Essays on a Digital Innovation in Healthcare Delivery:

The Case of Online Medical Consultations

by

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Contents

Executive Summary

Healthcare is the largest service sector in many economies worldwide, but it lags behind other industries in the use of efficient and innovative approaches to both patient care and service organization. Innovative, disruptive models of health care delivery that leverage current information, communication and decision technology platforms in novel ways have the potential to change the practice of healthcare delivery and management. To satisfy the growing demand for medical care, online medical consultation is a new virtualized healthcare delivery model that is currently being developed and piloted by provider organizations which does not rely on face-to-face visits for patient care. The growing interest in online medical consultation, or eVisit, is attributed to several factors such as immediacy of care, affordable cost, convenience, and efficient/flexible time management opportunities.

My dissertation investigates some key challenges and opportunities associated with eVisits from the perspective of the patient, the provider and the service delivery organization, respectively. The first two chapters provide an overview of virtualized healthcare delivery with a focus on patient portals and eVisits, followed by an analysis of users and their usage patterns of these services, utilizing data from a major health system. Drawing on Innovation Diffusion Theory in Chapter 3, I analyze adoption of eVisits by patients who were given a trial opportunity with the new service when compared with patients who did not have such access. In Chapter 4, I apply Organizational Learning Theory to study the impact of individual and organizational usage experience on provider's service efficiency. The final study in Chapter 5 examines the eVisit operational efficiency gains in the organization as a result of provisioning the eVisit service delivery model. To the best of my knowledge, this is the first detailed, analytical investigation of online healthcare delivery from the multiple perspectives of key stakeholders, providing an early understanding of the factors that drive patients to go online to resolve their health issues, physicians' productivity gains by participating in the eVisit service, and the potential impact on the organization's operational efficiency.

Chapter 1

1. Disruptive Digital Innovation in Healthcare Delivery: The Case for Patient Portal and Online Clinical Consultations

Abstract: Healthcare is the largest service sector in many economies worldwide, but it lags behind other industries in the use of efficient and innovative approaches to both patient care and service organization. Thus, innovative, disruptive models of health care delivery that leverage current information, communication and decision technology platforms in novel ways have the potential to change the practice of healthcare delivery and management. To satisfy the growing demand for medical care, several new models are currently being developed and piloted, such as online medical consultations, which do not rely on face-to-face visits as the sole model of care delivery. Alongside, the current patient-centered-care imperative has also resulted in the use of portal technologies, among others, to inform, engage and empower the patient in shared decision making. In this chapter, we briefly introduce different types of digital service innovations in health care and provide some details about these current streams of care delivery innovations, particularly in the primary care setting given its broad influence on overall health care services. Furthermore, we focus on the potential of online care delivery that includes web portal services for patients and online medical consultations beyond simple email communications between patients and physicians. We conclude with a brief discussion of the implications of these models for the future of health care delivery in the digital age.

Key words: eHealth, patient portal, online medical consultation, eVisit, disruptive service innovation

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1.1 Introduction

1.1.1 Service Innovation in Health Care

For centuries, health care has relied heavily on face-to-face interactions for its service delivery due to the specialized, personalized and knowledge-intensive nature of the tasks associated with clinical care. However, enabled by new and advanced means of communication and message delivery, there has been a slow but steady change in the traditional approaches in the 21st century (Wilson 2003). Assisted by a virtual communication channel with advanced computing systems, health care industry has initiated significant changes to its core service by providing medical consultations with diagnosis and treatment plans via online transactions (Adamson and Bachman 2010; Wilson 2003; Whitten 2007).

1.1.1.1 Types of Innovations in Healthcare Delivery

Service innovation in health care can be categorized into embodied and disembodied innovations (Bower 2003). Embodied innovations are tangible such as medical devices and pharmaceutical products, and disembodied innovations are intangible and constructed from newly formed knowledge such as advanced surgical techniques and new care protocols (Bower 2003) that produce procedural changes. We can further subdivide these types of innovations into 1) healthcare process, 2) operational care delivery, 3) medical products, and 4) health care organizations. Innovations in medical products can be categorized as embodied innovations, and the rest of the types of innovations can be bound to the disembodied, except innovations in care delivery which include both tangible and intangible innovations. Traditional face-to-face encounters with healthcare providers have been reshaped into virtual encounters in which patients and providers can exchange messages asynchronously, or in sync if video conferencing is available. This online medical service delivery has created a new channel of healthcare services, potentially at a lower cost and higher convenience. Most innovations in the healthcare sector in the recent decade have focused on digitization via computing, communication and decision technologies, particularly internet technologies.

In this paper, we examine these digital innovations in healthcare service delivery that are poised to dramatically disrupt current practices. We summarize how these models are being architected, deployed and evaluated in care delivery settings. Furthermore, we investigate challenges and opportunities for adoption and use by examining current online medical consultation, also called eVisit, deployments by health systems to provide online consultation service to patients in the ambulatory care setting. The eVisit service provides patients with online consultation through a series of secure message exchanges with a physician, providing an alternative for onsite office visits and non-reimbursed phone-based care (Padman et al. 2010, Jung et al. 2011, Jung et al. 2013)). These are distinct from email consultations because they capture relevant information about the patient's acute, non-urgent condition for immediate diagnosis and treatment.

The key stakeholders are the physicians, patients, and insurers. The patients need to be convinced that the eVisit service provisioned via portal technologies can provide them with good quality of service while offering the additional convenience of accessing a physician's medical advice online. The physicians need incentives to participate in such services, primarily through reimbursement for their services, as well as providing better care (Tang et al. 2006). Insurers need a clear understanding of how this service is going to be implemented, its value, and the relevant policies and guidelines, so that it can be covered under current health plans. The success of portals and eVisits is dependent on the buy-in from the stakeholders mentioned above. Finally, these novel but challenging digital innovations have the potential to add considerable value in other care delivery settings as well, such as post-operative management and chronic care management, thus providing better access and service to patients and improved value and competitive advantage for the organization.

1.1.1.2 Theories of Service Innovation

Several theories of service innovation are applicable to the healthcare delivery context. Wang et al. (2010) organized the diverse definitions of service science into four major categories: discipline-oriented concepts by Bitner et al. (2008), systems approach concepts by Maglio and Spohrer (2008), value-oriented definition by Vargo and Lusch (2008), and content-based definition by Cai et al. (2008). Although these approaches differ in construction, there is agreement on the underlying purposes for studying service science – to drive innovation and improve productivity and quality (value) via rigorous scientific research methods.

More than two decades ago, it was noted that the emerging information technology's main adopter would be the service sector, and that advanced technologies will drive innovation in service industry (Barras 1986). Examining classical innovation dimensions (Schumpeter 1934) – product innovation, process innovation, market innovation, input innovation, and organizational innovation, we observe that technological innovation in healthcare delivery touches upon all these dimensions. Until more recently, information technology in healthcare had mainly focused on administrative and financial transactions rather than clinical care delivery (Audet et al. 2004), but this is changing quickly and dramatically.

Innovating clinical care delivery via internet technology is a complicated process not only because it involves many stakeholders such as end users (providers, patients), payers, hospital staff, system administrator, and technicians but also due to nature of the task performed via the system, which is knowledge intensive, case specific, and must be embedded with the current work flow. Thus, developing the system itself is an innovative move (product innovation), and providing care via the system is a process innovation. Using internet technologies, care providers can reach patients who, otherwise, would likely not have access to health care without the technology, and thus it has a potential to create a new market for underserved populations. As internet technologies allow virtual encounters, providers affiliated with a hospital offering such online medical services can also extend them to other patients within the hospital practices. This internal outsourcing may create input innovation. Lastly, additional care delivery channels will change the organizational structure or at least work process in healthcare organizations in order to perform the new service seamlessly with existing ones. This leads to organizational innovation. Overall, innovation in technology-enabled healthcare delivery is multi-dimensional (Agarwal & Selen, 2011), has the potential to generate a large impact on the healthcare industry resulting in elevated service offerings (Agarwal & Selen, 2009), as a result of an interplay of service concepts, service delivery practices, client interfaces and service delivery technologies (Den Hertog, 2000; Miles, 2005). Thus, it is important to understand what the new opportunities as well as barriers and challenges will be when innovating healthcare service delivery.

1.1.1.3 Digital Innovations in Health Care

Healthcare is entering the digital age aided via the wide-spread deployment of Electronic Medical Records (EMR), availability of Personal Health Record (PHR) systems, Decision Support Systems, and other healthcare information, communication and decision technologies. Paperless systems are gradually being adopted by providers and patients, and promoted by regulations such as the HITECH Act (Health Information Technology for Economic and Clinical Health) in 2009.

Ongoing digital transformation of medical care delivery, particularly primary care, is being driven in part by the increasing gap between provider availability and patient demand for high quality, easily accessible care (Margolinus and Bodenheimer 2010). With some studies reporting that 33% of the patient population were unable to get timely appointments (Strunk and Cunningham 2002), expanding access to all consumers is a fundamental challenge faced by the US health care reform initiatives (Rittenhouse and Shortell 2009). One approach to satisfy this growing demand for medical care is patient-centered care initiatives that do not rely on face-to-face visits as the sole model of care delivery (Margolius and Bodenheimer 2010; Rittenhouse and Shortell 2009; Stange et al. 2010; Rosenthal 2008). A sustainable service delivery model should address current challenges regarding providers' already overburdened workload, timely access to care for patients, and cost of care delivery. Telemedicine has been promoted as a means of bridging the gap (Grigsby et al. 2007). Since the 1990's, there has been increasing use of telemedicine technology enabled by the dramatic developments in digital communication (Zanaboni and

Wootton 2012; Menachemi et al. 2004). Although the first 'telemedicine' solutions emerged in 1920's when telephone communication was introduced to care for remote patients or for ordering tests, radio communication became useful for medical support during the World War I (Sosa-Iudicissa et al. 1998). More recently, telemedicine applications have focused on specific areas such as remote-monitoring of chronic patients and teleradiology (transmitting x-ray images to remotely located radiologists in order to obtain specialist opinions) (Zanaboni and Wootton 2012; Grigsby et al. 2007) that have been made possible by advanced internet technologies. Thus, use of telemedicine in primary care settings has great potential in solving provider capacity problems and timely access to care.

