the ANOVA can be found in Appendix A.

Table 10

ANOVA of Age

Construct	Significance
Privacy Concerns	**0.000**
Perception of Intrusion	**0.029**
Privacy Risk	**0.000**
Privacy Control	**0.007**
Privacy Policy	**0.000**
Privacy Seal	**0.000**
Disposition to Value Privacy	**0.000**
Privacy Awareness	0.106
Privacy Social Norm	**0.006**
Disposition to Trust	**0.003**
Institution-Based Trust	**0.013**
Trusting Beliefs	**0.000**
Trusting Intentions	**0.001**
Perceived Usefulness	**0.000**
Perceived Ease of Use	**0.000**
Intention to Access	**0.048**
Intention to Manage	**0.007**
Intention to Share with Healthcare Providers	**0.012**
Intention to Share with Third-Party Payers	0.112

Construct	Significance
Intention to Share with Public Health Organizations	**0.002**
Intention to Facilitate a Third-Party's ePHR	**0.002**

Income demographic information was not available from the UCC. However, the

UCC income % distribution of respondents was comparable to the total survey

respondents.

Table 11

Income Distribution

Income Group	$0-25,000	$25,001-50,000	$50,000-100,000	$100,001-150,000	Over $150,000
General Population	Average income for Southern Oklahoma and Northern Texas county residents over 18 is $20,410				
UCC Demographics	Not available				
Total survey respondents%	20.29	26.62	26.19	18.56	8.35
UCC - %	24.85	24.24	26.67	14.55	9.7
Presentation - %	1.3	24.68	28.57	37.66	7.79
Facebook & electronic requests-%	20	26.12	26.94	18.78	8.57
Interviews - %	4.71	25.88	27.06	28.24	11.76
Students - %	37.4	32.52	21.95	4.88	4.07

A statistical test, ANOVA, was conducted to determine if there was a statistical

significance in the difference in the responses of the survey based on level of income.

Results of this test are shown in Table 12 and are shown based on constructs in the

model. Those constructs with p values < 0.05 indicate that there is statistical significant

difference between the levels of income for those constructs. The SPSS output for mean

comparison and the ANOVA can be found in Appendix A.

Table 12

ANOVA of Income Levels

Construct	Significance
Privacy Concerns	**0.000**
Perception of Intrusion	**0.008**
Privacy Risk	**0.000**
Privacy Control	0.456
Privacy Policy	**0.000**
Privacy Seal	**0.000**
Disposition to Value Privacy	**0.000**
Privacy Awareness	**0.043**
Privacy Social Norm	**0.000**
Disposition to Trust	**0.000**
Institution-Based Trust	**0.000**
Trusting Beliefs	**0.018**
Trusting Intentions	0.104
Perceived Usefulness	**0.005**
Perceived Ease of Use	**0.001**
Intention to Access	**0.005**

Construct	Significance
Intention to Manage	**0.003**
Intention to Share with Healthcare Providers	**0.002**
Intention to Share with Third-Party Payers	**0.029**
Intention to Share with Public Healthcare Organizations	0.192
Intention to Facilitate a Third-Party's ePHR	**0.007**

Again, the educational demographic information was not available for the UCC,

however, the respondents from the UCC was very similar to the overall respondent

sample.

Table 13

Education Distribution

Education Group	High School	Some College	2-year College	4-year College	Graduate degree or higher
General Population	63.4	19.9% of residents of Southern Oklahoma and Northern Texas counties have 4 or more years of college			
UCC Demographics	Not available				
Total - %	20.29	32.23	15.68	19.28	12.52
UCC - %	26.06	35.15	12.12	14.55	12.12
Presentation - %	36.36	32.47	10.39	11.69	9.09
Facebook & electronic requests - %	14.29	32.65	20	17.14	16.33
Interviews - %	36.47	29.41	8.24	14.12	9.41

Education Group	High School	Some College	2-year College	4-year College	Graduate degree or higher
Students - %	3.25	29.27	20.33	38.21	9.76

A statistical test, ANOVA, was conducted to determine if there was a statistical significance in the difference in the responses of the survey based on level of education. Results of this test are shown in Table 14 and are shown based on constructs in the model. Those constructs with p values < 0.05 indicate that there is statistical significant difference between the levels of education for those constructs. The SPSS output for mean comparison and the ANOVA can be found in Appendix A.

Table 14

ANOVA of Education Levels

Construct	Significance
Privacy Concerns	**0.000**
Perception of Intrusion	**0.000**
Privacy Risk	**0.000**
Privacy Control	0.426
Privacy Policy	**0.000**
Privacy Seal	**0.003**
Disposition to Value Privacy	**0.028**
Privacy Awareness	**0.002**
Privacy Social Norm	**0.003**

Construct	Significance
Disposition to Trust	**0.000**
Institution-Based Trust	**0.000**
Trusting Beliefs	**0.000**
Trusting Intentions	**0.005**
Perceived Usefulness	**0.019**
Perceived Ease of Use	**0.000**
Intention to Access	**0.041**
Intention to Manage	**0.000**
Intention to Share with Healthcare Providers	**0.011**
Intention to Share with Third-Party Payers	0.070
Intention to Share with Public Health Organizations	**0.016**
Intention to Facilitate a Third-Party's ePHR	**0.002**

Normality of the demographic data was analyzed using skewness and kurtosis

measures. Normality of demographic data indicates that skewness measures the

symmetry of a distribution. Skewness values outside the range of -1 to 1 indicate a

substantially skewed distribution (Hair et al., 2006). Kurtosis measures the peakedness

or flatness of a distribution. A positive value indicates a relatively peaked and a negative

value a relatively flat distribution (Hair et al., 2006). A description analysis of the means

is presented in Table 15 below. Skewness levels are between the acceptable -1 to 1 and

therefore indicate acceptable levels of skewness in the demographic data. The kurtosis

measures indicate a flatness of distribution due to the relatively negative statistics. Kurtosis measures in the range of 1 to -1 are good, but 2 to -2 are also acceptable (Hair et al., 2006). The kurtosis measures fall within this acceptable range for the demographic data and are therefore within an acceptable level.

Table 15

Descriptive Analysis of Means

					Mean	Std. Deviation	Skewness		Kurtosis	
	Statistic	Statistic	Statistic		Statistic	Statistic	Statistic	Std. Error	Statistic	Std. Error
Location	95		5		2.52	1.290	.614	.093	-.700	185
Method of Survey	95		2		1.53	.499	-.130	.093	-1.989	185
Age *	95		10		4.59	2.494	.411	.093	-.753	185
Gender **	95		2		1.55	.497	-.218	.093	-1.958	185
Income ***	95		5		2.68	1.224	.235	.093	-.915	185
Education ****	95		5		2.72	1.322	.332	.093	-1.104	185
Valid N (listwise)	95									

In addition to the demographic variables, other control variables were analyzed. Computer self-efficacy, personal innovativeness, healthcare need and health literacy were measured and analyzed. Means and standard deviations related to these variables can be found in Table 16.

Table 16

Control Variables Distribution

Sample	Computer Self-Efficacy Scale 1-7	Personal Innovativeness Scale 1-7	Healthcare Need 0-11	Healthcare Literacy Scale 1-7
Total - Mean (Standard Deviation)	4.94 (1.57)	4.28 (1.13)	2.26 (1.37)	5.33 (1.66)
UCC	4.78 (1.57)	4.15 (1.22)	2.47 (1.17)	5.26 (1.73)
Presentation	4.14 (1.86)	4.11 (1.20)	1.90 (1.55)	4.43 (1.94)
Facebook & Electronic Requests	5.02 (1.46)	4.19 (1.06)	2.47 (1.17)	5.58 (1.44)
Interviews	4.45 (1.80)	4.14 (1.21)	2.20 (1.05)	4.85 (1.98)
Students	5.83 (.92)	4.28 (1.13)	2.31 (1.14)	5.33 (1.66)

Looking at the data, it is clear that students have a higher computer self-efficacy score than the general sample. Other measures appear to the relatively comparable. However, an ANOVA of the variables shows that there is statistical significance of each of the locations on self-efficacy scores, personal innovativeness, healthcare need and health literacy.

ANOVA determines in a single test whether the entire set of sample means suggests that the samples were drawn from the same general population (Hair et al., 2006). Because the surveys were drawn from five different groups, ANOVA testing for independent samples was run on the different groups to assess the differences of means among these groups. When the ANOVA tests shows statistical significance or a p value <.05, the conclusion is that there is a statistically significant difference between the

groups. Indicating that the differences between the group means is not likely due to change and is probably due to the location. All variables indicate that there is statistical significance between the groups. Results are shown in Table 17.

Table 17

Statistical Significance between Groups

Variable	p-value
Age	0.000
Gender	0.008
Income	0.000
Education	0.000
Self-efficacy	0.000
Innovativeness	0.000
Healthcare Need	0.004
Healthcare Literacy	0.000

CHAPTER 5

DATA ANALYSIS

Overview

This chapter includes the analysis of the survey instrument and the research

model. Structural equation modeling (SEM) was used to analyze the constructs and the

model based on the results of the survey. SEM models consist of a measurement model,

which relates to variables to the constructs, and a structural path model, which relates the

constructs to other constructs. Only completed questionnaires were used in this analysis

and therefore the analysis of missing data was not conducted for this study. Hypothesis

testing was conducted using SEM.

Measurement Model

First, LISREL software was used to analyze the measurement model for the

research. The measurement model encompasses the confirmatory factor analysis. In

confirmatory factor analysis (CFA), the hypotheses specify which variables will load on

which factors. The factor intercorrelations indicate whether the relationships are positive

or negative among the data and can be found in Appendix A. In addition, the

measurement model should be tested for construct validity and reliability, convergent

validity and discriminant validity.

Construct validity is the extent to which a set of measured items actually reflect

the theoretical latent construct those items are designed to measure (Hair et al., 2006).

Construct validity is made up of convergent validity and discriminant validity. In order to

assess the construct validity of the measured items in this research, methods are used to

provide confidence that item measures taken from the sample of survey respondents

represent the population of healthcare consumers. The summated scores of the items for

each construct were analyzed using average variance extracted (AVE) and critical

reliability (CR).

Convergent validity indicates that the items that are indicators of a construct

should converge or share a high proportion of variance in common (Hair et al., 2006). In

determining convergent validity, factor loadings greater than 0.70 are ideal and for this

research model, can be seen in Table 9. All factor loadings except one item for privacy

seal, one for privacy policy awareness, two items for trusting intentions and four items

measuring perceived usefulness met the rule-of-thumb measurement for convergent

validity. In CFA, the AVE is a summary indicator of convergence. The rule of thumb for

AVE is that a 0.50 or higher is a good rule of thumb suggesting adequate convergence

(Hair et al., 2006). The AVE for the constructs in this research model can be seen in

Table 9. All latent constructs in the measurement model showed adequate AVE except

perceived usefulness (PUSEFUL).

Reliability is also an indicator of convergent validity. SEM models often use the

construct reliability (CR) value to determine reliability in the measurement of a construct.

Reliability is calculated from the squared sum of factor loadings for each construct and

the sum of the error variance terms for the constructs (Hair et al., 2006). The rule-of-

thumb is that constructs with reliability estimates of 0.70 or higher suggest good

reliability. The CR for each construct in this measurement model can be seen in Table 18

below. Again, all constructs met the rule-of-thumb measurement except perceived

usefulness (PUSEFUL).

Table 18

Factor Loadings, AVE, Critical Reliability

Construct	Factor Loadings	AVE	CR
POLICY	.90 .92 .86	0.7987	0.9205
SEAL	.69 .87 .75	0.5985	0.8164
AWARE	.69 .88 .85	0.6577	0.8492
NORM	.79 .83 .77	0.6353	0.8385
DTRUST	.81 .76 .80 .77	0.6167	0.8915
IBTRUST	.79 .81 .84 .82 .73	0.6382	0.9171
PCON	.79 .87 .85 .86	0.7108	0.9365
INTRU	.86 .86 .86 .85	0.7353	0.9363
TRUSTB	.83 .85 .86	0.7170	0.8848

Construct	Factor Loadings	AVE	CR
TRUSTI	.84 .83 .83 .56 .58	0.5467	0.8543
PUSEFUL	.39 .33 .35 .36	0.1283	0.3695
PEASE	.83 .81 .82 .83	0.6766	0.9162
ACCESS	.79 .84 .74	0.6258	0.8313
MANAGE	.79 .84 .74	0.6258	0.8450
SHAREHP	.83 .84 .77	0.6625	0.8465
SHARETP	.83 .78 .79	0.6405	0.8649
THIRDP	.88 .86 .76	0.6972	0.8573
SHAREPHO	.83 .77 .80	0.6406	0.8409
RISK	.87 .88 .80	0.7109	0.9066
PCTL	.86 .91 .88	0.6480	0.8764
DTVP	.83 .74 .85	0.6530	0.8467

Discriminant validity is the extent to which a construct is truly distinct from other constructs. High discriminant validity provides evidence that a latent construct captures some occurrences other measures do not (Hair et al., 2006). The correlation matrix and the correlation matrix with squared correlation can be found in Appendix A. The conservative measure for discriminant validity testing is to compare the AVE for each factor with the squared interconstruct correlations associated with that factor. The AVE should be greater than the corresponding squared interconstruct correlation estimates.

The results of this test do suggest that there are problems with the discriminant validity of some constructs. In particular, all levels of usage indicate discriminant validity is violated: access, manage, share with healthcare provider, share with third party, share with public healthcare organization and authorized use as third party representative. In addition, there were some violations between trusting intentions, trusting beliefs, perceived ease of use, perceived usefulness, privacy concerns, intrusion, risk, privacy policy and risk. The majority of the violation was between the four levels of use as identified in the technology acceptance model (TAM) indicating that future research and empirical testing should be done in order to distinguish between the different levels of usage and thereby provide discriminant validity.

<div align="center">Structural Model   Full Model</div>

Next, the structural path model was analyzed utilizing LISREL software. The structural path model relates constructs to other constructs. Agreement from researchers indicates that the following profile of indices is important in assessing the research: the χ^2 would not be significant (p>0.05), the SRMR would be close to 0.09, and the CFI would

be close to 0.95 (Iacobucci, 2010). In addition, it has been suggested in literature that a

model demonstrates reasonable fit it the statistic adjusted by its degrees of freedom

(χ^2/df) does not exceed 3.0 (Kline, 2004). Other researchers indicate that multiple fit

indices should be used to assess the model's goodness-of-fit and should include the χ^2,

one absolute fit index (GFI), one incremental index (IFI), one goodness-of-fit index (CFI)

and one badness-of-fit index (RMSEA).

Then the sample is greater than 250 and when number of variables is greater 30,

as is in this research model, general guidelines indicate that a CFI above 0.90 and a

RMSEA < 0.07 can indicate acceptability of fit (Hair et al., 2006). Also, in large samples

the chi square is almost always significant and therefore other measures should be

analyzed. In order to find the best representation of the model, the modification index

option was requested and modification indices were examined and implemented in order

to find the most improved model. As can be seen in Table 19, seven versions of the

model, the original with six modifications, led to the final version with χ^2/DoF < 3, GFI

of 0.79, IFI of 0.97, CFI of 0.97 and RMSEA of 0.049 indicating reasonable fit of the

model (results can be seen in Table 19).

Table 19

Goodness-of-Fit Measures for Model Modifications

Model	χ^2	p-value	Degrees of Freedom	$\chi^2/$ DoF	GFI	IFI	CFI	RMSEA
No modification	8411.05	0.00	2567	3.28	0.75	0.96	0.96	0.057
A	7776.83	0.00	2566	3.03	0.77	0.96	0.96	0.054
B	7505.75	0.00	2565	2.93	0.77	0.96	0.96	0.053
C	7062.52	0.00	2564	2.75	0.78	0.97	0.97	0.050
D	7061.36	0.00	2563	2.75	0.78	0.97	0.97	0.050
E	6852.65	0.00	2562	2.67	0.79	0.97	0.97	0.049
Final Model	6641.07	0.00	2561	2.59	0.79	0.97	0.97	0.048

SEM conveys the important aspect of the confirmatory approach to the multivariate analysis of a structural theory based on some phenomenon (Byrne, 1998). If goodness-of-fit is acceptable, the model argues for the reasonableness of hypothesized relations among variables. Based on the model measurements of the model most appropriate in representing the sample data, this research model does argue for the reasonableness of the hypothesized relations. SEM also provides for the statistical significance of the coefficients and is presented in Table 20. In addition, the research model with T-statistics is presented in Figure 6 for pictorial overview of the research results. These relationships are presented in Table 21 with results and discussion in Chapter 6.

Table 20

Statistical Significance of the Coefficients

Endogenous Variable	Independent Variables	Standardized Coefficients	T-statistic
Behavioral Intention - Access	Privacy Concerns	-0.07	-0.43
	Perceived Usefulness	6.26	5.04
	Perceived Ease of Use	-1.13	-3.57
	Trusting Intentions	-1.64	-4.47
Behavioral Intention - Manage	Privacy Concerns	-0.05	-0.31
	Perceived Usefulness	6.12	5.04
	Perceived Ease of Use	-1.13	-3.64
	Trusting Intentions	-1.61	-4.47
Behavioral Intention Share with Healthcare Providers	Privacy Concerns	-0.10	-0.59
	Perceived Usefulness	6.39	5.03
	Perceived Ease of Use	-1.21	-3.74
	Trusting Intentions	-1.68	-4.45
Behavioral Intention Share with Third-Party Payers	Privacy Concerns	-0.07	-0.42
	Perceived Usefulness	6.34	5.02
	Perceived Ease of Use	-1.27	-3.93
	Trusting Intentions	-1.75	-4.67
Behavioral Intention Share with Public Health Organizations	Privacy Concerns	-0.13	-0.83
	Perceived Usefulness	5.92	5.00
	Perceived Ease of Use	-1.13	-3.75

Endogenous Variable	Independent Variables	Standardized Coefficients	T-statistic
	Trusting Intentions	-1.58	-4.50
Behavioral Intention Facilitate Third-Party ePHR	Privacy Concerns	-0.08	-0.49
	Perceived Usefulness	6.20	5.03
	Perceived Ease of Use	-1.17	-3.71
	Trusting Intentions	-1.64	-4.49
Perceived Usefulness	Privacy Concerns	0.00	0.03
	Trusting Intentions	0.29	7.84
	Perceived Ease of Use	0.23	6.36
Perceived Ease of Use	Privacy Concerns	-0.04	-1.10
	Trusting Intentions	0.12	2.99
Privacy Concerns	Privacy Risk	0.41	7.62
	Perception of Intrusion	0.54	9.63
	Privacy Control	0.03	1.67
	Trusting Intentions	0.12	5.93
Perception of Intrusion	Privacy Risk	0.85	24.50
	Disposition to Value Privacy	0.08	2.84
	Privacy Control	-0.03	-1.16
Privacy Risk	Perceived Effectiveness of Privacy Policy	-0.14	-3.05
	Perceived Effectiveness of Industry Self-Regulation	-0.01	-0.32

Endogenous Variable	Independent Variables	Standardized Coefficients	T-statistic
	Disposition to Value Privacy	0.22	4.95
Disposition to Value Privacy	Privacy Awareness	-0.13	-1.65
	Privacy Social Norm	0.30	3.17
Privacy Control	Perceived Effectiveness of Privacy Policy	0.83	22.38
	Perceived Effectiveness of Industry Self-Regulation	-0.04	-1.10
	Disposition to Value Privacy	0.03	0.88
Trusting Intentions	Trusting Beliefs	0.92	24.82
	Disposition to Trust	0.00	-0.06
	Institution-Based Trust	0.08	2.98
Trusting Beliefs	Disposition to Trust	0.25	5.04
	Institution-Based Trust	0.26	5.65
Institution-Based Trust	Disposition to Trust	0.36	7.99

The research model presented previously in the study is now shown with T-statistics noted for pictorial review of the SEM results. The model is presented in Figure 6 with statistically significant relationships (T-value > +/-1.96) in blue outline and those that are not in red outline. The values are also presented above in Table 20 for clarification and readability and the hypothesized relationships presented below in Table 21.

