Extending Adoption of Innovation Theory with Consumer Influence

The Case of Personal Health Records (PHRs) and Patient Portals

by

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ABSTRACT

A long tradition of adoption of innovations research in the information systems context suggests that innovative information systems are typically adopted by the largest companies, with the most slack resources and the most management support within competitive markets. Additionally, five behavioral characteristics (relative advantage, compatibility, observability, trialability, and complexity) are typically associated with demand-side adoption. Recent market trends suggest, though, that additional influences and contingencies may also be having a significant impact on adoption of innovative information systems—on both the supply and demand-sides. The primary objective of this dissertation is to extend our theoretical knowledge into a context where consumer influence is a key consideration. Specifically, this dissertation focuses on the Personal Health Record (PHR) and patient portal market due to its unique position as a mediator between supply (ambulatory care clinic) and demand-side (patient and health consumer) interests. Four studies are presented in this dissertation and include: 1) an econometric examination of the contingencies associated with supply-side (ambulatory care clinic) adoption of patient portals, 2) a behavioral assessment of patient PHR adoption intentions, 3) an integrated latent variable and discrete choice evaluation of consumer business model preferences for digital services (PHRs), and 4) an experimental evaluation of how digital service (patient portal) feature preferences are impacted by assimilation and contrast effects. The primary contribution of this dissertation is that adoption (and adoption intentions) of *consumer information systems* are significantly impacted by: 1) supply-side adoption contingencies (even when controlling for dominant-paradigm adoption of innovation characteristics), and 2) demand-side consumer preferences for business models and features in the context of assimilation-contrast (even when controlling for individual differences). Overall, this dissertation contributes a new understanding of how contingent factors, consumer perceived value, and assimilation/contrast of features are impacting adoption of *consumer information systems.*

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Chapter 1. Introduction

The objective of this dissertation is to examine the supply-side and demand-side influences of a specific case of *consumer information systems*—Personal Health Records (PHRs) and patient portals—and to use this context to make significant extensions to adoption of innovations theory. PHRs and patient portals are uniquely positioned digital intermediaries that lie between firms (ambulatory care clinics) and consumers (patients and health consumers). Recent research articles have suggested that such systems are likely to be valuable to patients and providers alike, but face many adoption barriers (Tang et al. 2006). It has been suggested that additional research be conducted to determine what may encourage adoption (Kaelber et al. 2008a). This dissertation begins to fill this research gap and extend adoption of innovation theory by assessing: 1) the characteristics of ambulatory care clinics adopting PHRs and patient portals and associated contingencies of adoption, and 2) consumer preferences associated with PHRs and patient portals. General supply-side research questions are addressed in the first study and more granular consumer preference research issues are addressed in the subsequent studies. In general, this dissertation contributes new theoretical understandings from both the supply-side and demand-side of the emerging class of information systems termed in this dissertation: *consumer information systems.* More specifically, this dissertation contributes to the literature as follows. First, it shows how supply-side adoption of *consumer information systems* is influenced by the nature of the relationship between the firm and the consumer (*service* *contingencies*), firms learning from one another within a local market (*learning externality contingencies*), and local market characteristics (*demand contingencies*). Second, it shows the ways in which the type of business model underlying a *consumer information system* influences demand-side preferences. Finally, it demonstrates that assimilation-contrast effects and individual differences impact demand-side preferences for *consumer information systems* at the feature level, especially when considering the level of technological sophistication of the individual.

The first study econometrically evaluates the characteristics of U.S. ambulatory care clinics (medical out-patient clinics) that adopt clinical patient portals (which include PHRs). While controlling for the 'dominant' characteristics of early supply-side adopters (i.e. size of the firm, slack resources, management support, compatibility, and competition) (Fichman 2004a), this dissertation asks whether or not contingent factors also impact strategic adoption decisions. Specifically, this dissertation evaluates whether or not *demand contingencies* associated with local market characteristics, *service contingencies* associated with the type of relationship between the patient and the provider, and *learning externality contingencies* associated with learning from peers in the same geographic region also impact supply-side adoption decisions. This dissertation finds strong support for *service contingencies* and *learning externality contingencies* and weak support for *demand contingencies.* These results suggest that dominant firm traits traditionally associated with adoption of innovations theory in the information systems context tell only part of the story—additional considerations must be taken into account when assessing *consumer information systems.*

While the first study demonstrates how adoption of innovation theory may be extended on the supply-side, it does not fully explore the demand-side. Specifically, it is not apparent in the first study whether or not healthcare consumers are interested in adopting PHRs or patient portals and how their perceptions may influence the market. In the second study, the behavioral intentions to adopt PHRs are explored with survey-based research. The objective of this study is to assess patient perceptions of PHRs in the context of adoption of innovations. The research design is based on a cross-sectional survey of 300 current patients at two ambulatory care clinics. 70% of the patients contacted for the survey responded (n=210) and non-response biases were not present with respect to age or gender. Survey questions were focused on PHR adoption intentions and constructs based on innovation research (*relative advantage*, *compatibility with work style*, *trialability*, *complexity*, and *observability*) as well as additional questions focused on demographics, health perceptions, and related consumer perceptions. This dissertation finds that a majority of respondents were aged 50 or older and 62% reported that they “Plan to use a PHR in the future.” Health perceptions only had a marginal impact on PHR adoption intentions. *Relative advantage* (i.e. viewing a PHR as better than paper records or leaving records at the clinic), *compatibility with work style* (i.e. a PHR is compatible with your preferences for managing medical records), and *complexity* (i.e. ease-of-use) all had a positive and significant impact on PHR adoption intentions. *Trialability* (using a "demonstration" version of a PHR before committing) and *observability* (seeing others use a PHR) did not have a significant impact on adoption intentions. This study suggests that to convince patients to adopt a PHR, efforts should be focused on showing the *relative advantage* of the PHR, showing how it is *compatible* with their current practice of medical record keeping, and demonstrating *ease-of-use.*

The second study generally demonstrated that while PHR adoption is currently low, adoption intentions for the future are high. However, it is not clear how these adoption intentions may be impacted by various business model choices consumer face in this market. As information systems are offered as digital services to consumers, it is unclear how the underlying business models may impact consumer preferences. Research within adoption of innovations has not yet considered this important research question. Therefore, in the third study, this dissertation assesses consumer preferences for PHR business models through the use of a cross-sectional, discrete choice survey. I find that overall utility for PHRs is high, but that a specific business model (PHRs offered by groups of medical clinics) is preferred by consumers. These findings suggest that even when an innovative digital service has high utility associated with it, consumer preferences for business models have a significant impact on the market. This finding has important implications for how digital services may be diffuse in the future.

Finally, in the fourth study, this dissertation suggests that consumer preferences for features are not homogenous and such heterogeneity must be considered when offering *consumer information systems*. In the context of patient portals, this dissertation asserts that patient portal adoption intentions may not convert to actual usage if feature bundles are not customized for the needs of specific consumer segments, especially when considering that consumers have varying degrees of *technological sophistication*. Using assimilation-contrast theory and a cross-sectional survey based on an experimental design (2 x 2) that assesses preferences for combinations of *service automation* patient portal features (i.e. self-service) and *service innovation* patient portal features (e.g. digitally enabled service delivery such as online consultations with a clinician), this dissertation evaluates consumer perceived value for a digital service at the feature level. The primary finding is that healthcare consumers at all levels of technology sophistication assimilate toward *service automation* features. I also find that assimilation effects toward *service innovation* features do not occur at the lower levels of technology sophistication and, interestingly, contrast effects toward *service innovation* features begin to occur as technology sophistication increases.

The primary contribution of this dissertation is that adoption (and adoption intentions) of *consumer information systems* (specifically, PHRs and patient portals) are significantly impacted by specific factors associated with (1) supply-side adoption contingencies (even when controlling for dominant-paradigm adoption of innovation characteristics), and (2) demand-side consumer preferences for business models and features (even when controlling for individual differences). These findings significantly contribute to adoption of innovation theory by identifying and characterizing the influence of heterogeneity in service offerings and heterogeneity in consumer preferences. These findings represent a first step toward extending information systems research into contexts where the consumer has a significant influence.

This dissertation also demonstrates that adoption of digital services may remain low if we do not fully consider the nuances of consumer preferences in a complex market where trade-off considerations are paramount. For instance, Chapter 4 demonstrates that privacy is a primary patient concern with PHRs and this trade-off is further demonstrated in Chapter 5 which finds that consumers will trade data control and some switching costs for higher privacy (and lower effort). Additionally, Chapter 6 also demonstrates that specific segments of consumers are attracted to feature bundles that match their prior experience or are slightly (but not extremely) different. These assimilation and contrast effects represent a new theoretical lens through which adoption and diffusion may be impacted. Therefore, this dissertation has also shown that new theoretical views are needed to fully understand digitally intermediated markets.

The remainder of this dissertation is organized as follows. The following chapter reviews the relevant diffusions of innovations theory literature as well as emerging literature in consumer information systems, the PHR and patient portal context, as well as relevant supply-side and demand-side literature. Chapters 3, 4, 5, and 6 examine PHRs and patient portal adoption in successively more specific contexts beginning with the supply-side context (Chapter 3), general behavioral considerations in the demand-side context (Chapter 4), and then providing more granular insights into consumer preferences for PHR business models (Chapter 5) and assimilation-contrast associated with patient portal feature preferences (Chapter 6). The last section brings these studies together and provides final discussions and conclusions related to consumer influence on adoption of innovations theory.

Chapter 2. Literature Review

2.1. Introduction

In information systems research, many outcome variables, theoretical constructs, and relationships have been predominantly studied within organizational boundaries and are firmly rooted in rational considerations (e.g. Banker and Kauffman 2004). Information systems researchers have continued to use this perspective in consumer oriented contexts with some success (e.g. Pavlou 2003). However, with digitization of products and consumer information systems, this dissertation suggests that our view of technology and its outcomes has to change significantly.

The differences between consumer context and corporate context of information systems are complex and significant. Consumers are emotive and subject to outside influences not typically considered within corporate environments. Emotional appeal is influenced by bandwagon effects, peer groups, social networking, the level of enjoyment attained from usage, the novelty of the app or system, and entertainment value. When confronted with platform-oriented decisions, consumers face trade-offs in feature benefits, service, and social complementarities. We do not yet fully know what influences consumer decisions in these contexts and what behavioral processes guide and govern the trade-off evaluations. Additionally, not much is known about what motivates firms to adopt technologies designed specifically with consumer interactions, collaborations, and information provisioning in mind. Thus, there is an opportunity for information systems researchers to expand the scope of technology adoption studies to investigate how firm strategies and social contexts can influence consumer behavior. The following sections explain the current status of the literature on *consumer information systems* in general, and then provide more specifics as to the context and theories used in this dissertation.

2.2. Consumer information systems

Consumer information systems are emerging as vital components of information-based societies. Everything around us is becoming digitized—from phones to government services to health records—and the impacts of living in such a digital society are still replete with unknowns. Markets eagerly await the introduction of these new consumer-oriented products and services such as Google+ (social networking), Hulu (streaming video), and iCloud (Apple's cloud-based storage and sharing between devices). The emergence of products and services that directly engage consumers is evidence of a fundamental shift towards consumer-centric business strategies.

In 2005, Gartner suggested that the next 10 years would be defined by "consumerization" of IT (Pettey 2005) and this trend is certainly evident today. A recent Forrester report suggests that the upcoming generations are digitally integrated to such a degree that consumer technology is not only a norm for these generations, but their views and behaviors will propagate dramatically as they age (Anderson September 21, 2010). I see the emergence of a new class of information systems, which I refer to as *consumer information systems.* This dissertation defines this class of information systems as: *A set of technologies (and devices), platforms, services, and processes that cater to the utilitarian and hedonic needs and desires of consumers.* This dissertation proposes that the market shift toward *consumer information systems* is underrepresented in information systems research and presents our discipline with an outstanding opportunity to open up new research streams not solely focused on supply-side productivity, efficiency, and acceptance (see Banker and Kauffman 2004 for a comprehensive literature review of such supply-side research).

Recent research in information systems is now beginning to identify and acknowledge the influence of *consumer information systems* on firm strategies. For example, Yoo et al. (2010) lay out an agenda for information systems research with a specific focus on firm strategies and corporate IT infrastructures in the context of digitized products. Additionally, recent studies have addressed consumer related research issues such as: perceived similarity in adoption decisions (Al-Natour et al. 2011), post-adoption considerations and outcomes related to the context of online banking (Kim and Son 2009a; Xue et al. 2011), and adaptive personalization of online features (Ho et al. 2010). While these are important first steps in expanding our discipline into this emerging area, this dissertation contends that it is time to make a more concerted effort to broaden the research domain. In this dissertation, I focus on a specific class of *consumer information system* related to healthcare: PHRs and patient portals.

2.3. The context of Personal Health Records (PHRs) and Patient Portals

Patient Portals and Personal Health Records (PHRs) are online tools used by patients to keep track of their personal health information and interact with healthcare providers. The follow sections define these terms and outline the existing literature.

2.3.1. Personal Health Records (PHRs)

The formal definition of a Personal Health Record (PHR) is often the subject of debate, but two enduring definitions are available from the Robert Wood Johnson Foundation (RWJF) and the American Health Information Management Association (AHIMA). RWJF defines a PHR as, "…a platform that gathers patient data from multiple sources and hosts a suite of applications that use those data to help patients understand and improve their health" (Robert Wood Johnson Foundation 2010). AHIMA simply suggests, "The PHR is a tool that you can use to collect, track and share past and current information about your health or the health of someone in your care" (AHIMA 2010).

Such digitized personal health information typically originates in the Electronic Medical Record (EMR) systems being adopted throughout the U.S. health care industry and has the potential to then be imported or transferred to the PHRs of individual consumers or caregivers. EMR systems are primarily focused on administrative and episodic acute patient care issues including: reducing paper within a hospital, increasing the ease of sharing information between departments, and increasing the quality and safety of patient care. In a hospital setting, EMRs typically include records management and analysis systems in key health information business processes (e.g. within patient units, radiology, the hospital pharmacy, and hospital labs).

PHRs, on the other hand, are predominantly developed from the patient's perspective and are designed to provide support outside of the hospital or clinic setting. In this dissertation, two primary types of PHRs are considered (more detail can be found in Detmer et al. 2008):

Tethered PHR: A tethered PHR is usually connected directly to an EMR or medical records system provided by a health care provider (usually a hospital or ambulatory care provider), but can also be provided by employers or insurers.

Integrated PHR: An integrated PHR is a third-party PHR service, such as Microsoft HealthVault, which is not directly connected to any health care provider. Integrated PHRs are typically based on a cloud-computing model and provide consumers with secure, online applications that permit import, aggregation, storage, analysis, and augmentation of personal health records and information (or records and information for family members) as well as additional features.

PHRs provide healthcare consumers with an entirely new and patient-centric way to manage medical records and medical information. While the potential benefits of PHR adoption are numerous, PHRs require a long-term commitment to records and information management by consumers seeking to accrue benefits that will eventually outweigh initial setup and learning costs (Robert Wood

Johnson Foundation 2010). While extensive research has been done on the use and adoption of Electronic Medical Records (EMRs) and Electronic Health Records (EHRs) by hospitals and doctor's offices (e.g. Furukawa et al. 2010; Hackbarth and Milgate 2005), very little in-depth research has been done on PHR usage.

Electronic Medical Records (EMRs) and Electronic Health Records (EHRs)—referred to collectively as EMRs henceforth—form the foundation for the electronic storage and dissemination of medical records (Berner et al. 2005; Walker 2005). The ability to transfer records electronically directly from a provider's EMR to an individual's PHR is one of the core goals of personalized health record management (Neupert and Mundie 2009) and the success of such goals is predicated on EMR diffusion. PHRs are built on the assumption of ubiquitous EMR adoption by healthcare providers. The infrastructure formed by EMRs provides the foundation for PHRs to flourish (Ball and Lillis 2001; Gaunt 2009). The research questions in recent EMR studies have begun to address the specific determinants of EMR adoption (Kazley and Ozcan 2007a) and the performance impacts of EMR adoption (Abdolrasulnia et al. 2008; Gans 2009; Hillestad et al. 2005).

In parallel to the adoption of EMRs, PHR system features have improved considerably and are beginning to demonstrate positive utility. It has been reported that more than *50 million patients are seen at practices and hospitals that use a PHR portal tethered to the EPIC EHR system and the Veterans*

Administration (VA) has a fully-functional PHR system available to over 25 million veterans (Kaelber et al. 2008a). As the healthcare industry increases demands on consumers to become more active in the management of their personal and family healthcare, the demand for consumer-centric medical records management technologies is likely to significantly increase (Krohn 2007).

However, even though PHR research is deemed important and valuable (Kaelber et al. 2008a), vital to an improved National Health Information Infrastructure within the U.S. (Detmer 2003), and possibly "the next big thing in healthcare" (Steinbrook 2008), extant PHR research is somewhat limited. Early studies have been done on PHR implementations at hospitals (Halamka et al. 2008), ideal PHR characteristics (Kahn et al. 2009; Kim and Johnson 2002), PHR governance (Reti et al. 2009), interoperability with EMRs (Ozdemir et al. 2009), as well as potential costs and benefits of PHR usage (Kim and Johnson 2002; Tang et al. 2006). These studies suggest that patient access to data, collaborative disease tracking, and continuous communication between patient and physicians are ideal benefits of PHRs (Tang et al. 2006).

Extant research on PHRs gives us early insights into PHR characteristics (e.g. Tang et al. 2006), motivators of PHR usage (e.g. Agarwal and Angst 2006), and information regarding potential barriers to PHR adoption such as *data ownership, privacy, security, interoperability, PHR literacy, and health literacy* (Krohn 2007; Raisinghani and Young 2008; Tang et al. 2006). And, recent analysis has identified the ideal PHR candidate as someone who is mobile; is a caregiver; sees multiple physicians; has complex health situation; has conditions requiring self-care activities; and is comfortable with computers (Chrischilles 2008).

Given the innovative nature of PHRs, it is important for researchers to understand consumer perceptions on barriers to adopt. Moreover, consumer perceptions of the innovation characteristics of PHRs will be critical in determining the speed and extent of PHR adoption. In this dissertation, I extend current findings by evaluating supply-side contingencies and demand-side preferences that may influence this emerging market.

2.3.2. Patient portals

The term "patient portal" is now used to describe online digital services offered to patients directly by their healthcare providers. These services may include tethered PHRs, as described in the previous section, and/or additional features that provide additional convenience to patients of a specific healthcare provider. For instance, patient portals may be used to schedule appointments, view lab results, request medication refills, track health conditions, and more (Bourgeois et al. 2009). This is an interesting change in healthcare delivery as patients are now faced with a physical service encounter that is being *augmented* with a digital alternative for portions of the service—the patient portal. Patients typically physically interact directly with both front-office administrative staff (e.g. checking-in, filling out paper work, etc.) and with back-office clinical staff (e.g. physical delivery of medical care via a doctor or medical service provider) during medical visits, but are now beginning to be have digital options, as well, that may increase convenience, reduce costs, and, potentially, improve health outcomes for those with chronic conditions requiring information-rich patient-provider interactions (Emont 2011).

While patient portals have a significant amount of potential, research in this area is only just emerging and is primarily focused on the characteristics of users and usage rates within specific health systems (e.g. use of the Epic portal by Geisinger as reported by Gardner 2010), early results associated with potential operational efficiencies (e.g. increased efficiency due to substitution of some office visits for telephone visits and web messaging as reported by Chen et al. 2009), and a very limited amount of early research on the impact of patient portals on health outcomes (e.g. Zhou et al. 2010). Research findings have been somewhat mixed, as to be expected with early adoption and usage. For instance, usage of Kaiser Permanente's patient portal called My Health Manager has been reported at more than 3 million users who most frequently use the patient portal to view lab test results, request prescription refills, and interact with providers via online e-mail and messaging capabilities (Silvestre et al. 2009). The U.S. Department of Veterans Affairs (VA) has had similar success with its patient portal, My HealtheVet (Nazi et al. 2010). However, other health systems have not had as much success. The British National Health Service reported that only a very limited number (0.13%) of potential users took the steps need to open a patient portal account (Greenhalgh et al. 2010) and the majority of patients who signed up to use PatientSite at Beth Israel Deaconess Medical Center in Boston were generally healthier and used the health system less than those who did not enroll (Weingart et al. 2006a). Additionally, while administrative and operational efficiencies may result due to use of a patient portal for tasks such as refilling prescriptions, scheduling appointments, and getting access to test and lab results (e.g. Liederman et al. 2005), some studies report patient concerns with possibility of patient portals hindering communication with their provider (as described by Emont 2011) and only using a patient portal if they are dissatisfied with the relationship with their provider (Zickmund et al. 2008a).

Overall, PHRs and patient portals could be the catalyst that drives the paradigm shift of traditional healthcare delivery models towards patient-centric models. However, such digital services will not be useful to all healthcare consumers and it is possible that some consumers will not show an interest in information systems that require additional effort and responsibility. Within organizations, information systems are adopted and implemented by management, with little choice of adoption or usage by individual employees. In a consumer setting, however, adoption is discretionary and subject to additional considerations. For instance, a consumer must not only evaluate whether or not he or she will be able to use a PHR or patient portal effectively, a consumer must also decide if it is worth the effort and time required to yield benefits from the investment required.

2.4. Healthcare provider considerations (supply-side)

Consumer portals are being adopted with ever greater frequency by organizations to reduce in-person costs, increase customer convenience, enhance communication options, and maintain lasting customer relationships. However, only limited research has explored what types of firms adopt customer-facing information systems such as PHRs and patient portals. Within the limited number of studies conducted in the context, Chatterjee et al. (2002) find that *top management championship, strategic investment rationale,* and *extent of coordination* positively affects adoption of customer-facing systems. Additional customer-facing information system research has found *that technology integration*, *web functionalities*, and *web spending* are significant predictors of adoption while *partner usage* is an inhibitor of adoption (Hong and Tam 2006) and that *relative advantage*, *competitive pressure*, and *technical resource competence* are significant predictors of adoption (To and Ngai 2006). Yet, relatively little is known about what types of organizations adopt such systems.

Empirical work on the supply-side of patient portals has primarily concentrated on the *communication* and/or *interaction* between patients and providers with many of the studies utilizing survey methodologies to ascertain usage, satisfaction, and perceptions with patient-provider e-mail (see Ye et al. 2009 for a systematic review of patient-provider e-mail). Some studies have focused on specific cases of patient-centric information system adoption and discuss the process of designing, developing, and implementing specific cases of such systems (Bourgeois et al. 2009; e.g. Grant et al. 2006a; Schnipper et al. 2008). A few studies extend this type of analysis by also including patient-provider usage, acceptance, and satisfaction analysis (e.g. Ralston et al. 2007). While there has been some empirical work on PHR adoption and usage (e.g. Cimino et al. 2002) and quite a bit of research on the efficacy of decision-aids in healthcare (see O'Connor et al. 1999 for a review), most patient-portal studies are context specific (Nordqvist et al. 2009; e.g. Weingart et al. 2006a) and very few are conducted on large, nationwide samples. In this dissertation, I extend such research by evaluating how diffusion of innovations theory and contingency theory impact strategic supply-side decisions associated with patient portal adoption. I use a nationwide sample of ambulatory care clinic technology adoption decisions as the empirical basis for this study.

2.4.1. 'Dominant-paradigm' of the adoption of innovations

Adoption of innovations theory generally suggests that innovations diffuse in an 'S' shaped pattern beginning with innovators (a small percentage of very early adopters) and progressing through subsequent stages of increasing adoption rates until reaching a plateau (Rogers 1995). A substantial amount of work has been done on adoption of innovation patterns on the supply side (Fichman 2000; Jeyaraj et al. 2006a; Rogers 1995) and has resulted in a 'dominant-paradigm' (Fichman 2004b). The 'dominant-paradigm' refers to a large number of studies related to IS adoption which have shown that variance in the "quantity of innovation" is well known to be explained by increasing levels of: organizational size and structure; knowledge and resources; management support; compatibility; and competitive environment (Fichman 2004b; Jeyaraj et al. 2006a; Jeyaraj et al. 2006b). Such adoption and diffusion research, though, has primarily focused on the adoption of information systems that improve the productivity and efficiency within firms. In terms of Swanson's (1994) multi-core model of firm adoption of information systems, extant information systems adoption research has predominantly focused on adoption of Type 2 information systems *internal* to a firm (e.g. accounting information systems Choe 1996) and Type 3 innovations that provide connections *between* loosely coupled firms (e.g. Electronic Data Interchange (EDI) Iacovou et al. 1995). Even within the health care context, a thoroughly developed theoretical health care technology adoption framework (Rye and Kimberly 2007) is primarily based on assessing adoption of innovative technologies that improve *internal* efficiencies of healthcare providers and communication capabilities between providers.

Research considering what types of firms adopt *customer-facing information systems* is emerging (e.g. Chatterjee et al. 2002; Hong and Tam 2006), but limited. Much of the existing research on supply-side adoption of innovative, customer-facing systems focuses on the context of transaction-based e-commerce. For instance, Chatterjee et al. (2002) find that *top management championship*, *strategic investment rationale*, and *extent of coordination* all impact the assimilation (use and routinization) of web technologies by firms. Hong and Zhu (2006) find that *technology integration*, *web spending*, *web functionalities*, *EDI* *use, partner usage*, and *perceived obstacles* impact adoption of e-commerce technologies by firms. TAM-based (and TAM hybrids) frameworks have also been used to extract supply-side predictors of adoption within the context of managerial decision making (Grandon and Pearson 2004; Plouffe et al. 2001; Riemenschneider et al. 2003). These models, while controlling for differences such as the age of the firm and experience with web technologies (Chatterjee et al. 2002) and the size of the firm and industry type (Hong and Zhu 2006), do not fully consider the firm contingencies associated with managerial decision making. This dissertation next considers how a contingency-based model may help to explain many of the interesting nuances within the context of patient portal adoption by ambulatory care clinics.

2.4.2. Contingencies of adoption

Contingency theory suggests that managers have the ability to make strategic decisions in order to find an appropriate fit with shifting technological and environmental conditions. Contingencies have been shown to impact technology adoption decision making in the contexts of health information technology (Devaraj and Kohli 2000; Wang et al. 2005), manufacturing technologies (Lee and Grover 1999), Internet adoption (Teo and Pian 2003), information systems development projects (Zhu 2002), and strategic alignment between technology adoption decisions and high-level strategy (Oh and Pinsonneault 2007). In Weill and Olson (1989), a contingency theory framework was developed to demonstrate that technological and environmental characteristics (in addition to other contingencies, such as size, structure, and strategy) often impact MIS decisions which in turn can impact MIS effectiveness, and, ultimately organizational effectiveness. In general terms, a better organizational fit (or “congruence”) with contingent variables is suggested to impact an organization’s ability to innovate and, ultimately, the effectiveness of the organization. Interestingly, overall performance is not seen as maximization of individual variables (e.g. maximizing size), but rather as making decisions that result in optimal overall levels of multiple supply-side characteristics resulting in appropriate matches with contingent considerations (Donaldson 2001).

This dissertation argues that ambulatory care clinics are making strategic technology adoption decisions to find congruencies with an environment characterized by shifting demand, a rapid pace of technology change (especially as patient portals become more pervasive in healthcare), and coordination of care as cost pressures increase and quality outcomes come under increasing scrutiny. Specifically, this dissertation suggests that the strategic decision made by an ambulatory care clinic to adopt a patient portal is made in the interests of maximizing organizational fit with such contingent factors. Following the framework by Weill and Olson (1989), which suggests that congruence is a multi-stage process, my study focuses on early stage contingencies associated with adoption decisions.

2.5. Patient considerations (demand-side)

2.5.1. Adoption of innovations behavioral characteristics

The classic definition of an innovation is the "generation, acceptance and implementation of new ideas, processes, products or services" (Thompson 1965). Five key behavioral characteristics of innovations established within traditional adoption of innovations theory are known to affect adoption: *relative advantage, compatibility, complexity, observability,* and *trialability* (Rogers 1995). In this dissertation, I examine whether these behavioral innovation constructs are significant influencers of PHR and patient portal adoption intentions, as well as additional considerations that may have a significant impact in the context of *consumer information systems*. Specifically, the five behavioral characteristics can be described as follows.

Relative advantage refers to the perception that the innovation is better than what is already in place. In this context, PHRs or patient portals may be perceived as better than keeping paper records or, perhaps, better than relying on healthcare providers to maintain records.

Compatibility refers to the level to which the innovation matches the adopter's work style. In adopting PHRs or patient portals, patients are responsible for managing and organizing their own records. If they prefer "their own way" of doing things, PHRs and patient portals may not be compatible with their style of records management.

Complexity refers to the challenges that may be present when using an innovation. A PHR or patient portal is a new software package that a consumer must learn how to use. Additionally, importing (or re-entering) records and information into a PHR or patient portal will require navigating the software, checking with providers to see if information can be shared, and verifying that information and records were correctly transferred (or entered).

Observability refers to whether or not the innovation was observed being used by others. For instance, a consumer may be influenced to adopt a new iPhone if he/she sees a friend use it first. Similarly, if a consumer sees others using PHRs or patient portals, especially those in their social group, they may be more apt to adopt.