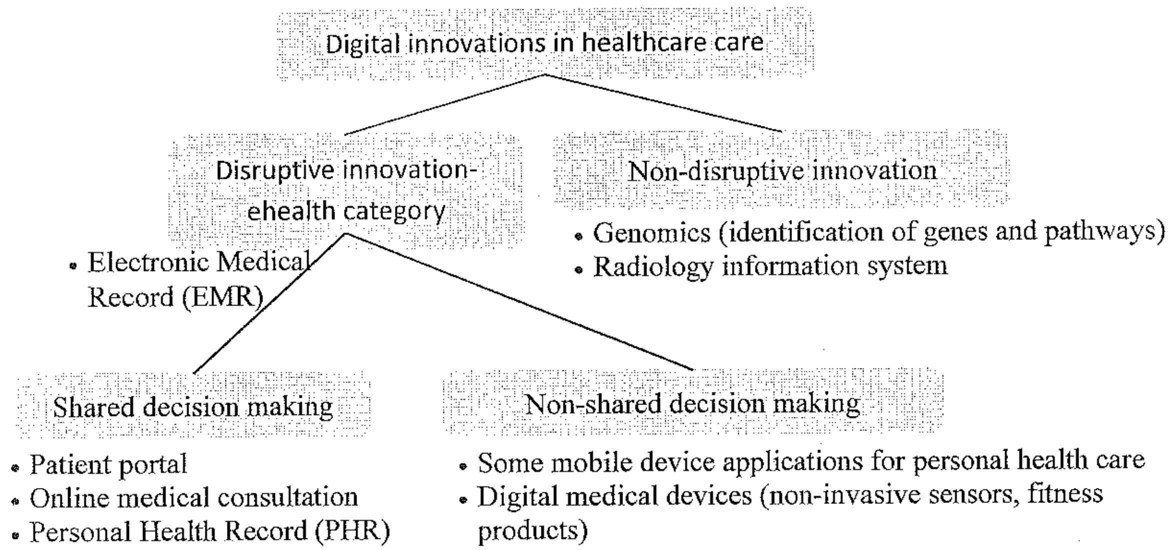
1.1.1.4 Disruptive Innovations in Primary Care

Expanding the deployment of telemedicine using internet and web technologies, patient portals and online medical consultation services are emerging as one of the most critical disruptive innovations in the healthcare sector. A disruptive innovation is one that affects its domain in large volume, which creates a new market and value, and eventually replaces existing technologies/processes (Hwang and Christensen 2008, Christensen 2000). This innovation provides products or services at relatively lower cost and in a less complex manner, and thus attracts customers with reduced needs or customers who are often ignored by existing market mechanisms. A well-known example is Ford's Model T automobile in early 1900's which was introduced at a lower price via mass-production. It replaced a large number of horse-carriages and eventually transformed the transportation market. Other examples include online classes and their potential to transform the education sector, and the role ATM has played over the past few decades in transforming the banking industry for consumers.

Unlike other industries, healthcare has remained expensive and lacks resources and accessibility regardless of advances in technologies and many other innovations (Hwang and Christensen 2008). However, the migration of services to online platforms has advanced technology-enablement of the healthcare industry via patient portals and online medical services because of their potential to improve dissemination of health care information and to enhance communication between patients and health care providers (Baker et al. 2003). This new development involving the use of internet and web technologies to deliver services has created a new field called e-health. These services empower patients to access necessary and valuable information relevant to their own health faster and easier than ever, such as information about particular diseases, test results, and ability to make appointments online and even communicate with their health care providers at almost no cost. This in turn helps patients to participate in health care decision making process with the knowledge that would not have been available without the power of internet. e-health, characterized as internet enabled medicine, is the latest development in the telemedicine stream of applications and is defined as health services and information delivered via internet and related technologies (Eysenbach 2001; Wilson and Lankton 2004). In addition, with the total internet-enabled population in the U.S. growing from less than 20 million in 1996 (Hoffman et al. 1996) to over 245 million in 2009 (CIA 2009), e-health services are now easily accessible and provide considerable convenience to these online consumers. This lower cost and greater convenience coupled with the instant information retrieval capability of e-health attracts patients, and therefore the demand is growing. More particularly, low-cost online medical consultation is a way to substitute physical clinic visits in cases where patients experience acute, non-urgent health concerns. Thus, e-health has the potential to be a disruptive innovation in health care industry. Details about its components, such as patient portals and online medical consultations, will be discussed in the next section.

One of the most important advantages that e-health is facilitating is shared decision making (Padman et al. 2010). Traditionally, patients have been passive participants in medical decision making because health care information and even patients' own medical records were hardly accessible in the past. Due to their lack of knowledge and lack of easy access to information, patients were unlikely to be involved in their treatment decision making process. In the internet enabled environment, when patients are able to retrieve necessary information as well as manage their healthcare records whenever they wish, they are better equipped with the necessary knowledge, and potentially more involved in their own health care if they so desire (Harle et al. 2011). This trend is shifting the decision making position from the physician to a shared view by the physician and patient (Hesse et al. 2005; Smith 1997; Wald et al. 2007), which is a necessary aspect of patient-centered care. In summary, Figure 1.1 depicts the positioning of e-health in healthcare innovation.

Figure 1.1 Envisioned structure and examples of digital innovations in health care



1.2 Patient Portal

1.2.1 What is a Patient Portal?

With secure internet transactions providing standard offerings in many industries and progressing to over 50 percent of online users in industries like financial services, the healthcare delivery sector is seeking to leverage deployment of the electronic medical record (EMR) to provide improved customer service and market differentiators to consumers by supporting appropriate levels of care in a secure, online environment (Padman et al 2010). As a consumer-facing extension of the EMR, patient health portals are becoming a critical part of a healthcare organization's service delivery strategy. While the EMR facilitates access to patient health information for providers and the care delivery team to make informed decisions at the point of care, health portals empower patients to access their clinical information and interact with their healthcare team (Weingart et al. 2006). It allows patients to take a more active role in their own health by providing secure and convenient electronic access to their own health information.

Patient portals provide value to the healthcare organization by streamlining workflow, empowering the patient, and creating new communication pathways. Through patient portals, users have the ability to self-service and research their own health information and health issues. By providing them with access, they can review and validate portions of their medical record such as test results, prescribed medications, and visits to clinics. Interactions with the office also become more user-friendly and efficient. Requests for prescription refills, appointments, medical advice – appropriate medication use and follow-up questions/updates after discharge – and other related information can be received electronically, automatically routed to the correct resource, and managed in a timely fashion that integrates into workflow with minimal disruption to the patient or staff (Carrell and Ralston 2006). Properly leveraged, patient portals can also be a valuable tool for an organization to inform patients of services and resources. Health reminders can be automatically and securely sent to patients reminding them of upcoming appointments, potentially decreasing no-show rates, the need to schedule appointments for annual physical or vaccinations, which may improve compliance with preventive care requirements, or informing them of new services available from the organization (Jung et al. 2011; Padman et al. 2010).

1.2.2 Patient Portal and Service Innovation

Most services deployed via patient portals have traditionally been served by telephone calls or physician office visits, such as to make an appointment and check test results for which patients sometimes needed to visit their physician's office. With internet-enabled self-services, patients obtain what they need without waiting since there is no queue in a virtual space. Patients can instantly make an appointment online, and check laboratory and radiology results without waiting on a telephone call or making a trip to doctor's office. Thus the traditional form of healthcare delivery for end-users is significantly being reshaped by technology.

With self-service patient portal features, patients can perform simple tasks without contacting their primary care providers or medical staff. Hence this self-service format has the potential to increase resource availability in the form of higher available capacity from care providers and better ability to meet the needs of patients who are in greater need of face-to-face consultations. Thus healthcare service innovation via patient portal can potentially enable redistribution of supply of limited resources including physician providers and clinical staff, as well as redistribution of high demand by segmenting patients based on their characteristics. These hypotheses have yet to be rigorously tested from portal deployments in diverse healthcare delivery settings. A recent study reported in the *Annals of Internal Medicine* found mixed evidence about the impact of patient portals on health outcomes, patient satisfaction, utilization and efficiencies, and also raised concerns about the digital divide in patient portal use (Goldzweig et al. 2013).

One of the most demanded services that can be provided by patient portal technology is communication with care providers (Adler 2006). 90% of internet users wish to communicate with their care providers (Harris Interactive 2002), however, development of such communication solutions has been very slow compared to other portal services (Wilson 2003). A basic form of online communication between patients and their physicians started with email, then developed into secure messaging within patient portal platform, and has finally evolved into paid online medical encounters with simple messaging features on the side. The online encounter service via patient portals with integrated EMR has great potential to substitute for traditional face-to-face healthcare service delivery.

1.2.3 Examples of Patient Portals

The different types of web-based patient portals can be grouped into three main categories. The first category includes patient portal applications integrated into the existing systems of the health care organization, which enables links between patients' electronic medical records (EMR), clinician work processes and the patient portal. This type of portal service is provided for its own patients by large health care provider organizations such as the University of Pittsburgh Medical Center and Veterans Affairs (My HealthVet: https://www.myhealth.va.gov/index.html, accessed November, 2013). They are capable of providing a range of services since all patient information is captured and can be retrieved from within the same system (Adamson and Bachman 2010; Nazi et al. 2010; Padman et al. 2010).

The second type of patient portal is provided by health insurance organizations such as Kaiser Permanente for their covered members (Sarkar et al. 2010). The integration of patient portal within the organizations' system is very similar to the first category, except that this is driven by payer organization, not hospitals or clinicians. This model mainly works as linkage between patients and physicians within the network. For example, Kaiser Permanente (KP) deployed a basic patient portal service in Northern California in 1999 with minimal features, adding prescription refill in 2001 and appointment scheduling feature in 2002. KP's laboratory test results and email communication with physicians became available in November 2005. Finally, its Personal Health Record (PHR) was later fully linked with the Electronic Health Record, KP Health Connect (Sarkar et al. 2010).

The third and final category comprises free-standing patient portals. Health care organizations and clinics without their own internet-enabled patient portal capacity can contract with vendors such as American Well who provide the communication environment and software products and platforms that allow registered patients to send messages to their providers or conduct simple tasks via the standalone system (Browning et al. 2012). In many cases, small-size providers are incapable of building their own patient portals due to high cost and low demand. For those providers, private companies provide patient portal solutions, serving patients via cloud-based communication services and platforms. In this context, self-managed online patient health record solutions are not considered as patient portals.

Most patient portals provide a basic service – asynchronous communication with healthcare providers. Some advanced and structured patient portals serve additional functionality such as appointment scheduling, reviewing laboratory/radiology test results, prescription renewals, reminders for appointments/medication, and so on. According to a survey (Klein 2007), patients in primary care setting are willing to use such systems for communication purposes. Studies and statistics show increasing accessibility, demand, and usage. Hsu et al. (2005) showed that portal service enrollees increased almost 6 fold in 3 years from 1999 to 2002. Despite increasing consumer demand, we observe digital divide in e-health as well. Patient portal users are generally younger, affluent, and healthier than the average patient (Weingart et al. 2006, Andreassen et al. 2007), predominantly female (Jung et al. 2011), with disparity in usage and accessibility by race/ethnicity and socioeconomic status (Hsu et al. 2005). The disparity caused by socioeconomic differences is of particular concern because it may exacerbate existing disparities in health care accessibility (Viswanath and Kreuter, 2007).

1.3 Online Medical Consultation

1.3.1 What are Online Medical Consultations?

Medical consultations through internet technologies, referred to as eVisits in some contexts, can be delivered using synchronous communication (e.g. video chat) or asynchronous communication via email or message service. The latter is an increasingly adopted form of online medical service, and is regarded as a digital innovation that has the potential to transform healthcare delivery (Wilson 2003), and provided by organizations with advanced e-health applications (Wilson and Lankton, 2004). Perhaps one of the most valuable capabilities of patient portals is the ability to provide services to treat patients for non-urgent health conditions (Padman et al. 2010; Adamson and Bachman 2010; Zhou et al. 2007). This offering provides patients with the ability to complete and submit basic information for designated non-urgent, episodic illnesses and receive an online evaluation from their physician, providing convenient, timely, and comprehensive access to care. Furthermore, this approach can evolve into a service that assists patients in managing chronic health conditions. By providing the tools to enter data such as blood glucose levels, weight, and blood pressure, and resources needed to monitor and control their health conditions over time, patients have an improved ability to actively participate in their health care and achieve more favorable health outcomes (Minetaki et al. 2011; Carrell and Ralston 2006). A survey of nearly 5,300 patients by Forrester Research reported that US health reform initiatives will necessitate online consultations between providers and patients as more consumers seek access to doctors (Boehm et al. 2010). Despite these perceived benefits and needs, adoption rates have been uneven across patient groups. There is little research that has investigated current forms of online service delivery, drivers of adoption of such services, understanding early adopters, and barriers and facilitators of online care in order to improve awareness and adoption. In particular, by applying innovation diffusion theory (Rogers

2003) to the field of online medical care, more efficient and effective strategic approaches to encourage adoption can potentially be developed and evaluated.