Figure 6. Final research model.

Table 21

Research Hypotheses Results

Hypothesis	Hypothesis Statement	Result
Hu1:	Perceived usefulness positively impacts a healthcare consumer's intent to access an electronic personal health record.	Supported
Hu2:	Perceived usefulness positively impacts a healthcare consumer's intent to manage an electronic personal health record.	Supported
Hu3:	Perceived usefulness positively impacts a healthcare consumer's intent to share via an electronic personal health record with a healthcare provider.	Supported
Hu4:	Perceived usefulness positively impacts a healthcare consumer's intent to share via an electronic personal health record with a third-party payer.	Supported
Hu5:	Perceived usefulness positively impacts a healthcare consumer's intent to share via an electronic personal health record with a public healthcare organization.	Supported
Hu6:	Perceived usefulness positively impacts a healthcare consumer's intent to facilitate an electronic personal health record for a third-party.	Supported
Hu7:	Perceived ease of use positively impacts a healthcare consumer's perceived usefulness.	Supported
Hu8:	Perceived ease of use positively impacts a healthcare consumer's intent to access an electronic personal health record.	Not supported
Hu9:	Perceived ease of use positively impacts a healthcare consumer's intent to manage an electronic personal health record.	Not supported
Hu10:	Perceived ease of use positively impacts a healthcare consumer's intent to share via an electronic personal health record with a healthcare provider.	Not supported
Hu11:	Perceived ease of use positively impacts a healthcare consumer's intent to share via an electronic personal health record with a third-party payer.	Not supported

Hypothesis	Hypothesis Statement	Result
Hu12:	Perceived ease of use positively impacts a healthcare consumer's intent to share via an electronic personal health record with a public healthcare organization.	Not supported
Hu13:	Perceived ease of use positively impacts a healthcare consumer's intent to facilitate an electronic personal health record for a third-party.	Not supported
Hp1:	Privacy concerns negatively impact a healthcare consumer's perceived usefulness of an electronic personal health record.	Not supported
Hp2:	Privacy concerns negatively impact a healthcare consumer's perceived ease of use of an electronic personal health record.	Not supported
Hp3:	Privacy concerns negatively impact a healthcare consumer's intent to access an electronic personal health record.	Not supported
Hp4:	Privacy concerns negatively impact a healthcare consumer's intent to manage an electronic personal health record.	Not supported
Hp5:	Privacy concerns negatively impact a healthcare consumer's intent to share an electronic personal health record with a healthcare provider.	Not supported
Hp6:	Privacy concerns negatively impact a healthcare consumer's intent to share an electronic personal health record with a third-party payer.	Not supported
Hp7:	Privacy concerns negatively impact a healthcare consumer'sintent to access an electronic personal health record with a public healthcare organization.	Not supported
Hp8:	Privacy concerns negatively impact a healthcare consumer's intent to facilitate an electronic personal health record for a third-party	Not supported
Hp9:	Perception of intrusion positively impacts a healthcare consumer's privacy concerns.	Supported

Hypothesis	Hypothesis Statement	Result
Hp10:	Privacy risk positively impacts a healthcare consumer's perception of intrusion.	Supported
Hp11:	Privacy risk positively impacts a healthcare consumer's privacy concerns.	Supported
Hp12:	Privacy control negatively impacts a healthcare consumer's privacy concerns.	Not supported
Hp13:	Privacy control negatively impacts a healthcare consumer's perception of intrusion.	Not supported
Hp14:	Disposition to value privacy positively impacts a healthcare consumer's perception of intrusion.	Supported
Hp15:	Disposition to value privacy positively impacts a healthcare consumer's perception of privacy risks.	Supported
Hp16:	Disposition to value privacy negatively impacts a healthcare consumer's privacy control.	Not supported
Hp17:	Privacy awareness positively impacts a healthcare consumer's disposition to value privacy.	Not supported
Hp18:	Privacy social norm positively impacts a healthcare consumer's disposition to value privacy.	Supported
Hp19:	Perceived effectiveness of privacy policy positively impacts a healthcare consumer's perception of privacy control.	Supported
Hp20:	Perceived effectiveness of privacy policy negatively impacts a healthcare consumer's privacy risk.	Supported
Hp21:	Perceived effectiveness of industry self-regulation will have a positive impact on a healthcare consumer's perception of privacy control.	Not supported
Hp22:	Perceived effectiveness of industry self-regulation will have a positive impact on a healthcare consumer's perception of privacy risk.	Not supported
Ht1:	Trusting intentions negatively impact a healthcare consumer's privacy concerns.	Not supported

Hypothesis	Hypothesis Statement	Result
Ht2:	Trusting intentions positively impact a healthcare consumer's perceived usefulness of an electronic personal health record.	Supported
Ht3:	Trusting intentions positively impact a healthcare consumer's perceived ease of use of an electronic personal health record.	Supported
Ht4:	Trusting intentions positively impact a healthcare consumer's intent to access an electronic personal health record.	Not supported
Ht5:	Trusting intentions positively impact a healthcare consumer's intent to manage an electronic personal health record.	Not supported
Ht6:	Trusting intentions positively impact a healthcare consumer's intent to share an electronic personal health record with a healthcare provider.	Not supported
Ht7:	Trusting intentions positively impact a healthcare consumer's intent to share an electronic personal health record with a third-party payer.	Not supported
Ht8:	Trusting intentions positively impact a healthcare consumer's intent to share an electronic personal health record with a public healthcare organization.	Not supported
Ht9:	Trusting intentions positively impact a healthcare consumer's intent to facilitate a third-party electronic personal health record	Not supported
Ht10:	Trusting beliefs positively impact a healthcare consumer's trusting intentions.	Supported
Ht11:	Disposition to trust positively impacts a healthcare consumer's institution based trust.	Supported
Ht12:	Disposition to trust positively impacts a healthcare consumer's trusting beliefs.	Supported
Ht13:	Disposition to trust positively impacts a healthcare consumer's trusting intentions.	Not supported

Hypothesis	Hypothesis Statement	Result
Ht14:	Institution-based trust in healthcare providers positively impacts a healthcare consumer's trusting beliefs.	Supported
Ht15:	Institution-based trust in healthcare providers positively impacts a healthcare consumer's trusting intentions.	Supported

Moderator variables

To test moderator variables: gender, age, income, education, computer self-efficacy, personal innovativeness, healthcare need and healthcare knowledge, MANOVA was utilized to analyze statistically significant group mean differences of constructs. First, age was analyzed to determine if it had an impact on the constructs in the model. The ilks' Lambda estimate showed that there was statistical significance (0.000) and therefore, the conclusion can be made that age does have an impact on the constructs. There are 10 levels of age in the research model. Survey respondents were categorized into 10 groups of age. Table 22 displays the means for each age group and indicates which groups have the highest mean for each construct. Each mean represents a composite score of means for items measured on a scale of 1-7 with 7 being strongly agree.

Table 22

Means for Each Age Group

CONSTRUCT	18-20	21-25	26-30	31-35	36-40	41-45	46-50	51-55	56-60	Over 60
Privacy concerns	5.23	5.45	5.18	4.99	4.59	4.58	4.94	5.28	4.92	5.48
Perception of Intrusion	4.61	4.64	4.44	4.68	4.42	4.42	5.03	5.03	4.62	4.94
Perceived Privacy Risk	4.78	5.15	5.15	4.70	4.33	4.33	4.83	4.70	4.75	4.85

CONSTRUCT	18-20	21-25	26-30	31-35	36-40	41-45	46-50	51-55	56-60	Over 60
Perceived Privacy Control	4.04	3.91	3.65	4.02	4.35	4.23	3.13	3.7	3.63	3.22
Perceived Effectiveness of Privacy Policy	4.5	4.9	4.31	4.38	4.44	4.33	3.47	4.09	3.92	3.78
Perceived Effectiveness of Privacy Seal	4.63	4.83	4.71	4.66	4.54	4.06	4.04	3.96	4.62	3.9
Disposition to value privacy	5.07	4.98	5.05	4.81	5.14	4.85	4.85	5.13	5.17	5.44
Privacy Awareness	4.74	4.96	5.17	5.1	4.76	5.06	5.24	4.8	5.17	4.7
Privacy Social Norm	5.18	5.28	5.4	5.22	4.99	5.17	5.37	5.2	5.4	5.44
Disposition to Trust	4.73	4.73	4.80	4.5	4.52	4.71	4.51	4.92	4.66	4.83
Institution-Based Trust	4.03	4.58	4.8	4.26	4.12	4.23	4.05	4.75	4.65	4.1
Trusting Beliefs	4.88	5.18	5.28	4.34	4.16	3.93	3.93	5.24	4.49	4.84
Trusting Intentions	4.36	4.72	4.68	4.33	3.95	3.94	3.75	4.7	4.3	4.48
Perceived Usefulness	4.52	5.03	4.85	4.58	4.51	4.30	3.97	4.48	4.55	4.32
Perceived Ease of Use	4.86	5.12	4.99	4.65	4.64	4.89	4.76	4.80	4.69	4.03
User Intention to Access	3.99	4.35	4.15	4.25	4.61	4.56	4.41	4.28	4.85	3.67
User Intention to Manage	4.05	4.33	4.20	4.4	4.73	4.36	4.3	4.21	4.85	3.46
User Intention to Share w/Healthcare Provider	4.06	4.29	4.24	4.27	4.53	4.49	4.51	4.36	4.55	3.89
User Intention to Share w/Third-Party payer	3.57	4.02	3.85	4.06	4.53	4.43	4.47	4.26	4.36	3.47

CONSTRUCT	18-20	21-25	26-30	31-35	36-40	41-45	46-50	51-55	56-60	Over 60
User Intention to Share w/Public Healthcare Org	3.96	4.06	3.90	4.12	4.50	4.37	4.13	4.06	4.37	3.41
User Intention to facilitate for Third-party	3.93	4.16	4.12	4.08	4.55	4.4	4.25	4.27	4.33	3.26

Next, gender was analyzed using MANOVA. The ilks' ambda estimate

showed that there was statistical significance (0.000) and therefore, the conclusion can be

made that gender does have an impact on the constructs. Table 23 displays the means for

each gender and indicates which groups have the highest mean for each construct. Each

mean represents a composite score of means for items measured on a scale of 1-7 with 7

being strongly agree.

Table 23

Means of Gender

CONSTRUCT	Male	Female
Privacy concerns	4.81	**5.25**
Perception of Intrusion	4.45	**4.83**
Perceived Privacy Risk	4.61	**4.91**
Perceived Privacy Control	3.68	**4.01**
Perceived Effectiveness of Privacy Policy	4.05	**4.56**
Perceived Effectiveness of Privacy Seal	4.35	**4.57**
Disposition to value privacy	4.79	**5.14**

CONSTRUCT	Male	Female
Privacy Awareness	4.94	**5.03**
Privacy Social Norm	5.11	**5.35**
Disposition to Trust	4.51	**4.85**
Institution-Based Trust	**4.35**	4.32
Trusting Beliefs	**4.64**	4.54
Trusting Intentions	**4.41**	4.23
Perceived Usefulness	4.36	**4.72**
Perceived Ease of Use	4.50	**5.06**
User Intention to Access	4.13	**4.5**
User Intention to Manage	4.13	**4.48**
User Intention to Share w/Healthcare Provider	4.24	**4.41**
User Intention to Share w/Third-Party payer	4.05	**4.2**
User Intention to Share w/Public Healthcare Org	4.05	**4.2**
User Intention to facilitate for Third-party	4.02	**4.31**

The household income levels of the survey respondents were analyzed using

MANOVA. The ilks' ambda estimate showed that there was statistical significance

(0.000) and therefore, the conclusion can be made that level of income does have an

impact on the constructs. There are five levels of income in the research model. Survey

respondents were categorized into five levels of income based on self-reported scales.

Table 24 displays the means for each level of income and indicates which groups have the highest mean for each construct. Each mean represents a composite score of means for items measured on a scale of 1-7 with 7 being strongly agree.

Table 24

Means of Income Group Levels

CONSTRUCT	$0-25,000	$25,001-50,000	$50,001-100,000	$100,001-$150,000	Over $150,000
Privacy concerns	**5.5**	4.5	5.3	4.99	5.16
Perception of Intrusion	4.75	4.15	4.6	4.76	**4.8**
Perceived Privacy Risk	**5.12**	4.28	5.01	4.76	4.87
Perceived Privacy Control	3.95	**4.08**	3.96	3.25	3.95
Perceived Effectiveness of Privacy Policy	**4.71**	4.63	4.04	3.53	3.97
Perceived Effectiveness of Privacy Seal	**4.59**	4.5	4.52	4.39	4.17
Disposition to value privacy	**5.16**	4.86	5.04	4.99	4.75
Privacy Awareness	5.09	**5.12**	4.86	5.04	4.66
Privacy Social Norm	**5.58**	5.25	5.16	5.15	4.90
Disposition to Trust	4.71	4.57	**4.82**	4.65	4.79

CONSTRUCT	$0-25,000	$25,001-50,000	$50,001-100,000	$100,001-$150,000	Over $150,000
Institution-Based Trust	4.42	4.32	**4.47**	4.23	3.96
Trusting Beliefs	**5.09**	4.61	4.45	4.28	4.51
Trusting Intentions	**4.63**	4.32	4.19	4.08	4.36
Perceived Usefulness	**4.89**	4.56	4.50	4.24	4.65
Perceived Ease of Use	4.8	4.82	4.71	4.84	**5.06**
User Intention to Access	4.08	4.15	4.52	4.34	**4.93**
User Intention to Manage	4.03	4.17	4.54	4.26	**5.03**
User Intention to Share w/Healthcare Provider	4.05	4.25	4.45	4.35	**4.88**
User Intention to Share w/Third-Party payer	3.76	3.91	4.34	4.33	**4.67**
User Intention to Share w/Public Healthcare Org	3.82	4.01	4.35	4.17	**4.58**
User Intention to facilitate for Third-party	3.91	3.97	4.4	4.19	**4.79**

Finally, the level of education of the respondents was analyzed using MANOVA. There are five levels of education in the research model. Survey respondents were categorized into five levels of education. Table 25 displays the means for each level of education and indicates which groups have the highest mean for each construct. Each mean represents a composite score of means for items measured on a scale of 1-7 with 7 being strongly agree. The ilks' ambda estimate showed that there was statistical significance (0.000) and therefore, the conclusion can be made that level education does have an impact on the constructs.

Table 25

Means of each Level of Education

CONSTRUCT	High School	Some College	2-year degree	4-year degree	Graduate school or higher
Privacy concerns	4.64	4.94	5.34	**5.41**	5.14
Perception of Intrusion	4.63	4.5	**4.89**	4.74	4.70
Perceived Privacy Risk	4.52	4.75	4.88	**5**	4.81
Perceived Privacy Control	3.75	3.91	3.80	**4.05**	3.86
Perceived Effectiveness of Privacy Policy	3.88	4.44	4.40	**4.5**	4.4
Perceived Effectiveness of Privacy Seal	3.74	4.48	4.68	**4.85**	4.82
Disposition to value privacy	**5.25**	4.79	5.18	4.95	4.87
Privacy Awareness	5.02	4.89	4.94	**5.10**	**5.10**

CONSTRUCT	High School	Some College	2-year degree	4-year degree	Graduate school or higher
Privacy Social Norm	5.35	5.05	**5.43**	5.35	5.2
Disposition to Trust	4.45	4.44	4.8	**5.07**	5.05
Institution-Based Trust	3.7	4.13	**4.81**	4.73	4.68
Trusting Beliefs	4.10	4.59	**4.83**	**4.83**	4.67
Trusting Intentions	4.04	4.34	4.16	**4.59**	4.41
Perceived Usefulness	4.09	4.44	4.72	**4.90**	**4.90**
Perceived Ease of Use	4.75	**4.88**	4.76	4.86	4.70
User Intention to Access	4.25	4.24	4.35	**4.60**	4.26
User Intention to Manage	4.26	4.16	4.31	**4.6**	4.49
User Intention to Share w/Healthcare Provider	4.23	4.25	4.26	**4.54**	4.46
User Intention to Share w/Third-Party payer	4.26	4.04	4.12	**4.22**	4.03
User Intention to Share w/Public Healthcare Org	**4.24**	4.17	4.05	4.11	3.95
User Intention to facilitate for Third-party	4.17	4.09	4.25	**4.35**	4.08

Next, the control variables, computer self-efficacy, personal innovativeness, healthcare need and healthcare knowledge were tested. The control variables for the respondents were analyzed using MANOVA. Computer self-efficacy was measured with

ten Likert-scale questions. Table 26 displays the statistical significance of computer self-efficacy on each construct in the research model. The ilks' ambda estimate showed that there was statistical significance (0.000) and therefore, the conclusion can be made that computer self-efficacy does have an impact on the constructs.

Table 26

MANOVA of Computer Self-Efficacy

Construct	Significance
Privacy Concerns	**0.001**
Perception of Intrusion	0.911
Privacy Risk	**0.004**
Privacy Control	**0.001**
Privacy Policy	**0.000**
Privacy Seal	**0.000**
Disposition to Value Privacy	0.923
Privacy Awareness	**0.004**
Privacy Social Norm	0.085
Disposition to Trust	**0.000**
Institution-Based Trust	**0.000**
Trusting Beliefs	**0.000**
Trusting Intentions	**0.000**
Perceived Usefulness	**0.000**
Perceived Ease of Use	**0.000**

Construct	Significance
Intention to Access	**0.000**
Intention to Manage	**0.000**
Intention to Share with Healthcare Providers	**0.034**
Intention to Share with Third-Party Payers	0.277
Intention to Share with Public Healthcare Organizations	0.215
Intention to Facilitate a Third-Party's ePHR	**0.001**

The control variables for the respondents were analyzed using MANOVA.

Personal innovativeness was measured with five Likert-scale questions. Table 27 displays

the statistical significance of personal innovativeness on each construct in the research

model. The ilks' ambda estimate showed that there was statistical significance

(0.000) and therefore, the conclusion can be made that personal innovativeness does have

an impact on the constructs.

Table 27

MANOVA of Personal Innovativeness

Construct	Significance
Privacy Concerns	0.180
Perception of Intrusion	0.577
Privacy Risk	0.481
Privacy Control	0.059
Privacy Policy	**0.001**

Construct	Significance
Privacy Seal	**0.000**
Disposition to Value Privacy	0.303
Privacy Awareness	**0.000**
Privacy Social Norm	0.154
Disposition to Trust	**0.019**
Institution-Based Trust	**0.000**
Trusting Beliefs	**0.000**
Trusting Intentions	**0.004**
Perceived Usefulness	**0.000**
Perceived Ease of Use	**0.000**
Intention to Access	**0.001**
Intention to Manage	**0.000**
Intention to Share with Healthcare Providers	**0.000**
Intention to Share with Third-Party Payers	**0.036**
Intention to Share with Public Healthcare Organizations	**0.035**
Intention to Facilitate a Third-Party's ePHR	**0.025**

The control variables for the respondents were analyzed using MANOVA.

Healthcare need was measured with three open-ended questions. Table 28 displays the

statistical significance of healthcare need on each construct in the research model. The

ilks' ambda estimate showed that there was no statistical significance (0.607) and

therefore, the conclusion can be made that healthcare need does not have an impact on

the constructs.