Trialability refers to the extent to which a user can try-out the innovation before committing to adoption. Since most PHRs and patient portals are available online and many offer demos of one sort or another, trialability may seem insignificant, but it is one thing to see an example of a new technology and another to actually use it with your own personal health information and records.

Extant business research has applied these innovation constructs to innovations such as online banking (Tan and Teo 2000) and e-commerce (Eastin 2002). Research has shown that social influence often has minimal impact on adoption, but perceptions of the advantages and convenience of the innovation as well as potential risks often have significant impacts (Tan and Teo 2000) along with perceptions of ease-of-use, self-efficacy, and financial benefits (Chau and

Lai 2003; Ho and Ko 2008; Mukherjee and Nath 2003). It has also been shown that more mature consumers (aged 50+) are likely to resist innovations when their perceptions of riskiness are high (Laukkanen et al. 2007). However, the target demographic for PHRs and patient portals appears to be very different from that of recent service innovations such as online banking and e-commerce. Given that the adoption of innovations often follows an S-shaped trajectory (Rogers 1995) (i.e. gradual adoption slope at first with a much steeper adoption slope as time progresses with an eventual transition back to a gradual adoption slope as the innovation matures) with early innovators and adopters having a major impact on the ultimate success of reaching a tipping point (Berwick 2003), I assert that a more complete understanding of early PHR and patient portal adopters and future adopters is essential for the success of PHR and patient portal adoption and diffusion.

2.5.2. Additional behavioral considerations

While the behavioral innovation characteristics mentioned in the previous section have been shown to have positive impacts on demand-side perceptions of value, other research streams have demonstrated that additional factors can have an effect when choosing between alternatives. Specifically, *satisfaction (with the physical healthcare provider), switching costs, interoperability (effort), privacy (risk),* and *data control* have all been identified as key aspects of value perceptions in digital services markets and are essential considerations in the PHR market (Kaelber et al. 2008b; Kaelber et al. 2008a; Tang et al. 2006).

Satisfaction with the physical service that a digital service augments has been shown to have a *positive* impact on perceived value of the digital service (given that the digital service meets expectations). In the context of e-commerce, when the consumer views the online retail channel as convenient and speedy with readily available product information and customer service, satisfaction is often high (Burke 2002).

Switching costs have been shown to have *mixed* impacts on the perceived value of a digital service. Switching costs are often treated as a moderator between satisfaction and loyalty. For instance, high switching costs often create the appearance of loyalty even when a consumer is dissatisfied because the consumer cannot easily switch to an alternative (Lee et al. 2001). Yang and Peterson (2004) find that switching costs only play a significant role when a firm's services are considered above average and, at that point, switching costs have a positive moderating effect on satisfaction and perceived value. The authors go on to suggest that such an effect may occur because net utility is higher when a consumer has a positive perception of a company and switching may not outweigh the benefits of the current relationship.

Reduced *effort* has been shown to have a *positive* impact on decision making strategies (Todd and Benbasat 1994). In the context of this study, consumers are highly likely to consider the start-up costs of using a PHR (learning how to use the features and potentially importing medical records into the PHR) as well as the *interoperability* of medical records (i.e. the ability to transfer medical records from a provider into a PHR) (see Kahn et al. 2009 for more details). This dissertation suggests that PHR business models designed to reduce effort will result in positive perceptions.

Increased perceptions of *risk* have been shown to have a *negative* impact on the perceived value of a digital service (Featherman and Pavlou 2003; Pavlou 2003). In the context of PHRs, *privacy* is a key risk that has been suggested to be a major barrier for adoption (Kaelber et al. 2008a). This dissertation suggests that PHR business models with more privacy (lower perceived risk) will be preferred. Additionally, this dissertation acknowledges that *security* is also a potential risk, but suggest that competitors within the PHR market do not compete on security (e.g. low vs. high security) and, thus, there is little to no variation in commitments to security between business models. Privacy, however, tends to vary between business models.

Increased perceptions of *control* have been shown to have a *positive* impact on the perceived value of a digital service, especially in the context of self-service technologies (SSTs). Meuter et al. (2000) found that 8% of their interview cases reported that being in control was a motivating factor for "satisfying incidents" in the use of SSTs. This qualitative work substantiated prior empirical work by Dabholkar (1996a) finding that *expected control* (and expected enjoyment) have positive and significant impacts on the perceived quality of SSTs and the intention to use SSTs.

This dissertation proposes that while these individual factors (switching costs, effort, data control, and privacy), as well as satisfaction with the physical service provider, have all been shown to impact consumer preferences, research studies have not yet looked at the combined impact of such factors when packaged together as business models—especially outside of the e-commerce context and when the digital service is intended to augment the primary physical service provided by an entity. This dissertation suggests that these factors represent the primary "interrelated set of decision variables" (Morris et al. 2005) consumers face when weighing preferences for alternatives in the digital services market for PHRs.

2.5.3. Assimilation-contrast effects associated with adoption

Assimilation-contrast theory is a theory with behavioral roots suggesting that consumers tend to judge contexts based on their current mental models (Herr et al. 1983; Schwarz and Bless 1992; Sherif and Hovland 1961). Specifically, assimilation-contrast suggests that consumers assimilate toward products and services that are perceived as beneficial or positive within a context and contrast away from products and services that are perceived as unnecessary or negative with a given context (e.g. Meyers-Levy and Sternthal 1993).

Recent marketing and consumer behavior research has applied this theory to the evaluation of consumer preferences associated with the consideration of attributes or features of new or upgraded products (e.g. Bertini et al. 2007; Gill 2008). This research stream has generally found that assimilation-contrast effects are often present in purchase decision making and that feature enhancements must be close enough to a consumers' current mental model to induce assimilation-effects, but different enough to encourage abandoning the base product for the new or upgraded product. For instance, Bertini (2007) find that upgrading existing features (e.g. more memory on the same camera) is less likely to induce purchase intentions for an upgraded product than offering the base product with a brand new or innovative feature. For instance, Gill (2008) gives the example of adding Internet access to a standard television as a way to induce an assimilation-effect (the television is something we know well), but also enough incongruity (currently, Internet access it not ubiquitously available on TVs) to encourage purchase. Such findings confirm that "moderate schema incongruity" is often needed to find a balance between attracting consumers to a product and encouraging purchase (Meyers-Levy and Tybout 1989; Ziamou and Ratneshwar 2003).

What is not known, though, is how such findings translate to digital services. Products are tangible and, while variations of a product can be marketed toward different consumer segments, it is often the case that primary features are generally "fixed" and an upgraded version of the product must be purchased to obtain new features. For instance, a laptop computer may come with a standard amount of memory (e.g. 4 GBs) that can be optionally upgraded (perhaps to 8 GBs), but the overall feature (memory) is fixed to a particular range (e.g. memory available ranges from 4 to 8 GBs). As memory requirements expand beyond that range, a new laptop may need to be purchased. Digital services, however, offer a significant amount of flexibility not often seen in tangible products. Cloud-based digital services, for instance, are much more adaptable and flexible, can be directly tailored to specific consumer segment preferences, often have the ability to track and often upgrade features dynamically, without requiring repurchase (Gillett 2008; Wang et al. 2010). In this study, I extend assimilation-contrast to the context of digital services and consider how patient portals features impact user preferences.

2.6. Conclusions

The literature on adoption of innovations theory is robust, but has not yet fully considered the theoretical and practical implications of supply-side and demand-side adoption of information systems and digital services that extend firm capabilities and resources directly to consumers. This dissertation seeks to fill this gap by extending this theoretical base into the emerging context of *consumer information systems* and by evaluating new hypotheses, constructs, and influences not considered before in the literature. The next chapter begins with the supply-side context and subsequent chapters narrow the focus within the demand-side context.

Chapter 3. Understanding early adoption of patient portals by ambulatory care clinics

3.1. Introduction

Clinical patient portals provide patients with web-based access to medical records and often offer additional features such as collaborative disease management capabilities and patient-clinician e-mail/messaging (Demiris et al. 2008; Weingart et al. 2006b). While customer-facing, web-based portals have become ubiquitous in other sectors—such as banking, travel, and retail—portal adoption in healthcare has been slow. Approximately 9% of surveyed medical practices (i.e. ambulatory care clinics) in the U.S. had adopted some form of a clinical patient portal by 2010.[1] Recently, adoption rates of patient portals have been increasing due to policies directed towards Health Information Technology (HIT) (Blumenthal and Tavenner 2010), the demand for patient-centered care (Berwick 2009), chronic disease management concerns (Green et al. 2006), and physician technology adoption incentives (Town et al. 2004). This presents a unique opportunity to more fully understand the characteristics of early supply-side adopters of patient portals in a context where firms (ambulatory care clinics) are extending collaborative, digital services to consumers (patients).

Transaction-oriented portals seen in other industries, such as online banking portals, e-commerce portals, and online travel portals, are often designed to increase customer convenience and reduce costs associated with physical service

[1] Obtained from the Health Information Management and Systems Society (HIMSS) Health Information Infrastructure survey for 2010.

encounters. Patient portals, however, represent an opportunity for patients and clinicians to work together to achieve improved health outcomes through coordination of care, sharing of pertinent data and records, and continuous tracking of patient health indicators (e.g. blood-pressure, glucose levels) (Tang et al. 2006). Additionally, many other interesting factors make the adoption of patient portals by ambulatory care clinics unique and make the study of supply-side adoption of patient portals an interesting research avenue for Information Systems (IS) researchers. Competition in the health care industry, especially between ambulatory care clinics, is typically local. Services provided by different specialized ambulatory clinics can be very diverse, and, as a result, relationships with patients can range from one-time emergency visits to long-term repeated encounters and disease management. The type and amount of information associated with encounters with ambulatory clinics can be quite diverse and complex, especially given the local market focus and that resource and knowledge constraints are often distinct from those faced by large, centralized corporate entities. It is also interesting to note that despite competition at the local level, physician professional organizations and communities of practice often collaborate and learn from each other.

Traditional research on the adoption of innovative information systems by firms suggests that the most frequent supply-side adopters of innovative information systems are large organizations with plenty of slack resources, capabilities, and management support motivated by competition (Fichman

2004b). This is referred to by Fichman (2004b) as the ‘dominant-paradigm’ of the adoption of innovations and is based on a long-tradition of research in this area (e.g. Fichman 2000; Jeyaraj et al. 2006b; Rogers 1995). However, as ambulatory care clinics seek congruencies (“fit”) with technological and environmental changes, managerial decision making related to patient portal adoption is likely to be impacted by more than the size of the firm, the resources available, and competitive motivations. To my knowledge, though, contingent models have not been used to extend adoption of innovations theory into the context of patient portal adoption by ambulatory care clinics. Patient portals, in particular, represent an interesting nexus between supply-side services provided by ambulatory care clinics and complex demand-side needs of patients who often possess long health histories.

In addition to traditionally dominant firm characteristics, this study uses contingency theory as a base to hypothesize on specific factors associated with the adoption of patient portals by ambulatory care clinics (Fichman 2004b). Specifically, this dissertation examines how *demand contingencies* within the local market may favor or hinder adoption; how *service contingencies* associated with the type of relationship between the service provider and the patient may impact adoption; and how *learning externality contingencies* where local physicians and practices learn and influence each other may impact adoption of patient portals by ambulatory care clinics within the U.S. Specifically, this study asks the following research question:

Do contingent factors (demand contingencies, service contingencies, and learning externality contingencies) impact the adoption of clinical patient portals by ambulatory care clinics?

Using a cross-sectional dataset that merges adoption decision data reported by ambulatory care clinics in the U.S. and county-level demand and wage data, this study develops a sample-selection model of supply-side adoption. This study assesses the impact of demand contingencies associated with localization, service characteristics associated with coordination of care, and learning externality contingencies present among adopters in the same vicinity, on adoption decisions by ambulatory care clinics.

This study finds partial support for the impact of *demand contingencies* on patient portal adoption and strong support for the impact of *service contingencies* and *learning externality contingencies* on patient portal adoption. My findings suggest that the adoption and diffusion of patient portals may be impacted by more than traditionally considered 'dominant' firm characteristics and provide insights into how contingent factors affect customer-facing systems.

The remainder of this study discusses the research background; the development of my hypotheses and conceptual research model; the data and methods used to analyze ambulatory care clinic adoption of clinical patient portals; results; and, final thoughts in the discussion and conclusion sections.

3.2. Context

A customer-facing portal is defined generally by Smith (2004) as, "an infrastructure providing secure, customizable, personalizable, integrated access to dynamic content from a variety of sources, in a variety of source formats, wherever it is needed" (p. 94). For the context of this study, I suggest that a *patient portal* is a web-based application that provides online digital access to healthcare services and information provided directly by an ambulatory care clinic. Ambulatory care clinics are "health services that do not require overnight hospitalization" and are growing rapidly in the U.S. due to the fact that a significant amount of health services that used to require hospitalization, such as surgery, are now often performed in ambulatory care settings (Sultz and Young 2006, p. 129). In this study, I focus on clinical patient portals tethered directly to ambulatory care clinic Electronic Medical Records (EMRs). Such patient portals can provide clinical information, patient records, communication capabilities, and collaborative disease management functionalities.

In this study, I argue that ambulatory care clinics are making strategic technology adoption decisions to find congruencies with an environment characterized by shifting demand, a rapid pace of technology change (especially as patient portals become more pervasive in healthcare), and coordination of care as cost pressures increase and quality outcomes come under increasing scrutiny. Specifically, I suggest that the strategic decision made by an ambulatory care clinic to adopt a patient portal is made in the interests of maximizing organizational fit with such contingent factors. Following the framework by Weill and Olson (1989), which suggests that congruence is a multi-stage process, my study focuses on early stage contingencies associated with adoption decisions. This study considers the following contingencies: *demand contingencies* within the local market including levels of education and income, *service contingencies* associated with the unique nature of how ambulatory care clinics must coordinate care for patients trying to navigate a fragmented healthcare delivery system, and *learning externality contingencies* associated with professional and social influences over healthcare providers.

This study posits that *demand contingencies* have not had a dominant influence in the information systems literature due to the fact that internal and enterprise information systems are not often directly influenced by local consumer oriented factors. It is interesting to note, though, that online services, such as online banking, are also examples of customer-facing portals, but research in this area has primarily focused on consumer *acceptance* (e.g. Tan and Teo 2000) and correlated constructs such as *satisfaction* and *channel* preference (e.g. Devaraj et al. 2003). The same trend is seen in the marketing literature on self-service where constructs mostly focus on consumer *attitudes*, *acceptance*, and *satisfaction* (e.g. Dabholkar and Bagozzi 2002; Meuter et al. 2005). The very nature of this research that focuses on the demand-side suggests that demand factors are important considerations. Research has long shown that demand factors—such as higher levels of resources (e.g. more education, more income) as well as younger consumer segments with more venturesome personality traits—are often predictors of demand-side adoption (Gatignon and Robertson 1985). For instance, the digital divide, often characterized by demographic characteristics such as income and age, has been shown to directly impact access to health information available on the Internet (Brodie et al. 2000). Additionally, economic research has suggested that local clusters of business activity are likely to be influenced by demand factors (as well as by other firms and suppliers in the local area) (Porter 2000). Thus, supply-side adoption decisions are likely to be contingent on the specific local factors that define the market. Therefore, this study suggests that local demand contingencies, such as consumers' levels of education and income, will impact supply-side decision making related to adoption of patient portals.

This study considers *service contingencies* to be contingencies associated with the unique nature of the relationship between the ambulatory care clinic and the patient. While many cases of self-service portals being offered to customers exist—e.g. instances of online banking portals and e-commerce portals—such self-service web-portals are primarily provided to consumers to increase convenience and reduce transaction costs associated with physical service encounters. Ambulatory care clinics, however, are representative of a class of targeted, localized businesses that cater to a wider variety of customer (patient) needs, ranging from one-time, emergent needs to longer-term repeated coordination of care and relationship building. Relationships have been considered in the B2B context, especially in supply chain management, where strategic technology adoption can increase provider-supplier value and relationship quality through collaboration and information sharing (e.g. Chae et al. 2005; Tai 2011). For instance, Iacovou et al. (1995) found that Electronic Data Interchange (EDI) adoption is more likely between partners who are dependent on each other. This finding suggests that an ongoing relationship where information exchange is needed can motivate adoption of technology designed to streamline the flow of information. Additionally, the co-creation of value research stream suggests mutual benefits for firms who embrace the potential value of their consumers (e.g. Payne et al. 2008; Vargo and Lusch 2004) and collaborative efforts are often at the core of health provider and patient relationships. However, to my knowledge, the nature of such lasting relationships between a firm and the firm's core customers has not been identified in other studies as a key predictor of supply-side adoption.

Learning externalities have traditionally been known to occur when information is shared between firms either through communication channels, through the movement of employees between firms, or through relationships with suppliers who supply multiple firms (Stokey 1986). One study found that the simple presence of public information on other firms making investment decisions had an impact on rival firms' investment decisions, resulting in decision making contingencies (Décamps and Mariotti 2004). In the information technology adoption context, learning externalities (also called "spillover effects") have been shown to impact demand-side adoption decisions, as in the case of the adoption of home computers when learning spillover effects were assessed at the city level (Goolsbee and Klenow 2002), as well as supply-side adoption decisions as in the case of “social contagion” between medical providers seeking to adopt EMRs (Angst et al. 2010). Additionally, local clusters of business and business partners are known to influence one another through both competition and sharing of knowledge (Porter 2000).

While controlling for select ‘dominant-paradigm’ characteristics (e.g. ambulatory care clinic size, structure, management support, and competition), in the following section, this study presents specific arguments for my hypotheses related to the impact of *demand contingencies*, *service contingencies*, and *learning externality contingencies* on patient portal adoption by ambulatory care clinics.

3.3. Hypothesis development and conceptual research model

3.3.1. Demand Contingencies

The delivery of healthcare in the U.S. is not uniform across all consumer segments. Characteristics of the patient population directly affect the way providers deliver healthcare and the digital divide has been shown to impact health information access for disadvantaged populations (Brodie et al. 2000). More specifically, education, income and age have been found to impact health information access via technology. It has also often been observed that consumer segments with more resources have better access to care (Berk et al. 1995) and those who are older often have a greater need for health care services (Kovner et al. 2011). Those with more income, more education, and access to health insurance have been shown to have more opportunities to receive care and disparities between those with and without such resources can result in fewer opportunities for preventive care and a lack of a single source of care (Zuvekas and Taliaferro 2003). Uninsured individuals are less likely to receive regular care from primary care providers (Newton et al. 2008), more likely to have unmet health needs than their insured counterparts (Berk et al. 1995), and often suffer lower quality of life and poorer health outcomes (Kovner et al. 2011). It has also been reported that a majority (90.7%) of Americans over the age of 65 have at least one chronic condition and many (73.1%) had two or more chronic conditions, as of 2006 (Kovner et al. 2011). Additionally, urban environments with dense populations of healthcare specialists may deliver care differently than rural providers (Larson and Fleishman 2003).

There is marked trend in the industry towards patient-centered care, especially in urban settings (Devers et al. 2003; Leong et al. 2005), as it has been shown to improve outcomes in specific settings (e.g. Stewart et al. 2000). Re-aligning the clinical support (including the underlying information systems) to focus on patient needs is expected to improve the care process, the ability of patients to manage their conditions, and the coordination of care between episodes of clinical intervention (Ball and Lillis 2001; Bergeson and Dean 2006).

To address patient-centric needs, many providers are beginning to implement patient portals with the capability for patients to become active participants in their own health care (e.g. Hess et al. 2006). In two recent case studies of patient portal usage by actual patients, individual differences were found to have significant impacts on usage patterns. For instance, in the case of a patient portal targeted toward diabetes patients, lower levels of health literacy, less income, and older age were all negatively correlated with signing on to the portal (Sarkar et al. 2010). In another case of a more general use patient portal, those who signed on to the patient portal the most were primarily younger, healthier, and more likely to have health insurance (Weingart et al. 2006b). Thus, there can be marked differences in the demand for patient portals among economically advantaged and disadvantaged individuals. Finally, it has been shown that rural health providers often have slower health information technology adoption rates than their urban counterparts (Burke et al. 2002; Furukawa et al. 2008) and this too may impact the demand for patient portals in areas where HIT is less prevalent.

Overall, these findings suggest that *demand contingencies* can have both positive and negative impacts on care delivery and supply-side adoption of patient portals. Thus, ambulatory care clinics are likely to seek congruence with the environment they operate in while also seeking to improve health outcomes by encouraging more active and responsible participation of their patients in their own healthcare.

H1 ("Demand Contingencies"): *Demand characteristics will influence ambulatory care clinic Patient Portal adoption decisions.*

a) Ambulatory care clinics in areas where patients have more college education or more income will be more likely to adopt patient portals.

b) Ambulatory care clinics in areas where fewer patients have health insurance (uninsured), where there is a higher proportion of the population aged 65 or older, or located in rural areas will be less likely to adopt patient portals.

3.3.2. Service Contingencies

Ambulatory care clinics are heterogeneous with respect to the *type of service* they provide and this difference in *service characteristics* may have a direct impact on patient portal adoption decisions. Specifically, this study considers adoption decision differences between types of clinics that focus on longer-term relationships (i.e. primary care, specialties, and multi-specialties) in contrast with clinics that focus on immediate needs (i.e. urgent care clinics). This study posits that clinics with a primary focus on immediate needs (urgent care) will be less likely to adopt patient portals than primary care, specialty, and multi-specialty ambulatory care clinics where information dependence and patient-physician collaboration are essential elements of improved health outcomes.

In the medical context, *coordination of care* (and continuity of care) is a central focus of ambulatory clinic types that must operate in a fragmented delivery of care environment while trying to maximize positive health outcomes, per patient. This is especially true when dealing with patients with chronic conditions who must visit multiple providers (Bodenheimer 2008). A recent analysis of Medicare claims found a wide dispersion of care between multiple providers for patients and found that such dispersion increases with the number of chronic conditions (Pham et al. 2007). Patients receiving coordinated continuity of care (as opposed to episodic delivery of care) from primary care, specialists, diagnostic centers, and other provider types are more likely to benefit from guideline-recommended care (Atlas et al. 2009). Coordinating care for patients can have a positive impact on the quality of care within the following contexts: surgery patients (Gittell et al. 2000), use of primary care as a central point of coordination (Rothman and Wagner 2003), and specialty care through referrals (Forrest et al. 2000). Primary care can be an effective hub for disease management for those with chronic conditions (Casalino 2005; Rothman and Wagner 2003; Stille et al. 2005). Continuity of care therefore is a key consideration for physicians and patients alike in both primary care and specialty settings in a health system often characterized by episodic care delivery models (Bodenheimer 2008; Haggerty et al. 2003).

The following table summarizes key differences between urgent care clinics, primary care clinics, specialty clinics, and multi-specialty ambulatory care clinics and demonstrates key considerations when comparing care associated with immediate needs versus long-term coordination and continuity:

Table 1: Ambulatory care clinic types and characteristics	
Ambulatory Care Clinic Type	**Characteristics**
Urgent Care Clinic	• Addresses immediate needs (where hospital admission or severe trauma needs are not required) • Lower cost than hospital Emergency Departments • Often encourage patients to seek routine and preventative care at local primary care providers
Primary Care Clinic	• Often first point of contact in healthcare system • Encourage preventative care • Establish relationships with patients and monitor health progress (not just immediate needs) • Typically refer more complex cases to specialty clinics • Becoming more of a central point of coordinated care for patients with one or more conditions • Traditionally were self-employed physicians, but increasingly becoming part of group practices (multiple physicians) and part of Integrated Delivery Systems (IDSs) (multiple providers owned by one corporation)
Specialty Clinic	• Specialize in the treatment of one specific condition or area of the body (e.g. Neurology, Cardiology, etc.) • Physician requires specialized training in area of specialty • Typically treat patients with chronic conditions • Often requires careful patient medical record keeping and information tracking • Beneficial for patients seeking very specific disease management, but fragmented delivery of care can lead to coordination problems or conflicting advice
Multi-Specialty Clinic	• Multiple healthcare providers each offering specialty care within the same group of providers • Provides for more coordination and continuity of care for patients who need to be referred to specialists • Allows for easier sharing of patient records, information, and disease management
Sources: (Kovner et al. 2011; Sultz and Young 2006)	

In recent years, ambulatory health care providers have come under increasing pressure to improve patient health outcomes, and reduce costs while dealing with changes in the healthcare environment ranging from new policy to changes in insurance practices. Models of ambulatory care that embrace patient-centered care, advanced information systems, and maintain and support ongoing relationships with patients have been touted in the literature as solutions to U.S. health system fragmentation (e.g. Martin et al. 2004). It has also been suggested that evidence based medicine (Sackett et al. 1996), sustained patient relationships with providers (Starfield et al. 2005), and preventive care services can lead to better outcomes (Starfield et al. 2005). Finally, specialty practices "require a high degree of initiative to maintain accurate, information on patient being treated by multiple specialists" (Sultz and Young 2006). Such specialty providers serving chronically ill populations with a large diversity of diagnoses are likely to deliver care differently than urgent care providers. Rather than treat symptoms through episodic delivery of care, chronic disease management models are emerging that require the evaluation of therapeutic adherence, adjustment, and outcome evaluation longitudinally for each affected patient. However, such models often require support from information systems that assist with longitudinal tracking and analysis of data (Green et al. 2006).

H2 ("Service Contingencies"): *Ambulatory care clinics offering services specializing in coordination of care and ongoing patient relationships (primary care, specialties, and multi-specialties) will be more likely to adopt Patient Portals than those representing episodic delivery of care models (i.e. urgent care clinics).*

3.3.3. Learning Externality Contingencies

Healthcare providers within the same geographical area often have influences on each other, especially in regards to health information technology proliferation. Angst et al. (2010) find that social proximity between hospitals and the influence of hospitals considered to be at the forefront of technology adoption have significant impacts on others' adoption of EMRs. Miller and Tucker (2009) demonstrate that the quantity of EMR installations within the local area (Health Service Area, HSA, in their context) has an impact on the "network benefits" within the HSA and the adoption self-perpetuates by leading to more local adoption of EMRs. Finally, Rye and Kimberly (2007) suggest in their framework of HIT adoption that "connectedness" between providers and health organizations is likely to impact HIT adoption.

Additionally, organizations such as the Health Information Management and Systems Society (HIMSS), the American Medical Association (AMA), and the Association of American Physicians (AAP) provide opportunities for members to obtain the most recent clinical practice and health information technology information from centralized sources and other members. Such associations provide digital and printed content and typically have regular, local meetings for health providers to share information, network, and stay up-to-date on current trends. Such opportunities are especially valuable to providers considering HIT, as adoption is characterized by a number of known barriers (up-front financial costs, disruptions of workflows, learning curves, etc.) (Ford et al. 2006; Ford et al.

2009). The “communities of practice” among local providers encourages active sharing of information and experiences with the goal of improving best practices for the membership as a whole (Davidson and Heslinga 2006). In fact, it has been suggested that social interactions between physicians can have an impact on HIT adoption decisions (Bower et al. 2005; Zheng et al. 2010) and that feedback loops within the local physician community can have impacts on medical behaviors (Paina and Peters 2011).

This study seeks to extend this understanding of *learning externality contingencies* to the context of customer-facing patient portals where ambulatory care clinics are likely to influence each other, share information between providers, and trade best practices. This study suggests that geographical areas with a higher percentage of clinics who have adopted patient portals are likely to have significant impacts on adoption decisions made by other clinics in the same area.

H3 (“Learning Externality Contingencies”): *Learning externalities associated with Patient Portals will have a positive effect on Patient Portal adoption by ambulatory care clinics within the same geographical area.*

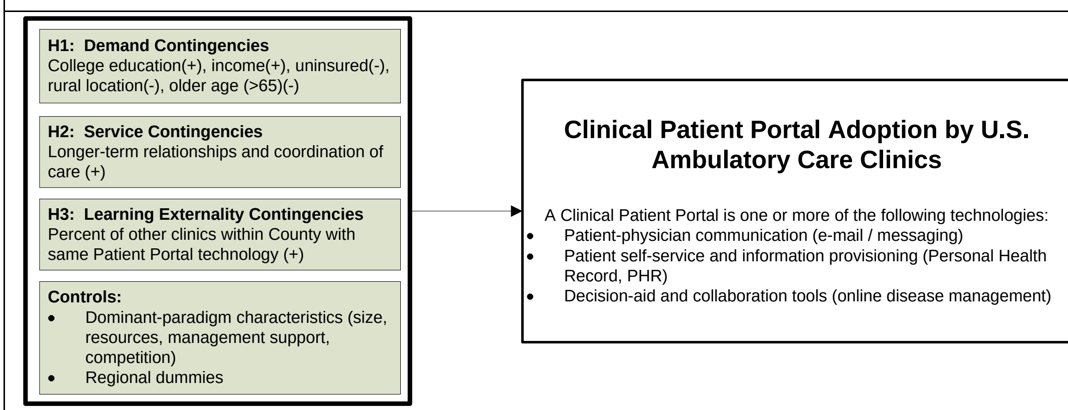
3.3.4. ‘Dominant-paradigm’ controls

Many studies have confirmed the ‘dominant-paradigm’ of the adoption and adoption of innovations within the context of health information technology adoption. Multiple studies positively associate hospital or ambulatory care clinic *size* (either number of beds or number of providers) with adoption (Angst et al.