The key stakeholders are physicians, patients, and insurers. The patients need to be convinced that the eVisit service provisioned via portal technologies can provide them with good quality of secure, reliable, service while offering the additional convenience of accessing a physician's medical advice online. The physicians need incentives to participate in such services, primarily through reimbursement for their services, as well as providing better care (Tang et al. 2006). Insurers need a clear understanding of how this service is going to be implemented, and the associated costs, benefits, regulatory policies and guidelines, so that it can be included in covered services. The success of portals and eVisits is dependent on the buy-in from the stakeholders mentioned above.

In summary, this novel but challenging digital innovation has the potential to add considerable valuable in diverse care delivery settings as well as in areas such as post-operative care management and chronic care management, thus providing better access and service to patients and improved value and competitive advantage for the organization.

1.3.2 Current Practice

Many organizations with patient portal application currently provide some kind of online medical consultation services via the portal solution. Large healthcare organizations serve their own patients with patient portals that are integrated with the organization's EMR. Others utilize technology platforms provided by private entities, such as Relay Health (http://www.relayhealth.com), to connect patients to their physicians whereas other sites like American Well (http://www.americanwell.com/), TelaDoc (http://www.teladoc.com/), and others are available for anyone as long as there are online consulting physicians contracted to the organization within the patient's state of residence. In the latter case, it might be difficult to receive appropriate diagnoses and treatment that has long term implications since the provider does not have access to any medical history of the patient other than information the patient provides with the consultation request. However, there are no studies reporting the effectiveness of the different type of online medical consultations, and thus it is an open area for research. Nonetheless, online medical consultation is a growing trend and, if appropriately organized, has the potential to substitute physician office visits for non-urgent, acute symptoms at lower cost (Adamson and Bachman 2010).

Online consultations managed by provider and insurer organizations have the capability to link the service with existing EMR systems, which is an ideal service delivery mechanism (Viswanath and Kreuter, 2007) because such e-health solutions can provide comprehensive information about patients to providers, hence the quality of the virtual clinical encounter can also be improved. When the service is provided by hospital organizations, there is an opportunity to physically visit physicians for follow-ups or physicians can ask patients to come in if deemed necessary. This possibility may increase the level of trust by patients. Some online medical consultation sites have reimbursement structure for physicians, and the rest are paid by patients out of pocket. We do not regard email communication or simple messages that are free of charge as online medical consultation. Email and message exchange are used for follow-up questions, updates, inquiry for medication advice, etc. that do not necessarily require diagnosis and prescriptions, and can be answered by nurse practitioners or other clinical staff. Most online consultations are free-text format where patients describe symptoms and health concerns that they experience. Structured consultations consist of context-driven questionnaires that are relevant to the patient's choice of symptom, are mostly multiple choice, clarification questions but allow a few free-text forms where patients enter details. Although healthcare practitioners and researchers agree on the usefulness of online clinician service for patients with chronic conditions, currently available sites are primarily being utilized for non-urgent, acute conditions. Figure 1.2 summarizes different characteristics of online medical consultations in current practice.

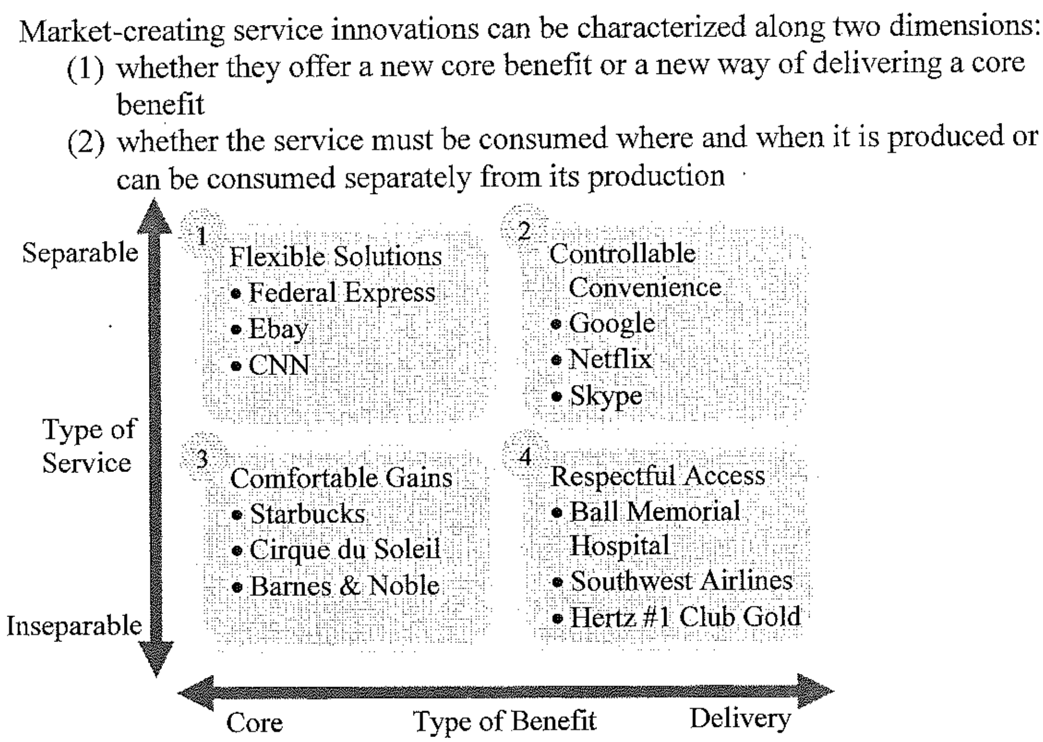
Figure 1.2 Characteristics of Online Medical Consultations

EMR Integration	Integrated with EMR
	Free standing (no link to EMR)
Follow-up Physical Contact	Available
	Unavailable
Submission Format	Structured
	Unstructured
Reimbursement	Payers reimburse – patients incur copay amounts
	No reimbursement structure – patients incur out of pocket costs
Treated condition	Chronic disease management
	Non-urgent, acute conditions

1.3.3 Analogy to Other Industries

Asynchronous communication between patients and physicians is an increasingly adopted form of care via patient portal in order to improve care quality and patient satisfaction (Wakefield et al. 2012) and it is a dominant online service format in primary care setting. Two types of innovative healthcare delivery via advanced internet technologies are synchronous communication such as video chatting, and asynchronous communication such as email/message exchange. Both synchronous and asynchronous communications transform traditionally inseparable healthcare services to separable services. Inseparable service by definition means that service production and consumption occur simultaneously (at the same time and place). Healthcare has traditionally been considered as an inseparable service sector since a patient and a physician need to be in the same room at the same time (Berry et al. 2006). Whereas synchronous communication only relaxes geographic restrictions, the more costly, asynchronous communication separates service production and consumption both in time and place, and thus provides higher level of flexibility. Borrowing the characterization of service innovation along the two dimensions of innovation – benefits offered (either core service product benefit or delivery benefit) and separability – from Berry et al. (2006), online medical consultation fits into 'controllable convenience' (Cell 2 from Figure 1.3) that is separable, revolutionizing consumer access via the new service delivery method. Thus the main contribution of asynchronous online medical consultation/communication to traditional health care sector are 'service separability' and delivery benefits.

Figure 1.3 Four types of market-creating service innovations (Berry et al. 2006)



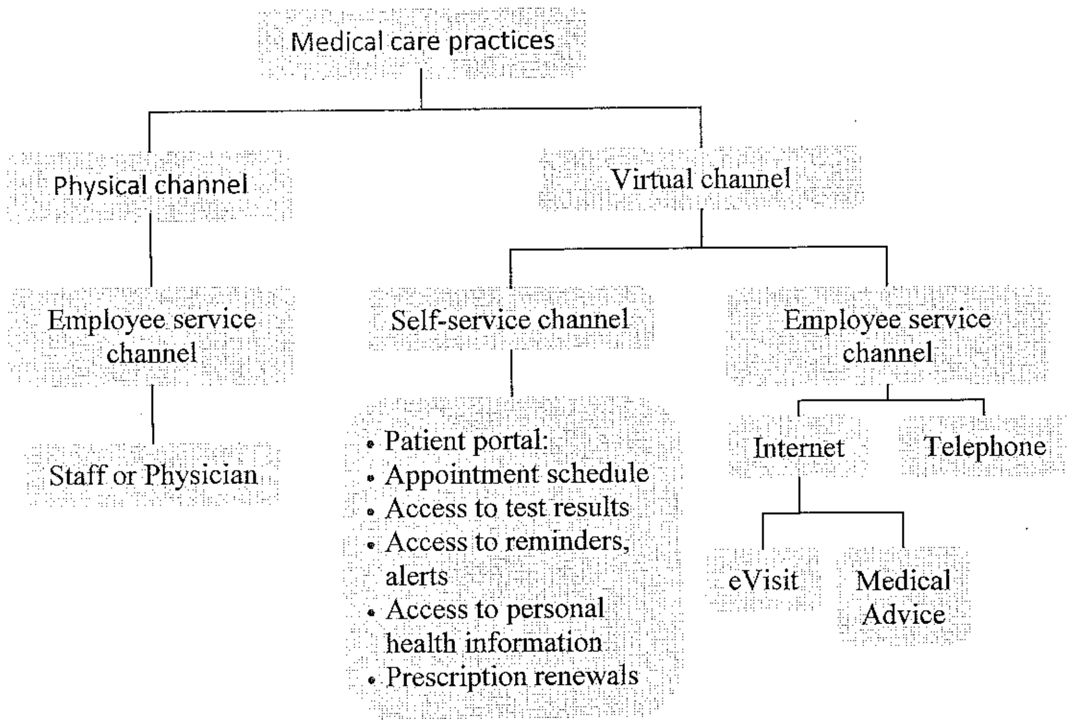
Digital innovations have led to new market creation, especially by reshaping the market place from physical to virtual environments. They have penetrated many fields such as commerce, travel, banking, education, governance, and journalism, and have become necessary for many industries to stay competitive. Due to the virtual delivery of service, consumers no longer need to physically face service providers, enabling non-simultaneous service consumption, which has transformed the traditionally inseparable service to separable through the innovation. Online banking, e-government, and e-commerce are examples with service separability and delivery innovation, while online class via video streaming lectures is separable and provides core product benefit.

There are clear analogies between online medical consultations and innovations in those other industries. Firstly, all of them traditionally served customers via face-to-face transactions. Products were sold in stores, travel agencies consulted in their offices, customers needed to visit banks for transactions, students had to attend classes physically, and read paper-based journalism options that were delivered to our homes and offices. Second, they now provide their core service via online channel which is convenient and reduces transaction cost for both providers and consumers. Retailers and travel agencies no longer need to maintain physical offices, banks can handle simple online transactions instantaneously, schools can offer their classes to broader audiences without geographic constraints, and governments can manage their tasks online with minimal workforce.