Table 28

MANOVA of Healthcare Need

Construct	Significance
Privacy Concerns	**0.000**
Perception of Intrusion	**0.000**
Privacy Risk	**0.000**
Privacy Control	**0.000**
Privacy Policy	**0.000**
Privacy Seal	**0.000**
Disposition to Value Privacy	**0.000**
Privacy Awareness	**0.000**
Privacy Social Norm	**0.000**
Disposition to Trust	**0.000**
Institution-Based Trust	**0.000**
Trusting Beliefs	**0.000**
Trusting Intentions	**0.000**
Perceived Usefulness	**0.000**
Perceived Ease of Use	**0.000**
Intention to Access	**0.000**
Intention to Manage	**0.000**

Intention to Share with Healthcare Providers	**0.000**
Intention to Share with Third-Party Payers	**0.000**
Intention to Share with Public Healthcare Organizations	**0.000**
Intention to Facilitate a Third-Party's ePHR	**0.000**

The control variables for the respondents were analyzed using MANOVA. Healthcare knowledge was measured with two Likert-scale questions. Table 29 displays the statistical significance of healthcare knowledge on each construct in the research model. The ilks' ambda estimate showed that there was statistical significance (0.000) and therefore, the conclusion can be made that healthcare knowledge does not have an impact on the constructs.

Table 29

MANOVA of Healthcare Knowledge

Construct	**Significance**
Privacy Concerns	**0.000**
Perception of Intrusion	0.078
Privacy Risk	**0.007**
Privacy Control	**0.013**
Privacy Policy	**0.000**
Privacy Seal	**0.000**
Disposition to Value Privacy	0.942
Privacy Awareness	**0.004**

Construct	Significance
Privacy Social Norm	**0.024**
Disposition to Trust	**0.000**
Institution-Based Trust	0.138
Trusting Beliefs	**0.000**
Trusting Intentions	**0.000**
Perceived Usefulness	**0.000**
Perceived Ease of Use	**0.040**
Intention to Access	0.510
Intention to Manage	0.814
Intention to Share with Healthcare Providers	0.610
Intention to Share with Third-Party Payers	0.195
Intention to Share with Public Healthcare Organizations	0.152
Intention to Facilitate a Third-Party's ePHR	0.240

CHAPTER 6

CONCLUSIONS AND IMPLICATIONS

Summary of Study

The purpose of this research study was to attempt to understand the antecedents of the healthcare consumer's behavior through analysis of behavioral intentions of use and also to understand the impact privacy and trust have on these behavioral intentions. A conceptual model was developed from prior theory and found to have statistical significance and acceptable levels of goodness-of-fit through the analysis of structural equation modeling (SEM). Hypotheses were developed based on these theories and analyzed with survey results also utilizing SEM. In SEM if goodness-of-fit is adequate as in this model, the model them argues for the plausibility of the hypothesized relations among the variables (Byrne, 1998).

In order to begin the process of understanding this relationship, three research questions were asked. First, this research looked at what attributes of healthcare consumers result in the intent to fully utilize electronic personal health records (ePHR). Attributes studied, based on the literature review, were age, gender, income level, education level, computer self-efficacy, personal innovativeness, healthcare need and healthcare knowledge. Statistical analysis found all of these attributes had statistical significance upon the intent to use ePHR by a healthcare consumer.

The second research question asked was whether privacy concerns of healthcare consumers impact the intent to fully utilize ePHR. It was expected that if privacy

concerns were high, then intent to utilize ePHR would be lower. While privacy concerns did have a negative impact on intent to utilize, the impact was not statistically significant.

Finally, the third research question asked if an individual's trust related behaviors impact the intent to fully utilize ePHR. Hypothesis testing indicated statistically significant relationships, but were opposite of theory. Based on theory, relationships in the research model were hypothesized that higher trusting intentions would result in higher intent to utilize ePHR. The trusting intentions items were framed in the context of the healthcare provider and the subsequent use of technology for the relationship with the healthcare provider. Since the actual results were opposite of the hypothesized relationship, it is possible that the survey participants were more focused on the trusting intentions of the healthcare provide than the technology used to communicate. It is also possible that the more a healthcare consumer trusts their healthcare provider, the less likely they are to intend to utilize ePHR due to lack of need.

<center>Summary of Findings</center>

Behavioral intentions were broken down in to four types of use based on the ePHR definition issued by the Markle Foundation: electronic applications through which individuals can access, manage and share their health information, and that of others for whom they are authorized, in a private, secure and confidential environment (Connecting for Health, 2003). As in the Klein (2007) study, this research attempted to study four components of usage: access, manage, share and use as authorized third-party representative. Because these levels did not show discriminant validity, the conclusions

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made regarding the relationships between the constructs in the modified technology acceptance model (TAM) may be incorrect.

The relationships in the modified TAM model indicated that perceived usefulness relationships were supported while perceived ease of use relationships were not. It may be possible that even though healthcare consumers see the usefulness in ePHR, the usefulness is not enough to overcome their perceived ease of use and therefore is not sufficient for their intent to utilize the ePHR. Perceived ease of use is the degree to which a person believes that using a particular system would be free of effort (Davis, 1989). The claim is that an application perceived to be easier to use than another is more likely to be accepted. The other use for electronic personal health records is to not have integration and not be able to have a repository for medical records that is accessible by the healthcare consumer, healthcare providers, third-party payers and the public healthcare facilities. On the other hand, the ePHR is electronic and there may be technology barriers in place that prevent the healthcare consumer from seeing the perceived ease of use.

The privacy model study in this research did find that privacy concerns negatively impact a healthcare consumer's technology acceptance, however the impact it was not statistically significant. However, in the context of healthcare, most other privacy constructs did show statistical significance. Privacy control was expected to have a negative impact on privacy concerns and perception of intrusion. Privacy control survey questions were in relation to the healthcare consumer's control over their information once it was stored in an ePHR. If the healthcare consumer's perception of privacy control

was high, then it was expected that their privacy concerns would be lower. Not only did the statistical analysis show no statistical significance, the relationship was positive. It might be argued that individuals that feel they have privacy control also have privacy concern and that has led to their effort toward privacy control. Industry self-regulation also did not show statistical significance on privacy risk or privacy control. Industry Self-regulation of ePHR websites, providers, third party payers, etc., relates to health information privacy and portability act (HIPAA) and also to privacy seals found on websites. It is likely that healthcare consumers do not understand their privacy rights and the industry self-regulation of the ePHR industry sufficiently to answer these questions.

Xu et al. (2008) failed to show statistical significance in the relationship between disposition to value privacy and perceived privacy control. However, this research tested the relationship in the context of healthcare on real healthcare consumers to determine if there was statistical significance in this environment. This research found a statistical relationship; however, the Xu et al. (2008) model indicated that the relationship between privacy concern and disposition to value privacy would be negative. This research showed that the relationship was statistically significant in a positive direction. In other words, this research showed that the higher a healthcare consumer's disposition to value privacy, the higher their perceived privacy control.

The trust model constructs were not supported for relationships to the modified technology acceptance model. Also, trusting intentions was expected to have a negative impact on privacy concerns. In other words, if trusting intentions were higher, privacy concerns should be lower. The statistical analysis showed a statistically significant

positive relationship of trusting intentions on privacy concerns. The trusting intention questions were asked in the context of information provided by the healthcare provider via an Internet site. However, it seems that it is possible the survey participant answered these questions in the context of the healthcare provider as an individual and not based on the interaction with them through the Internet. In that case, the higher the trusting intentions in their healthcare provider may lead them to higher privacy concerns of technology or websites and lower intent to use. The trust intentions questions should be adapted to explain clearly that the trusting intentions are in the technology the healthcare provider uses and expects the healthcare consumer to use. If this was the case, the statistical significance of the trust constructs justifies their greater reliance on trust in their healthcare provider which leads to higher privacy concerns with technology and is reasonably understandable in that context. While the McKnight et al. (2002) study did not measure trust-related behaviors in its research, it did call for future research to not only measure this construct but to also measure how trust related behaviors lead to trusting intentions such as intent to utilize an ePHR.

The demographics and control variables all showed statistical significance on at least some of the constructs. Not one demographic or control variable showed statistical significance on all constructs. However as a whole each one did show that they made a difference in the analysis of variance testing.

Limitations of the Study

While the research model did show acceptable levels of goodness-of-fit indices, there was one construct that did not have sufficient construct validity. Perceived

usefulness did not pass tests for construct validity or reliability thereby indicating that

this construct may not be relevant for a study in the context of healthcare and may not be

relevant to a healthcare consumer's decision to utilize ePHR.

Also, this study attempted to operationalize the four levels of usage for ePHR:

access, manage, share and use as a third-party representative. The four levels of usage

were asked each with a three item scale. Discriminant validity testing failed on these four

variables and therefore did not give adequate differentiation among those constructs.

Perceived ease of use, privacy concerns and trusting intentions relationships with these

constructs did not show statistical significance. By utilizing one level of usage or by

developing a better scale for measuring the differences between these constructs, the

study may have had a better impact on the understanding of privacy concerns and trusting

intentions on intent to utilize ePHR.

The research gathered survey information from five different groups: clinics,

Facebook and electronic requests, interviews, students and members of a presentation.

ANOVA showed statistical difference between the demographics and control variables of

the groups, and also the MANOVA of the model constructs indicated that some

constructs were impacted due to the different groups in the study. Due to the number of

constructs in the research model, a large sample was required.

<div align="center">Research Contributions</div>

This study utilizes common theories in information technology in a new context

and builds upon these existing theories to strengthen and identify contextual information

for healthcare settings. Also, this research integrates information boundary theory (IBT)

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with TAM in the context of ePHR in order to understand the impact privacy concerns and trust intentions may have on intent to use. Results of this study can provide valuable insights into the emerging field of electronic-health. This research also continues to develop the application of TAM into other contexts such as healthcare.

In addition, this study made the first attempt at distinguishing the different types of use for ePHR. Other studies have found that different types of use have statistically significant results in the TAM model. While future testing is needed, this is a first step in determining the need for analysis of uses of ePHR.

While perceived usefulness is a reliable construct in technology acceptance literature, it was shown in this context to lack validity and reliability. This discovery adds to the research of electronic health by indicating that in the context of electronic health, common theories may show different results indicate that testing of theories applicable in other contexts may be very informative in the context of e-health.

Practical Contributions

This research has a plethora of practical contributions. First, it contributes to a better understanding of what barriers there are to adoption of ePHR and the subsequent hope to overcome these barriers. The ultimate goal of the nationwide healthcare infrastructure is interoperability which can lead to an integrated nationwide healthcare system; integration is necessary to recognize the benefits expected. In order for integration to happen, some believe that the utilization of electronic health records by consumers or ePHR is necessary to continue forward. This research gives some insight

into the obstacles healthcare consumers are facing with the full utilization of ePHR and subsequently the barriers the nation is facing as a whole.

In particular, technology usage research shows that perceived ease of use is a strong indicator of intent to use however in this study did not show statistical significance. Therefore, proponents of the nationwide healthcare infrastructure particularly those who believe ePHR may be the key should focus on these indicators of barriers of utilization. The general population of healthcare consumers needs to learn and understand the components of ePHR and become familiar with them so that the perceived ease of use concerns can diminish. As technology becomes more ubiquitous, healthcare consumers will be less fearful of using and the subsequent lack of perceived ease of use will fade.

Next, this study contributes to practical applications in that it gives a better understanding of the healthcare consumer's identification of the levels of usage in ePHR. It appears that healthcare consumers do not distinguish between access, management, sharing with different vendors and authorized users as a third-party representative. For effective utilization to take place, healthcare consumers need to be educated on the different types of usage, the choices they are given in relation to these types of usage and how those types of usage impact their healthcare and the healthcare of the nation as a whole.

In addition, with the lack of statistical support for the industry self-regulation privacy seals, it also seems apparent that healthcare consumers are not familiar with HIPAA regulation of ePHR and the websites that support them as well as the regulation

over those with whom they may share. Privacy seals have made an impact on e-commerce and most consumers seem to understand their meaning. However, it may be that the privacy seals in the context of healthcare should be more obvious in their relationship to HIPAA.

<div style="text-align:center">Directions for Future Research</div>

First, future research should look into a deeper study of the construct validity and reliability issues found in this study. For example, perceived usefulness, a construct that has been used in a plethora of technology usage research studies. Future research should look into finding out why this construct, in the context of ePHR and viewed by healthcare consumers, was not valid or reliable.

In addition, future research should seek to understand the differentiation between the four types of usage as defined by the Markle Foundation for ePHR. It is possible that since ePHR are relatively new, healthcare consumers do not fully understand the different components of usage. A more focused study on these four types of usage and a better explanation to the research participants or a hands-on model might be used to get a better understanding of healthcare consumer's intent to utilize the ePHR in these different contexts.

Based on the research results, future research should look deeper into the perceived effectiveness of industry self-regulation in the context of ePHR. Privacy seals are commonly seen on websites; however it may be enlightening to research and examine the ePHR websites and the relationship the privacy assurances on these websites have with common e-commerce seals as well as the relationship these privacy assurances have

with HIPAA. Further, future research should look at healthcare consumer understanding of the privacy assurances of ePHR websites.

The demographic and control variables in this study showed statistical significance on the constructs in the research model. Future research should use stronger statistical analysis to determine what levels and specific attributes are less likely to lead to higher privacy concerns and lower trusting intentions in the context of ePHR. Also, these statistical studies should look deeper into finding exactly what specific attributes contribute toward the higher levels of intent to utilize and likewise, the lower levels. After that, future research should go back to these individuals with these traits and try to find more information related to their intentions toward ePHR possibly through exploratory study.

Conclusions

This research was conducted through an empirical examination of healthcare consumer's intent to utilize ePHR. The aim of the research was to develop a research model by combining three grounded theories: technology acceptance model, a privacy concerns model and a trust model. TAM was modified to include four levels of usage and was then analyzed with antecedent relationships of privacy concerns and trusting intentions. Actual behavior was not included in the model due to the small percentage of actual users of ePHR.

Results showed a statistically significant relationship to support perceived usefulness by healthcare consumers, but did not support perceived ease of use. Privacy concerns of healthcare consumers did not impact their intent to utilize nor did trusting

intentions. Trusting intentions had a positive statistically significant impact on privacy concerns and may have resulted from the healthcare consumer's focus on trust of healthcare provider rather than the intended trust in the healthcare provider's use of electronic health records and websites supporting these records. Demographic differences in healthcare consumers did make a difference in the results as did the control variables.

Findings indicate that future research needs to be done on healthcare consumer's understanding of the different components of utilization of ePHR as well as their understanding of HIPAA and privacy seals of websites supporting electronic health information. Overall, this study provided a good basis for the understanding of antecedents of the healthcare consumer's behavior on intentions to use ePHR and also on the impact privacy and trust have in this context. This study also presented an acceptable research model of three grounded theories combined and studied in a new context. It was also clear in this research that there is a need to educate the general public regarding e-health and the technologies that support the expected healthcare infrastructure.

APPENDIX A

STATISTICAL OUTPUT

Mean Comparison for Location

Location		PCON	INTRU	RISK	PCTL	POLICY	SEAL	DTVP	AWARE	NORM	DTRUST	IBTRUST	TRUSTB	TRUSTI	PUSEFUL	PUSE	UIA	UIM	UIH	UII	UIP	UIT
1	Mean	5.2576	4.9167	4.9909	3.5318	4.284848487	4.422222229	5.034343418	4.862626274	5.393939384	4.8561	4.469	4.923232334	4.619	4.9348	4.6864	4.252525262	4.284848483	4.367676764	4.298989889	4.185858582	4.266666663
	N	165	165	165	165	165	165	165	165	165	165	165	165	165	165	165	165	165	165	165	165	165
	Std. Deviation	1.63457	1.63501	1.53115	1.66637	1.5808193726	1.5583212016	1.5269149080	1.4979606210	1.3031506179	1.55713	1.6004	1.8667045051	1.6997	1.48054	1.62621	1.6683534207	1.7519847565	1.6794728537	1.7090640844	1.7026010380	1.7465412996
2	Mean	5.0589	4.5711	4.4482	4.0102	4.418699183	4.607046068	4.892953926	4.836043366	5.212737117	4.7419	4.403	4.566395659	4.228	4.5356	4.6972	4.173441736	4.131436315	4.189701897	3.856368567	3.974254744	4.058265595
	N	246	246	246	246	246	246	246	246	246	246	246	246	246	246	246	246	246	246	246	246	246
	Std. Deviation	1.54113	1.61040	1.56251	1.52108	1.5519522978	1.4898188144	1.5781429413	1.3508179768	1.3365269188	1.44241	1.3663	1.5761458510	1.5067	1.49096	1.50755	1.5564070430	1.5551468232	1.5724852426	1.6154477044	1.5584649312	1.6054730356
3	Mean	5.5383	4.6250	5.5706	4.0000	4.887096790	4.723118258	4.965053760	5.470430115	5.395161306	4.9415	4.903	5.556451618	5.003	5.1552	5.2379	4.779569870	4.771505352	4.623655902	4.241935484	4.282258065	4.491935484
	N	124	124	124	124	124	124	124	124	124	124	124	124	124	124	124	124	124	124	124	124	124
	Std. Deviation	1.31712	1.63408	1.06856	2.03676	1.3148358656	1.2102556244	1.4179253426	1.0977616380	1.0195620061	1.20555	1.2149	1.0999891481	1.0614	1.15496	.98868	1.2849536452	1.3630608350	1.3481344774	1.5740319918	1.5853007915	1.4454637073
4	Mean	4.7500	4.8052	4.6753	3.8474	3.792207804	4.467532486	4.870129857	5.000000012	4.969696982	4.1039	3.501	3.363636371	3.418	3.6429	4.7435	4.186147191	4.129870113	4.125541100	4.138528152	4.069264064	3.978354984
	N	77	77	77	77	77	77	77	77	77	77	77	77	77	77	77	77	77	77	77	77	77
	Std. Deviation	1.96808	1.98457	2.03912	1.72594	1.7463738389	1.9378197802	1.8686047416	1.6167978117	1.5598974960	1.77443	2.0393	1.6527328177	1.6083	1.74597	1.95634	1.9820049508	1.7992492210	1.7828282059	1.9371337867	1.7765016379	1.8718737446
5	Mean	4.2139	4.3253	4.2470	3.8645	3.815261035	3.819277125	5.301204825	4.983935737	5.080321301	4.4337	3.776	3.642570281	3.713	3.8554	4.8163	4.433734949	4.522088361	4.433734951	4.445783140	4.281124505	4.076305222
	N	83	83	83	83	83	83	83	83	83	83	83	83	83	83	83	83	83	83	83	83	83
	Std. Deviation	1.87210	1.86092	1.89290	1.77306	1.9228007219	1.9619008161	1.6679787135	1.6617028588	1.6184826524	1.79264	1.8036	1.7018904854	1.6593	1.74001	1.68072	1.6794105842	1.7220023487	1.7720618181	1.8005397457	1.7999412167	1.7983169686
Total	Mean	5.0565	4.6594	4.7784	3.8594	4.329016789	4.474340528	4.985611504	4.991366913	5.245563549	4.6971	4.333	4.584172664	4.308	4.5608	4.8104	4.332853718	4.328537165	4.331414864	4.131894485	4.126618705	4.178417271
	N	695	695	695	695	695	695	695	695	695	695	695	695	695	695	695	695	695	695	695	695	695
	Std. Deviation	1.66193	1.70159	1.64117	1.71552	1.6249773276	1.5975902291	1.5857749435	1.4331922484	1.3466443163	1.53437	1.5949	1.7389435317	1.5919	1.57492	1.54750	1.6182693842	1.6344560854	1.6153471118	1.7006236741	1.6531497011	1.6724628514