2010; Furukawa et al. 2008; e.g. Kazley and Ozcan 2007b). Additionally, multiple studies suggest that when hospitals or clinics are part of a health system (owned by a single entity)—which is a proxy for *structure*, *resources*, and *capabilities*—diffusion and adoption is positively impacted (e.g. (Angst et al. 2010; Jha et al. 2009; Kazley and Ozcan 2007b)). *Competition* has been also been shown to impact HIT adoption (Burke et al. 2002; Kazley and Ozcan 2007b; e.g. Teplensky et al. 1995). Finally, *management support*, in the form of the Chief Medical Information Officer (CMIO), may have a positive impact on HIT adoption within provider organizations (Fretwell and Loftstrom; Leviss et al. 2006). In the model, this study controls for these 'dominant' supply-side characteristics as well as the U.S. Census regions a clinic is in—as also done in DesRoches et al. (2008) and Angst et al. (2010).

3.3.5. Conceptual Research Model

Figure 1: Conceptual research model



3.4. Data Sources

To examine the contingencies associated with patient portal adoption by U.S. ambulatory care clinics, a cross-sectional dataset was developed by merging data from Health Information Management and Systems Society (HIMSS) Analytics Database 2010, the Area Resource File (ARF) 2009/2010, and the Bureau of Labor and Statistics (BLS) May 2009. The HIMSS data is an annual survey of non-federal health facilities in the U.S. including both acute care hospitals and ambulatory care providers. The ARF data contains U.S. county-level census and health data, including ambulatory care data statistics for nearly all U.S. counties. The BLS data contains U.S. wage estimates for metropolitan and non-metropolitan areas. When merged, the combined data (HIMSS, ARF, and BLS) contains detailed information for 21,375 ambulatory care providers (9,165 of which have Ambulatory EMR) as well as census, wage, and health data for nearly every U.S. County.

3.5. Method

Given that patient portal adoption by an ambulatory care clinic typically requires an EMR to be implemented first,[2] this study considers the adoption of patient portals to be subject to potential sample-selection bias (based on whether or not the observed clinic has adopted EMR). Sample-selection bias occurs when dependent variables are observed for a non-random portion of the sample that is dependent on another, potentially observable variable (Heckman 1979). In the

[2] EMRs are not necessarily a pre-requisite for patient-provider e-mail, but only 111 (or 0.52%) of ambulatory care providers in my dataset had adopted patient-provider e-mail or messaging and *did not* have an EMR.

original development of the sample-selection correction model, wages of females were only observed for females that were in the workforce—an obvious bias when considering that many females chose not to participate in the workforce (Heckman 1979). Such bias can be accounted for by using a two-stage model that includes a sample selection correction.

This study adopts a non-linear sample-selection model that uses ‘probit’ models at both stages (sample-selection and full-estimation stages) referred to as a *bi-variate probit with sample selection*. This study considers five binary dependent variables—adoption of any patient portal (PP_ANY), adoption of disease management (DMGT), e-mail/messaging (EMAIL), Personal Health Records (PHR), or more than one of the three functions (PP_MULT). My sample selection variable is also binary and equals one if the clinic has adopted ambulatory EMR. Correlation is assumed between the two error terms in the two equations and maximum likelihood is applied for parameter estimation (Van de Ven and Van Praag 1981). The model is as follows and is based on the discussion of sample selection models by Vella (1998), the two-stage probit sample selection model used by Van de Ven and Van Pragg (1981), the discussion of sample-selection models by (Wooldridge 2002), and the guidelines and formulas discussion in the Stata manual (Anonymous2010).[3]

The econometric model assumes a latent, underlying relationship that is not observed:

[3] I utilized the ‘heckprob’ command in Stata for estimation.

Latent Equation: $$y_j^* = \boldsymbol{x}_j\beta + u_{1j} \tag{1}$$

Such that a binary outcome is observed, for each observation *j*:

Probit Equation: $$y_j^{probit} = (y_j^* > 0) \tag{2}$$

But, the dependent variable is only observed when (where ***z*** includes ***x*** and at least one exclusion restriction):

Selection Equation: $$y_j^{selection} = (\boldsymbol{z}_j\gamma + u_{2j} > 0) \tag{3}$$

Therefore, the econometric model is similar to a two-stage least squares model, but rather than assuming a linear relationship, it assumes non-linearity in both stages, requires at least one exclusion restriction (similar to an econometric instrument) in the selection equation (the first stage equation) that is not present in the second-stage equation, and assumes that the second equation has a dependent variable that is only observed when the $y_j^{selection}$ dependent variable (from the first stage sample-selection equation) is greater than one.

My empirical specification is an operationalization of this econometric model and explains EMR adoption by vectors of explanatory variables (*Z*) and controls (*C*) and explains adoption of patient portal systems by the same vectors (minus the exclusion restrictions), but patient portal adoption is only observed when EMR has also been adopted (EMR=1).

First-stage probit selection equation:
$$Prob(EMR = 1 \mid Z, C) = y_1 = (Z\gamma_1 + C\gamma_2 + u_1 > 0) \tag{4}$$

Second-stage probit equation:
$$Prob(PatientPortalSys = 1 \mid EMR = 1, X, C) = Y_2 = (X\beta_1 + C\beta_2 + u_2 > 0) \tag{5}$$

Where, Y_2 is one of the patient portal binary dependent variables that represent adoption of a patient portal (PP_ANY), adoption of one of the specific patient portal functions (DMGT, EMAIL, PHR) or more than one of the three patient portal systems (PP_MULT). y_1 is a binary representation of EMR adoption and represents the basis for sample-selection, X is a vector of exogenous explanatory variables, Z contains X as well as the exogenous exclusion restrictions (explained in detail in the following paragraphs), C is a vector of control variables derived from adoption of innovations theory and includes regional dummy variables, u_1 is the random error term in the first-stage, and u_2 is the random error term in the second-stage. This model assumes that the error terms are independent and have a bivariate normal distribution, but also that the errors are correlated (Wooldridge 2002) (p. 570). The correlation between the error terms is the reason for using sample-selection correction and the correlation between u_1 and u_2 is represented by ρ.

3.5.1. Exclusion Restriction

For a two-stage binary sample-selection model to be estimated without bias, at least one variable is needed in the first-stage model that is not present in the second-stage model (exclusion restriction) (Wooldridge 2002) (p. 569). However, if the exclusion restrictions are endogenous (correlated with both error terms) the model coefficients are subject to bias. Since the dependent variables are all information technology (IT) related, any variable that is also IT related is also likely to be endogenous (even if the IT performs a different function). Therefore, this study now considers ways in which EMR and patient portals are different and approach exclusion restriction selection by examining these differences.

This study considers EMR to be implemented by ambulatory care clinics to replace paper records and inefficient processes. Studies have suggested that EMRs are often adopted in the hopes of improving business process efficiency and productivity (e.g. Puffer et al. 2007), but I acknowledge that such efficiencies are not always realized (e.g. Poissant et al. 2005). Therefore, EMR adoption can be considered to be an information system designed with business process efficiency and improvement in mind, even if efficiencies do not always live up to expectations. In contrast, the clinical patient portals considered in this study are associated with patient relationship management, information provisioning, and health outcome collaboration. While EMR adoption can be moderated by operational costs to the clinical practices when EMR is implemented, these operational cost considerations would be less relevant to patient portal adoption by ambulatory care clinics. Therefore, this study considers the local wages of the jobs that might be replaced (or reduced) by EMR to be highly correlated with EMR, but not with patient portals, as good candidates for variables to be used as exclusions restrictions. The exclusion restrictions are valid as long as they are correlated with portal adoption only through the EMR variable.

It is suggested that EMR reduces the cost of medical transcription of patient records and staffing in regards to management of paper records (HIMSS 2007; Wang et al. 2003). Therefore, I obtained the wages of *Medical Transcriptionists* and *Medical Records and Health Information Technicians* for the BLS Area of each ambulatory care clinic within my sample. Due to the fact that absolute wages reflect labor expense and cost of living and that high wages are distinct from high prices in general (i.e. overhead such as rent), I adjust the wages by average wages for the entire BLS Area (for "All Occupations"). The unadjusted wages include cost-of-living, which is endogenous, so I normalize to isolate the wage effect. Therefore, my exclusion restrictions are defined as Adjusted Medical Transcriptionist Wage (ADJMTWAGE) and Adjusted Medical Records Wage (ADJMRWAGE) and are defined as follows (for each BLS Area):

$$ADJMTWAGE_{BLSArea} = \frac{MedTransWage_{BLSArea}}{AllOccupationsWage_{BLSArea}} \tag{6}$$

$$ADJMRWAGE_{BLSArea} = \frac{MedRecordsWage_{BLSArea}}{AllOccupationsWage_{BLSArea}} \tag{7}$$

Finally, one potential issue is that the variables representing *demand contingencies* come from the ARF data, which is aggregated by county. However, my full dataset contains data at the ambulatory clinic level. This means that the ARF data is repeated for every observation of an ambulatory care clinic within the same county. Therefore, it is possible that my results will be biased due to the non-independent nature of the grouped data as it is represented in my dataset. To correct for this issue, I take a conservative approach and cluster the standard errors by county.

3.6. Variables

The variables (and descriptive statistics) are described in more detail in the following table. Approximately 43% of ambulatory care providers have adopted ambulatory EMR within this dataset and approximately 22% of ambulatory care providers that have Ambulatory EMR have also adopted at least one patient portal system. The first two sections of the table (*selection dependent variable* and *dependent variables*) describe the dependent variables used in the two-stage sample-selection correction model. Sample-selection, as explained previously, is specific to whether or not a clinic has adopted Ambulatory EMR (EMR) and represents the first-stage of adoption. The second-stage of adoption, adopting a patient portal, is operationalized through the presence of at least one of the following patient-centric functions: *Disease management* (online, collaborative patient-clinician care for chronic conditions), *patient-clinician e-mail/messaging* (online communication between patient and clinician), and/or a *Personal Health Record (PHR)* (online medical records, visit summaries, and diagnostic results shared with patients).

The remaining sections describe the independent variables. *Demand contingencies* (Hypothesis 1) are operationalized as characteristics of the consumers within each U.S. County (from the ARF data). *Service contingencies* (Hypothesis 2) are binary variables representing four types of ambulatory care clinics where the reference category (urgent care clinics) represents transaction-based (episodic deliver of care) services. The remaining three binary variables represent ambulatory care clinic types that are typically associated with coordination of care and ongoing patient-provider relationships (primary care, specialty clinics, and multi-specialty clinics). *Learning externality contingencies* (Hypothesis 3) are operationalized as the percentage of adopters of the same practice type who have adopted a related patient portal system within the same County (similar proxies were used by Ayers et al. (2009) and Miller and Tucker (2009)).

To control for adoption of innovation (AOI) ‘dominant-paradigm’ characteristics, I have included proxies for size (log of the number of physicians), resources and capabilities (member of an Integrated Delivery System that provides care under a larger, corporate umbrella), management support (the presence of a Chief Medical Information Officer, CMIO), and the number of competitors (of the same practice type) within the same zip code (based on Garnick et al. 1987). The *region dummies* are from the U.S. census definition of regions and control for regional differences (Angst et al. 2010; used similarly in DesRoches et al. 2008). And, finally, the *exclusion restrictions* are variables correlated with EMR, but not directly with patient portal systems, and are used to remove (or reduce) bias in the two-stage model.

Table 2: Descriptive statistics for empirical model data						
Variable	**Description**	**Obs.**	**Mean**	**S.D.**	**Min**	**Max**
Sample Selection Dependent Variable						
EMR	1=Has Ambulatory EMR	21375	0.429	0.495	0	1
Dependent Variables						
PP_ANY	1=Has at least one of the three patient portal systems: DMGT, EMAIL, or PHR	9165	0.225	0.418	0	1
DMGT	1=Has online Disease Management	9165	0.125	0.331	0	1
EMAIL	1=Has patient-provider email or messaging	9165	0.209	0.407	0	1
PHR	1=Has Personal Health Record (PHR)	9165	0.111	0.314	0	1
PP_MULT	1=Has adopted 2 or 3 Patient Portal systems (DMGT, EMAIL, and/or PHR)	9165	0.148	0.355	0	1
Demand Contingency Variables						
COLLEGE	% pop. college educated	21374	23.896	9.449	0	63.700
LINCOME	Log of per capita income	21374	10.440	0.843	0	11.796
RURAL	1=Rural location	21375	0.162	0.368	0	1
UNINS	% pop. uninsured	21374	12.913	4.109	0	37.900
POP65	% pop. over 65	21375	13.465	3.505	0	36.188
Service Contingency Variables						
T_URG*	1=Urgent care / Emergency clinic	21375	0.035	0.183	0	1
T_PRIMCARE	1=Family practice, internal medicine, pediatrics, OB/Gyn, or primary care	21375	0.447	0.497	0	1
T_SPEC	1=Medical specialty practice or diagnostics provider	21375	0.430	0.494	0	1
T_MSP	1=Multi-specialty practice	21375	0.091	0.287	0	1
Learning Externality Variables						
PPANY EXTERN	Percent of same practice types (in same county) with any at least one of the three	21375	8.306	17.769	0	94.444

Table 2: Descriptive statistics for empirical model data						
Variable	**Description**	**Obs.**	**Mean**	**S.D.**	**Min**	**Max**
	(DMGT, EMAIL, or PHR) patient portal systems					
DMGT EXTERN	Percent of same practice types (in same county) with DMGT	21375	4.541	13.738	0	94.444
EML EXTERN	Percent of same practice types (in same county) with patient-provider e-mail or messaging	21375	7.755	17.407	0	94.444
PHR EXTERN	Percent of same practice types (in same county) with PHR	21375	4.011	12.900	0	91.667
PPMULT EXTERN	Percent of same practice types (in same county) with multiple (2 or 3) patient portal systems (DMGT, EMAIL, and/or PHR)	21375	5.436	15.212	0	94.444
EMR EXTERN (control)	Percent of same practice types (in same county) with Ambulatory EMR	21375	35.092	30.704	0	97.674
AOI Control Variables						
IDS	1=Practice is a member of integrated delivery system	21375	0.635	0.481	0	1
LPHYS	Log of num. of physicians	20694	1.207	0.995	0	6.686
CMIO	1=Parent hospital has Chief Medical Information Officer	21375	0.276	0.447	0	1
COMPBY ZIP	Number of same ambulatory practice types in the same zip code	21375	0.659	1.363	0	19.000
Regional Dummy Variables						
RGNNE*	1=Located in Northeast U.S. region	21375	0.219	0.413	0	1
RGNMW	1=Located in Midwest U.S. region	21375	0.337	0.473	0	1
RGNS	1=Located in Southern U.S. region	21375	0.294	0.456	0	1

Table 2: Descriptive statistics for empirical model data						
Variable	**Description**	**Obs.**	**Mean**	**S.D.**	**Min**	**Max**
RGNW	1=Located in Western U.S. region	21375	0.151	0.358	0	1
Exclusion Restriction Variables						
ADJMTWAGE	Medical Transcriptionist wage in BLS area adjusted by average wages across all occupations in the BLS area	20365	0.817	0.091	0.518	1.489
ADJMRWAGE	Medical Records and Health Information Technician wage in BLS area adjusted by average wages across all occupations in the BLS area	20365	0.823	0.087	0.574	1.259
* Reference category						

As indicated in the above Table, each of the three datasets aggregates data at a different level. HIMSS provides comprehensive *firm-level* data for a significant majority of ambulatory care clinics within the U.S, the ARF provides *county-level* data (by Federal Information Processing Standard, FIPS, state and country codes), and the BLS data is organized by Metropolitan Service Area (MSA), Non-metropolitan service area (Non-MSA), Metropolitan Division (MDiv), and New England City and Town Areas (NECTA). HIMSS and ARF were merged with corresponding FIPS codes and all but 5 observations matched directly. For those 5 'non-matched' observations, ARF data averaged for the state was used. BLS data was merged with the HIMSS and ARF data by matching MSAs, Non-MSAs, MDivs, and NECTAs with the corresponding FIPS codes. About 16% of the observations could not be matched directly with BLS data and, in those cases, BLS state-level data for the same time period, May 2009 (also available from the BLS), was applied.

3.7. Results

The following Table summarizes the results from the empirical analysis. The significance of the Wald-statistic (test of independent questions) in all two-stage models (bi-variate probit models) suggests that the unrestricted model (the model with the exclusion restrictions included) is favored over the restricted model. Additionally, the two exclusion restrictions (ADJMTWAGE and ADJMRWAGE) have significant and positive coefficients in the first-stage (selection) equation where adoption of ambulatory EMR (EMR) is the dependent variable. Due to some missing data for some variables (e.g. number of physicians was not available for all practices and some wage data was unavailable for some counties), 19,702 observations are used in the models (7.8% missing data). 11,225 observations are censored (i.e. do not have Ambulatory EMR); 8,477 observations are uncensored (i.e. have Ambulatory EMR and no missing data). Correlations between variables are within acceptable ranges. Psuedo-R^2 values range from 38.9% (PP_ANY) to 48.1% (DMGT and PP_MULT).

Table 3: Patient portal adoption two-stage model results						
	EMR	PP ANY	DMGT	EMAIL	PHR	PP MULT
	Probit (sel. eqn)	Bi-var. Probit	Bi-var. Probit	Bi-var. Probit	Bi-var. Probit	Bi-var. Probit
Demand Contingencies (H1)						
COLLEGE	-0.008*** (0.001)	0.000 (0.003)	0.007*** (0.002)	0.000 (0.003)	0.008*** (0.002)	0.008*** (0.002)
LINCOME	0.007 (0.013)	0.047 (0.040)	-0.003 (0.016)	0.04 (0.040)	-0.001 (0.022)	0.000 (0.028)
RURAL	0.210*** (0.046)	0.320*** (0.087)	-0.109+ (0.061)	0.297** (0.092)	-0.131* (0.052)	-0.035 (0.073)
UNINS	-0.024*** (0.004)	-0.015* (0.008)	0.013** (0.004)	-0.015+ (0.009)	0.014** (0.004)	0.012** (0.005)
POP65	-0.007+ (0.004)	-0.015+ (0.008)	-0.007 (0.006)	-0.012 (0.008)	0.005 (0.005)	-0.001 (0.005)
Service Contingencies (H2)						
T_PRIMCARE	-0.417*** (0.051)	-0.055 (0.085)	0.471*** (0.069)	-0.019 (0.097)	0.386*** (0.057)	0.411*** (0.062)
T_SPEC	-0.450*** (0.054)	-0.045 (0.088)	0.549*** (0.074)	-0.019 (0.100)	0.453*** (0.059)	0.458*** (0.064)
T_MSP	-0.162** (0.061)	-0.045 (0.092)	0.296*** (0.079)	-0.014 (0.099)	0.200** (0.066)	0.229** (0.071)
Learning Externality Contingencies (H3)						
PPANY EXTERN		0.042*** (0.002)				
DMGT EXTERN			0.036*** (0.002)			
EML EXTERN				0.043*** (0.003)		
PHR EXTERN					0.035*** (0.002)	
PPMULT EXTERN						0.036*** (0.002)
EMR EXTERN (control)	0.025*** (0.000)	-0.004* (0.002)	-0.027*** (0.001)	-0.005 (0.003)	-0.026*** (0.001)	-0.027*** (0.001)
AOI Controls						
IDS	0.028 (0.047)	0.190+ (0.100)	0.144 (0.094)	0.286** (0.105)	0.221** (0.072)	0.254* (0.118)
LPHYS	0.153*** (0.014)	0.117*** (0.027)	-0.076** (0.028)	0.132*** (0.029)	-0.080*** (0.023)	-0.058+ (0.030)
CMIO	0.168** (0.053)	-0.035 (0.087)	-0.172* (0.069)	0.014 (0.091)	-0.201*** (0.050)	-0.145* (0.064)
COMPBYZIP	-0.005 (0.008)	-0.011 (0.007)	-0.003 (0.005)	-0.010 (0.007)	-0.015* (0.008)	-0.003 (0.006)
Regional Dummies						
RGNMW	0.046 (0.031)	0.225* (0.089)	-0.052 (0.042)	0.262** (0.089)	-0.059 (0.041)	-0.021 (0.047)
RGNS	0.124***	0.090	-0.144**	0.100	-0.090*	-0.098+

Table 3: Patient portal adoption two-stage model results						
	EMR	**PP ANY**	**DMGT**	**EMAIL**	**PHR**	**PP MULT**
	(0.036)	(0.100)	(0.054)	(0.101)	(0.046)	(0.052)
RGNW	0.202*** (0.044)	0.216* (0.103)	-0.142** (0.050)	0.259* (0.106)	-0.225*** (0.051)	-0.136* (0.055)
Exclusion Restrictions						
ADJMTWAGE	0.355** (0.128)					
ADJMRWAGE	0.417** (0.149)					
Pseudo R^2	0.2495	0.389	0.481	0.403	0.459	0.481
Rho (ρ)		0.713	-0.980	0.650	-0.990	-0.970
Wald-stat p-val		0.003	0.000	0.045	0.000	0.000
Robust standard errors clustered by County in brackets; significant at ***p<0.001, **p<0.01, *p<0.05, +p<.10. [a] t_urg omitted. [b] rgnne omitted.						

3.7.1. Demand Contingencies

While higher per capita income (LINCOME) was not found to be associated with a higher propensity to adopt any of the patient portal systems, I do observe some positive effects of the percent of college educated individuals within a county on patient portal adoption. I observe that a higher percentage of college educated individuals within a county (COLLEGE) is negatively associated with EMR adoption, yet positively associated with a higher propensity to adopt disease management (DMGT), Personal Health Records (PHR), and multiple systems (PP_MULT). Therefore, these results provide weak partial support for H1a suggesting that college education and income would be positively associated with supply-side patient portal adoption. Discussion of why more education may negatively impact EMR adoption yet positively impact patient portal adoption is discussed later.

The effects for H1b suggesting that rural locations (RURAL), a higher percentage of uninsured individuals (UNINS) within a county, and a higher proportion of individuals over the age of 65 would be negatively associated with patient portal adoptions are mixed. A rural location (RURAL) positively impacts EMR adoption as well as adoption of at least one patient portal system (PP_ANY) and patient-provider e-mail or online messaging (EMAIL). However, RURAL is negatively associated with online disease management (DMGT) and PHR systems. Interestingly, though, a higher percentage of uninsured individuals (UNINS) within a county has a positive effect on the propensity to adopt DMGT, PHR, and multiple systems (PP_MULT), but has a negative effect in the selection equation (EMR) as well as a negative impact on EMAIL and PP_ANY, which is contrary to my hypothesis. Additionally, although a higher percentage of the population over 65 (POP65) has a negative impact on the propensity to adopt ambulatory EMR, the impact of POP65 on patient portal adoption is only marginally significant ($p<0.10$) for PP_ANY and insignificant for the remainder of the patient portal dependent variables. The implications of these findings are discussed later.

3.7.2. Service Contingencies

While all three types of ambulatory care clinics—primary care (T_PRIMCARE), specialties (T_SPEC), and multi-specialties (T_MSP)—are *less* likely to adopt ambulatory EMR than urgent care clinics (T_URG, the reference category), they are *more* likely to adopt online disease management (DMGT), PHR, and multiple systems (PP_MULT). Significant and relatively high magnitude positive effects are observed in all of these cases. Additionally, these results are consistent for each clinic type. Primary care (T_PRIMCARE) clinics are more likely to have disease management (DMGT), PHR, and multiple systems (PP_MULT). The same is true for specialties (T_SPEC) and multi-specialty clinics (T_MSP). These significant effects provide strong support for Hypothesis 2 ("Service Contingencies") in regards to the propensity to adopt patient portals for care delivery models focused on coordination of care and ongoing patient relationships as opposed to episodic delivery of care.

3.7.3. Learning Externality Contingencies

The highly significant (and positive) impacts of the adoption of other like clinics within the same county adopting the same patient portal system suggest strong support for learning externality contingencies. The adoption of at least one patient portal system by the same clinic type (PPANYEXTERN) had positive and significant impact on the propensity to adopt at least one system (PP_ANY). All other variables associated with externalities were found to have positive and significant impacts on patient portal adoption, within their respective models. These findings provide strong support for Hypothesis 3 ("Learning Externalities").

3.7.4. Control Variables

The 'dominant-paradigm' controls exhibited mixed results. Adoption of EMR is more likely for larger practices (LPHYS) and those that are associated with a Chief Medical Information Officer (CMIO), but does not appear to be impacted by competition within the same zip code (COMPBYZIP) or by membership in an

Integrated Delivery System (IDS). Membership in an IDS did impact the propensity to adopt at least one patient portal system (PP_ANY), multiple systems (PP_MULT), and EMAIL and PHR. However, the size of the practice (LPHYS) negatively impacted DMGT, PHR, and PP_MULT, but positively impacted PP_ANY and EMAIL. The presence of a CMIO negatively impacted DMGT, PHR, and PP_MULT. Finally, some regional effects were observed (e.g. some regions are more likely to adopt than others) and the significance of these regional factors suggests that inclusion of these dummies helps to reduce potential regional biases.

3.7.5. Summary of results

My findings are summarized in Table 3. The strongest support is observed for Hypothesis 2 (“Service Contingencies”) and Hypothesis 3 (“Learning Externality Contingencies”).

Table 4: Summary of results	
H1a (Demand contingencies): College Education (+) and Income (+)	College education weakly supported; income not supported
H1b (Demand contingencies): Uninsured (-), Rural (-), and Over 65 years of age (-)	Rural findings mixed; uninsured findings mixed; over 65 weakly supported
H2 (Service contingencies)	Strongly supported (for disease management, PHR, and multiple systems)
H3 (Learning externality contingencies)	Strongly supported (for all patient portal systems)
Control Variables: Dominant-Paradigm Characteristics	Mixed findings (effects are different for EMR vs. Patient Portal adoption)
Control Variables: Regional Dummies	Some regional effects are present

3.8. Discussion and Implications

This study sought to demonstrate that the supply-side adoption of patient portals by ambulatory care clinics is impacted by contingent factors. Specifically, using adoption of innovations literature and contingency theory as the theoretical base, I expanded upon the firm characteristics traditionally considered to be predictors of innovative, supply-side adoption (e.g. firm size, slack resources, competition, capabilities, management support, etc.) and examined how *demand contingencies, service contingencies,* and *learning externality contingencies* affect the propensity for patient portal adoption by ambulatory care clinics within the U.S. Additionally, I employed a two-stage empirical model that controlled for sample-selection, given that EMRs are often adopted prior to patient portals.

My primary finding is that ‘dominant’ firm traits are important indicators of patient portal adoption by ambulatory care clinics, but do not tell the entire story. Contingencies, particularly in regards to *service contingencies* related to ongoing patient relationships and coordination of care as well as *learning externalities* within the same geographical area have significant impacts on the propensity to adopt. To a lesser extent, I also observe some impacts from local *demand contingencies* that may play a small, but significant role in adoption decisions.

Some of my findings are supported by other studies that have demonstrated that relationships between firms and consumers are key business considerations (Sheth and Parvatiyar 1995), externalities are an essential consideration in HIT adoption (Ayers et al. 2009; Miller and Tucker 2009), and that demand characteristics are key indicators of innovation diffusion (Gatignon and Robertson 1985), especially in the context of the digital divide (Brodie et al. 2000). My study contributes by combining these considerations within the context of patient portal adoption and extends previous findings by demonstrating that such technology adoption is about the *link* between the supply-side and demand-side (and social interactions between providers), not just 'dominant' firm characteristics (Fichman 2004b) or technology 'acceptance' considerations (e.g. Venkatesh et al. 2003). Additionally, I utilize a two-stage model of adoption, which controls for sample-selection associated with Ambulatory EMR adoption. Current models in this context often employ structural equation models (e.g. Chatterjee et al. 2002). I demonstrate that the *bi-variate probit with selection model* is appropriate (and even necessary) for this context and suggest that future models of adoption in the context of customer-facing systems may need to control for the presence of pre-existing information systems (e.g. EMRs) to reduce coefficient bias.

3.8.1. Demand contingencies

I find that areas with a higher percentage of college educated individuals are more likely to have patient portal adoptions by ambulatory care clinics and do not find support for the impact of income on patient portal adoptions. These findings are somewhat consistent with previous research suggesting that populations with more resources are more likely to have better access to health care (e.g. Berk et al. 1995). However, with regards to income, it has been suggested that more of an emphasis on primary care can offset the disparity of healthcare delivery associated with lower income, and I may be observing such an effect in these results (Shi et al. 1999).

Interestingly, I find that a higher percentage of college educated individuals and individuals over the age of 65 has a negative impact on *EMR* adoption, yet college education has a positive impact on *patient portal* adoption and age only has a marginally significant negative effect in one model. Why the change in signs? It is possible that ambulatory care providers are comfortable with paper records, especially when dealing with an established base of patients with long histories. The many challenges of moving from paper to electronic records have been well-documented and incentives are needed to overcome such hurdles (Baron et al. 2005). Therefore, I believe these results provide support for recent policies that provide financial incentives to healthcare providers to adopt HIT.