Online banking, in particular, has very close resemblance to online medical consultation. Online banking is an innovation in service delivery (Miles 2005) similar to online medical consultation, and with some exceptions (internet banks and online doctors), both provide multi-channel service delivery system that deals with relatively simple tasks of their core business services. The noticeable distinction is that healthcare industry is a knowledge intensive business service (KIBS), requiring high skilled workers (Miles 2008). While online banking is self-service, online medical consultation requires responses from physicians.

Unlike majority of internet services in many industries, the online service delivery channel in healthcare does not depend entirely on self-service mechanisms although most service options are. Thus, there is a limited self-service path in health care sector. We depict the multichannel system of primary care practices with online portal and medical consultation capabilities in Figure 1.4 based on the retail banking structure configured by Xue et al. (2007). Patients need to interact with the staff or physician via online messages for medical advice. Apart from online messaging, some organizations provide asynchronous virtual encounter with physicians that are paid medical consultations that evaluate the patient's symptoms to provide diagnoses and medication prescriptions or even test orders, which serves patients in exactly the same way as physical clinic visits but without actual face-to-face encounter.

Figure 1.4 The Multichannel Service Delivery System in Primary Care Practice (adapted from Multi-channel Service Delivery System in Retail Banking by Xue et al. 2007)



1.4 Secure and Structured eVisit and Patient Portal

In this section, we describe a particular secure and structured online medical consultation solution provided by a large healthcare provider organization in Pennsylvania. This eVisit service provides patients with online consultation through a series of secure message exchanges with a physician, providing an alternative for onsite office visits and non-reimbursed phone-based care (Jung et at. 2011). The eVisit service is distinct from email consultations because it uses a set of structured template-driven questionnaires to capture relevant information about the patient's acute condition. We have examined actual usage data over time as well as survey and interview results for trends in adoption, demographic and temporal patterns of usage, clinician and patient expectations and experiences, and challenges to sustainability of the service (Padman et al. 2010, Jung et al. 2011, Jung et al. 2013).

Similar to other patient portal services (Weingart et al. 2006), our study site allows patients to take a more active role in their own health by providing secure and convenient online access to their electronic health information (Padman et al. 2010). Patients who are 18 years or old are eligible to sign up for the service and are provided information about the portal services in their primary care providers' offices. Once signed up, users can review clinical information such as health history, past visits, test results, and medications as well as business services such as appointment scheduling, pre-registration, prescription renewal, payment, and reminders for future appointment/health maintenance. If there is no user activity for a given amount of time, users are automatically signed out. The system allows members to manage their family members' health records by providing 'proxy' feature by which members can make an appointment, view health records and communicate with providers regarding test results, etc. on behalf of patients. The portal utilizes the underlying technical infrastructure and solutions offered by Epic Corporation via the EpicCare Electronic Medical Record (EMR) and MyChart patient portal (http://www.epic.com/software-phr.php, accessed November 2013). It has been in use for more than six years, has more than 150,000 current enrollees, and continues to grow along the two dimensions of users (patients and providers) and services.

A new online service, eVisit, was deployed within the portal in 2008 as a pilot, providing patients with an online consultation through a series of secure message exchanges with a physician (Padman et al. 2010). The pilot service was deployed at a single practice where hundred percent of physician participation was achieved. Instead of free text messaging used in many online medical messaging services, this service uses structured templates for each eVisit condition, which creates formatted documentation for the consultation. Structured/standardized template means that patients' symptom reporting page is constructed as a sequence of questions, which prompts patients to not miss important and relevant information to be delivered to physicians who use them in assessing patient's condition. Thus, the template captures best practices and produces clearer evidence for communication and decision making. Collecting critical information without unnecessary details of symptom reporting that characterize free text entry, the application is easy to use for both patients and physicians. It is integrated with practice workflow, and thus provides access to information that is stored in the Electronic Medical Record (EMR). A successfully completed eVisit is finally documented in the EMR as well.

More recently, eVisit service has been deployed in several additional practices and reimbursed by a few health plans. The physicians and staff at the offices encourage patients to sign up for the patient portal and to use eVisits for the treatment of the specified episodic illnesses, which currently consists of 20 conditions including one exceptional category 'Other' that allows patients to request eVisit for unspecified conditions. The use of the service is purely voluntary for patients and providers.

When a patient clicks to initiate an eVisit, the system first checks whether the patient needs an eVisit or a simple, free message is sufficient for follow-up questions from recent visits, referrals, and questions for clinical staff other than physicians. If the patient proceeds with eVisit, cost information is provided, followed by an emergency disclaimer. After accepting the disclaimer, the patient is guided to the next screen where he or she chooses a reason for eVisit and specifies the pharmacy of choice, in case it is needed. Next, there are multiple steps to verify the patient's information including address, health issues, medications, allergies, etc. When all verification is completed by simple click through, patients need to answer a template-driven sequence of questions specifically designed for the patient's choice of symptom, until the final submission. Patients can cancel and leave the eVisit at any point during the procedure.

The eVisit process starts when a patient, experiencing an acute, non-urgent health condition, chooses to complete and submit an eVisit via the patient portal after sign in. Based on the symptom a patient chooses, several multiple choice questions follow, including a few with free text entry. The completed message goes to a support staff pool that forwards the eVisit to a participating physician; if primary care provider is unavailable, an assigned on-call physician takes the responsibility to act on the submission. Physician assignment is autonomously decided by the practice. If the submission occurs outside of office hours, call center staff notifies an assigned physician. Once the physician reviews and responds with a diagnosis and treatment plan, the patient is alerted via their personal email to login for checking the response. The patient may choose to have further message exchanges before the physician closes the encounter, and thus one eVIsit can have multiple threads as email communications. Once the encounter is closed, the physician removes the message from personal inbox and the support staff is notified, and then a claim is submitted for reimbursement. The details of the pilot system's process flow are found in the literature. Pilot studies reveal the basic demographic characteristics of the users being mostly working age between 30 and 50, primarily female; both as eVisit submitters (Adamson and Bachman 2010) and as patients (Jung et al. 2011). Providers also face unique challenges in learning to use the technology and improve productivity (Jung et al. 2013).

1.5 Future of Medical Service in Primary Care Setting

1.5.1 Multiple Models of Online Care Delivery

The healthcare industry is experiencing multifaceted shifts, from hospital-centered to patient-centered care, and from traditional face-to-face care to e-health, mobile health (m-health), and ubiquitous health (u-health) environments that collect patient information in real time. Although both technology adoption and organizational change management are slower in healthcare than other industries (Christensen 2009; England et al. 2000, Jung et al. 2013), a clear direction where digital innovations in health care sector may lead us to is a collaborative self-management format that is assisted by automated care system and efficient service delivery channels. In this model, patients take a proactive role in health care management rather than passively following physicians' decisions, and this active involvement coupled with accessible information will propel preventive care, which in turn may improve population health.

Even as online medical consultations and patient portals are being widely adopted, other care delivery channels, particularly mobile and ubiquitous channels, are being developed. This highlights the importance and urgency of moving forward to advanced, integrated online healthcare systems that provide well-defined, structured, and connected health care services including online medical consultation, advanced portal services such as prescription renewals, appointment scheduling, automated reminders for vaccinations and preventive tests, laboratory test results review, test image and medical history retrieval, relevant information search, and free message exchange for simple updates and advice. The system must be linked to patients' EMR to provide continuity of care and equipped with capacity to expand for diverse patient population as well as managing broader spectrum of health conditions, and possibility to link with mobile queries.

These new technologies and channels of care delivery require new problems to be solved and novel approaches to analysis and research. Prior studies have shown that online medical support and consultations targeting chronic conditions empower patients to become actively involved in their health management and participate in decision making process (Cummings et al. 2009). Patient health outcomes and satisfaction levels have improved due to increased access and communication with care providers (Nilsson et al. 2006). Despite the predicted benefits, there is no large scale systematic approach to build internet portals targeting the population with chronic illness, particularly providing predictive analytics for disease management and tracking disease progression (Harle et al. 2012). Building such environments would require binding primary care providers and specialists together into the system in which triage becomes unnecessary, and continuity of care is assured. Under health reform initiatives in the US, patient-centered medical home and accountable care organizations, among others, are being developed and evaluated with significant information technology support to deliver the new requirements.

Second, little is known about users of such services such as portals and eVisits, which opens up new opportunities for future studies. Pilot studies in a few health organizations have identified some demographic characteristics that distinguish these users from the general patient population, but the driving factors for more frequent usage and adoption are still under scrutiny. In addition, it is important to understand to what extent eVisits, for example, will increase clinical staff and physicians' capacity or disrupt daily work processes. Their impact on health outcomes, efficacy and efficiency of the service, and patient/physician satisfaction level in various settings are yet to be investigated.

Third, there is a severe, imbalance in the supply and demand of online healthcare services. Surveys reveal a large gap in willingness to adopt between patients and physicians. As many as 90% of patients surveyed would like to have e-mail communication with their healthcare providers (Taylor and Leitman, 2002) and 75% of patients with internet access were willing to pay for online services (Adler 2006), whereas 82% of physicians prefer face-to-face interactions (Liederman and Morefield, 2003, Padman et al. 2010). Patients with chronic conditions also indicate interest in utilizing state of the art health services; a survey of diabetes patients found that more than 70 percent prefer using ubiquitous healthcare service despite their concerns about technological complexity (Lim et al. 2011). This huge gap between patients' eagerness to utilize online and advanced health systems and physicians concerns about providing the service may create larger discrepancy in accessibility to comprehensive health care. And although healthcare organizations and providers are investing to establish systems and environment to provide such online services, the new service market may not realize return on investment if patients' acceptance level is low. To resolve the issue, we must understand the barriers to adoption and find ways to address them.

1.5.2 Barriers and Solutions

From the providers' perspective, the barriers to the adoption of the service are lack of reimbursement, perceptions of overload by online patients' requests, liability concerns, and patient confidentiality (Sands 2004; Liederman and Morefield 2003; Katz and Moyer 2004; Whitten et al. 2007; Padman et al., 2010). However, earlier studies have found no evidence of inundation of workload on physicians (Leong et al. 2005; Liederman and Morefield 2003; White et al. 2004; Kittler et al. 2004). Confidential web portal development has addressed privacy concerns, and portals linked with EMR have addressed workflow concerns (Adler 2006). Despite these advances, lack of reimbursement has remained as the most significant concern among physicians as 80% of surveyed physicians have responded that they would be willing to provide online communication with patients if reimbursed (Kittler et al. 2004). More recently, reimbursement for online services is being increasingly accepted by payers, and thus it is clear that the concerns regarding online messaging and consultations are gradually being resolved, and we can anticipate physicians' increasing involvement in online healthcare services in the near future.

The key barriers for patients to adopt online medical services can be summarized into a few important issues - accessibility to internet, concerns about content privacy, trust, and perceptions about care quality. Healthcare organizations with messaging capability in their online services provide secure messaging in which the contents are securely protected. Alongside, the population with internet access has grown rapidly and is still on the increase. Therefore, eliminating the observable barriers to patients has become a feasible task. Trust is a common barrier to the adoption of many other online services. Online commerce has created rating/evaluation systems in which consumers can share each other's experiences. Similarly, online evaluations of healthcare providers and organizations by individual patients as well as availability of summary evaluations by public reporting systems are also on the rise (http://www.cms.gov/Medicare/Quality-Initiatives-Patient-Assessment-Instruments/HospitalQualityInits/HospitalCompare.html). However, the level of trust is relatively higher for using online medical services when it is provided by patients' own practice and providers. Finally, there is a body of literature concerning individual adoption – innovation diffusion (Rogers 2003), theory of reasoned action (Fishbein and Ajzen, 1975), technology adoption model (Davis 1989) and their many extensions that explain the level of individual adoption being affected by potential consumers' perceptions, such as perceived usefulness, ease of use, relative advantage, compatibility, and complexity. While these perceptions can be verified, updated and dispelled, when necessary, using actual usage data, designing a patient portal structure and online medical service site to meet requirements for both consumers and providers is an important but challenging task.