Mean Comparison for Method of Survey

Report																						
Method of Survey		PCON	INTRU	RISK	PCTL	POLICY	SEAL	DTVP	AWARE	NORM	DTRUST	IBTRUST	TRUSTB	TRUSTI	PUSEFUL	PUSE	UIA	UIM	UIH	UII	UIP	UIT
1	Mean	4.8708	4.7392	4.7262	3.6915	4.048205130	4.278974371	5.063589734	4.926153853	5.213333335	4.5700	4.063	4.226666674	4.103	4.3531	4.7331	4.283076931	4.308717946	4.327179482	4.298461538	4.182564101	4.149743590
	N	325	325	325	325	325	325	325	325	325	325	325	325	325	325	325	325	325	325	325	325	325
	Std. Deviation	1.82707	1.79287	1.77876	1.71066	1.7245308194	1.7768474637	1.6513880156	1.5658882227	1.4589584234	1.69624	1.8098	1.9102567716	1.7470	1.71654	1.71878	1.7471917845	1.7558668728	1.7266856934	1.7862877983	1.7415788705	1.7887788806
2	Mean	5.2196	4.5892	4.8243	4.0068	4.575675678	4.645945937	4.917117114	5.048648655	5.273873873	4.8088	4.571	4.898198197	4.488	4.7432	4.8784	4.376576570	4.345945938	4.335135131	3.985585588	4.077477478	4.203603612
	N	370	370	370	370	370	370	370	370	370	370	370	370	370	370	370	370	370	370	370	370	370
	Std. Deviation	1.48545	1.61636	1.51099	1.70851	1.4914621793	1.4017636579	1.5247752440	1.3050430323	1.2409536576	1.36922	1.3369	1.5072333078	1.4203	1.41647	1.37846	1.4969378501	1.5220422254	1.5131650695	1.6099012454	1.5721157640	1.5652001436
Total	Mean	5.0565	4.6594	4.7784	3.8594	4.329016789	4.474340528	4.985611504	4.991366913	5.245563549	4.6971	4.333	4.584172664	4.308	4.5608	4.8104	4.332853718	4.328537165	4.331414864	4.131894485	4.126618705	4.178417271
	N	695	695	695	695	695	695	695	695	695	695	695	695	695	695	695	695	695	695	695	695	695
	Std. Deviation	1.66193	1.70159	1.64117	1.71552	1.6249773276	1.5975902291	1.5857749435	1.4331922484	1.3466443163	1.53437	1.5949	1.7389435317	1.5919	1.57492	1.54750	1.6182693842	1.6344560854	1.6153471118	1.7006236741	1.6531497011	1.6724628514

Mean Comparison for Gender

Report																						
Gender **		PCON	INTRU	RISK	PCTL	POLICY	SEAL	DTVP	AWARE	NORM	DTRUST	IBTRUST	TRUSTB	TRUSTI	PUSEFUL	PUSE	UIA	UIM	UIH	UII	UIP	UIT
1	Mean	4.8145	4.4468	4.6121	3.6782	4.047311827	4.350537634	4.792473118	4.939784952	5.113978502	4.5056	4.354	4.635483873	4.408	4.3589	4.4984	4.131182801	4.134408586	4.244086020	4.049462367	4.046236564	4.017204300
	N	310	310	310	310	310	310	310	310	310	310	310	310	310	310	310	310	310	310	310	310	310
	Std. Deviation	1.70814	1.67276	1.59937	1.76785	1.6263466851	1.5599230808	1.6357259545	1.4379011964	1.3297896396	1.57645	1.5660	1.6570691380	1.5568	1.55015	1.57242	1.5781211655	1.5793294251	1.6233616100	1.6993742279	1.6523696885	1.6293750570
2	Mean	5.2513	4.8305	4.9123	4.0052	4.555844161	4.574025976	5.141125530	5.032900440	5.351515146	4.8513	4.317	4.542857146	4.228	4.7234	5.0617	4.495238092	4.484848488	4.401731595	4.198268399	4.191341987	4.308225117
	N	385	385	385	385	385	385	385	385	385	385	385	385	385	385	385	385	385	385	385	385	385
	Std. Deviation	1.59956	1.70745	1.66408	1.66017	1.5900300815	1.6224394321	1.5288496340	1.4299064163	1.3524941090	1.48379	1.6197	1.8032479165	1.6172	1.57787	1.48207	1.6338940580	1.6631433746	1.6075262061	1.7009315949	1.6530818123	1.6973576643
Total	Mean	5.0565	4.6594	4.7784	3.8594	4.329016789	4.474340528	4.985611504	4.991366913	5.245563549	4.6971	4.333	4.584172664	4.308	4.5608	4.8104	4.332853718	4.328537165	4.331414864	4.131894485	4.126618705	4.178417271
	N	695	695	695	695	695	695	695	695	695	695	695	695	695	695	695	695	695	695	695	695	695
	Std. Deviation	1.66193	1.70159	1.64117	1.71552	1.6249773276	1.5975902291	1.5857749435	1.4331922484	1.3466443163	1.53437	1.5949	1.7389435317	1.5919	1.57492	1.54750	1.6182693842	1.6344560854	1.6153471118	1.7006236741	1.6531497011	1.6724628514

Mean Comparison for Age

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Age *		PCON	INTRU	RISK	PCTL	POLICY	SEAL	DTVP	AWARE	NORM	DTRUST	IBTRUST	TRUSTB	TRUSTI	PUSEFUL	PUSE	UIA	UIM	UIH	UII	UIP	UIT
1	Mean	5.2321	4.6116	4.7813	4.0357	4.500000009	4.625000000	5.071428570	4.744047616	5.184523813	4.7277	4.029	4.880952384	4.364	4.5223	4.8616	3.988095221	4.047619034	4.059523788	3.571428589	3.964285709	3.934523812
	N	56	56	56	56	56	56	56	56	56	56	56	56	56	56	56	56	56	56	56	56	56
	Std. Deviation	1.36753	1.49766	1.50685	1.30160	1.4508792310	1.5505782450	1.3584219719	1.4452864212	1.4535496589	1.42325	1.4974	1.4431007083	1.2312	1.36121	1.32109	1.4312024747	1.5419108711	1.4398472593	1.5185243942	1.4698018361	1.4639363615
2	Mean	5.4493	4.6419	5.1537	3.9122	4.898648652	4.828828813	4.979729721	4.963963969	5.283783799	4.7348	4.578	5.180180183	4.719	5.0253	5.1216	4.351351350	4.333333327	4.283783789	4.015765764	4.058558561	4.159909916
	N	148	148	148	148	148	148	148	148	148	148	148	148	148	148	148	148	148	148	148	148	148
	Std. Deviation	1.25762	1.47921	1.19043	1.48056	1.1636071247	1.1411935646	1.4073698294	1.2122673252	1.0819517616	1.21995	1.2526	1.2885790512	1.3122	1.14759	.98823	1.4411004950	1.4067110454	1.4245259477	1.5952188834	1.4737389821	1.4398861897
3	Mean	5.1771	4.4427	5.1458	3.6510	4.305555554	4.708333331	5.048611102	5.166666658	5.402777765	4.8021	4.796	5.284722219	4.683	4.8542	4.9896	4.152777783	4.201388896	4.236111112	3.847222221	3.902777790	4.118055558
	N	48	48	48	48	48	48	48	48	48	48	48	48	48	48	48	48	48	48	48	48	48
	Std. Deviation	1.84215	1.98816	1.76764	1.65087	1.6240412075	1.5507567018	1.5755063376	1.4472603957	1.2241817605	1.45130	1.4935	1.4811496129	1.3707	1.50339	1.46225	1.7982896250	1.8625836727	1.8980621453	1.7930234250	1.7877417341	1.9660109436
4	Mean	4.9873	4.6758	4.7013	4.0191	4.375706197	4.655367235	4.810734468	5.098870064	5.223163835	4.7458	4.256	4.336158187	4.327	4.5805	4.6547	4.245762722	4.398305090	4.265536719	4.059322036	4.124293790	4.084745773
	N	118	118	118	118	118	118	118	118	118	118	118	118	118	118	118	118	118	118	118	118	118
	Std. Deviation	1.78217	1.79574	1.75936	1.76902	1.7100044102	1.6083425646	1.7303935247	1.4377288653	1.4000780649	1.62249	1.7412	1.7347877680	1.6475	1.62278	1.69398	1.8342670295	1.8044255471	1.7716557697	1.8793784444	1.8834999134	1.8624017402
5	Mean	4.5909	4.4156	4.3312	4.3506	4.441558444	4.536796547	5.138528135	4.757575784	4.987012991	4.5195	4.119	4.155844165	3.951	4.5097	4.6396	4.610389609	4.727272722	4.528138530	4.532467526	4.502164499	4.554112548
	N	77	77	77	77	77	77	77	77	77	77	77	77	77	77	77	77	77	77	77	77	77
	Std. Deviation	1.90434	1.84988	1.79521	2.28635	1.7231155863	1.5276743925	1.5925178097	1.6001063502	1.5164223392	1.71188	1.7027	2.0601938955	1.8793	1.63707	1.86444	1.4623966979	1.5031422010	1.4881114026	1.6070565779	1.5724448914	1.5964236379
6	Mean	4.5833	4.4233	4.3333	4.2267	4.328888916	4.057777787	4.848888889	5.057777768	5.173333309	4.7067	4.237	3.933333339	3.939	4.2967	4.8867	4.560000000	4.355555560	4.488888871	4.431111113	4.373333320	4.400000005
	N	75	75	75	75	75	75	75	75	75	75	75	75	75	75	75	75	75	75	75	75	75
	Std. Deviation	1.76649	1.83940	1.70072	1.60140	1.5378052157	1.7802497913	1.7495544874	1.4850337777	1.4636332288	1.63232	1.7078	1.9575065405	1.8090	1.65765	1.72829	1.7859646301	1.7810592771	1.7078983797	1.7266445193	1.7449713221	1.8199759128
7	Mean	4.9428	5.0271	4.8343	3.1265	3.469879527	4.040160633	4.847389548	5.240963863	5.365461840	4.5060	4.051	3.927710843	3.749	3.9729	4.7590	4.405622499	4.297188733	4.506024088	4.465863441	4.136546177	4.253012070
	N	83	83	83	83	83	83	83	83	83	83	83	83	83	83	83	83	83	83	83	83	83
	Std. Deviation	1.73703	1.65464	1.72733	1.55213	1.7897905080	1.9688616489	1.7952822739	1.4754662595	1.4572633356	1.74694	1.7065	1.8471747950	1.6999	1.92742	1.76796	1.5016235125	1.4997850165	1.5852995429	1.5892079699	1.5969450490	1.5483100236
8	Mean	5.2803	5.0303	4.6970	3.6970	4.090909106	3.959595973	5.131313076	4.797979818	5.191919221	4.9242	4.752	5.242424264	4.679	4.4773	4.8030	4.282828276	4.212121173	4.363636336	4.262626279	4.060606058	4.272727233
	N	33	33	33	33	33	33	33	33	33	33	33	33	33	33	33	33	33	33	33	33	33
	Std. Deviation	1.79926	1.68142	1.70564	1.55468	1.4702435901	1.7435547637	1.4017335071	1.5454669300	1.6030143256	1.39822	1.6163	1.5029432329	1.4958	1.73359	.98971	1.6353754564	1.7135452329	1.8321276871	1.8042341871	1.7449421946	1.7706216223
9	Mean	4.9135	4.6154	4.7500	3.6346	3.923076915	4.615384662	5.166666654	5.166666677	5.397435896	4.6635	4.654	4.487179477	4.292	4.5481	4.6923	4.846153838	4.846153858	4.551282062	4.358974377	4.371794888	4.333333338
	N	26	26	26	26	26	26	26	26	26	26	26	26	26	26	26	26	26	26	26	26	26
	Std. Deviation	1.56994	1.62670	1.67183	1.91863	2.0006836637	1.7014825440	1.7795130240	1.3800160930	1.2000712041	1.72329	1.6440	1.6172150671	1.4235	1.63710	1.74113	1.6579257956	1.7844532808	1.6136702320	1.6704572221	1.5841630697	1.7256238921
10	Mean	5.4274	4.9355	4.8548	3.2177	3.774193529	3.903225823	5.440860216	4.698924748	5.440860226	4.8306	4.097	4.838709690	4.484	4.3226	4.0323	3.666666661	3.462365587	3.892473129	3.473118290	3.408602161	3.258064519
	N	31	31	31	31	31	31	31	31	31	31	31	31	31	31	31	31	31	31	31	31	31
	Std. Deviation	1.46514	1.63677	1.83913	1.66676	1.7435321524	1.3882937898	1.1968696731	1.5619428629	1.0728539107	1.64239	1.6296	1.5773183171	1.4512	1.46514	1.79437	1.5916448557	1.5815543541	1.6247782882	1.5934453650	1.5604122902	1.5722352064
Total	Mean	5.0565	4.6594	4.7784	3.8594	4.329016789	4.474340528	4.985611504	4.991366913	5.245563549	4.6971	4.333	4.584172664	4.308	4.5608	4.8104	4.332853718	4.328537165	4.331414864	4.131894485	4.126618705	4.178417271
	N	695	695	695	695	695	695	695	695	695	695	695	695	695	695	695	695	695	695	695	695	695
	Std. Deviation	1.66193	1.70159	1.64117	1.71552	1.6249773276	1.5975902291	1.5857749435	1.4331922484	1.3466443163	1.53437	1.5949	1.7389435317	1.5919	1.57492	1.54750	1.6182693842	1.6344560854	1.6153471118	1.7006236741	1.6531497011	1.6724628514

Mean Comparison for Income

Income ***		PCON	INTRU	RISK	PCTL	POLICY	SEAL	DTVP	AWARE	NORM	DTRUST	IBTRUST	TRUSTB	TRUSTI	PUSEFUL	PUSE	UIA	UIM	UIH	UII	UIP	UIT
1	Mean	5.5000	4.7465	5.1188	3.9521	4.711583926	4.591016539	5.158392426	5.085106383	5.579196228	4.7110	4.423	5.089834521	4.627	4.8936	4.7961	4.075650120	4.033096928	4.047281330	3.756501185	3.820330967	3.907801421
	N	141	141	141	141	141	141	141	141	141	141	141	141	141	141	141	141	141	141	141	141	141
	Std. Deviation	1.34430	1.49940	1.41692	1.55061	1.3009275418	1.3600704936	1.3078405453	1.2639094522	1.0309845672	1.24006	1.2667	1.4664931928	1.3871	1.31856	1.28439	1.4482440432	1.4983085513	1.4609094603	1.5342023612	1.5677897267	1.5176769958
2	Mean	4.4973	4.1500	4.2811	4.0824	4.628828832	4.499099114	4.864864854	5.117117130	5.246846841	4.5689	4.323	4.605405414	4.323	4.5635	4.8243	4.149549551	4.171171169	4.248648640	3.913513521	4.005405404	3.965765769
	N	185	185	185	185	185	185	185	185	185	185	185	185	185	185	185	185	185	185	185	185	185
	Std. Deviation	1.79881	1.79980	1.77468	1.56634	1.4892157041	1.6185534878	1.6965784186	1.4295370681	1.2918234988	1.63821	1.7069	1.8034038164	1.6789	1.60217	1.62945	1.6629963454	1.6608987507	1.6823643796	1.6687570107	1.6715420259	1.6952349845
3	Mean	5.2995	4.9959	5.0069	3.9615	4.404761910	4.518315007	5.043956037	4.860805857	5.164835164	4.8228	4.468	4.448717946	4.192	4.5014	4.7102	4.523809525	4.538461536	4.452380940	4.336996334	4.349816853	4.399267404
	N	182	182	182	182	182	182	182	182	182	182	182	182	182	182	182	182	182	182	182	182	182
	Std. Deviation	1.54434	1.58408	1.50607	1.65724	1.5632054677	1.4871973650	1.5667734591	1.4515425894	1.2963315273	1.49303	1.5782	1.8148139263	1.6568	1.55904	1.50050	1.5481967241	1.5625051346	1.5392921530	1.6642667786	1.5631882029	1.6043371147
4	Mean	4.9864	4.7578	4.7558	3.2519	3.534883714	4.385012924	4.992248055	5.043927657	5.147286824	4.6473	4.226	4.227390185	4.079	4.2364	4.8353	4.338501290	4.263565871	4.343669245	4.325581399	4.116279077	4.193798453
	N	129	129	129	129	129	129	129	129	129	129	129	129	129	129	129	129	129	129	129	129	129
	Std. Deviation	1.72649	1.77079	1.74929	1.65167	1.8472100826	1.8945506714	1.6710697597	1.5328463141	1.5689627373	1.71693	1.7133	1.7224944072	1.6067	1.77116	1.76486	1.7882644488	1.7982796596	1.7984068797	1.8015546568	1.7318759807	1.8393356702
5	Mean	5.1552	4.7974	4.8707	3.9526	3.971264379	4.172413807	4.752873581	4.655172443	4.902298841	4.7888	3.962	4.505747116	4.355	4.6509	5.0603	4.931034481	5.034482750	4.879310353	4.666666650	4.580459752	4.787356336
	N	58	58	58	58	58	58	58	58	58	58	58	58	58	58	58	58	58	58	58	58	58
	Std. Deviation	1.66348	1.73234	1.53486	2.46975	1.7839270483	1.6849770636	1.6945737826	1.5075709214	1.6672614510	1.55160	1.6972	1.7113784603	1.4495	1.53250	1.51405	1.5034186209	1.4625802337	1.4247851635	1.8289421082	1.7533708508	1.5779897840
Total	Mean	5.0565	4.6594	4.7784	3.8594	4.329016789	4.474340528	4.985611504	4.991366913	5.245563549	4.6971	4.333	4.584172664	4.308	4.5608	4.8104	4.332853718	4.328537165	4.331414864	4.131894485	4.126618705	4.178417271
	N	695	695	695	695	695	695	695	695	695	695	695	695	695	695	695	695	695	695	695	695	695
	Std. Deviation	1.66193	1.70159	1.64117	1.71552	1.6249773276	1.5975902291	1.5857749435	1.4331922484	1.3466443163	1.53437	1.5949	1.7389435317	1.5919	1.57492	1.54750	1.6182693842	1.6344560854	1.6153471118	1.7006236741	1.6531497011	1.6724628514