Specifically, the Health Information Technology for Economic and Clinical Health (HITECH) provisions of the American Recovery and Reinvestment Act (ARRA) of 2009 are incentivizing and removing significant barriers to HIT adoption. As such barriers to the first stage of technology investment (EMR, in this case) are removed or reduced, the valuable second-order effects of extending patient portals to consumers are more likely to materialize. My findings suggest that overcoming the hurdle of EMR adoption is challenging, which is why the relationship between some demographic characteristics and providers types are negative for EMR adoption, but once the hurdle is overcome, adoption of a patient portal is much easier. I believe that these findings could motivate future research in the area of increasing returns to scope when barriers in the first stage(s) of adoption are reduced and potential improvements to health outcomes related to reaching out to patients through a follow-on investment (the patient portal).

I also note that a higher percentage of uninsured within a County is positively associated with some forms of patient portal adoption (contrary to my hypothesis), while negatively associated with other forms, and that rural location also exhibit somewhat mixed results. While unanticipated, these findings seem to reinforce some recent empirical research in this area. A recent study found that adoption of ambulatory EMR by physician practices is not significantly impacted by urban versus rural location and also did not find a significant impact of the presence of more uninsured on such HIT adoption decisions (DesRoches et al.

2008). Additionally, lack of insurance does not always result in being turned away from non-emergency care clinics and other options, such as prepayment, are also available (Weiner et al. 2004). Finally, I find that rural locations are more likely to adopt patient-provider e-mail/messaging and this could suggest that rural providers are seeking to increase convenience and provide alternative communication channels to patients in areas with limited provider availability. However, some of the more advanced technologies, including online disease management and PHRs, are less likely to be adopted by rural providers and this is consistent with prior research finding that rural providers often have slower HIT adoption rates (e.g. Burke et al. 2002; Furukawa et al. 2008).

3.8.2. Service contingencies

I find strong support for increased propensity of adoption among ambulatory care services specializing in primary care, specialty care, and multi-specialty care when compared to the propensity of adoption among urgent care clinics, particularly for online disease management, PHRs, and adoption of multiple systems. These findings suggest that information dependence and collaboration capabilities are key considerations when service delivery is focused on longer-term needs and establishment of relationships versus one-time transactions (i.e. immediate needs addressed by urgent care). This appears to be especially true for those who may have chronic conditions as online disease management and PHRs are targeted toward those with information intensive conditions, such as diabetes (e.g. Sidorov et al. 2002). Just as information systems established for information sharing and processing are beneficial to both buyers and suppliers in supply chain relationships (e.g. Subramani 2004) and for reducing uncertainty in cooperative partnerships between organizations (e.g. Bensaou 1997), so too can information sharing and collaborative health management tools be beneficial for the patient-physician relationship.

3.8.3. Learning externality contingencies

My findings related to *learning externality contingencies* show that 'social contagion' (Angst et al. 2010) is often present in consumer facing HIT adoption decisions and that adopters within the same geographic area often have influence over other potential adopters in the same area (Miller and Tucker 2009). Positive learning externalities may encourage adoption through information sharing and best practices emerging among physicians who share between themselves (Angst et al. 2010; Ayers et al. 2009). These findings provide support for developing initiatives targeted toward motivating adoption through peer influences.

3.9. Key findings and implications of chapter 3

This study has demonstrated that patient portal adoption is dependent on prior technology adoption and is influenced not only by the 'dominant-paradigm' of the adoption of innovations (Fichman 2004b), but also *service contingencies* associated with longer-term relationships and coordination of care, *learning externalities contingencies*, and, to a lesser extent, select *demand contingencies*.

The findings are particularly relevant from the perspective of real-options literature (e.g. Benaroch and Kauffman 1999) that suggests that return on investments are often gained with secondary investment decisions that build upon initial investments. Ambulatory care clinics that have adopted patient portals have exercised an option resulting from an initial and likely costly, investment into an EMR. The patient portal is a follow-on option that represents risks (e.g. Will patients actually use patient portals?) as well as many potential rewards (e.g. rural patients will have a more effective communication medium and chronic diseases are easier to manage). Therefore, there are uncertain returns based on demand factors and even externality effects. If other ambulatory care clinics in the same market area adopt patient portals, then consumers may find more benefit from adoption given the potential to electronically transmit and share records and information between providers. However, the unknowns associated with adoption by neighboring providers and the diversity of demand creates an environment where patient-portal adoption is potentially risky. Therefore, future research into whether and how EMR adoption may realize better returns-on-investment through follow-on investments (e.g. patient portal adoption) would be an interesting extension of this work.

The findings also provide support for examining multiple levels of innovation sophistication in patient portal adoption. Clinical patient portals are not just one system, but often a combination of systems including disease management, e-mail/messaging, and Personal Health Records. My models accounted for adoption of a single system or multiple systems. Therefore, I suggest that future models consider consumer technology adoption as a choice of innovation sophistication among a range of options that may aid various consumer segments in distinct ways.

I acknowledge that this study is limited by a single context (U.S. healthcare) and self-reported data. However, I believe that the model developed in this research could be extended to other industries where there is an increasing emphasis on information and relationship dependence between the firm and the consumer. I have demonstrated that dominant firm traits tell only part of the story and, as firms directly engage and rely on consumer input and collaboration, firms will need to strategically consider how consumer demand, relationship expectations, and the need to learn from others who have already adopted will impact the technology adoption decision making process.

Chapter 4. What can innovation adoption constructs tell us about patient perceptions of Personal Health Record (PHR) adoption?

4.1. Introduction

Little is known about what motivates patients to begin using Personal Health Records (PHRs). Consumers who are concerned about their health, but not yet chronically ill, may have ambivalent thoughts about PHR adoption. For PHR implementations to attain goals of increased patient involvement and streamlined workflows, patients must actively accept the PHR as a useful tool and voluntarily make use of the PHR on a regular basis.

PHRs are a clinically motivated, core set of technical capabilities that have the potential to drastically change patient-provider interactions, entice patients to be engaged in their care, improve records management, and support collaborative, patient-centered care models (Kaelber et al. 2008a; Robert Wood Johnson Foundation 2010; Tang and Lansky 2005; Tang et al. 2006). Despite the potential for major benefits, significant barriers to adoption currently threaten this emerging market (Detmer et al. 2008; Tang et al. 2006). Recent market surveys have identified privacy, security, perceived usefulness, and interoperability as primary PHR adoption concerns (Undem 2010). As a result, PHRs remain in the early adoption phase and questions persist as to what would motivate patients to overcome perceived adoption barriers.

This study examines patients' attitudes toward PHR adoption from an behavioral innovation adoption perspective. I suggest that further understanding of patient perceptions of PHRs (a core component of now emerging patient portals) is an essential foundation from which to build additional research programs that encompass a wide range of features. Through the use of a cross-sectional survey of 300 patients at two Mayo Clinic primary care clinics, I assess the impact of behavioral adoption of innovation constructs (Moore and Benbasat 1996; Moore and Benbasat 1991; Rogers 1995) on patients' intentions to adopt a PHR. Additionally, I assess the impact of health perceptions, demographics, risk aversion, and perceived barriers to adoption on intentions to adopt a PHR. A recent JAMIA article indicated the need to study PHR adoption factors such as patient attitudes, specific population segments, and adoption intentions (Kaelber et al. 2008a) and I begin to fill this gap by providing insights on how likely adopters differ from those who are resistant to PHR adoption.

4.2. Background and Significance

The American Health Information Management Association (AHIMA) defines a PHR as, "…a tool that you can use to collect, track and share past and current information about your health or the health of someone in your care" (AHIMA 2010). In this study, I follow a relatively strict interpretation of this definition and specifically consider a PHR to be used for personal (or caregiver) *medical records management*. Such clinically motivated PHRs can transform the tradition of episodic care to a continuous communication channel between physicians and patients. This can eventually lead to more patient involvement and, potentially, lower health care costs (Tang et al. 2006). However, PHRs require a long-term commitment to records and information management by consumers with considerable initial setup and learning costs (Robert Wood Johnson Foundation 2010). Therefore, PHR adoption is often viewed with skepticism.

Recent PHR market analyses suggest that early adopters of PHRs are often between 30 and 44 years of age, have a long-term health condition, visit the doctor at least 7 times per year, are Hispanic, live in the West, and are comfortable with Internet use (Lemieux 2010). PHR adoption is currently in the early adoption phase with less than 15% of respondents stating current usage or high usage intentions (Lemieux 2010). This is a relatively low adoption rate when considering that 78% of U.S. adults are reported as of 2011 to use the Internet and, of the 78% reported to use the Internet, many buy products online (71%), make travel reservations online (65%), use online banking (61%), and even look-up medical information online (83%) (Pew Internet Research 2012). Due to the relative newness of PHRs in comparison to other online services (such as online banking and e-commerce), my knowledge is limited in regards to how current health care consumers perceive PHRs beyond often cited privacy and security concerns (e.g. Krohn 2007; Raisinghani and Young 2008). Additionally, little is known about how current patients perceive PHRs and such knowledge is key to encouraging adoption—especially as more complex and feature-heavy patient-portals emerge.

4.3. Methods

This study is based on a survey offered to a convenience sample of patients coming in for office visits at two ambulatory care clinics over a period of five months from the end of 2010 to the beginning of 2011. Ambulatory care clinics represent the most likely entry point into the health system, are often considered as early adoption sites for PHRs, and represent a consumer segment with real (rather than hypothetical) health concerns. This study was exempted by the institutional review board (IRB) at Arizona State University and approved by the Mayo Clinic IRB.

All survey participants were provided with a brief overview of the scope of a PHR (i.e. medical records management and recommendations) and given specific information that highlighted the clinical aspects of PHR. The information provided pertained to the features available in the Mayo Clinic Health Manager. The specific screenshots and verbiage are available in the full copy of the survey instrument in the web-appendix. In addition to a PHR definition, the participants were alerted to two key features of PHRs: (1) clinical information organization, and (2) personalized recommendations. Thus, the survey participants were specifically prompted to consider the clinical convenience features of PHRs.

4.3.1. Survey question development and validation

I developed a 55-item survey with the goal of determining the PHR adoption intentions of respondents and their perceptions of innovation adoption constructs (Rogers 1995) (*relative advantage, compatibility, complexity, observability,* and *triability*). Additionally, the survey included questions in the following areas: demographics, health perceptions, risk aversion tendencies, interest in keeping medical records organized, likelihood of adopting if interoperability effort was reduced, privacy concerns, and confidence in security. Details are available in the following Table.

Table 5: Survey measures, sources, related statistics, and selected items

Measure	**Source**	**Mean**	**S.D.**	**α**	**Selected Items**
Behavioral Intentions	(Ajzen 1991; Venkatesh et al. 2003)	NA	NA	NA	Which of the following best describes your use of a Personal Health Record? I currently use a Personal Health Record (PHR) I plan to use a Personal Health Record (PHR) in the future I don't plan on using a Personal Health Record (PHR)
Health Concerns	(Ware et al. 1978)	NA	NA	NA	e.g. "In general, would you say your health is excellent, good, fair, or poor?"
Behavioral Adoption of innovation Constructs					
Relative Advantage (RA)	Adapted from (Moore and Benbasat 1991; Rogers 1995)	3.477	1.193	0.865	e.g. "PHRs are a better way to manage records and information than solely relying on healthcare providers and insurers to manage records and information for me."
Trialability (TR)	Adapted from (Moore and Benbasat 1991; Rogers 1995)	5.218	1.301	0.807	e.g. "I would prefer to use a PHR on a trial basis before making a full commitment."
Compatibility (CPT)	Adapted from (Moore and Benbasat 1991; Rogers 1995)	5.175	1.315	0.958	e.g. "Using a PHR would fit well with the way I like to manage my health records and information."
Complexity (ease of use)	Adapted from (Moore and	1.365	1.106	0.877	e.g. "I believe it would be easy to get a PHR to do

Table 5: Survey measures, sources, related statistics, and selected items					
Measure	**Source**	**Mean**	**S.D.**	**α**	**Selected Items**
(CPX)	Benbasat 1991; Rogers 1995)				what I want it to do."
Observability (OBS)	Adapted from (Moore and Benbasat 1991; Rogers 1995)	3.154	1.208	0.740	e.g. "I have seen other people use a PHR."
PHR Perception Constructs					
Desire to Organize Records	New items adapted from the "Involvement" construct (Zaichkowsky 1985)	5.442	1.065	0.410	e.g. "Given the opportunity, I would keep all of my medical records and information in one place."
Privacy Concerns	New items adapted from concepts in (Berman and Mulligan 1998)	4.880	1.652	0.928	e.g. "If I used a PHR, I would be concerned about the confidentiality of my personal health information within my PHR."
Security Confidence	New items adapted from concepts in (Win et al. 2006)	4.111	1.477	0.954	e.g. "I am confident that PHR security is strong and reliable."
Degree of Effort (Interoperability)	New items based on PHR adoption barriers (Undem 2010)	4.796	1.271	0.635	e.g. "I would *not* use a PHR if I had to manually enter my own medical records and information into the PHR."
Risk Aversion	(Cho 2006; Gray and Meister 2004)	4.484	1.405	0.900	e.g. "I am a cautious person who generally avoids risk."
NA = Not applicable; All constructs, with the exception of Behavioral Intentions and Health Concerns, were measured using a 7-point Likert scale ranging from 1-Strongly Disagree to 7-Strong Agree.					

The survey was pilot tested with 70 graduate students at a major U.S. university prior to being administered to the Mayo Clinic respondents (Baird et al. 2011). The survey was refined after statistically analyzing the results from the pilot test. Survey questions within constructs with low Cronbach's Alphas (used to assess validity of multiple survey questions measuring a construct) were improved by either rewording or selecting other available questions for the same construct.

4.3.2. Study setting and subject recruitment

The final, revised survey was provided as a voluntary, anonymous survey to patients over 18 years of age at two Mayo Clinic primary care clinics (a Family Medicine Clinic in Scottsdale, Arizona and an Internal Medicine Clinic in Rochester, Minnesota). A total of 300 patients were asked if they would voluntarily participate in the research study during the course of a clinic visit. Patients filled out the survey either in the waiting room, in the exam room, or at home and returned the survey by mail.

4.3.3. Data analysis

Of the 300 patients contacted, 210 provided responses (70% response rate). 28 of the 210 survey responses had missing data on one or more questions. Missing data was handled in Stata with listwise deletion. Post-hoc analyses concluded that non-response biases were not present with respect age or gender. Demographic results are presented in results section.

My data analysis began by assessing the impact of health perceptions (e.g. “During the past 3 months, how much has your health worried or concerned you?”) on the respondents’ intention to use a PHR (e.g. “Which one of the following best describes your usage of a Personal Health Record (PHR)?”). Table 3, in the following section, provides the health perception results and reports the results of chi-square tests of homogeneity. These results were obtained by calculating the Pearson's χ^2 and the Fisher's Exact test for each contingency table. The Fisher's Exact test is reported because some cells had a frequency less than 5. I believe that these tests are an accurate assessment of significance of health perceptions because the sample is randomly drawn from Mayo Clinic patients and is less than 10 times the population of patients.

I created composite scores for the PHR Perception constructs and calculated the percentage of respondents with an average score of 5 ("Somewhat Agree") or higher. The results are reported in the following section and further broken down as a comparison between those *who use a PHR* or *intend to use a PHR in the future* (Group 1) and those who *do not plan to use a PHR* (Group 2). Trends of composite scores were assessed with least squares regression and OLS estimation. The specifics of this trend analysis and the creation of the composite scores are also described in detail.

For the analysis of the behavioral adoption of innovation constructs (Rogers 1995), I created composite scores for each of the five innovation characteristics discussed previously. Each of the five composite scores were created by using three or more survey questions for each construct with a 7-point Likert scale response ranging from 1=Strongly Disagree to 7=Strongly Agree. PHR usage intention (3 = Currently use a PHR, 2 = Plan to use, 1 = Don't plan to use) was regressed on the innovation characteristic composite scores with the use of an 'ordered probit' regression in Stata to assess the impact of each construct on the likelihood of adopting a PHR. High correlation between relative advantage (RA), compatibility (CPT), and complexity (CPX) was a concern, but I corrected for this issue by running multiple models with and without the correlated constructs.

4.4. Results

Overall, I found that: 1) a majority of respondents "Plan to use a PHR in the future" (62%), 2) health perceptions do not have much impact on PHR adoption intentions, 3) the majority of respondents have a desire to keep their medical records and information organized (72%), 4) *relative advantage*, *compatibility*, and *complexity (ease-of-use)* have significant and positive impacts on adoption intentions, 5) *trialability* and *observability* do not have significant impacts on adoption intentions, 6) increased interoperability would increase PHR adoption intentions, and 7) privacy and security perceptions are major barriers to adoption.

4.4.1. Demographics

Most demographic variables can be considered to be average or close to average (gender, income, number of household residents) with the exception of age. National averages were obtained from the census bureau: females=50.7%, median annual income=$50,221, and persons per household=2.6. Approximately 76% of my sample was 50 years of age or older with a mean age of 57.7 years (including non-responders).

Table 6: Demographics of respondents (n=210)				
	Response	**%**	**Mean**	**St. Dev.**
Gender	1. Male	40%	NA	NA
Age	1. Under 20	0.5%	NA	NA
	2. 20 to 30	8%		
	3. 31 to 39	8%		
	4. 40 to 49	9%		
	5. 50 or older	76%		
Annual household income	1. < $20,000/year	3%	NA	NA
	2. $20,000 to $49,999	19%		
	3. $50,000 to $99,999	51%		
	4. > $100,000	28%		
Number of children (age <18) living at home	0	82%	0.319	0.794
	1	9%		
	2	6%		
	3	1%		
	4	2%		
Total household adults >70 years of age	0	69%	0.457	0.745
	1	17%		
	2	14%		
	3	0.5%		
Total number of household residents (including self)	0	0.5%	2.281	0.974
	1	14%		
	2	58%		
	3	15%		
	4	10%		
	5	1%		
	6	1%		

Note: Some percentages may not add up to 100% due to rounding. NA=Not Applicable

4.4.2. PHR usage intentions and health concern impacts

Current health perceptions and short-term (within the past 3 months) family health perceptions have a marginally significant ($p<0.10$)[4] impact on PHR usage when considering the significance of the Fisher's Exact test on the contingency

[4] This manuscript considers $p<0.05$ as statistically significant. We refer to p-values greater than 0.05 but less than 0.10 as "marginally significant."

tables (with health perceptions as row variables and PHR usage intentions as column variables). Short-term personal health concerns (within the past 3 months) health perceptions do not have a significant impact on usage intentions. These results suggest that health concerns have a limited influence on PHR adoption intentions.

Table 7: Health perception impact on PHR adoption intentions (n=210)

Characteristic	Response	Currently use a PHR	Plan to use a PHR	Don't plan to use a PHR	Total %
PHR usage intention	Total	6%	62%	32%	100%
Current personal health perception[a]	Excellent	46%	21%	25%	24%
	Good	46%	59%	70%	62%
	Fair	8%	15%	3%	11%
	Poor	<1% or 0%	5%	2%	3%
	Total	100%	100%	100%	100%
Past 3 months personal health concern[b]	A great deal	<1% or 0%	13%	3%	9%
	Somewhat	31%	22%	14%	20%
	A little	54%	45%	55%	48%
	Not at all	15%	20%	28%	23%
	Total	100%	100%	100%	100%
Past 3 months family health concern[c]	A great deal	23%	19%	6%	15%
	Somewhat	15%	33%	29%	30%
	A little	38%	34%	38%	35%
	Not at all	23%	14%	27%	19%
	Total	100%	100%	100%	100%

Note: Some columns do not total to 100% due to rounding.

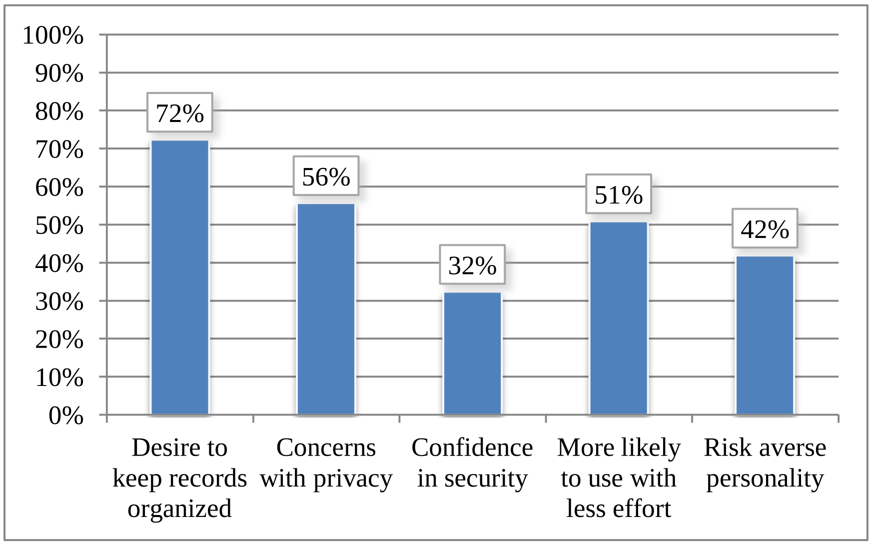
a: N=203, Pearson χ^2 p-value = 0.063, Fisher's Exact = 0.058
b: N=203, Pearson χ^2 p-value = 0.115, Fisher's Exact = 0.120
c: N=201, Pearson χ^2 p-value = 0.116, Fisher's Exact = 0.078

4.4.3. PHR Perception Constructs

As shown the next figure, a majority (72%) of respondents report a desire to keep their medical records and information organized. However, more than half (56%)

report concerns with privacy and about one-third (32%) report low confidence in security of records and information. This is the case even though less than half of the sample (42%) are risk averse. One encouraging sign is that about half of the sample (51%) would be more likely to use a PHR if it involved less effort.

Figure 2: Percent of respondents who "Somewhat Agree," "Agree," or "Strongly Agree" with PHR perception questions



Note: These percentages were calcuated by summing the total number of respondents with a composite score for each of the above listed constructs at greater than or equal to 5 and then dividing by the total sample size (N=210). The composite scores for each construct range from 1 to 7 (based on a 7-point Likert scale for all survey questions) and a composite greater than or equal to 5 suggests that the respondent at least "Somewhat Agrees" with the construct.

All respondents were then divided into two groups: those who either *currently use a PHR* or *plan to use a PHR in the future* (Group 1) and those who *do not plan on using a PHR in the future* (Group 2). Linear regressions were run using Stata to compare the trends between composite scores (e.g. *desire to keep records organized*, *degree of effort required*, etc.) between the PHR usage intention groups (Group 1 and Group 2). The results are shown in more detail in the following table. OLS estimation was used with the composite scores as the dependent variables and the following independent variables: dummy variables for PHR usage category (Currently use/Plan to use a PHR=0, Don't plan to use=1), personal health concern, family health concern, age, gender, annual household income, and total number of household occupants. While none of the health concern or demographic variables were significant in any of the regressions, the dummy variable for *don't plan to use a PHR in the future* was significant in almost all regressions (with *currently use/plan to use* as the omitted reference category). The results are as follows and suggest a significant difference between PHR usage intentions (*currently/plan to use a PHR* vs. *Don't plan to use a PHR*) for all composite scores except for *privacy concerns*. The significance was only marginal ($p<0.10$) for *privacy concerns* and this result suggests a potentially insignificant difference between groups for this construct. Additionally, I found a marginally significant age effect for *privacy concerns* and a marginally significant income effect for *risk aversion.*

Table 8: Trend analysis details					
	Desire to keep records organized	**More likely to use given less effort**	**Privacy concerns**	**Confidence in security**	**Risk aversion**
Dummy = 1 for those who "Don't plan to use a PHR in the future"[a]	-0.520** (0.168)	-0.854*** (0.206)	0.516+ (0.275)	-1.048*** (0.226)	0.934*** (0.227)
Personal health concerns	0.041 (0.082)	-0.021 (0.099)	0.028 (0.134)	0.115 (0.110)	0.144 (0.110)
Family health concerns	0.100 (0.0840)	0.150 (0.102)	0.093 (0.138)	-0.029 (0.113)	-0.000 (0.113)
Gender (M=1)	0.130 (0.155)	-0.130 (0.190)	0.120 (0.255)	0.030 (0.209)	0.303 (0.209)
Age	-0.013 (0.092)	-0.160 (0.160)	-0.259+ (0.151)	0.187 (0.124)	0.132 (0.124)
Annual household income	-0.095 (0.103)	0.084 (0.125)	-0.062 (0.170)	0.070 (0.139)	-0.233+ (0.138)
Total household residents	0.051 (0.084)	-0.067 (0.103)	-0.177 (0.138)	0.135 (0.113)	0.155 (0.114)
Num of obs	187	182	187	187	184
Prob > F	0.0275	0.0017	0.2994	0.0001	0.0011
R-squared	0.0831	0.1226	0.0452	0.1478	0.1259

Results reported from linear regressions using OLS estimation with composite scores for each of the PHR Perception constructs (i.e. desire to keep records organized, privacy concerns, confidence in security, degree of effort required, and risk aversion) as dependent variables; Standard errors reported in parentheses; ***p<.001, **p<.01, *, p<.05, +p<.10

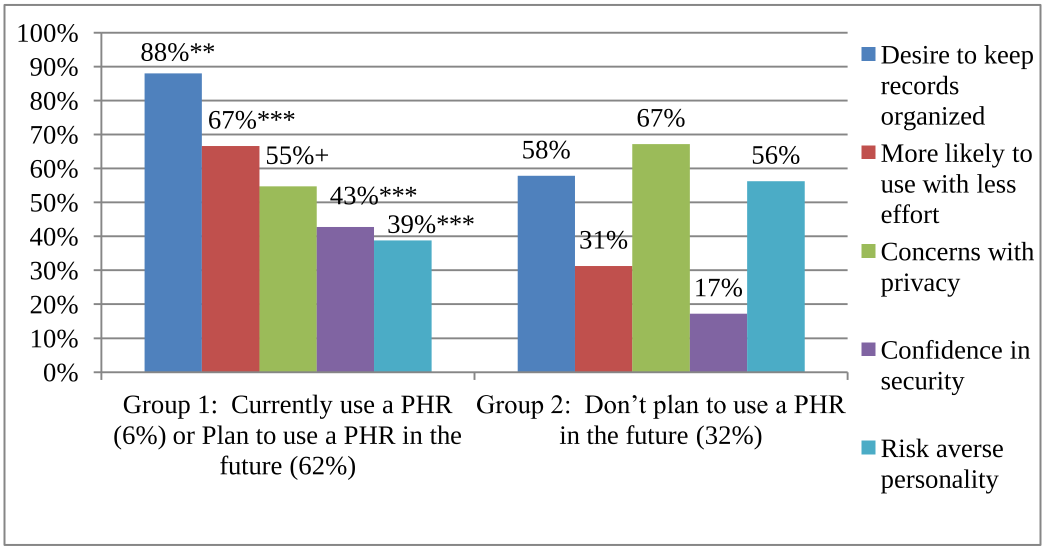
[a]The other group of respondents, those who either "Currently use a PHR" or "Plan to use a PHR in the future," make up the omitted category (e.g. Dummy = 0)

More generally, when the responses to these constructs were broken into two groups (i.e. those who intend to adopt a PHR vs. those who do not), as shown in Figure 2, the following findings emerged:

Profile for those with high adoption intentions (Group 1): Significant desire to keep records organized, somewhat confident with current security measures, more likely use if effort is reduced, less risk aversion than those who "Don't plan to use a PHR in the future," but only a marginally significant difference for privacy concerns.

Profile for those stating they "Don't plan on using a PHR" (Group 2): Often have a desire to keep records organized (but less so than those who currently use a PHR or plan to use a PHR in Group 1), but also have high privacy concerns and the lowest confidence in security. They also are highly risk averse and only 31% report being more likely to use a PHR if effort is reduced.

Figure 3: Comparison of PHR perception constructs between intended adopters and stated non-adopters



Significance levels reported as the statistical significance of the difference between Group 1 and Group 2 on each construct (more details available in the Technical Appendix); ***p<.001, **p<.01, *, p<.05, +p<.10

Note: This figure uses the same method as Figure 1 (reports those who "Somewhat Agree," "Agree" or "Strongly Agree" with PHR perception questions), but goes one step further by dividing the responses into two groups. For example, 88% of respondents in Group 1 had an average composite score of 5 or higher (i.e. "Somewhat Agree" or higher) for "Desire to keep records organized." This is a statistically significant difference (at p<.01) between Group 1 and Group 2 on this construct.

4.4.4. Adoption likelihood based on perceptions of innovation constructs

For the analysis of the patient perceptions of PHRs using innovation constructs, I apply an 'ordered probit' method. An ordered probit is based on the same principles as linear regression, but instead parameterizes the dependent variable as a non-linear normal probability distribution bounded by 0 and 1. The ordered probit requires that the dependent variable be ordinal and is used to measure the probability that one or more covariates have an impact on the ordinal dependent variable. In this case, PHR usage intention is the ordinal dependent variable and has the following, ordered values: 3=I currently use a PHR, 2=I plan to use a PHR in the future, 1=I don't plan to use a PHR. Table 4 presents the results of three models. All three models use the same method (the ordered probit) and the same dependent variable mentioned above. The only differences are the omitted constructs that were omitted due to high correlation.