The lesson from the story of Dvorak keyboard is that technological innovation does not diffuse by itself. Dvorak keyboard design that achieves equal usage of both hands by allowing hand-alternating is considered more efficient, but it never diffused into the public arena and we continue to use the QWERTY keyboard for which the layout was designed more than 100 years ago (Rogers, 2003). This tells us an important lesson that innovation alone may not survive or be sufficient to influence and reshape healthcare services in a way that improves the productivity and quality. We need to carefully devise a plan to help it diffuse as well.

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Chapter 2

2. Understanding Users and Their Usage Patterns of Online Medical Consultations

ABSTRACT

Background: Virtualization of healthcare delivery via patient portals has facilitated the increasing interest in online medical consultations due to its benefits such as improved convenience and flexibility, lower cost, and time savings. Despite this growing interest, adoption by both consumers and providers has been slow, and little is known about users and their usage and adoption patterns.

Objective: To learn characteristics of online healthcare consumers and understand their patterns of adoption and usage of online clinical consultation services (or eVisits delivered via the portal) such as adoption time for portal users, whether adoption hazard changes over time, and what factors influence patients to become early/late adopters.

Methods: Using online medical consultation records from four ambulatory practices affiliated with a major healthcare provider, we conduct simple descriptive analysis to understand the users of online clinical consults and their usage patterns. Multilevel Logit regression is employed to measure the effect of patient and primary care provider characteristics on the likelihood of eVisit adoption by the patient. Finally, survival analysis and Ordered Logit regression are applied to study eVisit adoption patterns that delineate elements describing early or late adopters.

Results: On average, eVisit adopters are younger and predominantly female. Their primary care providers participate in the eVisit service, highlighting the importance of physician's role in encouraging patients to utilize the service. Patients who are familiar with the patient portal are more likely to use the service, as are patients with more complex health issues. Younger and female patients have higher adoption hazard, but gender does not affect the decision of adopting early vs. late. These adopters also access the patient portal more frequently before adoption, indicating that they are potentially more involved in managing their health. The majority of eVisits are submitted during business hours, with female physicians responding faster (from submission to reply), on average.

Conclusions: This study addresses virtualization of primary care delivery via patient portals and online clinical consultations and examines factors that distinguish eVisit adopters from patient portal users. Among many delineating characteristics, it is particularly significant that familiarity with the patient portal service and participation of primary care provider are found to be key elements that motivate patients to become an eVisit user and early/late adopter. These findings can be used by provider organizations to design and implement strategies to improve uptake of online medical consultations to complement traditional office visits. Offering such alternative channels of care delivery may potentially improve access, efficiency and outcomes for both patients and providers alike.

Jung, C. and Padman, R. (2014). Virtualized Healthcare Delivery: Understanding Users and their Usage Patterns of Online Medical Consultations. The International Journal of Medical Informatics 83(12):901-914.

2.1 Introduction

Healthcare is the largest service sector in many economies worldwide, but it lags behind other industries in the use of efficient and innovative approaches to both patient care and service organization [1–3]. Thus, innovative, disruptive models of virtualized health care delivery that leverage current information, communication and decision technologies in novel ways have the potential to change the practice of healthcare delivery and management [4]. To satisfy the growing demand for medical care, several new models are currently being developed and piloted, such as online medical consultations, which do not rely on face-to-face visits as the sole model of care delivery [5]. Alongside, the current patient-centered-care imperative has also resulted in the use of portal technologies [6], among others, to inform, engage and empower the patient in shared decision making [7].

There is growing interest in online medical consultation due to its benefits such as convenience, cost, flexibility, and time savings [1, 8]. To receive online medical consultation service, or eVisit, no appointment scheduling is required since patients initiate patient-physician interaction asynchronously. Patients can submit their health concerns at home/work using internet technology enabled applications at potentially lower cost. Many healthcare organizations are setting a new service delivery strategy that empowers patients to access their clinical information and interact with their healthcare provider [9]. Patient internet portals, for example, are widely available [10], and adopted by 40% of U.S. hospitals [11]. They enable users to activate self-service healthcare management electronically, such as checking their own medical records, researching related health issues, making/changing appointments, requesting prescription renewals, and interacting with clinicians with minimal disruption [5, 12]. Online communication between patients and physicians that provide medical consultation for non-urgent health conditions can potentially support management of chronic health conditions by providing the tools to enter data such as blood glucose levels, weight, and blood pressure, and resources needed to monitor and control their health conditions over time [5, 13–15]. Thus patients have an improved ability to actively participate in their health care and may achieve more favorable health outcomes [11, 12].

Patient eVisits are gaining momentum due to increasing consumer demand for improved access to clinical services, availability of new technologies to deploy such services and development of reimbursement initiatives by major payers [13–16]. The eVisit service provides patients with access to a series of structured, secure message exchanges with a physician using portal technology, providing an alternative for onsite office visits and non-reimbursed phone-based care [13]. This can potentially increase the volume of patient access to health providers [5, 13, 14]. Surveys indicate that online communication with healthcare provider is the most preferred service for patients with internet access [17]. They have been shown to prevent an office visit for about 40% of the patients who signed up for the service [14], and the availability of this service decreased spending on the clinic visit [18]. Despite increasing interest in online health consultations by consumers, adoption has been slow and little is known about the users of such services other than that they are more educated and have higher household income compared to non-users [15, 18]. A national survey of health IT use among 18-64 year old consumers confirmed that despite wide interest in accessing health information, women are overwhelmingly more likely than men to look up online health information, request prescription refills, seek medical advice and other interactions with their health provider [19]. As portals and eVisits become more widely available to patients and more increasingly sought, it is important to understand the key characteristics of actual consumers of online health consultations in contrast to survey respondents, in order to design appropriate services and deliver the most effective experiences for providers and patients alike.

In this study, we address this question by analyzing the deployment of eVisits within a patient portal environment at four primary care clinics associated with a major health system in Western Pennsylvania. We examine the key demographic and usage characteristics of consumers accessing the portal and eVisit service from Sep 2008 to May 2010. Using data that includes eVisit records, patient demographics, portal logon information, and diagnoses, we estimate the odds of eVisit submission based on individual patient demographic characteristics and their utilization of online healthcare information on the portal at the four clinics. Each practice has different characteristics that may affect patients' eVisit use such as rate of physician participation on eVisit service, whether it is an academic/non-academic practice, having a physician champion in the practice, and so on. Thus we use Multilevel regression model that allows us to estimate practice-level effects, even with the small number of data points in a practice and available data attributes. In this study, we distinguish between two categories of patients - those who utilized only the patient portal service ('PP only' patients) which allows them to make appointments, update demographic information, submit billing/insurance information, and find related health information; and those who additionally submitted at least one eVisit (eVisit patients) during the study period.

A related, critical concern is: when do patients start to use eVisit? Time-to-event is potentially a more informative method of analysis since it enables us to observe effect of treatment (or any important variables) over time rather than comparing outcomes at a single point in time such as end of trial. This study method is widely used in clinical analyses [20] and technology adoption studies such as MRI adoption in 1990's and early 2000's [21]. Thus, we apply survival analysis to understand time to adoption by consumers, rather than technology adoption by service providers. Furthermore, we observe that some patients submit eVisit immediately after their first patient portal (PP) access while others use eVisit service several months after their first PP access. Hence, we model early vs. late users by categorizing patients by days till adoption, and use Ordered Logit regression to delineate the elements that characterize these patients.

2.2 Background

The study site is a major academic medical center in Western Pennsylvania. Similar to other patient portal services provided by large healthcare organizations, it allows patients to take a more active role in their own health by providing secure and convenient online access to their electronic health information and provides various services including checking medical history, review of test results, appointment scheduling, pre-registration, prescription renewal, health maintenance reminders and soliciting medical advice from their healthcare team. The portal is integrated with the ambulatory electronic health record (EHR) which allows the health care team to interact with patients through their current applications and workflow. The portal utilizes the underlying technical infrastructure and solutions offered by Epic Corporation and MyChart Patient Portal [22]. The portal has been in use for more than eight years, with over 100,000 patient users in 2012, and continuously growing.

A new online service, eVisit, was deployed via the portal at a single practice in August 2008, providing patients with an online consultation through a series of secure message exchanges with a physician [13]. Instead of unstructured text messaging that is characteristic of many online medical messaging services, a standardized template is used in the eVisit, which creates structured documentation of the consultation. Since it is integrated with the EHR and the practice workflow and the captured information is stored in the EHR, it is easy to use for both patients and physicians, and possibly produces clearer communication by capturing all the necessary information. In April 2009, eVisits was deployed in four practices and reimbursed by a few health plans. The physicians and staff at the offices encouraged patients to sign up for the patient portal and use eVisits for treatment of specific episodic conditions. Thus use of the service was purely voluntary for patients and providers.

The eVisit process starts when a patient selects a condition, completes the structured documentation and submits the eVisit via the portal. The support staff reviews and forwards the submission to a physician. Once the physician completes the review and responds with diagnosis and treatment decisions, the patient gets notification via email, and may choose to have further message exchanges before the physician closes the encounter. This alerts the support staff who file the encounter fro reimbursement. Further details of the process flow can be found in [5].

2.3 Data

This study is based on de-identified eVisit transaction records between April 1, 2009 and May 31, 2010, including patient portal activation and login data for the patients of the participating clinics, patient demographics, physician and payer information and diagnosis records of eVisit. Attributes of eVisit transaction data include a unique message identifier, patient and physician identifiers, date, time and subject of the message (one of the 8 conditions: sinus/cold, cough, back pain, diarrhea, urinary symptoms, red eye, vaginal irritation/discharge, and other), and whether the visit provided diagnoses/medications/lab test orders. eVisit records during the pilot study period (between August 20, 2008 and March 31, 2009) at a single practice are also available, which allowed us to check whether a patient experienced eVisit before it was formally rolled out with payment structure. This pilot period data is used in the eVisit adoption analysis (survival analysis). Patient demographics included age, gender, race, marital and employment status, primary care provider (PCP), PCP practice, and portal account inactivation date. Throughout the study, we define 'patient population' as the patients of the four study clinics who had activated portal access. This is to minimize potential bias that will arise if all patients regardless of their accessibility to computers and internet are included. To understand the drivers of eVisit service and adoption, we thus compare eVisit users and non-users with similar familiarity to computers and the internet since they are all portal users.

In summary, 600 eVisits were submitted by 448 unique patients, with 98 patients submitting requests more than once. 1,551 total messages were exchanged between patients and physicians, including the original submission. Practices 1 – 4 had 51, 12, 8 and 3 physicians, respectively, with participation rate in the eVisit service at 12 percent, 100 percent, 50 percent and 100 percent, respectively. Since the service was provided by voluntarily participating physicians, we may expect more eVisits from a practice where more physicians participate in the service. Therefore, it is not surprising that the number of eVisits is the highest in practice 2. This practice is the study target for our survival analysis, and the data includes 2,512 patients who accessed PP during the pilot period, and 324 patients among them used eVisit service.