Mean Comparison for Education

Education ****		PCON	INTRU	RISK	PCTL	POLICY	SEAL	DTVP	AWARE	NORM	DTRUST	IBTRUST	TRUSTB	TRUSTI	PUSEFUL	PUSE	UIA	UIM	UIH	UII	UIP	UIT
																		Report				
1	Mean	4.6401	4.6348	4.5230	3.7500	3.884160761	3.737588657	5.252955082	5.018912523	5.352245850	4.4504	3.695	4.104018911	4.044	4.0887	4.7518	4.250591030	4.260047266	4.229314413	4.257683224	4.241134742	4.165484652
	N	141	141	141	141	141	141	141	141	141	141	141	141	141	141	141	141	141	141	141	141	141
	Std. Deviation	2.01675	2.01213	2.02549	1.67305	1.6921789354	1.8130079007	1.6010416697	1.6118475365	1.4680583430	1.82547	1.7702	1.9194636935	1.7535	1.70533	1.75954	1.6485472377	1.7575651310	1.7617491352	1.7525973324	1.8037105203
2	Mean	4.9386	4.4955	4.7455	3.9051	4.443452386	4.482142867	4.788690464	4.892857157	5.046130954	4.4408	4.132	4.586309528	4.337	4.4431	4.8839	4.244047621	4.156249994	4.249999996	4.040178568	4.168154768	4.089285717
	N	224	224	224	224	224	224	224	224	224	224	224	224	224	224	224	224	224	224	224	224	224
	Std. Deviation	1.64674	1.67295	1.61238	1.59145	1.6438730689	1.6107754349	1.6881990382	1.5229284334	1.4335835682	1.53987	1.6657	1.8132796609	1.6523	1.64076	1.61895	1.7162909036	1.6931794300	1.6967391523	1.7333082555	1.7014305036	1.7145481720
3	Mean	5.3417	4.8945	4.8807	3.7982	4.403669732	4.675840970	5.183486236	4.938837922	5.428134578	4.7982	4.813	4.831804289	4.160	4.7179	4.7592	4.351681933	4.311926595	4.262996931	4.128440366	4.048929656	4.247706417
	N	109	109	109	109	109	109	109	109	109	109	109	109	109	109	109	109	109	109	109	109	109
	Std. Deviation	1.47771	1.49548	1.52016	1.56143	1.3295265200	1.2913599504	1.3732349039	1.3140309209	1.2717990171	1.27588	1.1367	1.5082924834	1.4368	1.35063	1.21903	1.4450389515	1.3312292323	1.3623942501	1.5173267055	1.4140867440	1.3626436282
4	Mean	5.4086	4.7407	5.0000	4.0485	4.499999995	4.848258699	4.945273629	5.104477616	5.350746273	5.0746	4.727	4.828358212	4.594	4.9049	4.8601	4.597014922	4.597014935	4.544776127	4.218905468	4.114427870	4.348258707
	N	134	134	134	134	134	134	134	134	134	134	134	134	134	134	134	134	134	134	134	134	134
	Std. Deviation	1.30663	1.58808	1.31647	2.02881	1.5144803799	1.3242899303	1.4452954298	1.2561746722	1.0770773053	1.31362	1.3331	1.5396378381	1.4437	1.46923	1.38450	1.4630364271	1.5278394779	1.5154680283	1.7148934640	1.6447706966	1.6066204260
5	Mean	5.1351	4.7011	4.8075	3.7040	4.398467429	4.819923369	4.873563207	5.091954041	5.195402283	5.0489	4.678	4.670498082	4.407	4.9023	4.7040	4.264367831	4.490421451	4.463601522	4.034482769	3.950191566	4.080459775
	N	87	87	87	87	87	87	87	87	87	87	87	87	87	87	87	87	87	87	87	87	87
	Std. Deviation	1.62189	1.62951	1.59154	1.75726	1.8592871028	1.5591727390	1.6876518907	1.2896824401	1.3367705006	1.44262	1.5604	1.6732383956	1.5061	1.39160	1.61863	1.7299145988	1.7423432324	1.6684922754	1.7283429109	1.6693998729	1.8022133470
Total	Mean	5.0565	4.6594	4.7784	3.8594	4.329016789	4.474340528	4.985611504	4.991366913	5.245563549	4.6971	4.333	4.584172664	4.308	4.5608	4.8104	4.332853718	4.328537165	4.331414864	4.131894485	4.126618705	4.178417271
	N	695	695	695	695	695	695	695	695	695	695	695	695	695	695	695	695	695	695	695	695	695
	Std. Deviation	1.66193	1.70159	1.64117	1.71552	1.6249773276	1.5975902291	1.5857749435	1.4331922484	1.3466443163	1.53437	1.5949	1.7389435317	1.5919	1.57492	1.54750	1.6182693842	1.6344560854	1.6153471118	1.7006236741	1.6531497011	1.6724628514

ANOVA Of Location

		Sum of Squares	df	Mean Square	F	Sig.
PCON	Between Groups	101.625	4	25.406	9.657	.000
	Within Groups	1815.220	690	2.631		
	Total	1916.846	694			
INTRU	Between Groups	23.885	4	5.971	2.075	.082
	Within Groups	1985.529	690	2.878		
	Total	2009.414	694			
RISK	Between Groups	136.348	4	34.087	13.573	.000
	Within Groups	1732.903	690	2.511		
	Total	1869.251	694			
PCTL	Between Groups	25.762	4	6.441	2.204	.067
	Within Groups	2016.677	690	2.923		
	Total	2042.439	694			
POLICY	Between Groups	85.017	4	21.254	8.392	.000
	Within Groups	1747.526	690	2.533		
	Total	1832.543	694			
SEAL	Between Groups	48.074	4	12.019	4.812	.001
	Within Groups	1723.218	690	2.497		
	Total	1771.292	694			
DTVP	Between Groups	11.850	4	2.962	1.179	.319
	Within Groups	1733.340	690	2.512		
	Total	1745.189	694			
AWARE	Between Groups	37.138	4	9.285	4.614	.001
	Within Groups	1388.366	690	2.012		
	Total	1425.504	694			
NORM	Between Groups	14.799	4	3.700	2.053	.085
	Within Groups	1243.736	690	1.803		
	Total	1258.535	694			
DTRUST	Between Groups	44.924	4	11.231	4.877	.001
	Within Groups	1588.946	690	2.303		
	Total	1633.869	694			
IBTRUST	Between Groups	123.612	4	30.903	12.988	.000
	Within Groups	1641.770	690	2.379		
	Total	1765.382	694			
TRUSTB	Between Groups	324.563	4	81.141	31.559	.000
	Within Groups	1774.040	690	2.571		
	Total	2098.604	694			
TRUSTI	Between Groups	167.848	4	41.962	18.200	.000
	Within Groups	1590.899	690	2.306		
	Total	1758.746	694			
PUSEFUL	Between Groups	173.238	4	43.309	19.303	.000
	Within Groups	1548.131	690	2.244		
	Total	1721.369	694			
PUSE	Between Groups	28.703	4	7.176	3.032	.017
	Within Groups	1633.259	690	2.367		
	Total	1661.962	694			
UIA	Between Groups	34.563	4	8.641	3.344	.010
	Within Groups	1782.881	690	2.584		
	Total	1817.444	694			
UIM	Between Groups	40.352	4	10.088	3.838	.004
	Within Groups	1813.632	690	2.628		
	Total	1853.984	694			
UIH	Between Groups	19.880	4	4.970	1.915	.106
	Within Groups	1791.006	690	2.596		
	Total	1810.886	694			
UII	Between Groups	32.964	4	8.241	2.880	.022
	Within Groups	1974.167	690	2.861		
	Total	2007.132	694			
UIP	Between Groups	11.528	4	2.882	1.055	.378
	Within Groups	1885.107	690	2.732		
	Total	1896.635	694			
UIT	Between Groups	20.972	4	5.243	1.884	.111
	Within Groups	1920.237	690	2.783		
	Total	1941.210	694			

ANOVA of Method of Survey

		Sum of Squares	df	Mean Square	F	Sig.
PCON	Between Groups	21.053	1	21.053	7.696	.006
	Within Groups	1895.793	693	2.736		
	Total	1916.846	694			
INTRU	Between Groups	3.895	1	3.895	1.346	.246
	Within Groups	2005.519	693	2.894		
	Total	2009.414	694			
RISK	Between Groups	1.667	1	1.667	.619	.432
	Within Groups	1867.584	693	2.695		
	Total	1869.251	694			
PCTL	Between Groups	17.192	1	17.192	5.883	.016
	Within Groups	2025.247	693	2.922		
	Total	2042.439	694			
POLICY	Between Groups	48.139	1	48.139	18.695	.000
	Within Groups	1784.404	693	2.575		
	Total	1832.543	694			
SEAL	Between Groups	23.300	1	23.300	9.238	.002
	Within Groups	1747.992	693	2.522		
	Total	1771.292	694			
DTVP	Between Groups	3.712	1	3.712	1.477	.225
	Within Groups	1741.477	693	2.513		
	Total	1745.189	694			
AWARE	Between Groups	2.596	1	2.596	1.264	.261
	Within Groups	1422.908	693	2.053		
	Total	1425.504	694			
NORM	Between Groups	.634	1	.634	.349	.555
	Within Groups	1257.901	693	1.815		
	Total	1258.535	694			
DTRUST	Between Groups	9.865	1	9.865	4.210	.041
	Within Groups	1624.004	693	2.343		
	Total	1633.869	694			
IBTRUST	Between Groups	44.658	1	44.658	17.985	.000
	Within Groups	1720.724	693	2.483		
	Total	1765.382	694			
TRUSTB	Between Groups	78.025	1	78.025	26.760	.000
	Within Groups	2020.579	693	2.916		
	Total	2098.604	694			
TRUSTI	Between Groups	25.537	1	25.537	10.211	.001
	Within Groups	1733.209	693	2.501		
	Total	1758.746	694			
PUSEFUL	Between Groups	26.339	1	26.339	10.769	.001
	Within Groups	1695.030	693	2.446		
	Total	1721.369	694			
PUSE	Between Groups	3.653	1	3.653	1.527	.217
	Within Groups	1658.309	693	2.393		
	Total	1661.962	694			
UIA	Between Groups	1.513	1	1.513	.577	.448
	Within Groups	1815.932	693	2.620		
	Total	1817.444	694			
UIM	Between Groups	.240	1	.240	.090	.765
	Within Groups	1853.744	693	2.675		
	Total	1853.984	694			
UIH	Between Groups	.011	1	.011	.004	.948
	Within Groups	1810.875	693	2.613		
	Total	1810.886	694			
UII	Between Groups	16.937	1	16.937	5.898	.015
	Within Groups	1990.195	693	2.872		
	Total	2007.132	694			
UIP	Between Groups	1.911	1	1.911	.699	.403
	Within Groups	1894.725	693	2.734		
	Total	1896.635	694			
UIT	Between Groups	.502	1	.502	.179	.672
	Within Groups	1940.708	693	2.800		
	Total	1941.210	694			

ANOVA Of Gender

		Sum of Squares	df	Mean Square	F	Sig.
Location	Between Groups	6.548	1	6.548	3.949	.047
	Within Groups	1148.900	693	1.658		
	Total	1155.447	694			
Method of Survey	Between Groups	1.135	1	1.135	4.578	.033
	Within Groups	171.886	693	.248		
	Total	173.022	694			
Age *	Between Groups	16.216	1	16.216	2.612	.106
	Within Groups	4301.548	693	6.207		
	Total	4317.764	694			
Income ***	Between Groups	.287	1	.287	.192	.662
	Within Groups	1038.801	693	1.499		
	Total	1039.088	694			
Education ****	Between Groups	.312	1	.312	.178	.673
	Within Groups	1213.280	693	1.751		
	Total	1213.591	694			
Self-efficacy	Between Groups	.179	1	.179	.072	.789
	Within Groups	1730.576	693	2.497		
	Total	1730.755	694			
Innovativeness	Between Groups	4.025	1	4.025	3.166	.076
	Within Groups	880.959	693	1.271		
	Total	884.984	694			
Need	Between Groups	26.890	1	26.890	14.711	.000
	Within Groups	1266.706	693	1.828		
	Total	1293.596	694			
Literacy	Between Groups	70.359	1	70.359	26.553	.000
	Within Groups	1836.265	693	2.650		
	Total	1906.624	694			
PCON	Between Groups	32.762	1	32.762	12.050	.001
	Within Groups	1884.084	693	2.719		
	Total	1916.846	694			
INTRU	Between Groups	25.289	1	25.289	8.833	.003
	Within Groups	1984.126	693	2.863		
	Total	2009.414	694			
RISK	Between Groups	15.480	1	15.480	5.787	.016
	Within Groups	1853.771	693	2.675		
	Total	1869.251	694			
PCTL	Between Groups	18.359	1	18.359	6.286	.012
	Within Groups	2024.080	693	2.921		
	Total	2042.439	694			
POLICY	Between Groups	44.409	1	44.409	17.211	.000
	Within Groups	1788.133	693	2.580		
	Total	1832.543	694			
SEAL	Between Groups	8.577	1	8.577	3.372	.067
	Within Groups	1762.715	693	2.544		
	Total	1771.292	694			
DTVP	Between Groups	20.875	1	20.875	8.390	.004
	Within Groups	1724.315	693	2.488		
	Total	1745.189	694			
AWARE	Between Groups	1.489	1	1.489	.725	.395
	Within Groups	1424.015	693	2.055		
	Total	1425.504	694			
NORM	Between Groups	9.689	1	9.689	5.377	.021
	Within Groups	1248.845	693	1.802		
	Total	1258.535	694			
DTRUST	Between Groups	20.517	1	20.517	8.813	.003
	Within Groups	1613.352	693	2.328		
	Total	1633.869	694			
IBTRUST	Between Groups	.231	1	.231	.091	.763
	Within Groups	1765.151	693	2.547		
	Total	1765.382	694			
TRUSTB	Between Groups	1.473	1	1.473	.487	.486
	Within Groups	2097.130	693	3.026		
	Total	2098.604	694			
TRUSTI	Between Groups	5.577	1	5.577	2.204	.138
	Within Groups	1753.170	693	2.530		
	Total	1758.746	694			
PUSEFUL	Between Groups	22.816	1	22.816	9.309	.002
	Within Groups	1698.553	693	2.451		
	Total	1721.369	694			
PUSE	Between Groups	54.490	1	54.490	23.491	.000
	Within Groups	1607.472	693	2.320		
	Total	1661.962	694			
UIA	Between Groups	22.760	1	22.760	8.789	.003
	Within Groups	1794.684	693	2.590		
	Total	1817.444	694			
UIM	Between Groups	21.089	1	21.089	7.974	.005
	Within Groups	1832.895	693	2.645		
	Total	1853.984	694			
UIH	Between Groups	4.268	1	4.268	1.637	.201
	Within Groups	1806.619	693	2.607		

	Total	1810.886	694			
UII	Between Groups	3.803	1	3.803	1.315	.252
	Within Groups	2003.329	693	2.891		
	Total	2007.132	694			
UIP	Between Groups	3.616	1	3.616	1.324	.250
	Within Groups	1893.020	693	2.732		
	Total	1896.635	694			
UIT	Between Groups	14.544	1	14.544	5.231	.022
	Within Groups	1926.666	693	2.780		
	Total	1941.210	694			

ANOVA of Age

		Sum of Squares	df	Mean Square	F	Sig.
PCON	Between Groups	66.835	9	7.426	2.750	.004
	Within Groups	1850.010	685	2.701		
	Total	1916.846	694			
INTRU	Between Groups	29.391	9	3.266	1.130	.339
	Within Groups	1980.023	685	2.891		
	Total	2009.414	694			
RISK	Between Groups	58.969	9	6.552	2.479	.009
	Within Groups	1810.283	685	2.643		
	Total	1869.251	694			
PCTL	Between Groups	95.473	9	10.608	3.732	.000
	Within Groups	1946.966	685	2.842		
	Total	2042.439	694			
POLICY	Between Groups	127.881	9	14.209	5.710	.000
	Within Groups	1704.662	685	2.489		
	Total	1832.543	694			
SEAL	Between Groups	74.698	9	8.300	3.351	.001
	Within Groups	1696.595	685	2.477		
	Total	1771.292	694			
DTVP	Between Groups	16.983	9	1.887	.748	.665
	Within Groups	1728.207	685	2.523		
	Total	1745.189	694			
AWARE	Between Groups	20.770	9	2.308	1.125	.342
	Within Groups	1404.734	685	2.051		
	Total	1425.504	694			
NORM	Between Groups	10.279	9	1.142	.627	.775
	Within Groups	1248.256	685	1.822		
	Total	1258.535	694			
DTRUST	Between Groups	8.822	9	.980	.413	.928
	Within Groups	1625.047	685	2.372		
	Total	1633.869	694			
IBTRUST	Between Groups	46.087	9	5.121	2.040	.033
	Within Groups	1719.296	685	2.510		
	Total	1765.382	694			
TRUSTB	Between Groups	186.537	9	20.726	7.425	.000
	Within Groups	1912.067	685	2.791		
	Total	2098.604	694			
TRUSTI	Between Groups	83.438	9	9.271	3.791	.000
	Within Groups	1675.309	685	2.446		
	Total	1758.746	694			
PUSEFUL	Between Groups	72.312	9	8.035	3.338	.001
	Within Groups	1649.057	685	2.407		
	Total	1721.369	694			
PUSE	Between Groups	40.921	9	4.547	1.921	.046
	Within Groups	1621.040	685	2.366		
	Total	1661.962	694			
UIA	Between Groups	40.089	9	4.454	1.717	.082
	Within Groups	1777.355	685	2.595		
	Total	1817.444	694			
UIM	Between Groups	48.823	9	5.425	2.059	.031
	Within Groups	1805.161	685	2.635		
	Total	1853.984	694			
UIH	Between Groups	20.058	9	2.229	.852	.568
	Within Groups	1790.828	685	2.614		
	Total	1810.886	694			
UII	Between Groups	67.784	9	7.532	2.660	.005
	Within Groups	1939.348	685	2.831		
	Total	2007.132	694			
UIP	Between Groups	37.689	9	4.188	1.543	.129
	Within Groups	1858.947	685	2.714		
	Total	1896.635	694			
UIT	Between Groups	46.781	9	5.198	1.879	.052
	Within Groups	1894.429	685	2.766		
	Total	1941.210	694			

ANOVA of Income Level

		Sum of Squares	df	Mean Square	F	Sig.
PCON	Between Groups	66.835	9	7.426	2.750	.004
	Within Groups	1850.010	685	2.701		
	Total	1916.846	694			
INTRU	Between Groups	29.391	9	3.266	1.130	.339
	Within Groups	1980.023	685	2.891		
	Total	2009.414	694			
RISK	Between Groups	58.969	9	6.552	2.479	.009
	Within Groups	1810.283	685	2.643		
	Total	1869.251	694			
PCTL	Between Groups	95.473	9	10.608	3.732	.000
	Within Groups	1946.966	685	2.842		
	Total	2042.439	694			
POLICY	Between Groups	127.881	9	14.209	5.710	.000
	Within Groups	1704.662	685	2.489		
	Total	1832.543	694			
SEAL	Between Groups	74.698	9	8.300	3.351	.001
	Within Groups	1696.595	685	2.477		
	Total	1771.292	694			
DTVP	Between Groups	16.983	9	1.887	.748	.665
	Within Groups	1728.207	685	2.523		
	Total	1745.189	694			
AWARE	Between Groups	20.770	9	2.308	1.125	.342
	Within Groups	1404.734	685	2.051		
	Total	1425.504	694			
NORM	Between Groups	10.279	9	1.142	.627	.775
	Within Groups	1248.256	685	1.822		
	Total	1258.535	694			
DTRUST	Between Groups	8.822	9	.980	.413	.928
	Within Groups	1625.047	685	2.372		
	Total	1633.869	694			
IBTRUST	Between Groups	46.087	9	5.121	2.040	.033
	Within Groups	1719.296	685	2.510		
	Total	1765.382	694			
TRUSTB	Between Groups	186.537	9	20.726	7.425	.000
	Within Groups	1912.067	685	2.791		
	Total	2098.604	694			
TRUSTI	Between Groups	83.438	9	9.271	3.791	.000
	Within Groups	1675.309	685	2.446		
	Total	1758.746	694			
PUSEFUL	Between Groups	72.312	9	8.035	3.338	.001
	Within Groups	1649.057	685	2.407		
	Total	1721.369	694			
PUSE	Between Groups	40.921	9	4.547	1.921	.046
	Within Groups	1621.040	685	2.366		
	Total	1661.962	694			
UIA	Between Groups	40.089	9	4.454	1.717	.082
	Within Groups	1777.355	685	2.595		
	Total	1817.444	694			
UIM	Between Groups	48.823	9	5.425	2.059	.031
	Within Groups	1805.161	685	2.635		
	Total	1853.984	694			
UIH	Between Groups	20.058	9	2.229	.852	.568
	Within Groups	1790.828	685	2.614		
	Total	1810.886	694			
UII	Between Groups	67.784	9	7.532	2.660	.005
	Within Groups	1939.348	685	2.831		
	Total	2007.132	694			
UIP	Between Groups	37.689	9	4.188	1.543	.129
	Within Groups	1858.947	685	2.714		
	Total	1896.635	694			
UIT	Between Groups	46.781	9	5.198	1.879	.052
	Within Groups	1894.429	685	2.766		
	Total	1941.210	694			