The study sample views PHRs to have a *relative advantage* over other methods of organizing medical records (e.g. keeping paper records or letting the doctor's office manage the records), to be *compatible* with how they currently manage records, and see PHRs as relatively *easy-to-use*. Additionally, my results suggest that consumer segments that "Currently use a PHR" or "Plan to use a PHR in the future" see more *relative advantage*, *compatibility*, and *ease-of-use* (complexity) with PHRs than those who "Don't plan to use a PHR in the future." These results are shown in the following table. While not shown in the table, a follow-up marginal effects analysis at the mean of each outcome group suggests that the probability of being in the "Plan to use a PHR" or "Currently use a PHR" groups increases as *relative advantage*, *compatibility*, and *complexity (ease-of-use)* increases.

Age, income, and number of household residents did not significantly impact the intention to adopt a PHR in this sample. Gender, however, had a marginally significant impact in models 2 and 3 (i.e. females may be more likely to adopt).

Table 9: Impacts of innovation constructs and demographics on intentions to use a PHR[a]

	Model 1	Model 2	Model 3
	CPT omitted[b]	RA omitted[b]	RA and CPT omitted[b]
Relative Advantage (RA)	0.356** (0.105)	--	--
Trialability (TR)	-0.065 (0.074)	-0.098 (0.076)	0.001 (0.070)
Compatibility (CPT)	--	0.402*** (0.107)	--
Complexity (Ease-of-use) (CPX)	0.163 (0.111)	0.010 (0.117)	0.382*** (0.090)
Observability (OBS)	0.052 (0.077)	0.024 (0.078)	0.062 (0.076)
Gender (M=1, F=2)	0.280 (0.190)	0.317+ (0.190)	0.336+ (0.187)
Age	0.053 (0.113)	0.082 (0.112)	0.111 (0.111)
Household Income	0.107 (0.130)	0.119 (0.130)	0.151 (0.127)
Number of residents in household over 70 years of age	0.013 (0.136)	-0.014 (0.137)	-0.014 (0.134)
Total household residents	0.005 (0.104)	0.030 (0.104)	0.014 (0.102)
Number of Observations[c]	182	182	182
Prob > Chi^2	0.000	0.000	0.000
Pseudo-R^2	0.1391	0.1488	0.0997

[a] Results reported from ordinal probit regression. Standard errors are reported in parentheses. The dependent variable (PHR_USE) is ordinal and takes the form: 3 = Currently use a PHR, 2 = Plan to use, 1 = Don't plan to use); ***p<.001, **p<.01, *, p<.05, +p<.10

[b]Omission of constructs between the models is due to high correlation between RA, CPT, and CPX. By running three different models which include and omit the affected constructs, I correct for potential bias associated with such correlations. Full information on the correlations is available in the Technical Appendix.

[c]Missing observations due to omitted answers to one or more questions associated with the results.

4.5. Discussion and implications

My main finding suggests that providing an opportunity to use a PHR prior to commitment and observing others use PHRs are not likely to have significant impacts on PHR adoption intentions. This is notable given that this sample has an older average age (m=57.7 years), but not entirely surprising. These results can be interpreted as respondents prioritizing relative advantage, compatibility, and ease-of-use over simply observing others use a PHR or trying one out themselves. These findings demonstrate that the utility of a PHR is at an individual level and shows that social impacts are less important when considering, "Will a PHR help *me*?" Therefore, PHR education and advertising campaigns should focus on how easy a particular PHR is to use (specifically in regards to interoperability and import of records), how PHRs provide advantages over other methods, and how PHRs are not that much different than what many people already do with paper records, rather than solely focusing on the social desirability of centralizing records. Additionally, I believe these results suggest that PHR roll-outs should focus on simplicity in features. A phased roll-out of more complex features (e.g. patient portal features) could occur after adoption rates and usage rates reach a sustainable level where complexity will not lead to backlash or non-adoption.

I suggest that PHRs could diffuse at a similar rate as other online innovations (e.g. Kolodinsky et al. 2004) if consumers are sold on the benefits of PHRs while addressing privacy, security, and effort concerns. Early online services faced many similar adoption barriers but have now diffused broadly as a result of increasing convenience and ease-of-use of online services. However, one significant difference between transaction based online services (e.g. e-commerce) and PHRs is that PHRs represent a long-term interaction with health providers with complex informational requirements, rather than simple transactions or aggregations. Moreover, PHRs may require manual import or data entry of records. Therefore, patients are likely to use PHRs that do not require manual data entry of records or personal effort to import records from an outside system. This suggests that "tethering" a PHR to the current EMR system or providing an interface to an external PHR system will increase usage intentions.

Interestingly, I find that health perceptions only have a marginally significant impact on the intention to use a PHR, even though the older average age of my sample would intuitively suggest otherwise. Providers should not assume, therefore, that all patients, especially those with more severe conditions, will be automatically attracted to PHRs.

As mentioned in the results section, significant effort would have to be expended to convince those who "Don't plan to use a PHR" to actually use a PHR. Due to the fact that adoption often follows an S-shaped trajectory with critical mass being reached at the half-way point of diffusion, I suggest that adoption efforts should be aimed directly at those with an intention to adopt a PHR in the future. Given that this consumer segment is less risk averse and has a high desire to keep records organized, critical mass could be reached by focusing on this segment alone. At such a point, contagion effects, reduced barriers to adoption, and further technology and policy maturity may convince the skeptics to adopt.

I acknowledge the trend of moving toward more feature-rich patient portals (rather than only offering basic, clinical PHRs). Even though this trend is full of research potential, I believe my study makes an important contribution toward the understanding of how consumers perceive a *base* technology (the PHR), prior to the addition of many new features. Consumer behavior researchers have demonstrated that consumers generate mental “schemas” based on prior experience that are used to simplify information processing when presented with new products or features (e.g. Cohen and Basu 1987). Such research has since shown that being presented with a moderately different product or service than what one is used to is typically much more effective at bolstering perceived value than presenting an entirely new product or service requiring an entirely new way of thinking (e.g. moderate schema incongruity is more typically effective than extreme schema incongruity—(Kolodinsky et al. 2004). Therefore, gradually augmenting a product or service with new features may be more effective than hoping that a consumer will make a one-time mental jump to a full-featured, complex service.

In the context of this study, I believe a basic, clinical PHR to be moderately different than keeping medical records on paper, but not an extreme difference. Just as online banking has successfully encouraged adoption by starting small with a core set of features (e.g. view your account details online) and then expanding to a more full-featured model (e.g. online bill payment built on top of account management capabilities) (Gopalakrishnan et al. 2003), patient portals too can follow a similar path. In fact, I demonstrate that while privacy and security concerns are significant barriers, there is a sizable consumer segment attracted to the benefits of organizing their health information within a PHR, if the PHR is shown to have *relative advantage*, *compatibility* (with work style), and, importantly, *ease-of-use* (not overly complex).

4.6. Limitations

I acknowledge that my sample is relatively small (N=210) and may be biased by only surveying Mayo Clinic primary care patients. However, I believe that this sample represents a high utilization segment that is likely to have a significant impact on the health care system in the near future.

The higher average age of this sample could be considered a limitation, but according to data provided by the U.S Department of Health and Human Services, this age group (50+) represents one of the consumer segments with the highest utilization of health services and the most money spent on health care (Anonymous2011). Therefore, even though these results are not nationally representative with respect to age, they appropriately represent a high utilization segment that is likely to have a significant impact on health services (and, by extension, PHR adoption and diffusion) in the near future.

I acknowledge that PHRs are often delivered to consumers with varying underlying business models. *Integrated* PHRs are offered by third-parties (one example is Microsoft HealthVault) and have the ability to aggregate records from multiple, often unaffiliated, providers (Detmer et al. 2008). *Tethered* PHRs, on the other hand, are often offered by health care providers and are “tethered” directly to that provider’s EMR (Detmer et al. 2008). Therefore, one limitation of this study is that I did not explicitly distinguish between these different types of PHRs in my survey, but I found that reduced effort associated with medical records management can increase adoption intentions. More nuanced findings may be discovered if the consumer preferences associated with different varieties of PHRs are explored in depth, particularly in the case of the *tethered* PHR.

4.7. Future Research

Future research could expand the scope of this study into the patient portal context and explore how additional features (including administrative features) may affect adoption intentions (and usage as well as outcomes). My findings could also be extended by evaluating the effects of additional covariates on adoption (e.g. a wider age range, gender, race, region, PHR type, etc.) as well as by assessing adoption intentions of other high health care utilization consumer segments.

4.8. Conclusion

Many hospitals have begun to offer multi-featured patient portals in recent years, but research has not fully demonstrated whether or not consumers are fully ready to adopt the core clinical component of such portals—PHRs. This study suggests that current patients of ambulatory care clinics see many advantages in PHR use and that diffusion could increase if health providers emphasize the PHR benefits for the individual consumer. Strategies focused solely on emphasizing social and peer influences or only targeting patients with high concern for health may not be as effective. The findings of the study emphasize a focus on convenience and simplicity to stimulate adoption. PHRs are currently in the early adoption phase of diffusion, but could easily follow the positive trajectory of other recent innovations (e.g. online banking and e-commerce) if trust is increased and risks are mitigated early on. Despite facing many of the same obstacles, online banking portals have flourished by gradually exposing consumers to more and more capabilities (i.e. starting with basic transaction viewing capabilities and now offering online bill pay and much more). If full-featured patient portals are to flourish, I suggest that a fuller understanding of how consumers perceive the base product, the PHR, is essential and will provide a better foundation for future research into consumer perceptions of more advanced capabilities.

4.9. Key findings and implications of chapter 4

This chapter has demonstrated that PHR adoption intentions are high, even for an older aged sample, and are not significantly impacted by health concerns. My primary finding is that *relative advantage* along with *compatibility* of work style and *ease-of-use* are associated with positive intentions to adopt a PHR. Additionally, those who intend to adopt a PHR have different characteristics than those who do not intend to adopt including having a strong desire to keep records organized, less concern with security, are more likely to use PHRs if less effort is required, and are less risk averse. While these findings provide interesting behavioral insights above and beyond the standard behavioral characteristics associated with the adoption of innovations, PHRs are not homogenous with regard to business model. Therefore, an open question remains as to whether or not the business model of a digital service such as a PHR plays a significant role in adoption intentions. The next chapter addresses this question.

Chapter 5. Associating consumer preferences with business models for Personal Health Record (PHR) digital services

5.1. Introduction

Consumers are typically expected to adopt (or consider adopting) information systems without regard to the underlying business model. In essence, if a technology is perceived to be relatively advantageous, trialable, compatible, observable, and not overly complex (easy-to-use), adoption intentions should be positive (Rogers 1995). Yet, variations in the fundamental components of the business model a technology is based upon are also likely to have significant impacts on consumer preferences—especially in the now burgeoning consumer information systems market. Information systems adoption is usually predicated upon its usefulness and ease of use as a technology artifact. However, research in information systems has seldom considered the business models overlaying the technology artifact. With the advent and augmentation of traditional services through digitization, business models often become the differentiating factor in adoption decisions associated with technologies. I suggest that consumer preferences for competing digital services are heterogeneous when the underlying business models vary, even though the core technologies and features may be similar or based on increasingly commoditized content.

Substantial research has been conducted in the areas of behaviorally motivated predictors of consumer adoption and diffusion (Rogers 1995) and technology acceptance (Davis 1989; Venkatesh et al. 2003). Additional predictors, such as trust and risk (e.g. Pavlou 2003), have also been shown to impact acceptance. However, such models of intention to adopt and accept technologies are typically based on research questions applied to an entire category of information systems. For instance, TAM has been extended through additional constructs such as trust and risk that are theorized to impact consumer acceptance of *e-commerce* as a whole (e.g. Pavlou 2003). More recent research has refined the acceptance question to specific contexts —e.g. technology acceptance on mobile devices (Wu and Wang 2005) and acceptance of online banking (Pikkarainen et al. 2004)—but such research has not yet examined how business model selection may affect consumer preferences. Further, it has been suggested that new research models (other than TAM) be used to explore adoption and diffusion in contexts outside of the traditionally considered "organization" (Kim and Han 2009). Given the differentiation of business models in these contexts, researchers have yet to examine how business model choices are associated with consumer preferences.

Many digital services compete on business models by differentiating themselves on dimensions valued by consumers such as: privacy (risk), interoperability (effort), switching costs, data control, and even satisfaction of the physical service that the online service augments, such as preference for bricks-and-clicks—e.g. leveraging Barnes and Nobles physical stores with the Barnes and Nobles' e-commerce web site, versus an online only service such as Amazon.com (Gulati and Garino 2000). As a recent example, Google+ is fundamentally similar to other social media sites, such as Facebook, but competes primarily on privacy.

Anecdotally, it is interesting to note that underlying business models are also affecting consumer choice in a number of areas including: online music distribution, video streaming and rental services, news and media consumption, and even office productivity software (cloud-based vs. desktop based). Thus, consumers face complex choices in such digital markets and must weigh the competing values of multiple alternatives. Such choices are especially complicated when a digital service augments, but does not replace, a physical service. However, little is known about how an underlying business model may affect the demand-side preference for a given digital service.

The purpose of this study is to assess the association of business models with consumers' perceived value of a digital service when controlling for satisfaction of the physical service and traditional adoption of innovation characteristics of adoption (relative advantage, trialability, compatibility, complexity, observability) (Rogers 1995). I use the context of consumer adoption of free, online Personal Health Records (PHRs) and assess the intent to adopt between three PHR business models: 1) a free, online PHR offered by a standalone medical practice (i.e. a doctor's office that is not part of a group of practices), 2) a free, online PHR offered by a group of medical practices, and 3) a free, online PHR offered by a third-party (e.g. Microsoft HealthVault) without any direct connection to any medical practice.

It has been suggested that "without substantiated PHR use cases for patients, providers, and other constituents, and *business models* that clearly articulate the value of PHR, PHR adoption will not reach its full potential" (italics ours) (Kaelber et al. 2008a, p. 731). Additionally, a recent opinion article in The New England Journal of Medicine debates the advantages and disadvantages of PHR business models and suggests that intermediaries may disappear in this market as the benefits of PHRs tied directly to health care providers are realized (Tang and Lee 2009). In fact, recent market events appear to support this claim as Google Health (a third-party PHR not affiliated directly with any provider) has been discontinued due to low adoption rates (Andrews 2011). Yet, a direct competitor, Microsoft HealthVault, remains a strong presence in this market and the resilience of such a competitor suggests that the debate is still ongoing. Additionally, market and industry issues associated with PHRs are not only impacting the U.S. The use of PHRs within Europe still faces many barriers (Iakovidis 1998) and health technologies such as health-information exchange (HIE) and Electronic Medical Records (EMRs), which often are prerequisites to PHRs, still face barriers throughout the world (Jha et al. 2008).

In this study, I find that while perceived value (utility) of a PHR is high among the respondents, a *PHR offered by a group of medical practices* is preferred over the other business models. These findings suggest that consumers are acutely aware of how business models affect perceived value. The following sections go into more detail about the theoretical background used for this study, the differences between specific PHR business models, the development of my research model, my results, and, finally, discussion and conclusions.

5.2. Theoretical background and model development

Business models are typically considered to be fundamental drivers of supply-side strategy that provide the foundation (and direction) for attaining (and sustaining) economic value. (Morris et al. 2005) suggest the following definition: "A business model is a concise representation of how an interrelated set of decision variables in the areas of venture strategy, architecture, and economics are addressed to create sustainable competitive advantage in defined markets" (p. 727). Traditionally, firms deliver products or services to the market through some combination of unique resources, activities (within the value chain), and strategy (Hedman and Kalling 2003).

These fundamental principles also guide business model selection in the digital services market. Yet, the range of business models applied in the digital services market is quite broad (Timmers 1998) and research on digital markets tends to focus on supply-side economic value. For instance, discussions of the "digital economy" (Henry et al. 1999) and "digital markets" (Smith et al. 2000) are typically focused on how technology and firms will drive GDP growth (Henry et al. 1999) and on abstract pricing and market issues that affect market efficiency (Smith et al. 2000). It is well understood that economic principles and theories apply to digital markets (Shapiro and Varian 2000), but demand-side preferences associated with business models is currently an underrepresented research domain.

Shapiro and Varian (2000) suggest: "You can learn a great deal about your customers by offering them a menu of products and seeing which one they choose" (pg. 53). Yet, research into the influence of self-selection on markets is limited and often focused on analysis of various firm strategies for effectively dealing with segmentation and self-selection (Hanson and Martin 1990; e.g. Moorthy 1984). Which business models do consumers value in the in digital services markets? This remains an open question.

5.2.1. Demand-side preferences associated with digital services

Developing better "customer value" has been identified in the marketing literature as a potential next wave of competitive advantage seeking activities (Woodruff 1997). Woodruff (1997) contributes a definition of customer value: "Customer value is a customer's perceived preference for and evaluation of those product attributes, attribute performances, and consequences arising from use that facilitates (or blocks) achieving the customer's goals and purposes in use situations."

Adoption of innovations research suggests that five characteristics are associated with positive perceptions of innovations: relative advantage, triability, compatibility, complexity (ease-of-use), and observability (Rogers 1995). *Relative advantage* is the perceived benefits a consumer sees in the innovation (as compared to the current situation—e.g. going to a video store to rent a video versus renting it online). *Triability* is the impact that using the innovation in advance may have on adoption intentions. *Compatibility* is how compatible the innovation is with current patterns of behavior (or "work style"). *Complexity* is another term for ease-of-use and refers to consumer perceptions of the ease of learning and using the innovation. *Observability* refers to the influence of viewing others use the innovation prior to adoption. These characteristics have been applied to the adoption of IT within organizations (Moore and Benbasat 1996), adoption of information systems by small businesses (Thong 1999), and even evaluations of relative advantage of digital channels (Choudhury and Karahanna 2008). The long tradition of applying these behavioral constructs to information system innovations has generally empirically proven that each of these constructs typically have positive impacts on innovation perceptions. Therefore, in my model, I hypothesize that each of these constructs will have a positive impact on the perceived value (utility) of PHRs.

While these innovation characteristics have been shown to have positive impacts on demand-side perceptions of value, other research streams have demonstrated that additional factors can have an effect when choosing between alternatives. While many factors have been shown to impact consumer preferences (e.g. pricing strategies, network effects, affective commitment, calculative commitment, brand loyalty, resistance to change, social norms, policies, etc.), I focus on key factors pertinent to the business models currently offered in the free, online PHR market. Such an approach provides model parsimony and limits confounding variables while demonstrating the effect of the business model as a whole (rather than individual effects of factors studied in prior research). Specifically, *satisfaction (with the physical provider), switching costs, interoperability (effort), privacy (risk),* and *data control* have all been identified as key aspects of value perceptions in digital services markets and are essential considerations in the PHR market (Kaelber et al. 2008a; Tang et al. 2006).

Satisfaction with the physical service that a digital service augments has been shown to have a *positive* impact on perceived value of the digital service (given that the digital service meets expectations). In the context of e-commerce, when the consumer views the online retail channel as convenient and speedy with readily available product information and customer service, satisfaction is often high (Burke 2002). I suggest that satisfaction with the current health care provider (doctor's office) will enhance a consumer's perception of a PHR just as satisfaction with a bricks-and-mortar store may enhance the perception of the associated e-commerce channel.

Switching costs have been shown to have *mixed* impacts on the perceived value of a digital service. Switching costs are often treated as a moderator between satisfaction and loyalty. For instance, high switching costs often create the appearance of loyalty even when a consumer is dissatisfied because the consumer cannot easily switch to an alternative (Lee et al. 2001). Yang and Peterson (2004) find that switching costs only play a significant role when a firm's services are considered above average and, at that point, switching costs have a positive moderating effect on satisfaction and perceived value. The authors go on to suggest that such an effect may occur because net utility is higher when a consumer has a positive perception of a company and switching may not outweigh the benefits of the current relationship. Therefore, I suggest that consideration of switching costs will play an important role in a consumer's decision of which PHR business model to select.

Reduced *effort* has been shown to have a *positive* impact on decision making strategies (Todd and Benbasat 1994). In the context of this study, consumers are highly likely to consider the start-up costs of using a PHR (learning how to use the features and potentially importing medical records into the PHR) as well as the *interoperability* of medical records (i.e. the ability to transfer medical records from a provider into a PHR) (see Kahn et al. 2009 for more details). I suggest that PHR business models designed to reduce effort will result in positive perceptions.

Increased perceptions of *risk* have been shown to have a *negative* impact on the perceived value of a digital service (Featherman and Pavlou 2003; Pavlou 2003). In the context of PHRs, *privacy* is a key risk that has been suggested to be a major barrier for adoption (Kaelber et al. 2008a). I suggest that PHR business models with more privacy (lower perceived risk) will be preferred. Additionally, I acknowledge that *security* is also a potential risk, but suggest that competitors within the PHR market do not compete on security (e.g. low vs. high security) and, thus, there is little to no variation in commitments to security between business models. Privacy, however, tends to vary between business models.

Increased perceptions of *control* have been shown to have a *positive* impact on the perceived value of a digital service, especially in the context of self-service technologies (SSTs). Meuter (2000) found that 8% of their interview cases reported that being in control was a motivating factor for "satisfying incidents" in the use of SSTs. This qualitative work substantiated prior empirical work by Dabholkar (1996a) finding that *expected control* (and expected enjoyment) have positive and significant impacts on the perceived quality of SSTs and the intention to use SSTs.

I propose that while these individual factors (switching costs, effort, data control, and privacy), as well as satisfaction with the physical service provider, have all been shown to impact consumer preferences, research studies have not yet looked at the combined impact of such factors when packaged together as business models—especially outside of the e-commerce context and when the digital service is intended to augment the primary physical service provided by an entity. I suggest that these factors represent the primary "interrelated set of decision variables" (Morris et al. 2005) consumers face when weighing preferences for alternatives in the digital services market for PHRs.

It is unclear as to how the perceived value associated with adoption of innovation characteristics may explain consumer preferences when faced with heterogeneous underlying business models. Therefore, as digital services increasingly deal with commodity offerings (i.e. digital content and features that are similar between service providers), service providers seek to differentiate themselves with variations in their business models (and target markets). I seek to demonstrate that consumer preferences for the business models may be quite different even when they have similar preferences for the underlying technology characteristics.

5.2.2. PHR business models explained

PHRs are digital intermediaries between patients and health care providers that are optional for patients (and caregivers), but provide many potential benefits including: active patient participation in health care, aggregated data and knowledge from disparate sources, collaborative disease tracking, and continuous communication between patients and healthcare providers (Tang et al. 2006). Despite the expected benefits, PHR adoption faces many hurdles including: physician incentives, concerns about liability and trust, equal access to digital technologies (digital divide), technical concerns (such as a lack of interoperability standards), and business concerns (such as unknown market demand and value appropriation) (Detmer et al. 2008). Specifically, I consider the two primary business models currently dominating the PHR market:

Tethered PHR: A tethered PHR is usually connected directly to an Electronic Medical Record (EMR) system provided by a health care provider (usually a hospital or ambulatory care provider). A PHR *tethered* directly to a health care provider will be easy-to-use with little or no need to import medical records, but may not be able to aggregate medical records from other providers, specialists, or even medical devices. Such PHRs aggregate the service being provided (healthcare) with informational needs (medical records management) and can either be tethered to an individual practice or, alternatively, to a group of medical practices (affording additional data sharing capabilities).

Integrated PHR: An integrated PHR is a third-party PHR service, such as Microsoft HealthVault, which is typically not directly connected to any health care provider. Integrated PHRs are usually based on a cloud-computing model and provide consumers with secure, online applications that permit import, aggregation, storage, analysis, and augmentation of personal health records and information (or records and information for family members) as well as additional features. Healthcare consumers can create a free account within this online service and begin keeping track of their personal health information immediately. Such a business model is very attractive to those that must aggregate ("integrate") information from multiple sources, but it also requires additional effort to import records—especially given that medical information is not always easily shareable.

Recent articles debate which model will succeed with some authors suggesting that integrated PHRs hold the most promise for social welfare (e.g. Detmer et al. 2008) and other authors suggesting that intermediaries such as Google Health are only a temporary phenomenon and that tethered PHRs will ultimately succeed (e.g. Tang and Lee 2009). Therefore, I suggest that consumer preferences will play a pivotal role on the success and failure of various business models as their preferences are likely to tip the market in the direction most favorable to the majority.

The following table describes how these business models vary on the following dimensions: privacy, effort, switching costs, and data control. All PHR business models considered are available free-of-charge over the Internet with little or no variation in the amount of security offered.

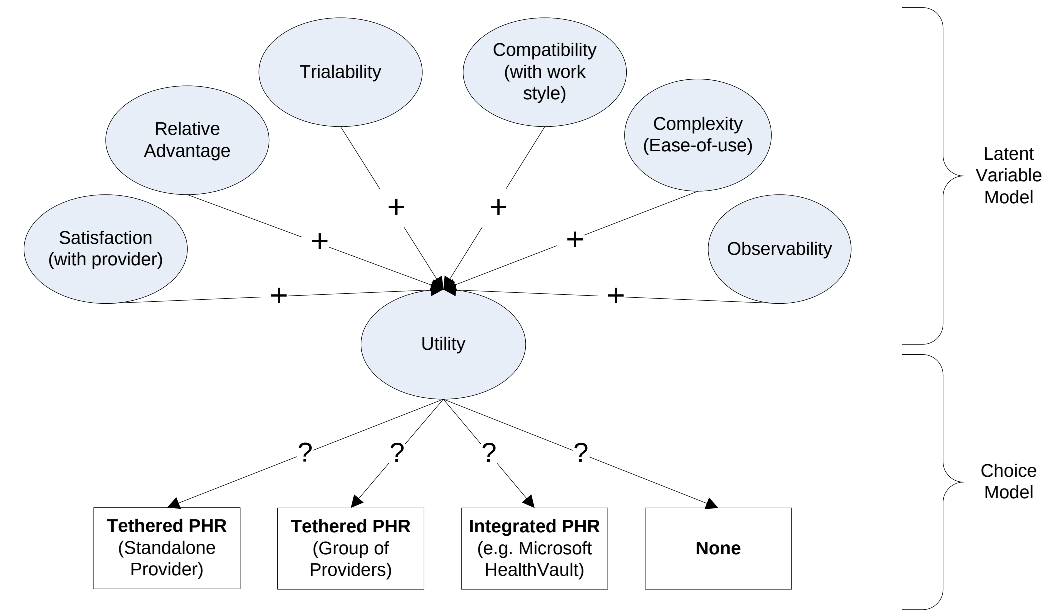
Table 10: PHR business models and related attributes

Attributes	Levels	**Tethered PHR** (to a standalone medical practice)	**Tethered PHR** (to a group of medical practices)	**Integrated PHR**
Privacy	High	X	X (within the group)	
	Medium			X
Effort (start-up costs; importing digital records)	High			X
	Low	X (for this practice only)	X (within the group)	
Switching Costs (transferring records to and from providers; learning how to use a new provider's PHR)	High	X		
	Low		X (within the group)	X
Data Control	Patient			X
	Provider	X	X	
Cost	Free	X	X	X
Delivery Method	Internet	X	X	X

The PHR business models presented in Table 1 form the basis for the choices consumers have when selecting which PHR adopt. Therefore, my conceptual model includes both standard adoption of innovation characteristics and a choice set of these PHR business models. The full, conceptual model is presented in Figure 1 and is composed of two (simultaneously estimated) parts (based on Ben-

Akiva et al. 2002): 1) the latent variable model and, 2) the choice model. The latent variable model is used to test whether or not the theoretically derived constructs and relationships have a positive impact on overall perceptions of PHR utility, without regard to underlying business model. This could be compared to asking digital consumers about their overall perceptions for online, digital music delivery and consumption, without regard to service provider. The second portion of the model, the choice model, seeks to elicit new understandings of how business model choices (based on the pertinent PHR business model characteristics described previously) affect consumer preferences. This is akin to evaluating the preference for delivery and consumption mechanisms for online music that vary by factors unrelated to the digital content (e.g. switching costs associated with the digital music service provider, control of the content, privacy capabilities, etc.)

Figure 4: Conceptual research model



5.3. Study results

5.3.1. Research Design

Data was collected through the use of a one-time (cross-sectional) survey e-mailed to patients who had recently completed medical appointments at a large, multi-facility, urgent care and primary care health services provider for a large university system in the western U.S. The survey was pilot tested in a large undergraduate class prior to final administration and received 661 responses. The survey instrument was refined prior to final administration based on statistical analysis of the data collected in the pilot test. The results of the choice model analysis in the final model were not significantly different than the choice model results within the pilot test, even though the average age in the pilot test was lower than that of the final sample. The final survey was e-mailed to 2,498 patients during a two-week period in the spring of 2011. The survey was conducted online and was sent out along with a request for filling out a standard patient satisfaction survey e-mailed to patients after every visit by the provider. 178 responses were received (7.1% response rate). While the response rate is a little low, this seems consistent with declining e-mail response rates, especially for longer surveys, reported by (Sheehan 2001), and is further explained by being combined with the request for the patient satisfaction survey. 44 surveys had missing data on one or more questions (24% missing data in final response set).

The sample characteristics are described in the following table. While this sample is somewhat younger than the national average and has a higher incidence of female respondents, these respondents represent actual patients of a large health provider with real (not hypothetical) health concerns. This population is also transient (mix of traditional and non-traditional undergraduate and graduate students who will need to find healthcare elsewhere once they graduate) and the health service provider emphasizes speed of care over relationship development (e.g. for typical cases, whichever physician, nurse practitioner, or physician assistant is available sees the patient). Therefore, the respondents represent consumers who have recently interacted with a health provider, but have not necessarily developed a strong relationship with that provider. It is also interesting to note that the respondents in this sample report high Internet use and relatively frequent travel. Both of these indicators may motivate PHR usage and further enhance my findings by demonstrating preferences among potential early (innovative) adopters.