2.4 Methods

2.4.1 eVisit user analysis

We explore characteristics of eVisit users and measure the effect of patient and physician factors on eVisit use and adoption using descriptive statistics and empirical methods. Descriptive statistics summarize individual patient-level features that distinguish eVisit users from 'portal only' users, i.e., those without any eVisits. Next, we employ empirical methods to estimate the effect of these factors on eVisit utilization and determine the significant factors that differentiate these two groups, taking into account practice-specific elements and physician-level attributes.[12] Physicians' role in raising awareness of this service among patients was critical; there was no public marketing tool to advertise the service during the study period, and therefore word of mouth at each practice was the main channel to inform patients about the new service.[12] Specifically, we estimate the effect of patient demographics, severity of health conditions, familiarity with the patient portal, availability of insurance coverage, and PCP's eVisit participation on the odds of eVisit use. Patient's health condition is approximated by the number of health problems noted by physicians (i.e., number of unique ICD9 codes), with more problems indicating higher severity. The volume of portal site access is used as a proxy for familiarity with portal navigation and features. This is defined as the number of log-ins by each patient prior to the study period in order to avoid endogeneity issues. During the study period, eVisit users are likely to have higher volume of portal access. Insurance coverage indicates whether the patient's health plan covers eVisit for reimbursement.

The unit of analysis is the individual patient. The logistic regression model includes the following variables: the outcome variable, *eVisit,* is binary (1 if a patient used eVisit service during study period, 0 otherwise), and explanatory variables are *Portal*, indicating volume of portal access before the study period, *Female*, *Fulltime*, *Retired*, *Unemployed*, *Married*, *Single*, *White*, *Black*, *Problem* (number of distinct health problems noted by physician), *Cover* (1 if patient's health insurance covers eVisit, 0 otherwise), and *PCP.eVisit* (1 if patient's PCP provides eVisit service, 0 otherwise). There are several categories in patient's employment status, marital status and ethnicity, and thus we narrow down the categories based on the number of observations and *t-test* statistics; categories treated as 'others' either do not have significant variation between eVisit users and PP only users or do not have sufficient number of observations.

The four participating practices have different characteristics such as the presence or not of a physician leader for the eVisit project, academic/non-academic status, and clinic location that provides an indication of their patients' socio-economic characteristics. We execute separate logistic regression models for each practice, as well as the Chow-test for the combined model to determine which explanatory variables have differing effects (varying slope) on the odds of eVisit use across practices. The Chow-test result (Appendix A) shows that effect of *PCP.eVisit* is significantly different by practice. Intraclass Correlation (ICC) computation suggests that practice level fixed effect model produces better estimates and the descriptive statistics (Appendix D) indicates that there exist statistical differences in demographics, portal access, and patient condition across four practices. Thus we include practice fixed effects and allow varying coefficients of *PCP_eVisit.* The basic model is as follows:

$$(1)\ Logit(P[eVisit_{ij}=1]) = \alpha_0 + \alpha_1 Portal_{ij} + \alpha_2 Female_{ij} + \alpha_3 Age_{ij} + \alpha_4 Fulltime_{ij} + \alpha_5 Retired_{ij} + \alpha_6 Marital_{ij} + \alpha_7 Ethnic_{ij} + \alpha_{8j} PCP\_eVisit_{ij} + \alpha_9 Cover_{ij} + Practice\ Fixed\ Effect_j$$

where i = patients, j = practices

As mentioned above, physicians played an important role in spreading awareness of the new service availability on the portal. Thus, we expect that in addition to physician's eVisit participation, other physician characteristics may influence patients' knowledge and usage of eVisit. Hence, it may seem better to allow varying effect across physicians rather than practices. However, some physicians had as few as one patient enrolled in PP, so physician fixed effect model was not feasible. To resolve this issue, we estimate varying effects on eVisit by using Multilevel (hierarchical) model with individual patients as the first level unit and physician as a second level group. The logistic regression applies to level 1 of Multilevel regression model. For the group level parameter estimation, the unit is physician and the outcome variable is the intercept from the first level model. Since we have varying intercepts for groups (α_{0j} in the model below), there is no need to keep an intercept (α_0) in the classical regression model (2). Additional explanatory variables for physician attributes are *PCP.Leader, PCP.Age, PCP.Female, PCP.Exper, PCP.Avg_eV, PCP.Pat_Vol, and PCP.Particip. PCP.Leader* is 1 if a physician is a leading physician of eVisit project (one of the physicians in practice 2), *PCP.Exper* means years since graduation from medical school, *PCP.Avg_eVisits* is the average monthly eVisits the physician handled, *PCP.Pat_Vol* is the number of patients enrolled in patient portal whose primary care provider is the physician, and *PCP.Particip* is whether the physician provided eVisit service at least once, which is the same variable as *PCP_eVisit* in (1). Thus if a physician does not provide eVisit service, *Participation* and *Avg_eVisits* have value zero. Note that label $i = 1, \ldots, 14{,}451$ is for individual patients and group-level label $j = 1, \ldots, 69$ is for physicians. Some physicians were heavily involved in eVisit deployment and use whereas others started to provide the service 10 months after it started. Physicians who handled eVisit more than others tended to have more eVisit patients, which may indicate that they have informed their patients of the eVisit service. Thus the number of eVisits per PP patients (weighted eVisit = eVisits / patients, *w_eVisit* hereafter) of each physician might be another indicator of how willing the physicians are to service eVisits. These physician characteristics as well as demographic information of physicians are included in the Multilevel regression model below. Physician's age is not included since experience is also a proxy for the age (correlation = 0.985).

Multi-level Model

(2) $$eVisit_{ij} = \alpha_{0j} + \alpha_1 Portal_{ij} + \alpha_2 Female_{ij} + \alpha_3 Age_{ij} + \alpha_4 Fulltime + \alpha_5 Retired + \alpha_6 Marital + \alpha_7 White + \alpha_8 Black + \alpha_9 Cover + \alpha_{10} PCP\_ID + \varepsilon_{ij}$$

(3) $$\alpha_{0j} = \beta_0 + \beta_1 PCP.Particip_j + \beta_2 PCP.Female_j + \beta_3 PCP.Exper_j + \beta_4 PCP.W\_Avg_{ev\,j} + \beta_5 PCP.Leader_j + \eta_j$$

Where $\alpha_{0j} \sim N(\boldsymbol{U}_j\boldsymbol{\beta}, \sigma_{\alpha_0}^2)$ represent physician-specific random effect, and U_j is the matrix of physician explanatory variable in level 2 with i = patients, j = physicians.

2.4.2 Adoption analysis

While prior analysis focused on the average effect of patient and physician characteristics on a patient's decision to submit eVisit, hazard analysis allows us to observe the duration until a patient's adoption of eVisit, and whether patients are more or less likely to adopt eVisit after specific periods of time. This analysis can provide some insights into the key characteristics that are associated with the duration of patients' eVisit adoption.

In order to clearly define the time line, we analyze patients from a single practice - practice 2 - since practice 2 was the first practice to deploy the service during a pilot period. Other practices followed 7 months later when reimbursement structure was also introduced. In addition, all practice 2 physicians participated in the eVisit service. Hence, we assume that all patients were exposed to similar environmental characteristics within this practice. Furthermore, physician participation and cultural/operational differences across practices are assumed to have significant impact on eVisit usage. In addition, more practices (practice 1, 3 and 4) start providing eVisit from April 1, 2009, which might have brought unobserved synergy/network effect among physicians and practices after this period. Thus we do not include other practices in this specific analysis.

The eVisit service was initiated on August 20, 2008 as a pilot application and made available to patients at practice 2. Target subjects are 2,152 patients who accessed PP between August 20, 2008 and March 31, 2009 for the first time (see Fig. 1). It is unclear exactly when patients became aware of the availability of eVisit service, and thus we set the first PP access as the proxy for awareness of the availability of the service. Thus, we analyze the adoption of the service by patients who are exposed to this test/marketing period.

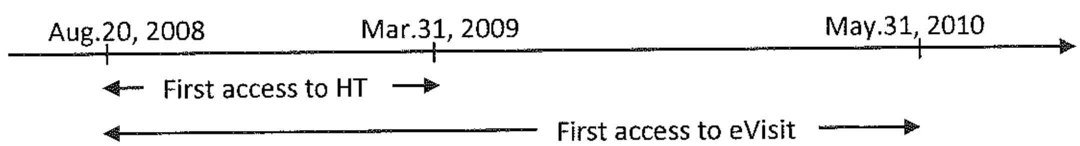

Fig. 1 – Timeline of the study

If a patient from the data pool used eVisit during this time, then it is regarded as an event having occurred. The time elapsed until event is calculated in days from the first access to PP to the first use of eVisit, defined as the survival duration. It is the same concept as the continuous involvement of study subjects in clinical events [23]; patients enter the study by getting a treatment at a different time, and then the survival time clock starts when the treatment is provided. Throughout the paper, survival means non-adopting (event has not occurred), and failure means adoption of eVisit service (event has occurred). Small number of eVisit adoptions is less of a concern (15.1% (324) events out of 2,152 subjects) since hazard rate can be estimated with a failure rate of as low as 10 percent.[24, 25] We use Cox-proportional hazard model. Hazard rate is the conditional rate of failure, i.e., the rate of an event given that a person has survived up to that time.[26]

If a patient did not use eVisit until the end of our study period, it is censored. We assign 0.1 to survival days for those records where eVisit and PP access occurred on the same day in order not to censor the records. Zero day duration means that patients may have signed up for PP in order to use eVisit, which is an important indicator of usage, and thus this record should not be dropped. Literature and our prior logistic regression results show that younger, female patients tend to use online consultations more than the rest of population [5, 13] and thus we hypothesize that these characteristics also positively influence the adoption speed.

We describe the distribution of failure (survival) time by using a proportional hazard model. Hazard function is based on two factors - arbitrary risk function or baseline hazard, $h_0(t)$, and proportionality factor that depends on the explanatory variables, x (Appendix C.6). (Additional details are found in

Appendix C.) An advantage of this semi non-parametric approach over parametric approach is the freedom from assumptions regarding the specific distribution of hazard over time [27]. Thus Cox-proportional hazard model is applied to estimate the hazard of adopting eVisit service. Cox model presumes that the ratio of hazard rate to baseline hazard rate is an exponential function of the parameter vector (Appendix C.7).

With the assumption that proportional hazard ratio stays constant, we can convert it to a linear regression model by taking log:

(4) $\ln(h(t)) = \ln(h_0(t)) + b_1x_1 + b_2x_2 + \cdots + b_px_p$

$\ln(h_0(t))$ is considered to be constant. This component expresses hazard rate changes as a function of survival time, whereas the covariate vector expresses the natural log of the hazard rate as a function of the covariates.

First, we conduct univariate analysis in order to decide whether each variable needs to be included; for categorical variables such as gender, employment status, etc., log-rank test of equality is used (non-parametric test), and for continuous variable (*Age* and *Problems*), we use the univariate Cox proportional hazard regression (semi-parametric model). Since none of the variables are time dependent, we do not consider time dependency in our model. Unlike prior literature on diffusion in which adoption rate depends on interaction between adopters and potential adopters, it is not necessary to consider the interactions between patients because it is reasonable to assume that most patients are not related to each other and there is no patient forum in the patient portal that enables discussion/information exchange among patients. We assume that censoring is random [28].

Based on the results from the univariate analysis, we decided to include gender, age, marital status, and employment as explanatory variables. Exhaustive testing of all possible interactions among the variables also eliminated interaction terms. Therefore, the final model is shown in (5) below. In addition, we check the significance of the explanatory variables after adding ethnicity variable and physician fixed effect.