ANOVA of Education level

		Sum of Squares	df	Mean Square	F	Sig.
PCON	Between Groups	53.581	4	13.395	4.960	.001
	Within Groups	1863.265	690	2.700		
	Total	1916.846	694			
INTRU	Between Groups	13.162	4	3.290	1.137	.338
	Within Groups	1996.253	690	2.893		
	Total	2009.414	694			
RISK	Between Groups	17.231	4	4.308	1.605	.171
	Within Groups	1852.020	690	2.684		
	Total	1869.251	694			
PCTL	Between Groups	9.457	4	2.364	.802	.524
	Within Groups	2032.982	690	2.946		
	Total	2042.439	694			
POLICY	Between Groups	35.781	4	8.945	3.435	.009
	Within Groups	1796.761	690	2.604		
	Total	1832.543	694			
SEAL	Between Groups	110.100	4	27.525	11.433	.000
	Within Groups	1661.192	690	2.408		
	Total	1771.292	694			
DTVP	Between Groups	24.342	4	6.086	2.440	.046
	Within Groups	1720.847	690	2.494		
	Total	1745.189	694			
AWARE	Between Groups	5.176	4	1.294	.629	.642
	Within Groups	1420.328	690	2.058		
	Total	1425.504	694			
NORM	Between Groups	15.849	4	3.962	2.200	.067
	Within Groups	1242.686	690	1.801		
	Total	1258.535	694			
DTRUST	Between Groups	54.270	4	13.567	5.927	.000
	Within Groups	1579.599	690	2.289		
	Total	1633.869	694			
IBTRUST	Between Groups	122.673	4	30.668	12.882	.000
	Within Groups	1642.709	690	2.381		
	Total	1765.382	694			
TRUSTB	Between Groups	47.831	4	11.958	4.023	.003
	Within Groups	2050.773	690	2.972		
	Total	2098.604	694			
TRUSTI	Between Groups	24.226	4	6.056	2.409	.048
	Within Groups	1734.521	690	2.514		
	Total	1758.746	694			
PUSEFUL	Between Groups	63.234	4	15.808	6.578	.000
	Within Groups	1658.135	690	2.403		
	Total	1721.369	694			
PUSE	Between Groups	3.297	4	.824	.343	.849
	Within Groups	1658.665	690	2.404		
	Total	1661.962	694			
UIA	Between Groups	12.518	4	3.130	1.196	.311
	Within Groups	1804.926	690	2.616		
	Total	1817.444	694			
UIM	Between Groups	19.279	4	4.820	1.813	.125
	Within Groups	1834.705	690	2.659		
	Total	1853.984	694			
UIH	Between Groups	11.085	4	2.771	1.062	.374
	Within Groups	1799.801	690	2.608		
	Total	1810.886	694			
UII	Between Groups	5.957	4	1.489	.513	.726
	Within Groups	2001.175	690	2.900		
	Total	2007.132	694			
UIP	Between Groups	5.621	4	1.405	.513	.726
	Within Groups	1891.014	690	2.741		
	Total	1896.635	694			
UIT	Between Groups	7.027	4	1.757	.627	.644
	Within Groups	1934.183	690	2.803		
	Total	1941.210	694			

Factor Intercorrelations

Correlation Matrix of ETA and KSI

	PCON	INTRU	RISK	DTVP	PCTL	IBTRUST
	--------	--------	--------	--------	--------	--------
PCON	1.00					
INTRU	0.90	1.00				
RISK	0.88	0.87	1.00			
DTVP	0.23	0.25	0.21	1.00		
PCTL	-0.06	-0.11	-0.10	0.03	1.00	
IBTRUST	0.04	-0.01	-0.01	0.01	0.09	1.00
TRUSTB	0.11	-0.01	-0.01	0.01	0.08	0.32
TRUSTI	0.12	-0.01	-0.01	0.01	0.08	0.38
PUSEFUL	0.07	-0.03	-0.03	0.00	0.06	0.30
PEASE	-0.03	-0.04	-0.04	-0.01	0.01	0.05
ACCESS	-0.06	-0.08	-0.07	-0.02	0.02	0.07
MANAGE	-0.04	-0.06	-0.06	-0.01	0.02	0.07
SHAREHP	-0.09	-0.10	-0.10	-0.02	0.02	0.07
SHARETP	-0.06	-0.07	-0.06	-0.02	0.01	0.03
SHAREPHO	-0.12	-0.13	-0.13	-0.03	0.02	0.06
THIRDP	-0.06	-0.08	-0.08	-0.02	0.02	0.07
POLICY	-0.09	-0.14	-0.14	0.01	0.79	0.11
SEAL	-0.04	-0.06	-0.06	0.01	0.24	0.06

AWARE	0.01	0.00	0.00	0.06	0.06	0.02
NORM	0.03	0.03	0.02	0.16	0.06	0.04
DTRUST	0.01	-0.04	-0.04	0.02	0.25	0.34

Correlation Matrix of ETA and KSI

	TRUSTB	TRUSTI	PUSEFUL	PEASE	ACCESS	MANAGE
	--------	--------	--------	--------	--------	--------
TRUSTB	1.00					
TRUSTI	0.97	1.00				
PUSEFUL	0.75	0.78	1.00			
PEASE	0.12	0.12	0.60	1.00		
ACCESS	0.19	0.19	0.63	0.29	1.00	
MANAGE	0.19	0.19	0.62	0.27	1.00	1.00
SHAREHP	0.18	0.19	0.61	0.25	1.00	1.00
SHARETP	0.08	0.08	0.46	0.15	0.91	0.90
SHAREPHO	0.14	0.14	0.53	0.22	0.94	0.93
THIRDP	0.17	0.17	0.58	0.25	0.97	0.97
POLICY	0.10	0.10	0.08	0.02	0.03	0.03
SEAL	0.05	0.05	0.04	0.01	0.01	0.01
AWARE	0.02	0.02	0.01	0.00	0.00	0.00
NORM	0.04	0.04	0.03	0.00	0.01	0.01
DTRUST	0.31	0.32	0.25	0.04	0.06	0.06

Correlation Matrix of ETA and KSI

	SHAREHP	SHARETP	SHAREPHO	THIRDP	POLICY	SEAL
	--------	--------	--------	--------	--------	--------
SHAREHP	1.00					
SHARETP	0.92	1.00				
SHAREPHO	0.95	0.85	1.00			
THIRDP	0.98	0.88	0.91	1.00		
POLICY	0.03	0.02	0.03	0.03	1.00	
SEAL	0.01	0.01	0.01	0.01	0.34	1.00
AWARE	0.00	0.00	0.00	0.00	0.07	0.09
NORM	0.00	0.00	0.00	0.00	0.08	0.07
DTRUST	0.06	0.03	0.05	0.06	0.33	0.16

Correlation Matrix of ETA and KSI

	AWARE	NORM	DTRUST
	--------	--------	--------
AWARE	1.00		
NORM	0.75	1.00	
DTRUST	0.05	0.12	1.0

Correlation Matrix with squared correlations

	PCON	INTRU	RISK	DTVP	PCTL	IBTRUST	TRUSTB	TRUSTI	PUSEFUL	PEASE	ACCESS	MANAGE	SHAREHP	SHARETP	SHAREPHO	THIRDP	POLICY	SEAL	AWARE
AVE	0.7108	0.7353	0.7109	0.653	0.648	0.6382	0.717	0.5467	0.1283	0.6766	0.6258	0.6258	0.6625	0.6405	0.6406	0.8573	0.7987	0.5985	0.6577
PCON		0.81	0.7744	0.0529	0.0036	0.0016	0.0121	0.0144	0.0049	0.009	0.0036	0.0016	0.0081	0.0036	0.0144	0.0036	0.0081	0.0016	0.0001
INTRU			0.7569	0.0625	0.0121	0.0001	0.0001	0.0001	0.0009	0.0016	0.0064	0.0036	0.001	0.0049	0.0169	0.0064	0.0196	0.0036	0
RISK				0.0441	0.01	0.0001	0.0001	0.0001	0.0009	0.0016	0.0049	0.0036	0.001	0.0036	0.0169	0.0064	0.0196	0.0036	0
DTVP					0.0009	0.0001	0.0001	0.0001	0	0.0001	0.0004	0.0001	0.0004	0.0004	0.0009	0.0004	0.0001	0.0001	0.0036
PCTL						0.0081	0.0064	0.0064	0.0036	0.0001	0.0004	0.0004	0.0004	0.0001	0.0004	0.0004	0.6241	0.0576	0.0036
IBTRUST							0.1024	0.1444	0.09	0.0025	0.0049	0.0049	0.0049	0.0009	0.0036	0.0049	0.0121	0.0036	0.0004
TRUSTB								0.9409	0.5625	0.0144	0.0361	0.0361	0.0324	0.0064	0.0196	0.0289	0.001	0.0025	0.0004
TRUSTI									0.6084	0.0144	0.0361	0.0361	0.0361	0.0064	0.0196	0.0289	0.001	0.0025	0.0004
PUSEFUL										0.36	0.3969	0.3844	0.3721	0.2116	0.2809	0.3364	0.0064	0.0016	0.0001
PEASE											0.0841	0.0729	0.0625	0.0225	0.0484	0.0625	0.0004	0.0001	0
ACCESS												1	1.0404	0.8281	0.8836	0.9409	0.0009	0.0001	0
MANAGE													1.0201	0.81	0.8649	0.9409	0.0009	0.0001	0
SHAREHP														0.8464	0.9025	0.9604	0.0009	0.0001	0
SHARETP															0.7225	0.7744	0.0004	0.0001	0
SHAREPHO												0.8281	0.0009	0.0001	0	0	0.0025	0.6406	SHARE
THIRDP																	0.0009	0.0001	0
POLICY																		0.1156	0.0049
SEAL																			0.0081
AWARE																			
NORM																			
DTRUST																			

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APPENDIX B

SURVEY

Before beginning this survey, it is important that you understand what an electronic Personal Health Record (ePHR) is:

The electronic Personal Health Record (PHR) is an Internet-based set of tools that allows people to **access** and **coordinate** their lifelong health information and make appropriate parts of it **available** to those who need it. PHRs offer an integrated and comprehensive view of health information, including information people generate themselves such as symptoms and medication use, information from doctors such as diagnoses and test results, and information from their pharmacies and insurance companies. Individuals access their PHRs via the Internet, using state-of-the-art **security** and **privacy** controls, at any time and from any location. Family members, doctors or school nurses can see portions of a PHR when necessary and emergency room staff can retrieve vital information from it in a crisis. People can use their PHR as a communications hub: to send email to doctors, transfer information to specialists, receive test results and access online self-help tools. PHR connects each of us to the incredible potential of modern healthcare and gives us control over our own information (Connecting for Health, 2003).

ePHRs can be **created, accessed and/or managed** by healthcare consumers. In addition, **authorized third-parties** can create, access and manage an ePHR for others such as parents or children. If you understand what an ePHR is well enough to continue, please proceed. Otherwise, please re-read the definition or contact XXXXXXXXXXXXXXXXX for further information.

What is your age?

- o 18-20
- o 21-25
- o 26-30
- o 31-35
- o 36-40
- o 41-45
- o 46-50
- o 51-55
- o 56-60
- o Over 60

What is your gender?

- o Male
- o Female

What is your household income level?

- o $0-25,000
- o $25,001-50,000
- o $50,001-100,000
- o $100,001-$150,000
- o Over $150,000

What is your highest level of education?

- o High School
- o Some College
- o 2-year College Degree
- o 4-year College Degree
- o Graduate school degree or higher

Please read each question carefully and check the response that best expresses your view about technology in general.
Computer Self-Efficacy

	Strongly Disagree	Disagree	Weakly Disagree	Neutral	Weakly Agree	Agree	Strongly Agree
I COULD COMPLETE an ePHR USING A COMPUTER AND SOFTWARE …							
1. …if there was no one around to tell me what to do as I go.	⬭	⬭	⬭	⬭	⬭	⬭	⬭
2. …if I had never used a package like it before.	⬭	⬭	⬭	⬭	⬭	⬭	⬭
3. …if I had only the software manuals for reference.	⬭	⬭	⬭	⬭	⬭	⬭	⬭
4. …if I had seen someone else using it before trying it myself.	⬭	⬭	⬭	⬭	⬭	⬭	⬭
5. …if I could call someone for help if I got stuck.	⬭	⬭	⬭	⬭	⬭	⬭	⬭
6. …if someone else had helped me get started.	⬭	⬭	⬭	⬭	⬭	⬭	⬭
7. …if I had a lot of time to complete the job for which the software was provided.	⬭	⬭	⬭	⬭	⬭	⬭	⬭
8. …if I had just the built-in help facility for assistance.	⬭	⬭	⬭	⬭	⬭	⬭	⬭
9. …if someone showed me how to do it first.	⬭	⬭	⬭	⬭	⬭	⬭	⬭
10. …if I had used similar packages before this one to do the same job.	⬭	⬭	⬭	⬭	⬭	⬭	⬭

Personal Innovativeness

	Strongly Disagree	Disagree	Weakly Disagree	Neutral	Weakly Agree	Agree	Strongly Agree
11. If I heard about a new information technology such as ePHR, I would look for ways to experiment with it.	⬭	⬭	⬭	⬭	⬭	⬭	⬭
12. Among my peers, I am usually the first try out new information technologies.	⬭	⬭	⬭	⬭	⬭	⬭	⬭
13. In general, I am hesitant to try out new information technologies.	⬭	⬭	⬭	⬭	⬭	⬭	⬭
14. I like to experiment with new information technologies.	⬭	⬭	⬭	⬭	⬭	⬭	⬭
15. If I heard about a new information technology, I would look for ways to experiment with it.	⬭	⬭	⬭	⬭	⬭	⬭	⬭

Healthcare Need

Please read each question carefully and complete the spaces with appropriate information about your healthcare in general.

16. How many face-to-face visits to a healthcare provider have you had in the past six months?

17. How many different physicians have you seen during the past six months?

18. Do you have a chronic disease (such as diabetes or asthma) that requires special medical attention?

Yes   No

Health Literacy

	Strongly Disagree	Disagree	Weakly Disagree	Neutral	Weakly Agree	Agree	Strongly Agree
19. I am very knowledgeable regarding my care for my health problems.	○	○	○	○	○	○	○
20. I understand my health problems and how to care for them.	○	○	○	○	○	○	○

Privacy Concerns (PCON)

Please read each question carefully and check the response that best expresses your

view about privacy.

	Strongly Disagree	Disagree	Weakly Disagree	Neutral	Weakly Agree	Agree	Strongly Agree
21. It bothers me when websites ask for too much information.	○	○	○	○	○	○	○
22. I am concerned that websites are collecting too much personal information about me.	○	○	○	○	○	○	○
23. I am concerned that unauthorized people may access my personal information.	○	○	○	○	○	○	○
24. I am concerned about submitting information to websites.	○	○	○	○	○	○	○

Privacy Intrusion (INTRU)

	Strongly Disagree	Disagree	Weakly Disagree	Neutral	Weakly Agree	Agree	Strongly Agree
25. I feel that as a result of my using ePHR websites, others know about me more than I am comfortable with.	○	○	○	○	○	○	○
26. I believe that as a result of my using ePHR websites, the information about me that I consider private is now more readily available to others than I would want to.	○	○	○	○	○	○	○
27. I feel that as a result of my using ePHR websites, the information about me is out there that, if used, will invade my privacy.	○	○	○	○	○	○	○
28. I feel that as a result of my using ePHR websites, my privacy has been invaded by the others that collect all the data about me.	○	○	○	○	○	○	○

Privacy Risks (RISK)

	Strongly Disagree	Disagree	Weakly Disagree	Neutral	Weakly Agree	Agree	Strongly Agree
29. In general, it would be risky to give personal information to ePHR websites.	○	○	○	○	○	○	○
30. There would be high potential for privacy loss associated with giving personal information to ePHR websites.	○	○	○	○	○	○	○
31. Personal information could be inappropriately used by ePHR websites.	○	○	○	○	○	○	○
32. Providing ePHR websites with my personal information would involve many unexpected problems.	○	○	○	○	○	○	○

Privacy Control (PCTL)

	Strongly Disagree	Disagree	Weakly Disagree	Neutral	Weakly Agree	Agree	Strongly Agree
33. I believe I have control over who can get access to my personal information collected by ePHR websites.	○	○	○	○	○	○	○
34. I think I have control over what personal information is released by these ePHR websites.	○	○	○	○	○	○	○
35. I believe I have control over how personal information is used by these ePHR websites.	○	○	○	○	○	○	○
36. I believe I can control my personal information provided to these ePHR websites.	○	○	○	○	○	○	○

Perceived Effectiveness of Privacy Policy (POLICY)

	Strongly Disagree	Disagree	Weakly Disagree	Neutral	Weakly Agree	Agree	Strongly Agree
37. I feel confident that ePHR websites' privacy statements reflect their commitments to protect my personal information.	○	○	○	○	○	○	○
38. With their privacy statements, I believe that my personal information will be kept private and confidential by websites that collect personal health information.	○	○	○	○	○	○	○
39. I believe that websites that collect personal health information privacy statements are an effective way to demonstrate their commitments to privacy.	○	○	○	○	○	○	○

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Perceived Effectiveness of Privacy Seal (SEAL)

	Strongly Disagree	Disagree	Weakly Disagree	Neutral	Weakly Agree	Agree	Strongly Agree
40. I believe that privacy seals from third-party approval programs or HIPAA governance will impose sanctions (penalties) for online companies' noncompliance with its privacy policy.	⬭	⬭	⬭	⬭	⬭	⬭	⬭
41. Third-party privacy seal of approval programs or HIPAA compliance will stand by me if my personal information is misused during and after transactions with online companies.	⬭	⬭	⬭	⬭	⬭	⬭	⬭
42. I am confident that privacy seal of approval programs or HIPAA compliance are able to address violation of the information I provided to online companies.	⬭	⬭	⬭	⬭	⬭	⬭	⬭

Disposition to Value Privacy (DTVP)

	Strongly Disagree	Disagree	Weakly Disagree	Neutral	Weakly Agree	Agree	Strongly Agree
43. Compared to other people, I am more sensitive about the way online companies handle my personal health information.	⬭	⬭	⬭	⬭	⬭	⬭	⬭
44. To me, it is the most important thing to keep my online privacy.	⬭	⬭	⬭	⬭	⬭	⬭	⬭
45. Compared to others, I tend to be more concerned about threats to my personal privacy.	⬭	⬭	⬭	⬭	⬭	⬭	⬭

Awareness to Privacy (AWARE)

	Strongly Disagree	Disagree	Weakly Disagree	Neutral	Weakly Agree	Agree	Strongly Agree
46. I am aware of the privacy issues and practices in our society.	◯	◯	◯	◯	◯	◯	◯
47. I follow the news and developments about the privacy issues and privacy violations.	◯	◯	◯	◯	◯	◯	◯
48. I keep myself updated about privacy issues and the solutions that companies and the government employ to ensure our privacy.	◯	◯	◯	◯	◯	◯	◯

Social Norm (NORM)

	Strongly Disagree	Disagree	Weakly Disagree	Neutral	Weakly Agree	Agree	Strongly Agree
49. People who influence my behavior think that keeping personal information private is very important.	◯	◯	◯	◯	◯	◯	◯
50. My friends believe I should care about my privacy.	◯	◯	◯	◯	◯	◯	◯
51. People who are important to me think I should be careful when revealing personal information online.	◯	◯	◯	◯	◯	◯	◯

Please read each question carefully and check the response that best expresses your view about trust.
TRUST

Disposition to Trust

	Strongly Disagree	Disagree	Weakly Disagree	Neutral	Weakly Agree	Agree	Strongly Agree
52. In general, people really do care about the well-being of others.	◯	◯	◯	◯	◯	◯	◯
53. In general, most folks keep their promises.	◯	◯	◯	◯	◯	◯	◯
54. I believe that most professional people do a very good job at their work.	◯	◯	◯	◯	◯	◯	◯
55. I usually trust people until they give me some reason not to trust them.	◯	◯	◯	◯	◯	◯	◯

Institution-Based Trust

	Strongly Disagree	Disagree	Weakly Disagree	Neutral	Weakly Agree	Agree	Strongly Agree
56. I feel good about how things go when I do purchasing or other activities on the Internet.	◯	◯	◯	◯	◯	◯	◯
57. I feel that most Internet vendors would act in a customer's best interest.	◯	◯	◯	◯	◯	◯	◯
58. I am comfortable relying on Internet vendors to meet their obligations.	◯	◯	◯	◯	◯	◯	◯
59. In general, most Internet vendors are competent at serving their customers.	◯	◯	◯	◯	◯	◯	◯
60. The Internet has enough safeguards to make me feel comfortable using it to transact personal business.	◯	◯	◯	◯	◯	◯	◯

Trusting Beliefs

	Strongly Disagree	Disagree	Weakly Disagree	Neutral	Weakly Agree	Agree	Strongly Agree
61. I believe that an authorized user of my ePHR would act in my best interest.	⬭	⬭	⬭	⬭	⬭	⬭	⬭
62. An authorized user of my ePHR would be trustful in dealings with me.	⬭	⬭	⬭	⬭	⬭	⬭	⬭
63. An authorized user of my ePHR would be competent and effective in providing performing their duties.	⬭	⬭	⬭	⬭	⬭	⬭	⬭

Trusting Intentions

	Strongly Disagree	Disagree	Weakly Disagree	Neutral	Weakly Agree	Agree	Strongly Agree
64. When an important healthcare issue or problem arises, I would feel comfortable depending on the information provided to me by an authorized user of my ePHR.	⬭	⬭	⬭	⬭	⬭	⬭	⬭
65. If I had a challenging healthcare condition, I would want to use an authorized user of my ePHR.	⬭	⬭	⬭	⬭	⬭	⬭	⬭
66. I would not hesitate to use the information an authorized user of my ePHR supplied me.	⬭	⬭	⬭	⬭	⬭	⬭	⬭
67. Suppose you wanted specific healthcare information and you could consult an authorized user of your ePHR via the Internet free of charge. For this service, please answer: In this situation, I would not hesitate to share my name, address and social security number.	⬭	⬭	⬭	⬭	⬭	⬭	⬭

68. Suppose you wanted specific healthcare information and you could consult an authorized user of your ePHR via the Internet for a fee. For this service, please answer: In this situation, I would not hesitate to share my name, address and social security number.