Table 11: Sample characteristics[a]		
Characteristic	**Quantity**	**Percentage**
Current PHR usage		
I currently use a PHR	5	2.79%
I plan to use a PHR in the future	82	45.81%
I don't plan on using a PHR	48	26.82%
Personal Health Perception		
Excellent	29	16.20%
Good	74	41.34%
Fair	26	14.53%
Poor	6	3.35%
Age		
Under 20	21	11.73%
20 to 29	69	38.55%
30 to 39	26	14.53%
40 to 49	9	5.03%
50 to 59	8	4.47%
60 or older	2	1.12%
Gender		
Male	32	17.88%
Female	103	57.54%
Annual Income		
Under $25,000	67	37.43%
$25,000 to $49,999	20	11.17%
$50,000 to $99,999	25	13.97%
$100,000 or more	23	12.85%
Family Structure		
Single without children	90	50.28%
Single with child(ren)	3	1.68%
Spouse or partner without children	26	14.53%
Spouse or partner with child(ren)	16	8.94%
Internet usage (per week)		
None (zero)	0	0.00%
1 to 10 hours	17	9.50%
10 or more hours	118	65.92%
Medical insurance coverage		
Yes	124	69.27%
No	10	5.59%
I don't know	1	0.56%
Travel (in past 12 months)		
None (zero)	6	3.35%
1 to 5 times	80	44.69%
More than 5 times	49	27.37%

All research measures used within the survey are described below, in the following tables, which contain the full survey and full descriptions of the business models present in the choice set. The measures for the first-order, latent variables (satisfaction and adoption of innovation constructs) were all taken from previously validated scales and were adapted to seek general perceptions of PHRs. The choice model questions (the PHR business models) were developed by the authors for this study and were developed to highlight the unique properties of each business model along the dimensions of: effort, privacy, switching costs, and data control.

Table 12: Research constructs			
Construct	**Abbr.**	**Description**	**# of Items**
Theoretically-based constructs			
Satisfaction (with provider)[a]	SAT	The perceived satisfaction with the current health care provider.	3
Relative Advantage[b]	RA	The perceived advantage the respondent sees in using a PHR instead of an alternative (such as leaving the records on paper or letting the provider manage the records).	6
Trialability[b]	TR	The preference to use a PHR on a trial basis prior to making an adoption commitment.	3
Compatibility (work style)[b]	CPT	The perceived compatibility of a PHR with the current method of managing records (i.e. someone who already keeps organized records may be more attracted to a PHR).	3
Complexity (ease-of-use)[b]	CPX	The perceived ease-of-use associated with learning and using a PHR.	4
Observability[b]	OBS	The degree to which you have seen others use a PHR.	3
Choice Set (different types of business models currently offered in the PHR market)			
Tethered PHR (Standalone provider)	CH1	A web-based PHR that provides online access to pertinent records within the EMR of an individual medical provider (and only that provider).	1
Tethered PHR (Group of providers)	CH2	A web-based PHR that provides online access to pertinent records within the EMR of a group of medical providers.	1
Integrated PHR (e.g. Microsoft HealthVault)	CH3	A web-based PHR offered by a technology company (e.g. Microsoft HealthVault) and is not directly affiliated with a specific provider or group of providers and acts as an “aggregator” of information.	1
None of the above PHRs	CH4	The respondent would prefer not to use any of the PHRs described above.	1
[a] Source: Hausknect 1990 [b] Source: Moore and Benbasat 1991, Rogers 2003			

The individual research measures are described in the following table.

Table 13: Survey questionnaire items		
Construct	**Item**	**Measure**
Theory-based constructs [a]		
Satisfaction	SAT1	I am satisfied with my current health care provider(s).
	SAT2	What I get from current health care provider(s) *falls short* of what I expect.[b]
	SAT3	I plan to remain with my current health care providers(s).
Relative Advantage	RA1	I believe the benefits of using a PHR would be greater than the costs.
	RA2	There are more advantages than disadvantages when using a PHR.
	RA3	PHRs are better than only keeping health records and information on paper.
	RA4	PHRs are better than solely relying on health care providers to manage health records and information for me (or for my family).
	RA5	Using a PHR would save me (or my family) money.
	RA6	Using a PHR would save me (or my family) time.
Trialability	TR1	I would prefer to use a PHR on a trial basis before making a full commitment.
	TR2	Experimenting with a “demonstration” version of a PHR would be helpful.
	TR3	The opportunity to tryout various uses of a PHR *is not* available to me.[b]
Compatibility	CPT1	Using a PHR would be a good fit with my personal health record and information needs.
	CPT2	Using a PHR would fit well with how I manage personal health records and information.
	CPT3	If I used a PHR, I would *not* have to make drastic changes to the way I manage personal health records and information.
Complexity	CPX1	I believe that a PHR would be cumbersome to use.[b]
	CPX2	Using a PHR would be frustrating.[b]
	CPX3	Overall, I believe a PHR would be easy to use.
	CPX4	Learning to operate a PHR would be easy for me.
Observability	OBS1	I have seen other people use a PHR.
	OBS2	In my community or social group, many people use PHRs.
	OBS3	I have had plenty of opportunities to see a PHR being used.

[a] Instructions to respondents were: “Please CIRCLE the number which best represents your level of agreement or disagreement with the following statements.” Respondents were provided with a 7 point Likert scale ranging from 1 (Strongly Disagree) to 7 (Strongly Agree).
[b] Reverse coded in the analysis

To assess preferences for PHR business models, I applied the principles of a Discrete Choice Experiment (DCE). In a DCE, a set of choices, which vary by specific attributes, is presented to the respondent and the respondent must select which overall choice is preferred (or select “None of the above choices”) (e.g. Rubin et al. 2006). In my study, each respondent was randomly assigned to see descriptions of two of the three business models (which vary by the attributes and levels described previously) and always received the option to select a preference for “Neither of the above choices.” I opted to only ask respondents to choose between two business models due to the cognitive load (and amount of time) required to process the differences between more than two business models at a time. The full descriptions provided to the respondents for each of the business model choices are available in the following table. For the business models randomly displayed, each respondent was asked, “If you had to make a SINGLE choice, which ONE would you choose?” The respondent was then asked to choose between the two business models described or “Neither of the above choices.”

Therefore, one of the following three discrete choice sets of PHR business models was provided to each respondent to choose from (randomly ordered, with “Neither” always appearing as the last choice):

- A: {Tethered—Standalone, Tethered—Group, Neither}
- B: {Tethered—Standalone, Integrated, Neither}
- C: {Tethered—Group, Integrated, Neither}

33.9% of the respondents responded to discrete choice set A, 34.8% responded to discrete choice set B, and 31.4% responded to discrete choice set C.

Table 14: Discrete choice set of PHR business models[a]	
Choice	Description
Tethered PHR (Standalone)	You are a patient (or are a caregiver of a patient) at a medical practice (doctor's office) that is *not* part of a group of medical practices. This medical practice is offering a Personal Health Record (PHR) that ties directly to your patient records (or the records of those in your care) and information at *this* medical practice *only*. *Privacy:* High Privacy (HIPAA Compliant) *Effort required to get records into the PHR:* Little effort *Effort required to retains records when switching to a new provider:* High effort *Primary control of your data:* Health care provider
Tethered PHR (Group)	You are a patient (or are a caregiver of a patient) at a medical practice (doctor's office) that *is* part of a group of medical practices. This medical practice is offering a Personal Health Record (PHR) that ties directly to your patient records (or the records of those in your care) and information at this medical practice *AND* any medical practice within the group. *Privacy:* High Privacy (HIPAA Compliant) *Effort required to get records into the PHR:* Little effort *Effort required to retains records when switching to a new provider:* High effort (little effort required *within* the group) *Primary control of your data:* Health care provider
Integrated PHR	A Personal Health Record (PHR) is being offered by a big technology company (such as Microsoft or Google), but is *not* connected directly to any healthcare provider. *Privacy:* Medium privacy: HIPAA compliance does not always apply *Effort required to get records into the PHR:* High effort *Effort required to retains records when switching to a new provider:* Little effort *Primary control of your data:* You (as a patient or caregiver)
None of the above PHRs	N/A

[a] Respondents were randomly presented with two choices (selected from the three potential business models listed above). Instructions to respondents were to answer the following question:

If you had to make a SINGLE choice, which ONE would you choose? Please place an X next to your preferred choice:
_____ CHOICE #1: Online PHR attached directly to an *individual* medical practice
_____ CHOICE #2: Online PHR attached directly to a *group* of medical practices
_____ Neither of the above choice

5.3.2. Method

To estimate the impacts of business model choices on consumer preferences while controlling for latent perceptions, I applied a latent variable model integrated with a choice model (Ben-Akiva et al. 1998). Such a model simultaneously estimates: (1) the utility of a PHR (based on satisfaction and adoption of innovation latent constructs), and (2) the impact of utility on the preference for one of three PHR business models (or none at all). Estimation was performed using Structural Equation Modeling (SEM) with the use of MPlus (based on Temme et al. 2008). Alternative models were also tested and are described in the following section.

5.3.3. Data analysis and results

The means, standard deviations, and Cronbach's α (test of composite score reliability) as well as the correlations between the latent constructs are reported in Table 4 (all calculated within Stata). The constructs were developed as composite scores within Stata for the purposes of developing descriptive statistics. The alphas with values at about 0.80 and above suggest strong reliability. Trialability has an alpha somewhat lower (0.66), but is still within an acceptable limit. The correlations between the composite scores are all less than 0.80 while one correlation (the correlation between Relative Advantage, RA, and Compatibility, CPT) was in the marginal range of 0.60 to 0.80. This issue was reviewed in the final model by requesting modification indices within MPlus, but correlation between these two latent constructs was not flagged as a needed modification.

Table 15: Descriptive statistics and correlations for constructs									
	Mean	**S.D.**	**α**	**SAT**	**RA**	**TR**	**CPT**	**CPX**	**OBS**
SAT	2.37	1.29	0.84	1.00					
RA	4.91	1.29	0.89	0.02	1.00				
TR	5.29	1.11	0.66	0.16	0.48	1.00			
CPT	4.95	0.98	0.78	0.14	0.68	0.52	1.00		
CPX	-0.86	1.03	0.91	-0.09	-0.32	-0.17	-0.49	1.00	
OBS	1.97	1.09	0.83	-0.17	0.09	-0.25	-0.08	0.18	1.00
Note: These composite scores represent average perceptions on a 7 point Likert scale ranging from 1-Strongly Disagree to 7-Strongly Agree.									

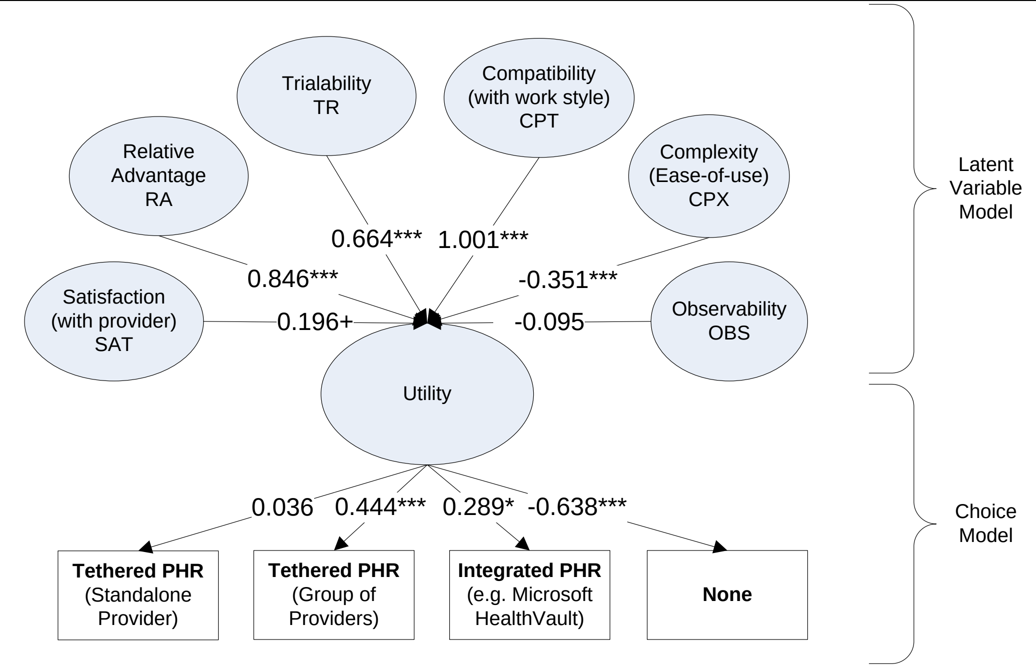
The means, standard deviations, and correlations between the discrete choice set items (the business models the respondents chose between) are reported in Table 5. The correlations were all below 0.80, but “None of the above PHRs” (i.e. the respondent would rather not use a PHR than select one of the available business models) was correlated with the other three choices at -0.46 (Choice 1), -0.61 (Choice 2), and -0.28 (Choice 3). Such correlation is to be expected, though, because respondents will either pick a business model or select none (i.e. two implicit “groups” of respondents). Therefore, the negative correlation between “None of the above PHRs” and the remaining choices suggests that most respondents preferred at least one of the PHR business models (which is affirmed in the latent variable model results).

Table 16: Descriptive statistics and correlations for PHR business model choices						
	Mean	**S.D.**	**CH1**	**CH2**	**CH3**	**CH4**
CH1: Tethered PHR (Standalone)	0.16	0.37	1.00			
CH2: Tethered PHR (Group)	0.24	0.43	-0.25	1.00		
CH3: Integrated PHR	0.07	0.25	-0.12	-0.15	1.00	
CH4: None of the above PHRs	0.53	0.50	-0.46	-0.61	-0.28	1.00

The standardized, SEM estimation results of the combined latent variable model and choice model are reported in Figure 2. The fit statistics suggest a relatively good fit (χ^2=150.113 at p<0.000 with 39 d.f., CFI=0.906, TLI=0.932, RMSEA=0.127). Within the latent variable model, Relative Advantage (RA), Trialability (TR), and Compatibility with work style (CPT) all had positive and significant (p<0.001) impacts on perceived utility associated with a PHR. These findings are consistent with prior research (discussed previously and outlined in the conceptual model). Satisfaction (SAT) also had a positive and significant impact on utility, but the significance was marginal (p<0.10). It is also interesting to note that Satisfaction with the health service provider is generally low (mean composite score of 2.37 on 7 point Likert scale ranging from 1-Strongly Disagree to 7-Strongly Agree). This suggests that the relationship with the healthcare provider was not a primary motivator for PHR preferences. Complexity (ease-of-use) (CPX) had a negative and significant impact on utility while Observability (OBS) had an insignificant impact on utility. These contrary findings are discussed further in the next section, but suggest that respondents do not see PHRs (as a whole) as easy-to-use and viewing others use a PHR is not likely to have a significant impact on utility perceptions.

In the second portion of the model, the impact of general PHR utility on PHR business model preferences was estimated. I find significant differences between preferences for the business models included in this study. Specifically, I find: 1) an insignificant preference for PHRs tethered to standalone medical providers, 2) a positive and significant preference for PHRs either tethered to a group of medical providers or integrated PHRs, and 3) a negative and significant preference for "None of the above PHRs." In addition, the magnitude of the preference for a *PHR tethered to a group of medical providers* is a little less than twice that (0.444 at $p<0.001$) of the preference for *integrated* PHRs (0.289 at $p<0.05$) while the preference for *None of the above PHRs* is negative and exhibits the highest magnitude of all preferences (-0.638 at $p<0.001$).

Figure 5: Results for the research model



Only latent variables and PHR business model choices are shown; Standardized regression coefficients reported; ***p<.001 **p<.01 * p<.05 +p<.10; Fit statistics: χ^2=150.113 at p<0.000 with 39 d.f., CFI=0.906, TLI=0.932, RMSEA=0.127

Additional models were estimated that replaced the latent utility variable with a binary variable representing those respondents who had positive adoption intentions (1=Currently use a PHR or plan to use a PHR in the future) versus those who did not plan to use a PHR in the future (value of 0). In these additional models, the results of the choice model were not significantly different from the choice model results reported. The results of that latent variable model (satisfaction and behavioral adoption of innovation constructs) were somewhat different in that many of the latent variables did not have a significant impact on adoption intentions. However, in all models, the Relative Advantage (RA) latent variable always had a positive and significant impact and this suggests overall positive utility associated with PHR adoption (without regard to the underlying business model).

My findings are summarized in the following table and suggest that the majority of the latent constructs have significant impact on utility. Additionally, my findings suggest that when modeling the impact of utility on business model preferences, increased utility results in a primary preference for a *PHR tethered to a group of medical providers* and secondarily to an *integrated PHR.*

Table 17: Summary of findings

Constructs / Choices	**Predicted**	**Finding**
Satisfaction (with provider)	+	+
Relative Advantage	+	+
Trialability	+	+
Compatibility (with work style)	+	+
Complexity (ease-of-use)	+	-
Observability	+	n.s.
Choice 1: Tethered PHR (Standalone Practice)	Exploratory	n.s.
Choice 2: Tethered PHR (Group of medical practices)	Exploratory	+
Choice 3: Integrated PHR	Exploratory	+
Choice 4: None	Exploratory	-

The last question on my survey asked if respondents had any additional comments about PHRs. A subset of these comments is available for review in the following table. Interestingly, the comments range from positive perceptions, “I have been waiting for something like this for years,” to skepticism, “My concern would be the online management of medical records and the possibility that the information could be lost, stolen, or misused.” These comments illustrate the challenges associated with picking a specific business model underlying an information system. PHRs as a whole may appear useful and effective, but there are obvious concerns with potential business practices.

Table 18: Subset of respondent comments
Respondent comments to the question, "If you have any final comments about PHRs, please enter them here:"
No matter what, it has to be easy for the physician and provider, using portals with consumer consent. Everything has to be seamlessly linked or tethered, so EMRs are quickly and seamlessly linked into a PHR portal for the patient and, with consent, the doctor for real-time access. World Medical Card and Healthy Circles are the two I'm using.
Without patient input you cannot have a complete Healthcare Record. PHRs would be a great tool for patients to input information outside the clinical setting.
Biggest barrier to PHR's seems to be compatibility with multiple systems. If I can only access my information from a primary doctor, then it's more work than it is worth. However, if it gives me a total view of my health, i.e. data on recent physicals, pharmacy records, insurance and billing, and referrals and records gathered from doctors outside of primary health provider is key.
I have been waiting for something like this for years. As a young adult, I have moved around a lot and have some conditions which would be helpful to have all of the information in one place (my cat's included!) I hope this becomes available to ASU students.
Wouldn't pay for a service like this
Example of neo-liberalism in medical care in America, shifting the personal responsibility to individual consumers/diffusing culpability for medical decisions. Really appalling privacy violation potential and absolutely disgusting idea for private care. Would absolutely support a program like this in a less corrupt system.
Never heard of this but it sounds awesome, I would give it a try since right now I am not very organized when it comes to my records.
I have never heard of a PHR. My concern would be the online management of medical records and the possibility that the information could be lost, stolen, or misused. Are these available through insurance companies, doctor's offices, or a third party source? What are the implications associated with who controls a patient's comprehensive medical records?
I believe my health records have always been a document in a doctor's office. I have requested sections of this document and had to pay for the Xeroxing-if it were online, this would mean I could access it when I needed to. Would I be able to if I moved to a foreign country? Would this record be protected like my tax information, not available to prescription drug companies looking to pay for patient information to zero in on a new market? Are they protected now? If not, why not?

5.4. Discussion and conclusion

This study sought to demonstrate that while satisfaction with a physical service provider (a medical practice, in this context) and behaviorally motivated constructs associated with the adoption of innovations (relative advantage, trialability, compatibility, complexity, and observability) may predict perceived utility of an information system (PHR), the business model the information system is built upon is likely to have a significant impact on consumer choice. I believe business models to be an important consideration in digital service adoption and diffusion due to the recent explosion of consumer-oriented information systems (e.g. online music distribution, online video rentals and purchase, news and media consumption, social media, cloud-based services, etc.), but little research focus on the impact of varying business models on consumer choice in technology adoption contexts.

My main finding is that while utility of PHRs is high among my sample (as suggested by the positive and significant impact of many of the latent constructs known to be associated with positive perceptions of innovations) and overall satisfaction with this particular health service provider is generally low, a *PHR tethered to a group of medical providers* is preferred over the other business models. This particular business model exhibits high privacy, low (or zero) initial effort to import records into the PHR (the medical group typically does it for you), high switching costs (if switching to a provider outside of the group—low switching costs within the group of providers), and limited data control (the medical group controls the data). This is an interesting finding for two reasons: 1) It demonstrates that the adoption of digital services is influenced not only by initial perceptions, but also by considerations of the amount of effort required and the potential for exploitation, and 2) The integrated model, suggested to have the most potential for social welfare (Detmer et al. 2008; Tang and Lee 2009) and potentially better suited to a more transient population (especially one with low service provider satisfaction), is less preferred by consumers.

Specifically, these findings suggest that, within the PHR market, consumers prioritize privacy and effort over data control (i.e. prefer higher privacy and lower initial effort, but find limited data control acceptable) while preferring middle-ground with switching costs and interoperability by indicating a preference for PHRs tethered to *groups* of medical practices that can share records and information between practices.

In regards to privacy, these findings demonstrate that consumers recognize the complex trade-offs inherent in needing to share data (with medical providers) while limiting the potential for exploitation by third-parties, such as entities desiring to use personal health information for marketing purposes (discussed further in (Wang et al. 1998) and (Baird et al. 2012 (Forthcoming))). The preference for a *PHR tethered to a group a providers* could be explained as a balance between privacy and data control: the data is not shared with third-parties (outside of the provider-patient relationship) and, in trade, some of the control is relinquished by consumers (patients).

In regards to effort (and interoperability), a preference for a *PHR tethered to a group of medical providers* suggests that consumers are minimizing effort associated with interoperability (transferring records between providers) in trade for additional switching costs (as compared to using an *integrated PHR*, which has little to no switching costs when a patient moves to a new medical provider). However, switching costs are lower than those associated with a *PHR tethered to a stand-alone provider* (especially for patients who switch often or see multiple providers). This again suggests that consumers prefer middle-ground when considering such trade-offs. Therefore, just as firms often seek middle ground in B2B relationships (e.g. Clemons et al. 1993), consumers may be exhibiting similar preferences. This could be an area for future research.

Secondarily, I find a that PHRs (as a whole) are not perceived as being particularly easy-to-use and that observing others use a PHR is not likely to have a significant impact on perceived utility. This sample, however, uses the Internet frequently (about 66% use the Internet 10 or more hours per week), plans to use PHRs in the future (about 45% report planning to use a PHR in the future), and is relatively young (about 64% are under the age of 40). Therefore, while many may not have seen others use a PHR yet (likely due to the fact that PHRs are in an early diffusion stage and only about 3% of this sample report PHR usage) and this may explain the insignificance of observability (OBS), technology aversion is not likely to explain their skepticism with ease-of-use. Consider, though, some of the comments: “Everything has to be seamlessly linked or tethered,” “Would this record be protected like my tax information, not available to prescription drug companies looking to pay for patient information to zero in on a new market?," "Biggest barrier to PHR's seems to be compatibility with multiple systems." These comments suggest that consumers may be considering much more than how easy it is to use certain features within an information system and are delving deeper into more personal concerns associated with actual usage (effort, privacy, interoperability, etc.). Therefore, I suggest that the negative impact of ease-of-use on utility indirectly suggests that the factors I included in the consideration of my business models (privacy, switching costs, effort, and data control) are likely to be simultaneously considered by consumers when picturing themselves using a digital service.

My study is limited by a relatively low sample size, a survey conducted in a limited set of locations, and a specific context (PHRs) which may limit generalizability. However, I believe this research to be an important first-step in considering "packages" of supply-side offerings (i.e. business models that package together certain assumptions about factors such as privacy, effort, switching costs, and data control) that consumers consider when selecting a specific digital service. Future research could extend these findings in other contexts and could also consider additional business model properties such as pricing and economic strategies (e.g. Porter 2001). Additionally, comparing and contrasting emerging business models versus traditional business models (such as comparing current online banking practices with newly emerging aggregated models such as Mint.com, or by comparing competing digital delivery and consumption models between companies such as Blockbuster, Netflix, and Amazon Instant Video) could yield additional insights.

5.5. Conclusion

I find that prior technology adoption research and constructs need to be extended when considered in the digital services context. In particular, consumers are voluntary adopters (rather than employees who are often required to adhere to mandates) and are sensitive to factors not traditionally considered in adoption research. Given that consumer choice is complex in digital markets characterized by many alternatives, research into how consumers perceive the underlying factors between such alternatives is paramount to our understanding of diffusion and adoption in this new area of consumer-oriented information systems. Especially poignant to consumer choice are business model factors that affect non-monetary costs and benefits of using the digital service. This study demonstrated that business models varying on the dimensions of privacy, effort, switching costs, and data control significantly affect consumer choice in a market where the technology is relatively homogenous. Therefore, business models are a key component to understanding how consumer preferences may impact technology adoption and diffusion.

5.6. Key findings and implications of chapter 5

This chapter has addressed a key demand-side question that has remained unanswered in the digital services context: How do business models affect consumer preferences, especially when trade-offs are present? I find a significant impact of business models on consumer preferences and find that PHR consumers look to balance the trade-offs by seeking middle ground. In this specific case, the middle ground is a PHR tethered to a group of healthcare providers. What is not known, though, is how consumers will react to heterogeneity of features offered in such a digital services. Patient portals are now being offered with increasing frequency by ambulatory care clinics and include features that vary from front-office self-service (e.g. schedule an appointment online), to back-office self-service (e.g. use a PHR to view and track medical records and information), to clinical service innovation (e.g. capability to have online consultations with a clinician). The following study uses assimilation-contrast theory to ascertain how consumer preferences for feature bundles are impacting adoption intentions of digital services that augment physical services.

Chapter 6. Assimilation-contrast effects associated with patient portal feature preferences

6.1. Introduction

A large health system in the southwest U.S. recently decided to begin offering patient portals to their patients. The opportunity for innovation was enormous. This would be the first time that the health system offered such digital services to patients and they were excited to explore a new channel for communication, collaboration, and information provisioning. Yet, rather than entice patients to use the new portal by offering exciting and innovative clinical features—such as patient-provider e-mail and messaging or even the ability to conduct online video consultations with clinicians and share data collaboratively—the health system decided to focus on more administratively oriented capabilities typically associated with self-service. For instance, in the new patient portal, patients will have the ability to request appointments online, search for doctors within the directory, and view test results. Why not innovate? Why not try to leverage the patient portal to provide innovative new ways to communicate with patients, manage health information, and collaboratively manage chronic conditions? Even in the online banking context, which is typically associated with self-service, many providers offer the ability to communicate with a banker or customer service representative online (either through chat, messaging or e-mail). Even more innovative features are becoming available through services such as Mint.com that aggregate financial information, provide useful graphs and recommendations, and use advanced data analysis to assist consumers with financial management. Why, then, in the healthcare context are patient portals (and Personal Health Records—PHRs) not embracing such innovation, especially when they are late entrants to the overall market for digitization of consumer services? This study explores this interesting phenomenon by evaluating patient preferences for various features within patient portals.

Adoption of innovative information systems has been conducted on the demand-side, but the majority of such literature in the information systems context is focused on *acceptance* (e.g. based on variations of the Technology Acceptance Model, TAM), such as acceptance of online banking by consumers (e.g. Tan and Teo 2000). Such models do not consider the features offered by the information system and do not consider the technical sophistication of individual adopters. Rather, such models consider acceptance of an entire digital service, assume consumer segments to be homogenous, and do not account for variations in individual differences and mental models associated with the context. In the marketing context, some work has been done to differentiate consumer perceptions of various product features, such as the perceptions of hedonic versus utilitarian features added to existing products (Gill 2008), but this work has yet to be extended to the context of digital services. Additionally, little is known about how the *type* of utilitarian features preferred in consumer-oriented digital service. This study begins to fill this gap by assessing assimilation-contrast effects associated with *service automation* (self-service) versus *service innovation* (digital service encounters between firm and consumer) feature bundles in the context of a consumer-oriented digital service.

I consider the emerging context of patient portals offered by Primary Care Providers (PCPs) in the U.S and assess patients' perceived value of various patient portal feature bundles. I suggest that sophisticated consumers now consider much more than general or overall impressions of an information system, as implied by TAM-based models (e.g. Davis 1989; Venkatesh et al. 2003). Using assimilation-contrast theory (Herr et al. 1983; Schwarz and Bless 1992; Sherif and Hovland 1961), I suggest that consumers either *assimilate* toward specific bundles of features that seem moderately congruent with their expectations and mental model associated with the context or *contrast* away from feature bundles that are incongruent with their expectations and mental model associated with the context. I believe that studying assimilation-contrast effects associated with consumer adoption of digital services is essential to further our understanding of how consumers perceive increasingly sophisticated digital services at the feature level, how perceptions and inferences can differ across consumer segments, and how firms can tailor digital services to specific consumer needs and wants.