(5) $\ln(h(t)) = b_0 + b_1 Age + b_2 Gender + b_3 Marital\ status + b_4 Employment$

2.4.3 Early adopters vs. late adopters

With the objective of determining the differentiators of early-adopters vs. late-adopters of the eVisit service, we categorize the 324 eVisit adopter patients from practice 2 by days to adoption and utilize an Ordered Logit model. K-means clustering is applied using R software (version 2.13.0 with max 20 iteration and 3 seeds) to categorize patients from 2 to 6 groups. K is selected based on the number of observations in each group and the proportion of between-ness (variance among groups divided by variance of total). As a drawback of clustering, finding optimal number of groups is somewhat obscure. Since partitioning is merely our means to find proper cut-offs for ordered groups, we rely on the proportional measure 'between group sum-of-squares (BSS)/total sum-of-squares (TSS)' and also consider the minimum number of observations in each group to avoid too few data points in a particular group. We chose K = 3, since the increment of proportion of between-ness out of total sum of square (BSS/TSS) significantly drops from K = 4, and disparity between minimum and maximum number of observations in the groups becomes much larger when K ≥ 4. The clustering results are provided in Appendix B. Based on the clustered groups, the first group used eVisit within 98 days of PP access (level 0), second group falls between 99 and 278 days (level 1), and the last group's duration is 279 days and beyond (level 2). The Ordered Logit regression model with the ordered groups (level 0 ~ 2) as a response variable is as follows:

$$y = \begin{cases} 0 & \text{if } y^* \leq 98 \\ 1 & \text{if } 98 < y^* \leq 278 \\ 2 & \text{if } y^* > 278 \end{cases}$$

$$(6)\ \ y^* = \alpha_0 + \alpha_1 age + \alpha_2 gender + \alpha_3 married + \alpha_4 fulltime + \alpha_5 white + \alpha_6 cover + \alpha_7 problems + \alpha_8 pcp\_leader$$

2.5 Results

2.5.1 Descriptive analysis – Patient characteristics

In summary, eVisit patients are younger, on average, primarily female, with higher levels of unemployment, smaller retired proportion, higher volume of past PP access, and have eVisit-participating primary care physicians. These differences in demographics between eVisit users and PP only users in aggregate are also observed amongst the four different primary care practices (Appendix). [5] The average age is higher in practice 4 for both eVisit and PP users, and unlike other practices, female proportion and fulltime employment percentage is lower in eVisit user than PP only user in practice 3. Other employment status, ethnicity, proportion of patients holding health insurance and of insurance covering eVisit also vary across the practices as well as the frequency of PP access and problems. More importantly, practice 2 has a higher proportion of eVisit users relative to its patient pool (Table 2) but has lower number of PP access, which may be partly due to each practice having a different strategy for building awareness of the eVisit service; this supports the use of practice fixed effect regression model in order to account for these observed differences among the four practices as well as other unobservables.

Table 1 – Demographics of eVisit vs. portal users

	eVisit patients	PP only patients	t-test *p-value*
Number of patients	446	12,207	N/A
Average age***	45.2	49.9	0.000
Min (Max) age	19 (78)	18 (96)	N/A
Female (%)***	74.7	61.3	0.000
Married (%)	66.8	67.1	0.761
Single (%)	22.6	24.1	0.223
Fulltime employed (%)+	65.5	61.3	0.068
Retired (%)***	5.4	13.5	0.000
Unemployed (%)**	17.5	12.1	0.001
Student (%)*	2.7	4.5	0.017
White (%)+	93.9	88.6	0.076
Black (%)	2.2	3.9	0.213
with Insurance (%)*	94.2	93.0	0.012
with coverage (%)	28.7	33.3	0.135
PCP participating (%)***	90.6	68.5	0.000
Avg. Problems	6.1	6.5	0.469
Past PP access*	14.7	9.9	0.024

+p<0.1, *p<0.05, **p<0.01, ***p<0.001

Table 2 – Patient proportion and number of physicians in practices

Practice	Total Patients	PP only User	eVisit User	eVisit volume	Number of Physicians	Participating Physicians
1	16,846 (35.7)	6,516 (46.5)	67 (15.0)	80 (13.3)	51 (68.9)	6 (24)
2	20,286 (42.9)	5,655 (40.4)	355 (79.6)	493 (82.2)	12 (16.2)	12 (48)
3	6,266 (13.3)	998 (7.1)	16 (3.6)	18 (3.0)	8 (10.8)	4 (16)
4	3,842 (8.1)	836 (6.0)	8 (1.8)	9 (1.5)	3 (4.1)	3 (12)
Total	47,240	14,005	446	600	74	25

(.): percentage

2.5.2 Descriptive analysis – Usage patterns

The eVisit service is utilized mostly during weekdays; only 54 submissions were made on weekend/ holidays. Among eVisits submitted during weekdays, the majority (431 eVisits) were submitted between 8am and 5pm (Fig. 2, 3). 38 percent of eVisits had sinus/cold symptoms as a major complaint (223 eVisits) and 9.8 percent were for cough symptom (Table 3). The frequency of eVisit use is higher during the winter as expected from the submitted symptoms whereas the frequency of PP access does not show any seasonality effect. The average number of volleys (messages between patient and physicians) excluding original eVisit submission is 1.59. In other words, most encounters are closed after 1 ~ 2 responses despite physicians' concerns about being overloaded by continuous messages and requests from patients. The average number of volleys for each subject is also summarized in Table 3.

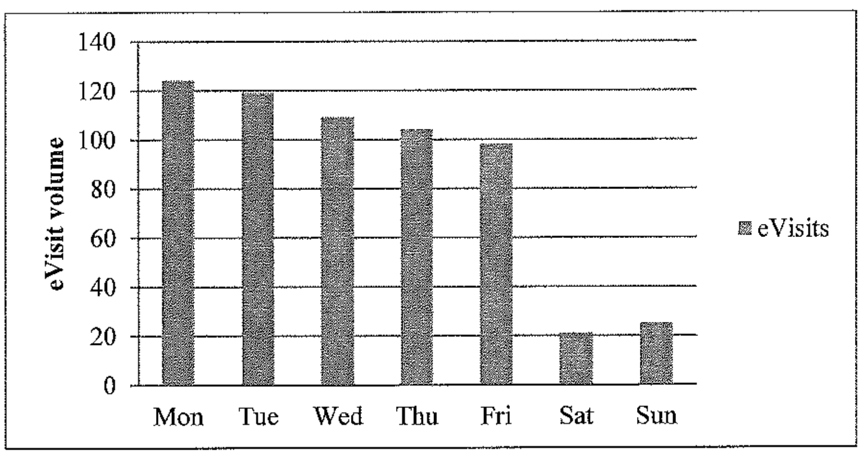

Fig. 2 – eVisit volume by day of the week

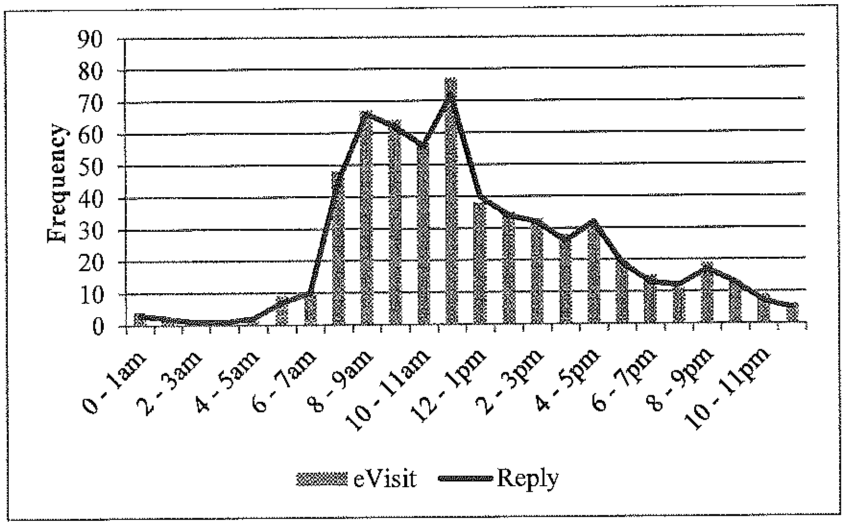

Fig. 3 – eVisit and response distribution by time window

Table 3 – eVisit summary by Subject

eVisit subject	Count	Proportion	Average volleys
Sinus/cold symptoms	223	37.2%	1.50
Cough	59	9.8%	2.08
Urinary symptoms	58	9.7%	1.26
Back pain	28	4.7%	1.93
Vaginal irritation/discharge	15	2.5%	1.40
Diarrhea	10	1.7%	1.60
Red eye	14	2.3%	1.07
Other	193	32.2%	1.63
Total	600	100%	1.59

As shown in Fig. 4, average time from eVisit submission to the first response was approximately proportional to the eVisit volume since September 2009. In other words, when there are fewer eVisits, physicians tend to complete the eVisit task faster, on average. Also, a physician's experience plays an important role in eVisit response time. The more eVisit services a physician provides, the response time is shorter on average. Interestingly female physicians tend to respond sooner (average 63 minutes) than male physicians (average 68.6 minutes). Note that out-of-business hours are not counted in the response time as the service provided consultation during business hours during the study period, and physicians are not obligated to respond to the submitted eVisits after business hours (this policy has since been changed to 24X7 response).

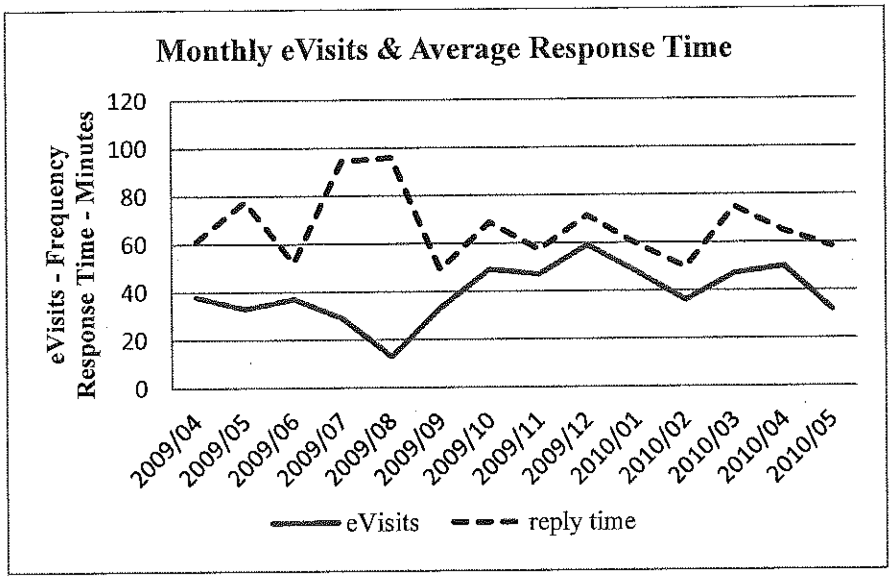

Fig. 4 – Monthly eVisit counts and average response time

The average time to event (from first PP access to first eVisit use) of the selected 324 eVisit users from practice 2 is 132.2 days (standard deviation = 153.2). The distribution of the time to event is right skewed as shown in Fig. 5, which shows that most eVisit users tend to adopt eVisit within 6 months from their first PP access.