○ ○ ○ ○ ○ ○ ○

INTENT TO USE

Perceived Usefulness

	Strongly Disagree	Disagree	Weakly Disagree	Neutral	Weakly Agree	Agree	Strongly Agree
69. Using ePHR would make it easier to handle healthcare related tasks.	○	○	○	○	○	○	○
70. Using ePHR would help me to accomplish healthcare related tasks more quickly.	○	○	○	○	○	○	○
71. Using ePHR would improve the quality of healthcare related tasks I do.	○	○	○	○	○	○	○
72. Using ePHR would enhance my effectiveness in my healthcare related tasks.	○	○	○	○	○	○	○

Perceived Ease of Use

	Strongly Disagree	Disagree	Weakly Disagree	Neutral	Weakly Agree	Agree	Strongly Agree
73. My interaction with ePHR will be clear and understandable.	○	○	○	○	○	○	○
74. I believe it would be easy to get ePHR to do what I want it to do.	○	○	○	○	○	○	○
75. Overall, I believe ePHR will be easy to use.	○	○	○	○	○	○	○

	Strongly Disagree	Disagree	Weakly Disagree	Neutral	Weakly Agree	Agree	Strongly Agree
76. Learning to use ePHR will be easy for me.	◯	◯	◯	◯	◯	◯	◯

Usage Intentions

	Strongly Disagree	Disagree	Weakly Disagree	Neutral	Weakly Agree	Agree	Strongly Agree
77. I intend to access or create an ePHR for healthcare related tasks in the future.	◯	◯	◯	◯	◯	◯	◯
78. I intend to manage an ePHR for healthcare related tasks in the future.	◯	◯	◯	◯	◯	◯	◯
79. I intend to share information in my ePHR for healthcare related tasks in the future with healthcare providers.	◯	◯	◯	◯	◯	◯	◯
80. I intend to share information in my ePHR for healthcare related tasks in the future with third-party payers.	◯	◯	◯	◯	◯	◯	◯
81. I intend to share information in my ePHR for healthcare related tasks in the future with public healthcare facilities.	◯	◯	◯	◯	◯	◯	◯
82. I intend to manage an ePHR for a third-party, such as a child or parent, for healthcare related tasks.	◯	◯	◯	◯	◯	◯	◯
83. For future healthcare related tasks, I would access or create ePHR.	◯	◯	◯	◯	◯	◯	◯
84. For future healthcare related tasks, I would manage an ePHR.	◯	◯	◯	◯	◯	◯	◯
85. For future healthcare related tasks, I would share an ePHR with other healthcare providers.	◯	◯	◯	◯	◯	◯	◯
86. For future healthcare related tasks, I would share an ePHR with third-party payers.	◯	◯	◯	◯	◯	◯	◯

Usage Intentions

	Strongly Disagree	Disagree	Weakly Disagree	Neutral	Weakly Agree	Agree	Strongly Agree
87. For future healthcare related tasks, I would share an ePHR with public healthcare organizations.	⬭	⬭	⬭	⬭	⬭	⬭	⬭
88. For future healthcare related tasks, I would manage an ePHR for a third-party such as a parent or child.	⬭	⬭	⬭	⬭	⬭	⬭	⬭
89. I plan to access or create ePHR.	⬭	⬭	⬭	⬭	⬭	⬭	⬭
90. I plan to manage an ePHR.	⬭	⬭	⬭	⬭	⬭	⬭	⬭
91. I plan to share an ePHR with other healthcare providers.	⬭	⬭	⬭	⬭	⬭	⬭	⬭
92. I plan to share an ePHR with third-party payers.	⬭	⬭	⬭	⬭	⬭	⬭	⬭
93. I plan to share an ePHR with public healthcare organizations.	⬭	⬭	⬭	⬭	⬭	⬭	⬭
94. I plan to manage an ePHR for a third-party such as a parent or child.	⬭	⬭	⬭	⬭	⬭	⬭	⬭

REFERENCE LIST

Aarts, J. & Koppel, R. (2009). Implementation of Computerized Physician Order Entry in
Seven Countries. *Health Affairs*, 404-415.

Abrahamsen, C. (2007). From Pong to PHRs: Advances in electronic record keeping.
Nursing management, 20-21.

Acquisti, A. & Grossklags, J. (2005). Privacy and Rationality in Individual Decision
Making. *Economics of Information Security*, 26-33.

Agarwal, R. & Karahanna, E. (2000). Time Flies When You are Having Fun: Cognitive
Absorption and Beliefs about Information Technology Usage. *MIS Quarterly*,
665-694.

Agarwal, R. & Prasad, J. (1998). A Conceptual and Operational Definition of Personal
Innovativeness in the Domain of Information Technology. *Information Systems
Research*, 204-215.

Agarwal, S., Milch, B., & Van Kuiken, S. (2009). Health care: Taking medical records
online. *McKinsey Quarterly*, 56-58.

Agrawai, R., Grandison, T., Johnson, C., & Kiernan, J. (2007). Enabling the 21st Century
Health Care Information Technology Revolution. *Communications of the ACM*,
35-42.

Altinkemer, K., De, P., & Ozdemir, Z. (2006). Information Systems and Health Care XII:

    Toward a Consumer-to-Healthcare Provider (C2H) Electronic Marketplace.

    Communications of the Association for Information Systems, 413-430.

Altman, I. (1975). *The Environment and Social Behavior.* Monterey, CA: Brooks/Cole.

Altman, I. (1976). Privacy: A Conceptual Analysis. *Environment and Behavior*, 7-29.

Amatayakul, M. (2008). Think a Privacy Break Couldn't Happen at Your Facility? Think

    Again. *healthcare financial management*, 100-101.

Amatayakul, M. (2009a). EHR Versus EMR: What's in a Name? *healthcare financial*

    management, 24.

Amatayakul, M. (2009b). Hospitals Are Selling (EHR) - But Will Physicians Buy?

    healthcare financial management, 124-125.

Americans Trust Health Providers to Handle Personal Information in Secure Manner.

    (2009, April 6). *Ethics Newsline*.

Anderson, C. L. & Agarwal, R. (2011). The Digitazation of Healthcare: Boundary Risks,

    Emotion and Consumer Willingness to Disclose Personal Health Information.

    Information Systems Research, 469-490.

Anderson, G., Reinhardt, U., Hussey, P., & Petrsyan, V. (2003). It's the prices, stupid:

    why the United States is so different from other countries. *Health Affairs*, 89-105.

Angst, C. & Agarwal, R. (2009). Adoption of Electronic Health Records in the Presence

    of Privacy Concerns: The Elaboration Likelihood Model and Individual

    Persuasion. *MIS Quarterly*, 339-370.

Audit Commission. (2001). *A Spoonful of Sugar: Medicines Management in NHS Hospitals.* Retrieved May 10, 2011 from http://www.audit-commission.gov.uk/nationalstudies/health/other/pages/aspoonfulofsugar.aspx

Azjen, I. (1991). Theory of Planned Behavior. *Organizational Behavior and Human Decision Processes*, 179-211.

Azjen, I. & Fishbein, M. (1980). *Understanding Attitudes and Predicting Social Behavior.* Engelwood Cliffs, N.J.: Prentice-Hall.

Bansal, G., Zahedi, F., & Gefen, D. (2010). The Impact of Personal Dispositions on Information Sensitivity, Privacy Concern and Trust in Disclosing Health Information Online. *Decision Support Systems*, 138-150.

Barlow, R. D. (2007). Making Sense of EHR's Struggle to Gain Traction. *Healthcare Purchasing News*, 24-25.

Barlow, R. D. (2010a). Alliance Subgroup Throws Down Device Data Standards Gauntlet. *Healthcare Purchasing News*, 12-13.

Barlow, R. D. (2010b). The Missing Links Between Supply Chain Data, EHR/EMR Software. *Healthcare Purchasing News*, 10-15.

Beaton, B. (2008). Walking the Federalist Tightrope: A National Policy of State Experimentation for Health Information Technology. *Columbia Law Review*, 1670-171.

Berner, E. (2008). Ethical and Legal Issues in the Use of Health Information Technology to Improve Patient Safety. *HEC Forum*, 243-258.

Boerner, C. (2004). Federal Web Site Provides Information on Patient Medical Record

    Standards. *Journal of Health Care Compliance*, 33-34.

Border, C. (2006, January 18). Survey: consumers concerned about control, access to

    medical info. Retrieved from *healthcareitnews*:

    http://www.healthcareitnews.com/prinstory.cms?id=4335

Bower, A. (2005). The Diffusion and Value of Healthcare Information Technology.

    Monographs of RAND (MG-272-1-HLTH).

Boyens, C., Krishnan, R., & Padman, R. (2004). On Privacy-Preserving Access to

    Distributed Heterogeneous Healthcare Information. *Proceedings of the 37th

    Hawaii International Conference on System Sciences* HICSS-37. Big Island,

    Hawaii.

Braller, D. J. (2005). Interoperability: The Key to the Future Health Care System. *Health

    Affairs*, 19-21.

Brodie, M., Flournoy, R., Altman, D., Beldnon, R., Benson, J., & Rosenbaum, M. (2000).

    Health Information, The Internet, And The Digital Divide. *Health Affairs*, 255-

    266.

Brooks, R. & Grotz, C. (2010). Implementation of Electronic Medical Records: How

    Healthcare Providers Are Managing the Challenges of Going Digital. *Journal of

    Business & Economic Research*, 73-84.

Brown, B. (2007a). The Number of Online Personal Health Records is Growing, But is

    the Data in These Records Adequately Protected? *Journal of Health Care

    Compliance*, 35-36;65.

Brown, B. (2007b). The Single Most Important Thing Everyone Needs to Know About
  HIPAA. *Journal of Health Care Compliance*, 37-40.

Brown, M. (2009, March 23). Computertized records giving doctors new tool. But some
  fear loss of privacy with U.S. Health Information Network. *Chicago Tribune*.
  Retrieved March 15, 2011, from.: www.chicagotribune.com/news/health

Burt, C. & Hing, E. (2005). Use of Computerized Clinical Support Systems in Medical
  Settings: United States, 2001-03. *Advance Data*, 1-9.

Burt, C. & Sisk, J. (2005). Which Physicians and Practices are Using Electronic Medical
  Records? *DataWatch*, 1334-1343.

Bush, G. The White House, Office of the Press Secretary. (2004). *Remarks by the
  president in the state of the union address* Washington, D.C.: Retrieved from
  http://www.whitehouse.gov/news/releases/2006/01/20060131-10.html

Byrne, B. M. (1998). *Structural Equation Modeling.* New York London: Lawrence
  Erlbaum Associates.

Callan, C., & DeShazo, C. (2007). How to Navigate Health Care Information Technology
  and Electronic Medical Records. *The Physician Executive*, 36-42.

Cannoy, S., & Salam, A. (2010). A Framework for Health Care Information Assurance
  Policy and Compliance. *Communications of the ACM*, 126-131.

Cantrill, S. (2010). Computers in Patient Care: The Promise and the Challenge.
  Communications of the ACM, 42-49.

Cassel, C., Johnston-Fleece, M., & Reddy, S. (2009). Aging: Adding complexity,
  requiring skills. *Information Knowledge Systems Management*, 47-69.

Certificate Commission for Health Information Technology. (2008). *Incentive Programs for EHR adoption growing.* Retrieved on September 10, 2010, from www.cchit.org/about/news/releases/2008/Incentive-programs-EHR-adoption-growing.asp

Chaudhry, B., Wang, J., Wu, S., Maglione, M., Mojica, W., Roth E., et al. (2006). Systematic Review: Impact of Health Information Technology on Quality, Efficiency and Costs of Medical Care. *Annals of Internal Medicine*, 12-18.

Chellappa, R. & Sin, R. (2005). Personalization Versus Privacy: An Empirical Examination of the Online Consumer's Dilema. *Information Technology and Management*, 181-202.

Clarke, I., Flaherty, T., Hollis, S., & Tomallo, M. (2009). Consumer Privacy Issues Associated With the Use of Electronic Health Records. *Academy of Health Care Management Journal*, 63-77.

Coile, R. (2003). Managing the Digital Hospital. *The Physician Executive*, 48-51.

Compeau, D. R. (1995). Computer Self-Efficacy: Development of a Measure and Initial Test. *MIS Quarterly*, 189-211.

Connecting for Health. (2003, July). *The Personal Health Working Group.* Retrieved February 15, 2010, from http://www.policyarchive.org/handle/10207/bitstreams/15473.pdf

Connecting for Health. (2004, July). *Connecting Americans to Their Healthcare. A Final Report of the Working Group on Policies for Electronic Information Sharing Between Doctors and Patients.* Retrieved February 10, 2011, from http://www.policyarchive.org/handle/10207/bitstreams/15525.pdf

Connecting for Health. (2008, June). *Americans Overwhelmingly Believe Electronic Personal Health Records Could Improve Their Health.* Retrieved February 10, 2011, from http://www.policyarchive.org/handle/10207/bitstreams/15533.pdf

Cottrell, C. (2005). Document Management, One Paving Stone in the Path of EHR. *Healthcare Financial Management*, 84-92.

Crane, J. & Crane, F. (2006). Preventing Medication Errors in Hopsitals through a Systems Approach and Technological Innovation: A Prescription for 2010. *Hospital Topics: Research and Perspectives on Healthcare*, 3-8.

Culnan, M. & Armstrong, P. (1999). Information Privacy Concerns, Procedural Fairness and Impersonal Trust: An Empirical Investigation. *Organization Science*, 104-115.

Davis, D. & Adams, J. (2007). IT Strategic Planning, What Healthcare CFOs Should Know. *Healthcare Financial Management*, 100-104.

Davis, F. (1989). Perceived Usefulness, Percevied Ease of Use, and User Acceptance of Information Technology. *MIS Quarterly*, 319-340.

Davis, F., Bagozzi, R., & Warshaw, P. (1989). User Acceptance of Computer Technology: A Comparison of Two Theoretical Models. *Management Science*, 982-1003.

Dell. (2009). *Electronic Medical Records 101*. Retrieved April 18, 2011, from

    http:/www.webbuyersguide.com/resource/resourceDetails.aspx?src=rdd&kc=rdd

    &id=15003

DeLone, W. & McClean, E. (1992). Information Systems Success: The Quest for the

    Dependent Variable. *Information Systems Research*, 60-95.

Denton, I. C. (2001). Will Patients Use Electronic Personal Health Records? Responses

    from a Real-Life Experience. *Journal of Healthcare Information Management*,

    251-259.

DeShazo, C., Fessenden, R., & Schock, P. (2005). Realizing IT's Potential. *The Physician

    Executive*, 26-29.

DesRoches, C., Campbell, E., Rao, S., Donelan, K., Ferris, T., & Jha, A. (2008).

    Electronic health records in ambulatory care: a national survey of physicians. *New

    England Journal of Medicine*, 50-60.

Dickinson, G. (2006). What's Good Today Isn't Going to be Nearly Enough Tomorrow.

    Healthcare Financial Management, 44-50.

Dinev, T. & Hart, P. (2006). An Extended Privacy Calculus Model for E-Commerce

    Transactions. *Information Systems Research*, 61-80.

Dixon, P. (2006). Medical Identity Theft: The Information Crime That Can Kill You. *The

    World Privacy Forum*, 13-22.

Dowling, G. & Staelin, R. (1994). A Model of Perceived Risk and Risk Handling

    Activity. *The Journal of Consumer Research*, 119-134.

Eastlick, M., Lotz, S., & Warrington, P. (2006). Understanding Online B-2-C

Relationships: An Integrated Model of Privacy Concerns, Trust and Commitment.

Journal of Business Research, 877-886.

Eddy, D. (2007). Linking Electronic Medical Records to Large-Scale Simulation Models:

Can We Put Rapid Learning on Turbo? *Health Affairs*, 125-136.

Electronic Medical Records Viewed Favorably, but Many Have Privacy Concerns.

(2008). *International Journal of Micrographics & Optical Technology*, 5-6.

Elgarah, W. & Falaleeva, N. (2005). Adoption of Biometric Technology: Information

Privacy in TAM. *Americas Conference on Information Systems* (pp. 1209-1212).

Omaha: AISeL.

Etzioni, A. (2000). The New Enemy of Privacy: Big Bucks. *Challenge*, 91-106.

Ewing, T. & Cusick, D. (2004). Knowing What to Measure. *Healthcare Financial

Management*, 60-63.

Ferguson, R. (2003, July 7). Digital Remedy: Platform will ease drug prescription. *eweek*,

28. Retrieved March 16, 2011, from http://www.eweek.com/c/a/Channel/Digital-

Remedy/

Ferris, N. (2006, December 7). Public Views EHRs as Mixed Blessing, Survey Finds.

Government Health IT. Retrieved November 14, 2010, from:

http://www.govhealthit.com/online/news/97034-1.html

Fishbein, M. & Azjen, I. (1975). *Belief, Attitude, Intention and Behavior: An Introduction

to Theory and Research.* Reading, Mass; Don Mills, Ontario: Addison-Wesley

Publishing Company.

Fridell, R. (2004). *Your Rights in Conflict: Privacy vs. Security.* Berkeley Heights, NJ: Enslow Publishers, Inc.

Fusilier, M. & Hoyer, W. (1980). Variables Affecting Perceptions of Invasion of Privacy in Personnel Selection Situation. *Journal of Applied Psychology*, 623-626.

Gallagher, P. (2004). Maintain Privacy with Electronic Charting. *Nursing Management*, 16-18.

Gans, D., Kralewski, J., Hammons, T., & Dowd, B. (2005). Medical Groups' Adoption of Electronic Health Records and Information Systems. *Health Affairs*, 1323-1333.

Garets, D. & Horowitz, J. (2008). Healthcare ICT in Europe: Understanding Trends in Adoption and Governance. *Journal of Management & Marketing in Healthcare*, 286-296.

Garrett, D. (2010). Tapping Into the Value of Health Data Through Secondary Use. *Healthcare Financial Management*, 76-83.

Garver, M. & Mentzer, J. (1999). Logistics Research Methods: Employing Structural Equation Modeling to Test for Construct Validity. *Journal of Business Logistics*, 33-57.

Glaser, J., Markell, P., & Stone, J. (2010, February). The Strategic Importance of Data. *Healthcare Financial Management*, 47-52.