Assimilation-contrast theory has been used in the consumer behavior literature (e.g. Kardes et al. 2004) and in the marketing literature (e.g. Gill 2008) to demonstrate how product enhancements may impact consumer inference and purchase intentions. For instance, Bertini et al. (2007) find that consumers, when faced with the choice of whether or not to purchase an upgraded product, generally prefer the addition of innovative, new features rather than simple, standard upgrades of existing features. Gill (2008) finds that for utilitarian products the addition of features that are somewhat different than expected (moderately incongruent, in his terms) lead to higher value perceptions. Additionally, Smeesters et al. (2010) extends previous assimilation-contrast findings by demonstrating the relative nature of such effects and finds that self-perception plays a key role in how individuals react to advertisements. Therefore, a firm must consider how consumer preferences and inferences play a role in product evaluation, selection, and purchase intentions while also taking into account the variability present in preferences and inferences across consumer segments. Yet, knowledge of how consumers assimilate toward feature bundles afforded by digital services or contrast away from such feature bundles given prior experiences with similar technologies is limited. To my knowledge, this is the first study to apply assimilation-contrast to the information systems and digital services context.

I use the context of patient portal adoption by U.S. healthcare consumers in this study. While current supply-side adoption of patient portals by ambulatory care providers stands at about 9 to 10% nationwide[5], there is reason to believe that such adoption will significantly increase in the future. The prerequisite systems, such as practice management and Electronic Medical Records (EMRs), are being adopted with increasing frequency, especially due to new policies incentivizing

[5] According to the HIMSS Analytics data collected via nationwide survey in 2010

providers to purchase, implement, and use such systems (such policy is discussed by Blumenthal and Tavenner 2010). Additionally, the U.S. healthcare system is experiencing a fundamental philosophical shift toward patient-centered care (Bates and Bitton 2010; Bergeson and Dean 2006; Berwick 2009). Therefore, the follow-on investment of a patient portal extends the capabilities of management and clinical information systems directly to patients and provides an opportunity to meet many patient-centered goals. For example, PCPs may offer patient portals to their patients to reduce costs associated with physical encounters, improve patient convenience, share clinical information and results, and offer opportunities for patients and providers to communicate and collaborate in new ways (Chou et al. 2010; e.g. Liederman et al. 2005; Zhou et al. 2010).

Using an cross-sectional survey based on an experimental research design (2 x 2), I assess the relative differences in consumer assimilation-contrast toward or away from features associated with the *service automation* of front-office (e.g. request an appointment online) and back-office (e.g. view health records or summaries from past office visits) self-service features versus *service innovation* features that fundamentally transform patient-provider interactions (e.g. collaborative data sharing, patient-provider messaging, and online video consultations with clinicians). I apply assimilation-contrast theory by assessing how consumer sophistication associated with online portals in other contexts (e.g. online banking and online travel) impacts the perceived value of *service automation* and *service innovation* feature bundles within the new context of patient portals. I also examine how patient satisfaction with the Primary Care Provider (PCP), current health condition, health perceptions, health system utilization, individual differences, and demographic characteristics impact perceived value associated with patient portal feature bundles. I find that *service automation* features result in assimilation effects for consumers of all technology sophistication levels, but, interestingly, find that *service innovation* features do not significantly impact perceived value and sometimes result in contrast effects, even for respondents who are technologically sophisticated. These results suggest that even though behavioral intentions to adopt and use information systems may be high (as is often suggested by TAM-based models), feature level considerations can significantly change perceived value and may impact the overall success of digital services.

I believe this study contributes to an early understanding of how assimilation-contrast impacts perceived value when considering feature bundles that vary between administratively oriented bundles offering basic self-service features to much more innovative, complex, and feature rich bundles that fundamentally change how patients and providers currently interact. Theoretically, this study offers a fresh perspective on how consumers perceive information systems at a more granular level than traditionally considered and offers unique insights into how consumers perceive feature bundles within digital services. Additionally, in a practical sense, I believe that tailoring feature bundles to the needs of specific consumer segments will be critical to any consumer-oriented digital service strategy going forward. More in-depth research at the feature level can provide valuable insights that may help both consumers and suppliers of such services overcome initial barriers to adoption. Ultimately, finding an appropriate match between digital service capabilities and consumer-level assimilation-contrast may provide the foundation needed to be successful when augmenting physical service delivery with digital information provisioning, collaboration, and communication.

6.2. Research Background

6.2.1. Assimilation-Contrast Theory and Feature Preferences

Assimilation-contrast theory is a theory with behavioral roots suggesting that consumers tend to judge contexts based on their current mental models (Herr et al. 1983; Schwarz and Bless 1992; Sherif and Hovland 1961). Specifically, assimilation-contrast suggests that consumers assimilate toward products and services that are perceived as beneficial or positive within a context and contrast away from products and services that are perceived as unnecessary or negative within a given context (e.g. Meyers-Levy and Sternthal 1993).

Recent marketing and consumer behavior research has applied this theory to the evaluation of consumer preferences associated with the consideration of attributes or features of new or upgraded products (Bertini et al. 2007; Gill 2008). This research stream has generally found that assimilation-contrast effects are often present in purchase decision making and that feature enhancements must be close enough to a consumer's current mental model to induce assimilation effects, but different enough to encourage abandoning the base product for the new or upgraded product. For instance, Bertini et al. (2007) find that upgrading existing features (e.g. more memory on the same camera) is less likely to induce purchase intentions for an upgraded product than offering the base product with the addition of a brand new or innovative feature. Gill (2008) gives the example of adding Internet access to a standard television as a way to induce an assimilation effect (the television is something I know well), but also enough incongruity (currently, Internet access it not ubiquitously available on TVs) to encourage purchase. Such findings confirm that "moderate schema incongruity" is often needed to find a balance between attracting consumers to a product and encouraging purchase (Meyers-Levy and Tybout 1989; Ziamou and Ratneshwar 2003).

What is not known, though, is how such findings translate to digital services. Products are tangible and, while variations of a product can be marketed toward different consumer segments, it is often the case that primary features are generally "fixed" and an upgraded version of the product must be purchased to obtain new features. For instance, a laptop computer may come with a standard amount of memory (e.g. 4 GBs) that can be optionally upgraded (perhaps to 8 GBs), but the overall feature (memory) is fixed to a particular range (e.g. memory available ranges from 4 to 8 GBs). As memory requirements expand beyond that range, a new laptop may need to be purchased. Digital services, however, offer a significant range of flexibility not often seen in tangible products. Cloud-based digital services, for instance, are: much more adaptable and flexible, can be dynamically tailored to specific consumer segment preferences, often have the ability to track and often upgrade features dynamically, without requiring repurchase (Gillett 2008; Wang et al. 2010). In this study, I extend assimilation-contrast to the context of digital services and consider how patient portals features falling into the categories of *service automation* and/or *service innovation* impact user preferences.

To establish relative differences between respondents, I consider how *technology sophistication,* in regards to how often the healthcare consumer uses various features of online portals in other contexts (features within online banking and online travel reservation portals), may impact the perceived value of patient portal feature bundles. Prior literature has suggested that consumers with more experience/sophistication with technology are often more likely to show positive adoption intentions toward newer technologies (Agarwal and Prasad 1999; Curran and Meuter 2005; Montoya-Weiss et al. 2003). For instance, Agarwal and Prasad (1999) find that *prior and similar experiences* with technology positively and significantly impact *beliefs about ease-of-use.* Montoya-Weiss et al. (2003) find that *general Internet expertise* positively impacts *online channel use*. Additionally, Yoh et al. (2003) find that previous Internet experience has a strong impact on intentions to purchase retail products through an online channel. Curran and Meuter (2005) find that 87% of their sample had never used online banking and did not find significant effects of *perceived ease-of-use* or *perceived usefulness* on online banking adoption intentions, but did find significant effects for ATM and phone use, both of which their sample reported higher experience with. In this study, I suggest that the relative nature of *technology sophistication*, based on assimilation-contrast theory, may provide additional insights.

6.2.2. Service automation vs. service innovation

My conceptualization of digital services as combinations of bundles of *service automation* and *service innovation* features is derived from the strategic view of supply-side information system investments. Dehning et al. (2003) suggest that information systems generally fall into three categories: *automation*, *information*, and *transformation*. The authors describe *automation* as replacing human labor with technology in an effort to make business processes more efficient. *Informating-up* and *informating-down* are described as using information systems in an effort to improve the flow of information for decision making needs. Finally, *transformation* is achieved when an information system is used in a truly new or unique way that fundamentally alters traditional processes. Transformational information systems are suggested to lead to the most sustained competitive advantage. Therefore, as suggested by Fichman (2004a) and Dehning (2003), information systems investments may only "payoff" under certain conditions and a key research issue going forward will be identifying the conditions of success needed to achieve such payoffs. I suggest that consumers will play a key role in these considerations and, just as strategic information systems investments impact supply-side value perceptions, the variety and type of features of an information system extended to consumers is likely to play a role in the success of digital services.

In many contexts, the digital delivery of services is augmenting or replacing the need for physical service encounters. For example, ATMs and online banking are replacing the need to visit bank branches for many services traditionally restricted to direct interaction with a bank teller. While the self-service literature has explored the potential value and potential pitfalls of introducing digitally enabled services to customers (e.g. Bitner et al. 2000), such considerations have primarily evaluated consumer preferences and decision making associated with broadly defined self-service systems (e.g. online banking considered as a whole) (e.g. Campbell and Frei 2010) and have not yet considered how variation in the features offered or variation in the sophistication or innovation of the features impacts preferences or decision making. In fact, such literature has often found mixed impacts of self-service and has generally concluded the self-service technologies must balance effectiveness and overall relative advantage with potential technology and process failures that may drive consumers away (e.g. Meuter et al. 2000). For instance, Kumar and Telang (2011) find that self-service technologies that provide ambiguous information result in *more* calls being made to call-centers for clarification, rather than a reduction in call volume. Campbell and Frei (2010) find that even though channel substitution occurs as consumers trade ATMs and phone banking for online banking, transaction volumes substantially increase, average costs increase, but customer retention also increases.

I suggest that digital services have enormous potential value that extends beyond the broadly considered realm of self-service and, even when considering basic self-service capabilities, consumer preferences are likely to vary significantly based on the bundle of features offered and the relative differences in technology sophistication between the individual consumers. Digital services have the unique capability to provide varying combinations of *service automation features* (e.g. self-service features) and/or *service innovation features* (e.g. digitally enabled service delivery such as online consultations). And, unlike physical products that must be manufactured with a generally fixed set of capabilities and functions, digital services can dynamically tailor the type and number of features available based on consumer preferences or supply-side enablement of certain functions (e.g. Wolfinger et al. 2008). In the healthcare context, extending such digital capabilities directly to patients may reduce office visits, increase patient interactions and collaborations, and improve information flows required for therapeutic adherence and medication adjustments. However, patient perceptions associated with such features are likely to drive the market.

6.2.3. Patient portals

Unlike purchasing a product such as a new MP3 player that may have new features (explored by Gill 2008) or substituting a physical service, such as shopping in the store, with a digital service, such as e-commerce (explored by

Kim et al. 2009), health care patients are now faced with a physical service encounter that is being *augmented* with a digital alternative for portions of the service—the patient portal. Patients often physically interact directly with both front-office administrative staff (e.g. checking-in, filling out paper work, etc.) and with back-office clinical staff (e.g. physical delivery of medical care via a doctor or medical service provider) during medical visits, but are now beginning to be have digital options, as well, that may increase convenience, reduce costs, and, potentially, improve health outcomes for those with chronic conditions requiring information-rich patient-provider interactions (Emont 2011).

While patient portals have significant potential, research in this area is only just emerging and is primary focused on the characteristics of users and usage rates within specific health systems (e.g. use of the Epic portal by Geisinger as reported by Gardner 2010), early results associated with potential operational efficiencies (e.g. increased efficiency due to substitution of some office visits for telephone visits and web messaging as reported by Chen et al. 2009), and a very limited amount of early research on the impact of patient portals on health outcomes (e.g. Zhou et al. 2010). Research findings have been somewhat mixed, as to be expected with early adoption and usage. For instance, usage of Kaiser Permanente's patient portal called My Health Manager has been reported at more than 3 million users who most frequently use the patient portal to view lab test results, request prescription refills, and interact with providers via online e-mail and messaging capabilities (Silvestre et al. 2009). The U.S. Department of

Veterans Affairs (VA) has had similar success with its patient portal, My HealtheVet (Nazi et al. 2010). However, other health systems have not had as much success. The British National Health Service reported that only a very limited number (0.13%) of potential users took the time to open a patient portal account (Greenhalgh et al. 2010) and the majority of patients who signed up to use PatientSite at Beth Israel Deaconess Medical Center in Boston were generally healthier and used the health system less than those who did not enroll (Weingart et al. 2006a). Additionally, while administrative and operational efficiencies may result due to use of a patient portal for tasks such as refilling prescriptions, scheduling appointments, and getting access to test and lab results (e.g. Liederman et al. 2005), some studies report patient concerns with possibility of patient portals hindering communication with their provider (as described by Emont 2011) and only using a patient portal if they are dissatisfied with the relationship with their provider (Zickmund et al. 2008b).

Emont (2011) extensively reviews the literature in the patient portal context and concludes: "All of these factors point to the importance of seeking regular feedback from patients on *portal features* as a mechanism to improve and expand capabilities and increase overall access" (italics ours). In this study, I address this open question in the theoretical context of assimilation-contrast by seeking answers to the following research question:

RQ: *How do assimilation and contrast effects associated with healthcare consumer technology sophistication and mixtures of service automation features* *and service innovation features impact the perceived value of patient portal feature bundles?*

6.3. Hypothesis Development

In the self-service literature, it has been generally suggested that typical consumers will find self-service technologies (SSTs) to be valuable if the SST is better than alternative channels of communication and information provisioning, the SST is reliable, and the SST provides benefits that are worth the cost of switching (Bitner et al. 2002). In the healthcare context, the drive toward patient-centric care and the need to support such care with patient-centric technologies is leading to adoption of patient portals that offer many self service features. It has been suggested that the first stages of patient-centric information systems will provide basic information tracking and information provisioning services (Krist and Woolf 2011), as would be expected in an early stage SST. For instance, the Centers for Medicare and Medicaid Services (CMS) has been pilot testing an online portal that will provide secure patient profile and claims information and the Department of Veterans' Affairs (VA) has offered basic self-service patient portal features for a number of years (Thompson and Brailer 2004). Empirical studies of patient portal usage by patients such as Gardner (2010) and Chou et al. (2010) suggest that self-service features such as viewing lab results, viewing billing information, maintaining personal health information, and requesting and keeping track of appointments are often found to be valuable by patients and their families. An empirical test of behavioral predictors of patient-portal acceptance found that perceived usefulness (as well as other key factors) had a positive and significant impact on behavioral intentions to use a patient portal for medical information purposes in a primary care setting (Klein 2007), which is akin to the *service automation* self-service features considered in this study. Therefore, I suggest that individuals with normal (average) *technology sophistication* will assimilate toward *service automation* features.

The marketing literature has also suggested that the addition of new and moderately different features often lead to purchase of upgraded products (e.g. Gill 2008). In the medical context, as patient-centric care places more demands on coordination of care, especially in the primary care setting (Stille et al. 2005), it is likely that more innovative features will be required of patient portals. For instance, Klein (2007), found that patient-provider communication was also perceived as useful by patient portal users. This is a more innovative use of patient portals than simply looking up records or medical information. In their staged model of functionalities for patient portals, Krist and Woolf (2011) suggest that advanced features will likely eventually include coordination and sharing of clinical and/or claims information, personalized recommendations for the patients, and even decision aids that use patient information to provide useful analyses. Additionally, it has been suggested that patient portals directed toward chronic conditions, such as diabetes, could improve "patient engagement with therapeutic care plans" as well as "medication adjustment by physicians" by offering more innovative and collaborative capabilities between patients and providers (Grant et al. 2006b). While I acknowledge that too many features can lead to "feature fatigue" (Thompson et al. 2005), I suggest that the addition of a few, key innovative features may provide the incentive needed to use a patient portal and overcome perceived initial learning and setup barriers. Therefore, I suggest that individuals with normal (average) *technology sophistication* will also assimilate toward *service innovation* features.

H1: *Healthcare consumers with normal (average) technology sophistication will assimilate toward both service automation and service innovation features.*

I also suggest that the perceived value associated with patient portal features may be negatively impacted by individuals on the more extreme ends of technology sophistication. Just as Smeesters et al. (2010) established the relative impacts of assimilation-contrast based on individual differences, I also evaluate the effect of relative individual differences on assimilation-contrast, but extend this model into the digital services context. I specifically evaluate how differences in *technology sophistication* among respondents impacts assimilation-contrast effects associated with digital service feature preferences. Those who are not technically savvy are likely to be intimidated by innovative features and are likely to contrast away from such features. For instance, some patient portal studies have reported that patients are concerned that patient portals may create unwanted barriers and complications to communicating with their health care providers or may only be used when the patient is dissatisfied with the patient-provider relationship (as described in the Emont 2011 literature review). On the other hand, individuals who are highly technically savvy are likely to prefer innovative features and simple self-service features may not provide enough motivation to take the time to register for an account and begin using the patient portal. For instance, Ross et al. (2006) find that sustained use of a patient portal targeted toward diabetes is much more likely if content is personalized rather than generic and Grant et al. (2008) found that overall enthusiasm was low for basic health maintenance functions associated with monitoring diabetes care through a patient portal. Therefore, I hypothesize:

H2a: *Patients with low (below average) technology sophistication will assimilate toward service automation features.*

H2b: *Patients with low (below average) technology sophistication will contrast away from service innovation features.*

H3a: *Patients with high (above average) technology sophistication will contrast away from service automation features.*

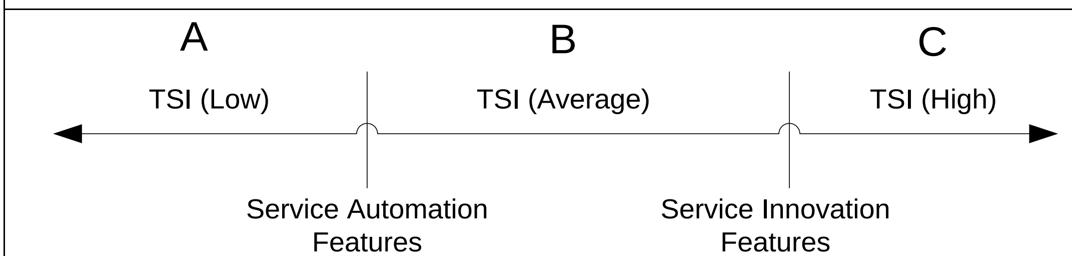
H3b: *Patients with high (above average) technology sophistication will assimilate toward service innovation features.*

Finally, I acknowledge that a number of additional factors could impact perceived value. These factors include demographic characteristics, PCP satisfaction (Harris et al. 1999), the relationship age and utilization levels associated with the PCP (Safran et al. 1998; Verhoef et al. 2002), and self-reported health perceptions (Ware Jr et al. 1996). I also acknowledge that *individual differences* are likely to play a key role in the adoption and usage process and control for such differences. For instance, individuals with a strong desire for physical interaction with a service provider (Need for Interaction, NFI, Dabholkar and Bagozzi 2002) are likely to perceive a patient-portal as less valuable than those without a strong NFI. In fact, Emont (2011) reviewed multiple articles suggesting that some patients were concerned that patient portals might hinder their ability to directly communicate with their providers. Those who have a high concern for privacy and security, which is often a primary concern with patient portal usage (Kaelber et al. 2008a), are also likely to view patient portals features with some skepticism. However, such negative effects may be offset by those who view technology optimistically (Technology Readiness—Optimism, Parasuraman 2000).

6.3.1. Conceptual Research Model

The above hypotheses and controls are summarized in the following diagram.

Figure 6: Conceptual research model



Note: When controlling for demographic characteristics, Primary Care Provider (PCP) perceptions, and individual differences (NFI, TRIOPT, and TTA), my hypotheses fall into the following ranges:

A. TSI Low individuals assimilate toward Service Automation features and contrast away from Service Innovation features.
B. TSI Average individuals assimilate toward all features.
C. TSI High individuals assimilate toward Service Innovation features and away from Service Automation features

6.4. Research Design

I conducted an online, cross-sectional (one time) survey of U.S. health care consumers in February of 2012. Respondents were randomly invited to participate. Institutional Review Board (IRB) exemption approval was obtained prior to administering the survey. A pilot test resulting in some refinements was conducted prior to the administration of the final survey. The pilot test consisted of an initial 68 responses that were evaluated for reliability (i.e. Cronbach's α for constructs), acceptable demographics (i.e. nationally representative), and reliability of experimental conditions. Some questions were refined to improve reliability of constructs, the experimental conditions appeared adequate and reliable, and the demographics were somewhat skewed toward an older aged sample and this issue was addressed in the final survey.

The survey was based on a 2 x 2 experimental design designed to expose respondents to varying levels of *service automation* (self-service encounters with a doctor's office) and *service innovation* (digital service encounter with physician) patient portal feature bundles. The *service automation* factor includes two levels: 1) *Low*—front-office self service features only, and 2) *High*—front-office *and* back-office self-service features. The *service innovation* factor also includes two levels: 1) *Not present*—no clinical, digital service encounter features available, and 2) *Present*—clinical, digital service encounters with the physician available. Respondents were randomly exposed to one of the four cells shown in the following table and asked to rate their *perceived value* of the bundle of features on a 7-point Likert scale ranging from 1-Not at all valuable to 7-Extremely valuable. Respondents were also asked to respond to questions used as controls in the following categories: perceptions and utilization of current PCP, individual differences, and demographics.

<table>
<tr><th colspan="4">Table 19: Experimental design for the survey based on variations in patient portal feature bundles</th></tr>
<tr><th></th><th></th><th colspan="2">Service Innovation (Digital service encounter with physician)</th></tr>
<tr><td></td><td></td><td>Clinical Features: None (0)</td><td>Clinical Features: Present (1)</td></tr>
<tr><td rowspan="2">Service Automation (Self-service encounters with doctor's office)</td><td>Administrative Features: Low (Front-office self-service only)</td><td>CELL A (Front office self-service)
• Request appointments
• View billing statements and history
• Maintain personal profile (contact information, insurance information, dependent information, etc.)</td><td>CELL C (Front-office self-service + Digital service encounter with physician)
• (all items from CELL A), plus…
• Send/receive non-urgent, secure e-mails/messages to doctor/provider.
• Keep track of your own information on a regular basis (such as weight, blood pressure, glucose readings, and/or peak flow measurements) and share information with physician.
• Online video consultations with physician (a.k.a. virtual office visit)</td></tr>
<tr><td>Administrative Features: High (Front and back-office self-service)</td><td>CELL B (Front-office + back-office self-service)
• (all items from CELL A), plus…
• View medical test results (laboratory, radiology, and/or pathology)
• Maintain lists of medical conditions, allergies, immunizations, and/or prescriptions
• View health records or summaries from past office visits</td><td>CELL D (All features)
• (all items from CELLS A, B, & C)</td></tr>
</table>

6.5. Research Measures and Variables

The following table describes the dependent variables and constructs used in the study. The dependent variable, *perceived value*, was measured with a single question: "Overall, how valuable would this set of patient portal functions be to you?" Responses were provided on a 7-point Likert scale ranging from 1 (Not at all valuable) to 7 (Extremely valuable).

The *Technology Sophistication Index (TSI)* is an index created for this study (motivated by Agarwal and Prasad 1999; Curran and Meuter 2005; Montoya-Weiss et al. 2003) based on responses to how frequently respondents had used three specific online banking functions and four specific online travel functions in the past 6 months using a 6-point Likert scale ranging from 1 (Not at all) to 6 (More than 15 times). For online banking, respondents were asked how many times they had used the following functions: 1) Transfer money between accounts online, 2) Pay bills with online bill payment options, and 3) Chat online (or through e-mail or secure online messaging) with a customer service representative or banker. For online travel, respondents were asked how many times they had used the following functions: 1) Search online for flights, hotels, car rentals, or other forms of travel, 2) Received online deal alerts, 3) Book a travel reservation online, and 4) Check-in online and/or print boarding passes (or reservation information).

Additionally, a few constructs were used as controls and include: satisfaction associated with the PCP, Need for Interaction (NFI), Technology Threat

Avoidance (TTA), and the Optimism scale of the Technology Readiness Index (TRI).

Table 20: Research constructs and measures				
Construct / Measure	**Abbr.**	**Description**	**# of Items**	**Source**
Dependent Var.: Perceived Value	DVPerc Val	Measures the perceived value of the feature bundle using a 7-point Likert scale ranging from 1(Not at all valuable) to 7 (Extremely valuable).	1	Created for this study and based on measures used in (Gill 2008)
Technology Sophistication Index	TSI	Average of frequency reported for usage of online banking and online travel functions in the past 6 months using a 6-point Likert scale ranging from using a feature 1 (Not at all) to 6 (More than 15 times).	7	Created for this study and based on concepts from (Agarwal and Prasad 1999; Curran and Meuter 2005; Montoya-Weiss et al. 2003)
Primary Care Provider (PCP) Satisfaction (with clinical services)	PCPSat Clin	An 11 item scale asking respondents to report their satisfaction with the clinical aspect of their PCP (such as, "Telling me what he/she found during the exam") using a 7-point Likert scale ranging from 1 (Very dissatisfied) to 7 (Very satisfied).	11	(Harris et al. 1999)
Need for Interaction	NFI	A 4 item scale asking respondents to rate how important they perceive physical interaction with a service provider. Items include, "It bothers me to talk to a machine when I would talk to a person instead," and responses range from 1 (Strongly disagree) to 7 (Strongly agree).	4	(Dabholkar 1996b; Dabholkar and Bagozzi 2002)
Technology Threat Avoidance	TTA	A 3 item scale used to assess privacy and security concerns using items such as, "My personal information collected	3	(Liang and Xue 2010)

Table 20: Research constructs and measures				
Construct / Measure	**Abbr.**	**Description**	**# of Items**	**Source**
		by a secure online portal could be misused." Responses range from 1 (Strongly disagree) to 7 (Strongly agree).		
Technology Readiness Index: Optimism	TRIOPT	A 10 item scales used to assess the optimism associated with technology using items such as, "I like the idea of doing business via computers because I am not limited to regular business hours." Responses range from 1 (Strongly disagree) to 7 (Strongly agree).	10	(Parasuraman 2000)

Additional variables in the study include: Demographic characteristics, health perceptions, the age of the relationship with the PCP, and the frequency of use of the PCP. Health perceptions (Ware Jr et al. 1996) are measured using a single item, "In general, would you say your health is…," and responses are based on a 5-point Likert scale ranging from 1-Excellent to 5-Poor (note: this variable is reverse coded in the analysis). The age of the relationship with the PCP (based on Safran et al. 1998; Verhoef et al. 2002) is a single item asking, "How long has your Primary Care Provider (PCP) been your primary health provider?" Responses are based on a 4-point Likert scale ranging from 1 (Less than 1 year) to 4 (More than 5 years). Finally, frequency of use of the PCP is also a single item (based on Safran et al. 1998) asking, "How many times have you visited your Primary Care Provider (PCP) in the past 6 months?" Responses are based on a 4-point Likert scale ranging from 1 (None) to 4 (More than 5 times). The variables used in the final analysis are summarized in the following table.

Table 21: Variables used in models and related descriptive statistics						
Variable	**Description**	**Obs**	**Mean**	**Std. Dev.**	**Min**	**Max**
Dependent Variable						
DVPercVal	Perceived value of the bundle of features seen	1034	5.241	1.506	1	7
Experimental Factors						
AdminFtrs	Binary variable representing whether or not Cells A or B were exposed to the respondent	1038	0.498	0.500	0	1
ClinicalFtrs	Binary variable representing whether or not Cells A or C were exposed to the respondent	1038	0.493	0.500	0	1
AdmClinFtrs	Interaction between AdminFtrs and ClinicalFtrs representing Cell D	1038	0.245	0.430	0	1
Demographic Controls						
Gender	1=Male, 2=Female	1029	1.532	0.499	1	2
Age	7-point Likert scale ranging from 18-20 years of age to 70 or older	1031	3.794	1.422	1	7
Education	8-point Likert scale ranging from 1 (Less than high school) to 8 (Professional degree—JD, MD)	1031	2.893	1.479	1	8
HealthPercep	Health perception on a 5-point Likert scale ranging from 1-Excellent to 5-Poor (reverse coded in analysis)	1029	3.572	0.896	1	5
Primary Care Provider (PCP) Controls						
PCPRelAge	Patient-PCP relationship time frame measured used a 4-point Likert scale ranging from 1 (Less than 1 year) to 4 (More than 5 years).	1028	3.158	1.033	1	4
PCPUtil	Frequency of utilization of the PCP in the past 6 months based on a 4-point Likert scale ranging from 1 (None) to 4 (More than	1030	1.976	0.765	1	4

Table 21: Variables used in models and related descriptive statistics						
Variable	**Description**	**Obs**	**Mean**	**Std. Dev.**	**Min**	**Max**
	5 times					
PCPSatClin	Satisfaction with clinical aspects of PCP (α=0.98)	1035	5.648	1.130	1	7
Individual Difference Controls						
NFI	Need for Interaction (α=0.82)	1031	5.089	1.250	1	7
TTA	Technology Threat Avoidance (α=0.84)	1032	4.308	1.293	1	7
TRIOPT	Technology Readiness Index: Optimism (α=0.95)	1031	4.990	1.175	1	7
Technology Sophistication						
TSI	Technology Sophistication Index (α=0.81)	998	2.171	0.988	1	6
TSILow	(same as above, but 1 s.d. was subtracted from all observations, based on Fitzsimons 2008)	998	1.183	0.988	0.012	5.012
TSIHigh	(same as above, but 1 s.d. was added to all observations, based on Fitzsimons 2008)	998	3.158	0.988	1.988	6.988

6.6. Method

I apply stepwise regression and OLS estimation to evaluate the relationship between *perceived value* (the dependent variable in all models) and the independent variables explained in the previous section. To test assimilation-contrast effects associated with the Technology Sophistication Index (TSI) calculated for each respondent, I apply the principles outlined by Fitzsimons (2008). Rather than dichotomize TSI into "low" and "high" values based on a median split, I run three separate models using mean shifting and compare the results. One standard deviation of TSI (a constant) is subtracted from each TSI value for all observations in the "TSI Low" model. This downward mean shift allows me to evaluate the slope and significance of the binary variables representing the experimental factors (Administrative Features, Clinical Features, and the interaction between the two) when the overall TSI is low. In the "TSI Average" model, no mean shifting is conducted. In the "TSI High" model, one standard deviation of TSI (the same constant) is added to each TSI value for all observations. Five models are reported in the results in stepwise format: 1) a basic model including binary variables (and the interaction) for the experimental factors as well as demographic and PCP controls, 2) a model that that builds upon the basic model by adding the individual difference controls, 3) the "TSI Low" model, 4) the TSI model (no mean shifting), and 5) the "TSI High" model.

6.7. Data Analysis and Results

I received 1,038 responses of which 961 had complete data (7.42% of responses had one or more missing items). All respondents were 18 years of age or older and reported having a PCP (which was required to continue with the survey). I achieved a response rate of 1.4% and, while somewhat low, this is consistent with declining rates of online survey completion where respondents are invited to participate at random. The survey was administered by a third-party and respondents were incentivized by receiving points for a completed survey which could then be used for rewards in the future. Approximately equal numbers of respondents were exposed to each of the four cells in the experimental condition: 263 respondents were exposed to Cell A (Administrative Features=0, Clinical Features=0), 263 were exposed to Cell B (Administrative Features=1, Clinical

Features=0), 258 were exposed to Cell C (Administrative Features=0, Clinical Features=1), and 254 were exposed to Cell D (Administrative Features=1, Clinical Features=1).

The sample characteristics are nationally representative of U.S. Census averages and are as follows: 46.84% male, average age of 43.02 years, 48.35% of the sample reported income at $49,999 per year or less, an average of 2.74 persons per household, 93.64% were born in the U.S., 77.25% White/Caucasian, 8.91% African American, 7.55% Hispanic, 60.52% had a high school education, none of the sample reported being unemployed, and 88.91% reported having medical insurance. Additionally, 54% of the sample reported their health condition to be Very Good or Excellent, 42% reported having a chronic medical condition themselves, and 22% reported caring for a family member or friend with a chronic health condition.

When asked whether or not their PCP currently offered a patient portal, 81% replied that a patient portal was not offered. 17% reported using a patient portal currently, 66% reported a desire to use a patient portal if it was offered to them, and 18% reported that they “do not plan to use a patient portal in the future.” It is interesting to note, as a quick aside, that this is the traditional “behavioral intentions” dependent variable typically used in TAM-based research (e.g. Venkatesh et al. 2003) and, in this study, as in many information systems studies based on acceptance, the majority of respondents report high behavioral intentions to adopt. However, as the results below demonstrate, assimilation-contrast effects end up telling a more complete story.

To control for potential biases toward online services, especially given that the survey was conducted online, I also asked questions related to service interaction preferences for banking and travel. For online banking I asked, "When interacting with your bank, what type of interaction do you generally prefer?" Responses permitted were: In-person, Over the phone, ATM, or Online (Internet). 47% of respondents reported a preference for in-person banking interactions and 32% reported an online (Internet) preference. For travel reservations and booking I asked, "When planning and/or booking personal travel, what type of interaction do you generally prefer?" Responses permitted were: In-person, Over the phone, Online (Internet). 27% reported a preference for in-person interactions and 57% reported a preference for online (Internet) interactions.

Stepwise regression results of all estimated models are reported in the following table. The coefficients were estimated using OLS and represent the change in average *perceived value* of patient portal features given a one unit increase of the variable in question. R^2 values range from 9% in the "Basic Model" to 23.8% in the "TSI" models. Individual difference control variables account for the largest increase in variance explained between the models.

Table 22: Results						
Category	**Variables**	**Basic Model**	**+ Indiv Diffs**	**TSI Low**	**TSI Average**	**TSI High**
Experimental Factors	AdminFtrs	0.333** (0.128)	0.310** (0.119)	0.476* (0.192)	0.640* (0.297)	0.803+ (0.412)
	ClinicalFtrs	-0.067 (0.128)	-0.028 (0.120)	0.266 (0.185)	0.522+ (0.289)	0.779+ (0.404)
	AdmFtrs* ClinFtrs	-0.233 (0.182)	-0.165 (0.170)	-0.345 (0.265)	-0.523 (0.409)	-0.7 (0.567)
Demographic Controls	Gender	0.241* (0.094)	0.321*** (0.088)	0.348*** (0.088)	0.348*** (0.088)	0.348*** (0.088)
	Age	-0.105** (0.034)	-0.026 (0.033)	-0.005 (0.034)	-0.005 (0.034)	-0.005 (0.034)
	Education	0.134*** (0.032)	0.074* (0.031)	0.052 (0.032)	0.052 (0.032)	0.052 (0.032)
	HealthPercep	-0.075 (0.053)	-0.104* (0.049)	-0.126* (0.050)	-0.126* (0.050)	-0.126* (0.050)
PCP Controls	PCPRelAge	-0.035 (0.046)	0.000 (0.043)	0.009 (0.043)	0.009 (0.043)	0.009 (0.043)
	PCPUtil	0.194** (0.061)	0.142* (0.057)	0.129* (0.058)	0.129* (0.058)	0.129* (0.058)
	PCPSatClin	0.261*** (0.043)	0.135** (0.042)	0.137** (0.043)	0.137** (0.043)	0.137** (0.043)
Individual Difference Controls	NFI		0.036 (0.038)	0.041 (0.038)	0.041 (0.038)	0.041 (0.038)
	TTA		-0.094** (0.035)	-0.081* (0.036)	-0.081* (0.036)	-0.081* (0.036)
	TRIOPT		0.483*** (0.039)	0.491*** (0.041)	0.491*** (0.041)	0.491*** (0.041)
Technology Sophistication (and interactions)	TSI			0.232* (0.095)	0.232* (0.095)	0.232* (0.095)
	TSI*AdmFtrs			-0.165 (0.124)	-0.165 (0.124)	-0.165 (0.124)
	TSI*ClinFtrs			-0.259* (0.124)	-0.259* (0.124)	-0.259* (0.124)
	TSI*AdmFtrs *ClinFtrs			0.179 (0.172)	0.179 (0.172)	0.179 (0.172)
Statistics and Sample Size	Intercept	3.331*** (0.386)	1.682*** (0.428)	1.324** (0.443)	1.095* (0.464)	0.866+ (0.502)
	R^2	0.09	0.22	0.238	0.238	0.238
	N	1000	996	961	961	961

Stepwise regressions reported using OLS estimation; *Perceived value* is the d.v.; ***p<0.001 **p<0.01 *p<0.05 +p<0.10

6.7.1. Assimilation-contrast results

In the basic and individual difference models, the coefficients for the perceived value of Administrative Features (which are features representing *service automation*) are positive and significant. However, in the same models, Clinical Features (which are features representing *service innovation*) and the interaction between the two factors (Administrative Features and Clinical Features) are insignificant. These initial results suggest that, without considering the technology sophistication of the individual respondents and individual differences, the presence of both front-office and back-office *service automation* features leads to increased perceived value of a patient portal (an assimilation effect). Yet, the inclusion of *service innovation* features (such as digital service encounters with the physician) does not have a significant impact on perceived value. And, although not reported directly, in a very basic model including only Administrative Features (AdminFtrs), Clinical Features (ClinicalFtrs), and the interaction (AdmFtrs*ClinFtrs), with *perceived value* as the dependent variable, the same results are observed.

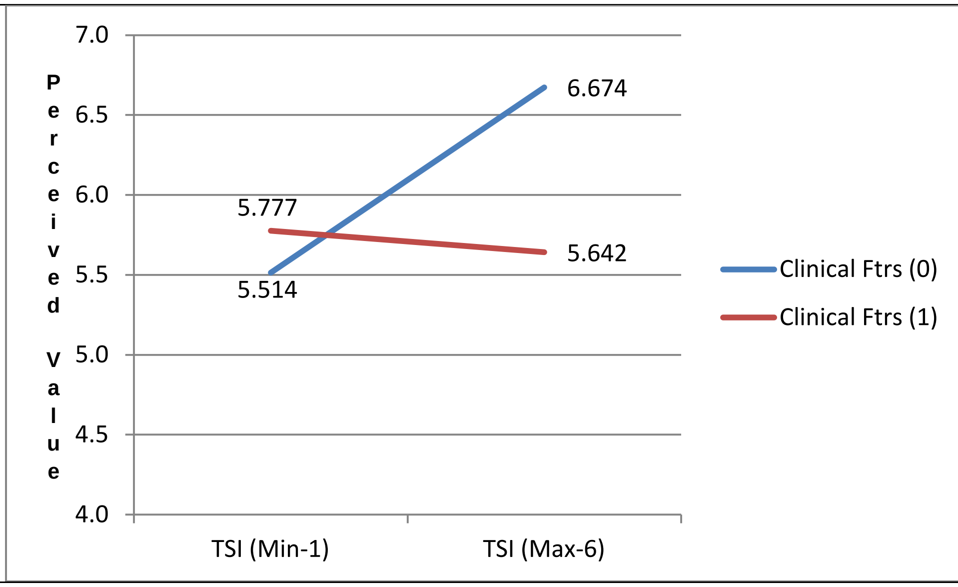
When additional considerations are included (individual differences and the moderating impacts of technology sophistication, TSI), the results begin to shift somewhat. For the "TSI Average" model (where TSI is not mean shifted, as explained next), I observe positive and significant coefficients for the experimental factors associated with Administrative Features *and* Clinical Features (although Clinical Features is marginally significant at $p<0.10$). These results suggest that those with average technology sophistication assimilate toward both *service automation* and *service innovation* features. I also observe that the coefficient for TSI is also positive and significant, suggesting higher overall perceived value as technology sophistication increases. However, I also observe that the interaction between the two experimental (AdmFtrs*ClinFtrs) is insignificant, yet the interaction between TSI and Clinical Features (TSI*ClinFtrs) has a significant and negative coefficient. This interesting result suggests that as TSI increases, the perceived value for Clinical Features decreases (and may explain the insignificant experimental factor interaction—AdmFtrs*ClinFtrs—due to offsetting effects). This result suggests something interesting and counterintuitive: the perceived value of *service innovation* features decreases as technology sophistication increases, within this context.

For the "TSI Low" model, where TSI is mean shifted downwards by one standard deviation, I observe a positive and significant slope for Administrative features and insignificant results for Clinical Features (and for the interaction between these factors). These results suggest that those with lower overall technology sophistication are likely to assimilate toward *service automation* features. While contrast effects are not observed due to the insignificance of the Clinical Features factor and the experimental factor interaction (AdmFtrs*ClinFtrs), the coefficients and significance of the TSI variables are unchanged in this model (due to subtracting a constant, one standard deviation of

TSI, from *all* observations). Therefore, the interaction between TSI and Clinical Features (TSI*ClinFtrs) remains negative and significant.

For the “TSI High” model, where TSI is mean shifted upward by one standard deviation, I observe positive and marginally significant ($p<0.10$) coefficients for both Administrative Features and Clinical Features. Once again, the interaction between the experimental factors (AdmFtr*ClinFtrs) is not significant. It is interesting to note, though, that the magnitudes of the coefficients are the highest in this model (0.803 for Administrative Features and 0.779 for Clinical Features). At first glance, this result seems suggest that those with higher technology sophistication assimilate toward Administrative and Clinical Features, but not the interaction between the two. However, the assimilation toward Clinical Features is offset by the same negative and positive interaction between TSI and Clinical Features (TSI*ClinFtrs) reported above. The following figure illustrates the difference in perceived value for Clinical Features based on TSI level and demonstrates that the presence of Clinical Features results in lower perceived value, especially as TSI increases. Therefore, this a contrast effect for Clinical Features suggesting that an increase in TSI results in a negative slope of perceived value for *service innovation* features in patient portal contexts.

Figure 7: Interaction between TSI and Clinical Features



6.7.2. Control variable results

For the demographic characteristics, while some effects related to age and education are observed in the basic and individual difference models, the strongest effects are observed for gender (females appear to have higher average perceived value) and health perceptions (as health perceptions move upward from Poor to Excellent, the perceived value of patient portal features decreases). A follow-up analysis including the interaction between gender and health perceptions resulted in an insignificant coefficient for the interaction. Therefore, it cannot be assumed that females with lower health perceptions will be an ideal segment for patient portal targeting. Additional demographics were originally included in the regressions (income, race, etc.), but did not result in significant effects and were dropped in favor of model parsimony.

For the PCP controls, higher PCP utilization (more frequency of visits) and higher satisfaction with the clinical aspect of the PCP increase average perceived value. Having a long-term relationship with the PCP (PCPRelAge) did not significantly impact perceived value. Additionally, while not directly reported, I also assessed whether or not affective commitment (loyalty) (Gustafsson et al. 2005) and calculative commitment (switching costs) (Kim and Son 2009b) associated with the PCP impacted patient portal perceived value. The results were not significant and were subsequently dropped from the model. I also evaluated whether or not satisfaction with the front-office at the PCP (e.g. front-desk personnel who manage appointments and follow-up) impacted perceived value (rather than just evaluating satisfaction with the back-office—e.g. clinical personnel) and did not find significant effects.

For individual differences, NFI is insignificant, but the coefficients for TTA and TRIOPT are significant. TTA has a negative coefficient, suggesting that increased concerns for privacy and security decrease overall perceived value while TRIOPT has a positive coefficient suggesting that increased technology optimism increases average perceived value. These individual differences account for a large jump in variance explained (R^2) over the basic model (from 9% to 22%).

Finally, as a check to determine whether or not my experimental design considered an appropriate quantity of features, I asked all respondents, "If <u>additional</u> patient portal functions were offered by your Primary Care Provider

(PCP), beyond what is listed above, would you be more or less satisfied?" (Note: "patient portal functions…listed above" references to the list of patient portal features the respondent was exposed to based on the randomly assigned experimental condition.) Responses were provided using a 7-point Likert scale ranging from 1 (Much less satisfied) to 7 (Much more satisfied). I used this response as a dependent variable (in place of *perceived value*) to determine whether or not the experimental factors had a significant impact on *potential satisfaction with more features*. The results were insignificant suggesting that the number of features and type of features selected for this study were appropriate.

6.7.3. Summary of results

The results are summarized in the following table.

Table 23: Summary of findings	
H1: Healthcare consumers with *normal (average)* technology sophistication will assimilate toward both service automation and service innovation features.	Partially Supported (assimilation effects occur for service automation features, but as TSI increases, contrast effects occur for service innovation features)
H2a: Patients with *low* technology sophistication will assimilate toward service automation features.	Supported
H2b: Patients with *low* technology sophistication will contrast away from service innovation features.	Partially Supported
H3a: Patients with high technology sophistication will contrast away from service automation features.	Unsupported (contrary findings)
H3b: Patients with high technology sophistication will assimilate toward service innovation features.	Partially Supported (as TSI increases, contrast effects occur)
Control Variables: Demographics	Strongest significance for a "female" effect and more perceived value as health perceptions deteriorate
Control Variables: PCP Perceptions	Higher PCP utilization and higher PCP satisfaction lead to more perceived value
Control Variables: Individual Differences	NFI (n.s.), TTA (-), TRIOPT (+)

6.8. Discussion

This study has evaluated the impact of assimilation-contrast effects on the perceived value of patient portal feature bundles, based on the relative nature of healthcare consumer technology sophistication. Rather than assess overall perceptions associated with patient portals in general (such as determining overall perceived usefulness or overall perceived ease-of-use), my research design was based on a 2 x 2 experimental design focused on eliciting the differences in perceived value associated with bundles of *service automation* and *service* *innovation* features. I began the study by telling the story of a large healthcare system in the southwestern U.S. seeking to offer a patient portal that included basic administrative features (e.g. request an appointment) rather than offering a more complete feature set including innovative new ways to interact with clinicians (e.g. online video consultations and collaborative data sharing). I asked why more innovation was not taking place, especially when health systems are late entrants into the portal market, and find that healthcare consumers may not yet be ready for such innovative features.

My primary finding is that healthcare consumers at all levels of technology sophistication assimilate toward *service automation* features. I also find that assimilation effects toward *service innovation* features do not occur at the lower levels of technology sophistication and, interestingly, contrast effects toward *service innovation* features begin to occur as technology sophistication increases. This is a somewhat counter-intuitive result as one would expect technologically-savvy individuals to naturally prefer the most innovative service delivery channels. For instance, as mentioned earlier, Montoya-Weiss et al. (2003) find that *general Internet expertise* positively impacts *online channel use*.

These primary findings lead to a number of interesting conclusions: 1) Behavioral aspects of information systems are more granular than perceptions measured for the system as a whole (i.e. feature-level considerations are just as important as perceptions associated with the entire information system, as assumed by TAM-based models), 2) when physical delivery of a service cannot be entirely substituted by a digital channel (such as in-person retail being substituted by e-commerce), technology must be positioned to *complement* existing service offerings without inducing contrast effects, and 3) innovative technologies are not automatically perceived as valuable by technologically sophisticated individuals (and, in fact, may be perceived negatively). Therefore, I suggest that in a context where the physical delivery of the service is standard and often required (i.e. physical interactions between patients and providers), digital services, such as patient portals, must be offered in a way that increases convenience and information provisioning through self-service (service automation) without innovating to such a degree where the value of the firm-consumer relationship is degraded. The use of digital services in such a context is more about finding the appropriate balance between the physical and digital delivery of services than applying the most innovative technology to the context.

One potential explanation for these findings is that relative “schema incongruity” (e.g. Meyers-Levy and Tybout 1989) is causing skepticism in regards to patient portals due to the newness of the market and surrounding uncertainty. Just as in assimilation-contrast, moderate levels of schema incongruity can be positive, and more extreme levels can lead to negative perceptions (e.g. Stayman et al. 1992). Therefore, patient portals with basic, digital *service automation* features may represent enough of a moderate difference in patient-provider interactions to encourage higher value perceptions, but the more innovative features may be too far removed from the norm and could be causing more extreme incongruities, even among the technologically sophisticated. For instance, not much is known about how online video consultations with physicians will impact health outcomes and interactions, especially if basic needs (such as taking vital signs) require high-touch. I suggest, then, that digital services take advantage of their unique capability to tailor their feature sets to specific consumer segments. Unlike physical products that must be manufactured with “fixed” features, digital services can dynamically adjust (and even be personalized) based on any number of factors. Thus, patients with limited technological sophistication and high skepticism can receive only the most basic feature set, which may or may not be expanded as time goes on, while more technologically sophisticated individuals can begin with the same feature set, but perhaps be exposed to more advanced features more quickly. This would be a case of intentionally limiting capabilities, even if more are available, in order to maintain appropriate levels of schema congruity/incongruity for targeted consumer segments. Additional features would only be introduced after careful evaluation of use and perceptions associated with the existing feature set and, if such features continue to be viewed as too extreme, their use should be limited.

Secondarily, I confirm prior research suggesting that privacy and security concerns will have a negative effect on perceived value of a digital service (Liang and Xue 2010) and that optimism associated with technology will have a positive impact on the perceived value of a digital service (Parasuraman 2000). I also observe a gender effect (females tend to have higher value perceptions for patient portal features), a health perception effect (as health perceptions improve, patient portals are seen as less valuable), a satisfaction effect (higher satisfaction with the PCP is associated with higher perceived value), and a utilization effect (more use of a PCP results in more perceived value). These findings could aid those who wish to target patient portals toward populations with the most potential for adoption and usage.

My study is limited by the hypothetical nature of my survey. Respondents were asked to rate their perceived value of an information system that they likely have never used or only have used on a limited basis. Therefore, future research could explore assimilation-contrast effects associated with the actual usage of a digital service. Additionally, my survey was conducted online and could have a bias toward those more comfortable with technology and the Internet. However, I did my best to control for this issue by asking for preferences associated with physical and digital channels, measuring levels of technology sophistication, and using a nationally representative sample of all ages and capabilities. I also believe some concerns associated with an online bias to be mitigated by the fact that technology sophistication had quite a bit of variance and initial adopters are likely to be those who have online access.

6.9. Key findings and implications of chapter 6

This study has demonstrated the value of assessing information systems from a more granular level than traditionally considered in information systems literature. I also demonstrate the importance of considering the relative differences between the features offered within a digital service and the technological sophistication of those considering the value of a digital service, as well as the importance of not falling into the trap of considering all innovation features to be valuable. I believe these results to be generalizable to the emerging context of augmenting physical delivery of services with digital services and believe these findings to be especially applicable to situations where the substitution of physical relationships with digital service offerings is only partially possible. I believe that finding complementarities between physical services and digital service features will become the frontier of future research in this area.

Chapter 7. Summary and Conclusions

7.1. Summary of Findings and Implications

The implications of this dissertation are: 1) Innovative information systems that target consumers are not "automatically" adopted by firms and consumers just because they are new and different, 2) adoption and diffusion of such systems requires finding the appropriate balance between innovativeness and relative advantage, and 3) the features offered by such digital services (and associated perceptions) will have a significant impact on overall adoption and diffusion patterns. These findings lend support to careful planning and evaluation prior to offering such systems to consumers and prior to consumer adoption.

This dissertation has sought to extend existing adoption of innovations research into a context where consumer influence is a key consideration. While the literature on adoption of innovations theory is robust, it has not yet fully considered the implications of supply-side and demand-side adoption of digital services that extend firm capabilities and resources directly to consumers. This dissertation begins to fill this gap by extending this theoretical base into the emerging context of consumer information systems and by evaluating new hypotheses, constructs, and influences not considered before in the literature.

In this dissertation, four distinct studies were presented in the PHR and patient portal contexts and included: 1) an econometric examination of the contingencies associated with supply-side (ambulatory care clinic) adoption of patient portals, 2) a behavioral assessment of patient PHR adoption intentions, 3) an integrated latent variable and discrete choice evaluation of patient business model preferences for PHRs, and 4) an experimental evaluation of how patient portal feature preferences are impacted by assimilation and contrast effects. This dissertation contributed a new understanding of how contingent factors, consumer perceptions, and assimilation/contrast of features are impacting patient portal and PHR adoption and diffusion.

The first study (Chapter 3) demonstrated that patient portal adoption is dependent on prior technology adoption and is influenced not only by the 'dominant-paradigm' of the adoption of innovations (Fichman 2004a), but also service contingencies associated with longer-term relationships and coordination of care, learning externalities contingencies, and, to a lesser extent, select demand contingencies. The findings provided support for examining multiple levels of innovation sophistication in patient portal adoption. Clinical patient portals are not just one system, but often a combination of systems including disease management, e-mail/messaging, and PHRs.

The second study (Chapter 4) demonstrated that PHR adoption intentions are high, even for an older aged sample, and are not significantly impacted by health concerns. The primary finding in this study is that relative advantage along with compatibility of work style and ease-of-use are associated with positive intentions to adopt a PHR. Additionally, those who intend to adopt a PHR have different characteristics than those who do not intend to adopt including having a strong desire to keep records organized, less concern with security, have a preference for less effort in usage, and exhibit lower risk aversion. While these findings provided interesting behavioral insights above and beyond the standard behavioral characteristics associated with the adoption of innovations, PHRs are not homogenous with regard to business model. Therefore, an open question remained as to whether or not the business model of a digital service such as a PHR plays a significant role in adoption intentions.

The third study (Chapter 5) addressed this open question: How do business models supporting digital services affect consumer preferences, especially when trade-offs are present? I found a significant impact of business models on consumer preferences and that PHR consumers look to balance the trade-offs by seeking middle ground. What remained unknown, though, is how consumers will react to heterogeneity of features offered in such a digital service. Patient portals are now being offered with increasing frequency by ambulatory care clinics and include features that vary from front-office self-service (e.g. schedule an appointment online), to back-office self-service (e.g. use a patient portal to view and track medical records and information), to clinical service innovation (e.g. capability to have online consultations with a clinician).

The final study (Chapter 6) demonstrated the value of assessing information systems from a more granular level than traditionally considered in information systems literature. I demonstrated the importance of considering the relative differences between the features offered within a digital service and the technological sophistication of those considering the value of a digital service, as well as the importance of not falling into the trap of considering all innovative features to be valuable.

7.2. Future Research

Future research could explore: 1) complementarities between the physical delivery of services and the digital augmentation of such services, 2) actual use of PHRs and patient portals and associated contingencies of use, 3) additional consumer preferences and behaviors that may impact diffusion, and 4) mapping use of consumer-oriented systems to outcomes, at both the firm-level and the consumer-level. An area of primary interest in this context would be whether or not a technological intervention, such as a patient portal, impacts overall health outcomes. Such findings could be extended to other consumer information system contexts and could ultimately be used to demonstrate linkages between systems, usage, performance, and behavioral contingencies. Given that more features can actually be detrimental to adoption, even when consumers are technologically savvy, it will be important to establish the tipping point of motivation versus de-motivation for adoption in the *consumer information systems* context.

In conclusion, this dissertation has demonstrated that adoption of innovation theory is a solid base for research in the emerging area of *consumer information systems*. I have demonstrated that this theory can be extended into this new domain and that many new considerations will be vital if this market is to fully succeed.

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APPENDIX A

IRB APPROVALS

IRB EXEMPTION APPROVAL FOR SURVEY CONDUCTED IN CHAPTER 4

ARIZONA STATE UNIVERSITY
RESEARCH AND ECONOMIC AFFAIRS

Office of Research Integrity and Assurance

To:	Raghu Santanam BA
From:	Mark Roosa, Chair Soc Beh IRB
Date:	03/23/2010
Committee Action:	**Exemption Granted**
IRB Action Date:	03/23/2010
IRB Protocol #:	1003004979
Study Title:	Personal Health Record (PHR) Consumer Adoption and Usage Survey

The above-referenced protocol is considered exempt after review by the Institutional Review Board pursuant to Federal regulations, 45 CFR Part 46.101(b)(2) .

This part of the federal regulations requires that the information be recorded by investigators in such a manner that subjects cannot be identified, directly or through identifiers linked to the subjects. It is necessary that the information obtained not be such that if disclosed outside the research, it could reasonably place the subjects at risk of criminal or civil liability, or be damaging to the subjects' financial standing, employability, or reputation.

You should retain a copy of this letter for your records.

IRB EXEMPTION APPROVAL FOR SURVEY CONDUCTED IN CHAPTER 5

ASU Knowledge Enterprise Development

Office of Research Integrity and Assurance

To:	Raghu Santanam BA
for **From:**	Mark Roosa, Chair SM Soc Beh IRB
Date:	02/23/2011
Committee Action:	**Exemption Granted**
IRB Action Date:	02/23/2011
IRB Protocol #:	1102006072
Study Title:	Personal Health Record (PHR) Consumer Adoption and Usage Survey

The above-referenced protocol is considered exempt after review by the Institutional Review Board pursuant to Federal regulations, 45 CFR Part 46.101(b)(2) .

This part of the federal regulations requires that the information be recorded by investigators in such a manner that subjects cannot be identified, directly or through identifiers linked to the subjects. It is necessary that the information obtained not be such that if disclosed outside the research, it could reasonably place the subjects at risk of criminal or civil liability, or be damaging to the subjects' financial standing, employability, or reputation.

You should retain a copy of this letter for your records.

IRB EXEMPTION APPROVAL FOR SURVEY CONDUCTED IN CHAPTER 6

ASU Knowledge Enterprise Development

Office of Research Integrity and Assurance

To:	Raghu Santanam BA
From:	Mark Roosa, Chair Soc Beh IRB
Date:	01/12/2012
Committee Action:	**Exemption Granted**
IRB Action Date:	01/12/2012
IRB Protocol #:	1201007274
Study Title:	Consumer Perceptions Associated with Patient Portal Functions

The above-referenced protocol is considered exempt after review by the Institutional Review Board pursuant to Federal regulations, 45 CFR Part 46.101(b)(2) .

This part of the federal regulations requires that the information be recorded by investigators in such a manner that subjects cannot be identified, directly or through identifiers linked to the subjects. It is necessary that the information obtained not be such that if disclosed outside the research, it could reasonably place the subjects at risk of criminal or civil liability, or be damaging to the subjects' financial standing, employability, or reputation.

You should retain a copy of this letter for your records.