Gleiner, A. (2000). Paving the Way for Electronic Medical Records. *The Physician Executive*, 32-36.

Goldschmidt, P. G. (2005). HIT and MIS: Implications of Health Information
Technology and Medical Information Systems. *Communications of the ACM*, 69-
74.

Goldstein, J. (2009). U.S. Hopsitals Slow to Adopt E-Records. *Wall Street Journal.*
Retrieved March 15, 2009, from
http://online.wsj.com/article/SB123802378615142009.html

Greenberg, D. (1999). Delete the Revolution. *The Lancet*, 764.

Gustafson, D., McTavish, F., Stengel, W., Ballard, D., Hawkins, R., Shaw, B., et al.
(2005). Use and Impact of eHealth System by Low-Income Women with Breast
Cancer. *Journal of Health Communication*, 195-218.

Hair, J., Black, W., Babin, B., Anderson, R., & Tatham, R. (2006). *Multivariate Data
Analysis.* New Jersey: Prentice Hall.

Harrison, J. P. & Daly, M. A. (2009). Leveraging Health Information Technology to
Improve Patient Safety. *Public Administration and Management*, 218-237.

Hartzband, P.,& Groopman, J. (2008). Off the Record-Avoiding Pitfalls of Going
Electronic. *New England Journal of Medicine*, 1656-1657.

Health Analytics. (2009). *Market Overview: Hospital Revenue Cycle Management
(RCM) Applications 2008 Year End Report.* Retrieved July 28, 2010, from
http://www.himss.org/foundation/docs/marketOverviews/2009_MO_RCM_Final.
pdf

Health Insurance Portability and Accountability Act of 1996, Public Law 104-191
(1996).

Henderson, M. (1995). Integrated Health Care Management. *Benefits Quarterly*, 48-56.

Hennington, A. & Janz, B. (2007). Information Systems and Healthcare XVI: Physican
    Adoption of Electronic Medical Records: Applying the UTAUT Model in a
    Healthcare Context. *Communications of the Association for Information Systems*,
    60-80.

Hillestad, R., Bigelow, J., Bower, A., Girosi, F., Meili, R., Scoville, R., et al. (2005). Can
    Electronic Medical Record Systems Transform Health Care? Potential Health
    Benefits, Savings and Costs. *Health Affairs*, 1103-1117.

Hodge, R. (2002). Myths and Realities of Electronic Medical Records. *The Physician
    Executive*, 14-20.

Hoffman, S. & Podgurski, A. (2009). E-health Hazards: Provider Liability and Electronic
    Health Record Systems. *Berkeley Technology Law Journal*, 1523-1581.

Holstein, A., Litzinger, P., & Dunn, J. (2010). Optimizing the Use of the Fiscal Stimulus
    for Health IT in the U.S. *Global Journal of Business Research*, 63-76.

Hu, P., Chau, P., Sheng, O. R., & Tam, K. Y. (1999). Examining the Technology
    Acceptance Model Using Physican Acceptance of Telemedicine Technology.
    Journal of Management Information Systems, 91-112.

Iacobucci, D. (2010). Structural equations modeling: Fit indices, sample, size and
    advanced topics. *Journal of Consumer Psychology*, 90-98.

Identity Theft 911. (n.d.). *Medical Identity Theft Case Pursued in Florida.* Retrieved May
    15, 2011, from http://www.identitytheft911-sunj.com/alerts/alter.ext?sp=631

Ilie, V., Van Slyke, C., Parikh, M. A., & Courtney, J. F. (2009). Paper Versus Electronic Medical Records: The Effects of Access on Physicans' Decisions to Use Complex Information Technologies. *Decision Sciences*, 213-241.

James, B. (2005). E-Health: Steps on the Road to Interoperability. *Health Tracking*, 26-30.

Joinson, A., Reips, U.D., Buchanan, T., & Schofield, C. B. (2010). Privacy, Trust and Self-Disclosure Online. *Human-Computer Interaction*, 1-24.

Jones, D. S. (2008). Quality, Defensibility, and the Electronic Medical Record. *Journal of Health Care Compliance*, 41-46;71-72.

Jones, D. S. & Kessler, H. (2010). Can Electronic Medical Records Really Improve Quality? The Obama Administration Bets Yes. *Journal of Health Care Compliance*, 39-42; 67-69.

Kash, B., Gamm, L. D., Bolin, J., & Peck, B. M. (2005). Opportunities for Administrators to Promote Disease Management. *Journal of Healthcare Management*, 297-309.

Kazley, A. S. & Ozcan, Y. A. (2007). Organizational and Environmental Determinants of Hospital EMR Adoption: A National Study. *Journal of Medical Systems*, 375-384.

Kerlinger, F. & Lee, H. (2000). *Foundations of Behavioral Research.* Thomson Learning.

Kim, D. (2008). Self Perception-based Versus Transference-based Trust Determinants in Computer-mediated Transactions: A Cross-cultural Comparison Study. *Journal of Management Information Systems*, 13-45.

Klein, R. (2007). An Empirical Examination of Patient-Physician Portal Acceptance. *European Journal of Information Systems*, 751-760.

Kline, R. (2004). *Principles and practice of structural equation modeling, 2nd ed.* New Yrok: Guildford.

Kralewski, J., Dowd, B., Zink, T., & Gans, D. (2010). Preparing Your Practice for the Adoption and Implementation of Electronic Health Records. *Physician Executive*, 30-33.

Krane, D. (2007). *Many U.S. Adults are Satisfied with Use of Their Personal Health Information.* Harris Interactive.

Krane, D. (2008, July 15). Millions Believe Personal Medical Information Has Been Lost or Stolen. *Harris Interactive*, p. #74.

Lafferty, L. (2007). Medical Identity Theft: The Future Threat of Health Care Fraud is Now. *Journal of Healthcare Compliance*, 11-18.

Landon, B. & Normand, S. L. (2008). Performance Measurement in Small Office Practice: Challenges and Potential Solutions. *Annals of Internal Medicine*, 353-357.

Laric, M., Pitta, D., & Katsanis, L. P. (2009). Consumer Concerns for Healthcare Information Privacy: A Comparison of US and Canadian Perspectives. *Research in Healthcare Financial Management*, 93-111.

Laufer, R. & Wolfe, M. (1977). Privacy as a Concept and a Social Issue - Multidimensional Developmental Theory. *Journal of Social Issues*, 22-42.

Liebhaber, A. & Grossman, J. (2007). Physicians Moving to Mid-Sized Single-Specialty

    Practices. Tracking Report #18: Results from the Community Tracking Study.

    Center for Studying Health Systems Change.

Lohr, S. (2009, February 10). *New York Times*. Retrieved from Electronic Health

    Records: How to Spend the Money Wisely.:

    http://bits.blogs.nytimes.com/2009/02/10/electronic-health-records-how-to-spend-

    the-money-wisely/

Long, K. (2010). *Healthleaders EXTRA! Addressing the Growing Threat of Medical*

    Identity Theft. Retrieved from Health Leaders Media:

    http://www.healthcareleadersmedia.com/view_feature.cfm?content_id=83793

Lumpkin, J. R. (2007). Archimedes: A Bold Step Into the Future. *Health Affairs*, 137-

    139.

Lynch-Afryl, S. (2006). Clinton Bill Would Broaden Scope of Covered Entity Definition.

    CCH Health Care Compliance Letter.

Maffeo, M. (2009). The Relationship of Privacy Provisions in the Stimulus Bill to Health

    Information Technology. *Journal of Health Care Compliance*, 55-74.

Magee, M. (2009). Powering Healthcare Visions: Taking Advantage of Complexity,

    Connectivity, and Consumerism. *Intel Technology Journal*, 6-19.

Malhotra, N., Kim, S., & Agarwal, J. (2004). Internet users' Information Privacy

    Concerns (IUIPC): The Construct, the Scale and a Causal Model. *Information*

    Systems Research, 336-355.

Marshall, P. (2009). How Personal Health Records are Changing the Face of Healthcare. *Marketing Health Services*, 21-25.

Mayer, R., Davis, J., & Schoorman, F. (1995). An Integrative Model of Organizational Trust. *Academy of Managment Review*, 709-734.

McCarthy, D., Shatin, D., Drinkard, C., Kleinman, J., & Gardner, J. (1999). Medical Records and Privacy: Empirical Effects of Legislation. *Health Services Research*, 417-426.

McCloskey, D. (2003-2004). Evaluating Electronic Commerce Acceptance with the Technology Acceptance Model. *Journal of Computer Information Systems*, 49-57.

McKnight, D. H., Choudhury, V., & Kaemar, C. (2002). Developing and Validating Trust Measures for e-Commerce: An Integrative Typology. *Information Systems Research*, 334-359.

MedeFile Becomes PHR Vendor for Soren. (2010, January 25). *Globe Newswire*.

Medical Experts Argue About EMRs and Their Value to Both the Industry and Patients. (2008, April). *Materials Management in Health Care*, p. 4.

Melvin, V. (2007, October 27). *VA and DOD Continue to Expand Sharing of Medical Information, but Still Lack Comprehensive Electronic Medical Records.* United States Government Accountability Office.

Merrill, M. (2009, May 19). *Study reveals patients' attitudes toward EMR conversion.* Retrieved November 8, 2010, from healthcareitnews: http://www.healthcareitnews.com/print/9758

Metzger, M. (2004). *Privacy, Trust, and Disclosure: Exploring Barriers to Electronic Commerce*. Retrieved November 30, 2010, from http://jcmc.indiana.edu/vol9/issue4/metzger.html

Metzger, M. (2004). Privacy, Trust, and Disclosure: Exploring Barriers to Electronic Commerce. *Journal of Computer-Mediated Communication*.

Miller, A. & Tucker, C. (2009). Privacy Protection and Technology Diffusion: The Case of Electronic Medical Records. *Management Science*, 1077-1093.

Musgrove, P. (2006). Life and Death and Who's Going to Pay. *Health Affairs*, 1664-1667.

National Alliance for Health Information Technology. (2008, May 20). *Defining Key Health Information Technology Terms.* Retrieved November 28, 2010, from healthit.hhs.gov/defining_key_hit_terms

National Research Council. (2000). *To Err is Human: Building a Safer Health System.* Washington, DC: The National Academies Press.

Neupert, P. & Craig, M. (2009). Personal Health Management Systems: Applying the Full Power of Software to Improve the Quality and Efficiency of Care. *Health Affairs*, 390-392.

Office of the National Coordinator for Health Information Technology. (2009, June 16). *Meaningful Use Matrix.* Retrieved August 2010, from U. S. Department of Health & Human Services: http://healthit.hhs.gov/portal/server.pt/gateway/PTARGS_0_11113_872719_0_0_18/Meaningful%20Use%20Matrix.pdf

Ozdemir, Z., Barron, J., & Bandyopadhyay, S. (2011). An Analysis of the Adoption of Digital Health Records Under Switching Costs. *Information Systems Research*, 493-503.

Parente, S., & McCullough, J. (2009). Health Information Technoloyg and Patient Safety: Evidence From Panel Data. *Health Affairs*, 357-360.

Perry, C. (2008). Is Your Organization Virtually Compliant? *Journal of Health Care Compliance*, 53-54;80-81.

Pestotnik, S. L., Classen, D. C., Evan, S., & Burke, J. P. (1996). Implementing Antibiotic Practice Guidelines Through Computer-Assisted Decision Support: Clinical and Financial Outcomes. *Annals of Internal Medicine*, 884-890.

Petronio, S. (1991). Communication Boundary Management: A Theoretical Model of Managing Disclosure of Private Information Between Marital Couples. *Communication Theory*, 311-335.

Phelps, J., Nowak, G., & Ferrell, E. (2000). Privacy Concerns and Consumer Willingness to Provide Personal Information. *Journal of Public Polocy and Marketing*, 27-41.

Platt, R. (2007). Speed Bumps, Potholes, and Tollbooths on the Road to Panacea: Making Best Use of Data. *Health Affairs*, 153-155.

Poll: Many Patients Withhold Health Data. (2011, June 1). *HealthData Management*.

Posner, R. A. (2007). Privacy, Surveillance and Law. *The University of Chicago Law School's Surveillance Symposium.* (pp. 245-260). Chicago.

Powell, J., Fitton, R., & Fitton, C. (2006). Sharing electronic health records: the patient view. *Inform Primary Care*, 55-57.

Raghupathi, W. & Tan, J. (2002). Strategic IT Applications in Health Care. *Communications of the ACM*, 56-61.

Rice, B. (2003). To Tell or Not To Tell. *Medical Economics*, 35-38.

Scanlon, J. (2009, April 6). GE Healthcare Unveils a Plan to Stop Epidemics. *Business Week*.

Schlafly, P. (1998, July). *Liberty vs. Totalitarianism, Clinton Style.* Retrieved June 2011, from The Phyllis Schlafly Report:

http://www.eagleforum.org/psr/1998/july98/psrjuly98.html

Schreiber, J., Nora, A., Stage, F. K., Barlow, E., & King, J. (2006). Reporting Structural Equation Modeling and Confirmatory Factor Analysis Results: A Review. *The Journal of Educational Research*, 323-337.

Schwartz, B. (1997). Psychology, Idea Technology and Ideology. *Psychological Science*, 21-27.

Sheehan, K. & Hoy, G. (2000). Dimensions of Privacy Concern among Online Consumers. *Journal of Public Policy and Marketing*, 62-73.

Simon, S. R., Evans, J. S., Benjamin, A., Delano, D., & Bates, D. (2009). Patients' Attitudes Toward Electronic Health Information Exchange: Qualitative Study. *Journal of Medical Internet Research*, Vol 11, No 3.

Smith, P. A. (2005). Missing Clinical Information During Primary Care. *JAMA*, 565-571.

Solove, D. (2006). A Taxonomy of Privacy. *University of Pennsylvania Law Review*, 477-560.

Stanton, J. & Stam, K. (2003). Information Technology: Privacy, and Power within

    Organizations: a view form Boundary Theory and Social Exchange Perspectives.

    Surveillance & Society, 152-190.

Stead, W. & Lin, H. (2009, January). Computational Technology for Effective Health

    Care: Immediate Steps and Strategic Directions. *National Academics Press*.

Steckler, D., Epstein, F., & Riner, R. (2009). Getting Ready for EHR, RHIOs and Next-

    Generation Co-Management Agreements. *Physician Executive Journal*, 48-52.

Steinbrook, R. (2008). Personally Controlled Online Health Data -- The Next Big Thing

    in Medical Care? *The New England Journal of Medicine*, 1653.

Stone, B. (2005, Summer). Get Ready to Get Wired. *Newsweek*, pp. 84-86.

Sullivan, M. (2010). Playing Catch-Up in Health Care Technology. *Journal of*

    Healthcare Compliance, 25-30.

Swartz, N. (2005). Electronic Health Records Could Save $81 Billion. *The Information*

    Management Journal, 6.

Symonds, W. (2000, December 11). How E-hospitals Can Save Your Life.

    BusinessWeek, pp. 70-72.

Tang, P. C., Ash, J. S., Bates, D. W., Overhage, M., & Sands, D. Z. (2006). Personal

    Health Records: Definitions, Barriers, and Strategies for Overcoming Barriers to

    Adoption. *Journal of the American Medical Informatics Association*, 121-128.

Taylor, S., & Todd, P. (1995). Understanding Information Technology Usage: A Test of

    Competing Models. *Information Systems Research*, 144-176.

Thielst, C. (2007). The Future of Healthcare Technology. *Technology*, 7-9.

Thompson, T. (2008). "Less Paper" Trumps Paperless. *Health Management Technology*, 42-43.

Thompson, T. G. & Brailer, D. J. (2004). *The Decade of Health Information Technology: Delivering Consumer-centric and Information-rich Health Care.* Retrieved on March 28, 2010, from

http://www.providersedge.com/ehdocs/ehr_articles/The_Decade_of_HIT-Delivering_Customer-centric_and_Info-rich_HC.pdf

Thorpe, K., Florence, C., & Joski, P. (2004). Which Medical Conditions Account for the Rise in Health Care Spending? *Health Affairs*. August.

Unifi Technologies and Doclopedia Announce Two Way PHR and EMR Integration. (2010, January 13). *PRNewswire*.

United States Department of Health & Human Services (2003). *Summary of the HIPAA Privacy Rule.* Retrieved September 18, 2010, from

http://www.hhs.gov/ocr/privacy/hipaa/understanding/summary/privacysummary.pdf

U.S. General Accounting Office. (2000, December). *Standards for Privacy of Individually Identifiable Health Information* (Publication No. DOCID: fr28de00-34). Retrieved July 2011, from General Accounting Reports Online via GPA Access: http://www.gpo.gov/fdsys/pkg/FR-2000-12-28/pdf/00-32678.pdf

U.S. General Accounting Office. (2006, September). *HHS is Continuing Efforts to Define Its National Strategy* (Publication No. GAO-06-107IT). Retrieved March 15, 2011, from http://www.gao.gov/new.items/d061071t.pdf

Van der Goes Jr., P. (1999). Opportunity Lost: Why and how to improve the HHS-
proposed legisltation governing law enforcement access to medical records.
University of Pennsylvania Law Review, 1009-1068.

Varian, H. (1997). *Economic Aspects of Personal Privacy.* Retrieved from US
Department of Commerce: www.ntia.doc.gov/reports/privacy/privacy-rpt.htm

Veazie, J. I. (2009). Hidden Impacts of the Stimulus Package. *Health Care Collector*, 7-
9.

Venkatesh, V., & Davis, F. (2000). A Theoretical Extension of the Technology
Acceptance Model: Four Longitudinal Field Studies. *Management Science*, 186-
204.

Venkatesh, V., Morris, M., David, G., & David, F. (2003). User Acceptance of
Information Technology: Toward a Unified View. *MIS Quarterly*, 425-478.

Veronneau, P. (2009). Leverage health data gathered from electronic records. *Managed
Healthcare Executive*, 29-30.

Versel, N. (2004). Connect the Docs. *Modern Healthcare*, 46-48.

Vijayan, J. (2009, April 14). Privacy rules hamper adoption of electronic medical records,
study says. *Computer World*.

Wagner, E., Austin, B., Davis, C., Hindmarsh, M., Schaefer, J., & Bonomi, A. (2001).
Improving chronic illness care: translating evidence into action. *Health Affairs*,
64.

Westin, A. (2001). *The Harris Poll: #49.* Rochester, NY: Harris Interactive.

Westland, J. C. (2010). Lower Bounds on Sample Size in Structural Equation Modeling. *Electronic Commerce Research and Applications*, 476-487.

Wild, K. R. (2010). The Evolution of HIPAA: The Only Constant is Change. *Journal of Health Care Compliance*, 33-36.

Willison, D., Schwartz, L., Abelson, J., Charles, C., Swinton, M., Northrup, D., et al. (2007). Alternatives to project-specific consent for access to personal information for health research. What is the opinion of the Canadian public? *Journal of American Medical Informatics Association*, 527-533.

Wilson, E. V., & Lankton, N. (2004). Modeling Patients' Acceptance of Provider-Delivered E-health. *Journal of American Medical Informatics Association*, 241-248.

Withrow, S. C. (2010). How to Avoid a HIPAA Horror Story. *Healthcare Financial Management*, 82-88.

Xu, H. (2007). The Effects of Self-Construal and Perceived Control on Privacy Concerns. *Proceedings of the 28th Annual International Conference on Information Systems.* Montreal: ICIS.

Xu, H., Smith, J., Dinev, T., & Hart, P. (2008). Examining the Formation of Individual's Privacy Concerns: Toward an Integrative View. *International Conference on Information Systems* (pp. 1-16). Paris: Association for Information Systems.

Yasnoff, W. A. (2008, December 22). Electronic Records are Key to Health-Care Reform. *BusinessWeek Online*, p. 27.

Zakaria, N., Stanton, J., & Stam, K. (2003). Exploring Security and Privacy Issues in

    Hospital Information System: An Information Boundary Theory Perspective.

    AMIA 2003 Symposium Proceedings, 1059.