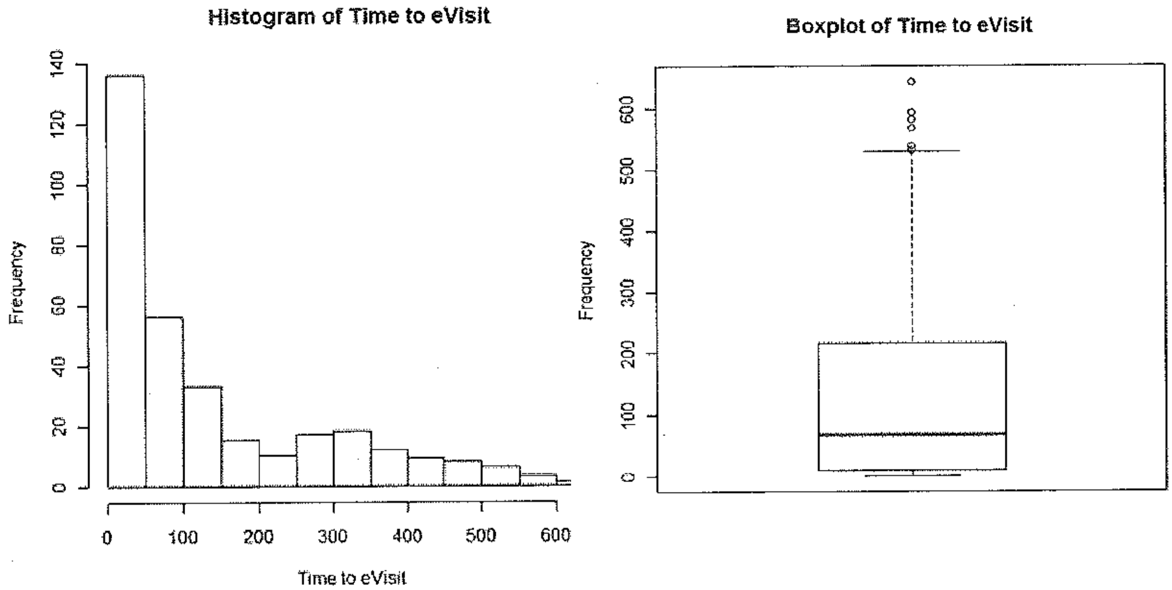

Fig. 5 – Histogram and boxplot of 'days to eVisit from the first PP use'

2.5.3 Regression results

Table 4 summarizes the effect of the selected variables on the odds of eVisit use. The first column shows the result from aggregated regression model with practice fixed effect and varying coefficient for PCP_eVisit which appears to be significantly different across practices (Chow test results in Appendix A). While we do not include it in our table, practice indicator is a significant explanatory variable when added to the model (p<0.001) with White clustered robust error [5]. The second column is from the Multilevel regression with physicians as the 2nd level along with practice fixed effect. On average, patients' odds of eVisit use is 21.3% greater than that of patients who are 10 years older, and female patients are more likely to use the service than male patients as we expected from the descriptive statistics (Table 1). Based on the estimates for the aggregated regression, for each additional past portal access, the odds of being an eVisit user increases by approximately 0.5%, and fulltime or unemployed users are more likely to use eVisit than those who are retired, part time, or students. While retired status is a significant factor that differentiates eVisit users from PP only users from the t-test result, the effect is not significant overall across the regression models and is dropped from further analysis. Regarding patients with complex health conditions, as indicated by the number of diagnoses in the problem list, one additional health problem is associated with 2.5% increase in the odds of eVisit use. This finding supports prior research in which adoption of patient portal services was shown to be higher among patients with greater medical need. [12]

Table 4 – Effect on the odds of eVisit use

	Reduced model	Extended	Physician FE
Age	-0.0245***	-0.0249***	-0.0257***
	(0.0049)	(0.0052)	(0.0050)
Female	0.4550***	0.4581***	0.5040***
	(0.1300)	(0.1310)	(0.1332)
Full Time	-0.0656	-0.0645	-0.0875
	(0.1440)	(0.1441)	(0.1452)
Part Time	0.5899*	0.5925*	0.5506*
	(0.2373)	(0.2374)	(0.2379)
Retired	-0.1598	-0.1509	-0.1433
	(0.2664)	(0.2680)	(0.2671)
Self-employed	0.4163	0.4118	0.4187
	(0.3583)	(0.3585)	(0.3609)
Student	-0.5952	-0.5778	-0.5947
	(0.3692)	(0.3735)	(0.3709)
Married		0.0440	0.0483
		(0.1342)	(0.1347)
White		-0.0204	-0.0195
		(0.1134)	(0.1139)
Observations	2152	2152	2152

Standard errors in parentheses
* $p<0.05$, ** $p<0.01$, *** $p<0.001$

From physician group-level, multilevel regression, patients' age, gender, number of problems and the volume of past portal access are significant factors, which is consistent with the aggregated model, and the estimated effects are similar. As to physician level predictors, physician's gender and experience are significant factors in the main level intercept estimation. Contrary to our expectation, in this model, individual physician's eVisit service involvement and the weighted eVisit are insignificant in the patient's decision regarding use of the service. There are physicians who served eVisit only once, and very few patients (1 to 3) of these physicians experienced eVisit service. This limited usage does not define a physician's involvement, and it cannot sufficiently predict the patients' decision. In addition, whether patient's health insurance covers eVisit or not does not contribute to patients' decision about using eVisit. During the study period, few payers were willing to consider eVisit as a reimbursable health service, hence patients' lack of awareness of coverage information and the cost difference between having coverage or not being only \$10~\$15 likely explains the health insurance not being a factor in encouraging (discourage) eVisit use.

2.5.4 Adoption hazard analysis

This analysis is based on eVisits completed at practice 2. Univariate analysis (Table 5) shows that *Gender, Employment*, and *Age* are significant enough to be included in the Cox-proportional hazard regression model, but marital status is only marginally significant. Most categorical variables show proportional pattern of Kaplan-Meier (KM) survival curve estimate except *Marital status*; we found marital status does not show parallel curves on KM survival estimate because of the relatively few observations in some categories of the variable such as divorced, widowed, etc. Thus we simplify the categories into *Married* or others, keeping *Married* as control. KM for Insurance *Cover* indicates almost no difference between two groups, verified using logrank test. 389 patients out of 2,152 (our study target) hold insurance that covers eVisit, and 63 of them adopted eVisit (16.2%) while 261 out of 1,763 non-holders adopted the service (14.8%). The average number of days to adoption is not significantly different (144 days with standard deviation 21.7 for holders and 129 days with standard deviation 9.2 for non-holders). If the difference matters, proper insurance holders taking longer time to adopt the service may imply that these patients are likely to adopt the service slowly because they are less cost conscious than non-holders using the service.

Table 5 – Univariate analysis (Log-rank test of equality for categorical variables)

Variables	p-value
Gender	0.000
Ethnicity	0.533
Marital status	0.066
Employment	0.0000
Insurance	0.486
Age	0.000
Problem	0.807

Note: variable 'Ins. Cover' indicates whether a patient's payer covers eVisit

Almost identical results to the univariate analysis are seen in the hazard regression analysis shown in Table 6. Only age, gender, and part-time employment status are important factors that affect hazard of service adoption. All coefficient estimates are similar in value across three different tests. First column shows the regression results for the model that includes age, gender, employment status only (reduced model), which are selected from univariate analysis. The second column shows results for the model that includes other patient demographics (white and married), and the third column provides results for the model that adds physician fixed effect to the second model. Physician identifiers from the physician fixed effect model are not significant, thus we conclude that physician characteristics do not influence patient's adoption hazard at least in practice 2 although it affects patient's decision regarding whether or not to use eVisit. Based on the second column results, we observe that if a patient is 10 years older, the hazard of eVisit adoption decreases by 22%; for female patients, the hazard increases by 66%; and part time employees have 73.9% higher adoption hazard than those who are unemployed or with unknown employment status. Assumption of proportionality is tested using Schoenfeld and scaled Schoenfeld residuals, and all (except 'fulltime' status) do not violate the assumption. Overall cumulative hazard rate $H(t)$ in Fig. 6 shows that if a patient waits (does not use eVisit after the first PP access) longer, the patient is less likely to adopt the service. Note that we have a small number of eVisit users (15.1%), thus it converged to a little above 0.15 (low likelihood of becoming an eVisit user) in Fig. 6.

Table 6 – Cox proportional hazard regression result

	Reduced model	Extended	Physician FE
Age	-0.0245***	-0.0249***	-0.0257***
	(0.0049)	(0.0052)	(0.0050)
Female	0.4550***	0.4581***	0.5040***
	(0.1300)	(0.1310)	(0.1332)
Full Time	-0.0656	-0.0645	-0.0875
	(0.1440)	(0.1441)	(0.1452)
Part Time	0.5899*	0.5925*	0.5506*
	(0.2373)	(0.2374)	(0.2379)
Retired	-0.1598	-0.1509	-0.1433
	(0.2664)	(0.2680)	(0.2671)
Self-employed	0.4163	0.4118	0.4187
	(0.3583)	(0.3585)	(0.3609)
Student	-0.5952	-0.5778	-0.5947
	(0.3692)	(0.3735)	(0.3709)
Married		0.0440	0.0483
		(0.1342)	(0.1347)
White		-0.0204	-0.0195
		(0.1134)	(0.1139)
Observations	2152	2152	2152

Standard errors in parentheses
* p<0.05, ** p<0.01, *** p<0.001

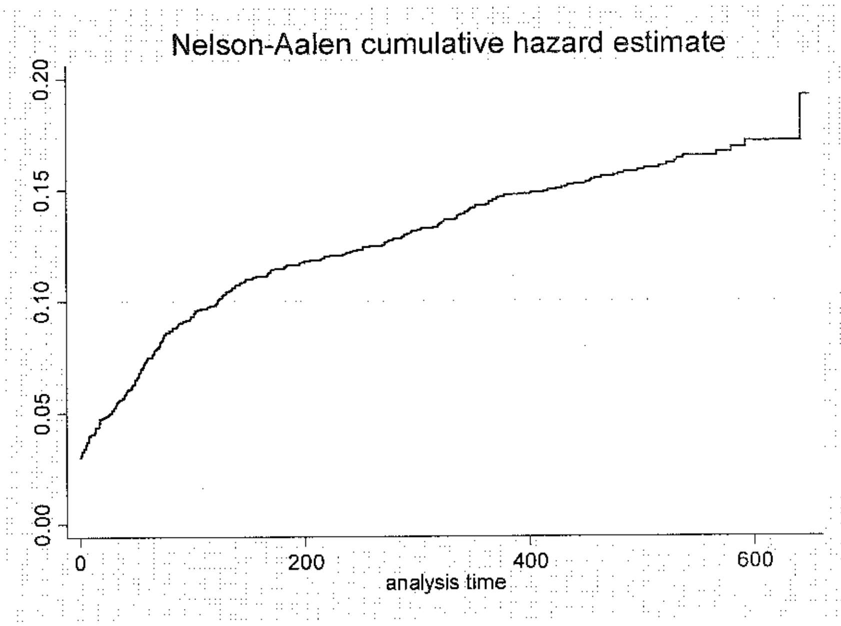

Fig. 6 – Cumulative hazard curve $H(t)$

2.5.5 Early vs. late adopters

Coefficient values from Ordered Logistic regression represent change in the logged odds ratio of being in a higher category (taking longer time to adopt the service) for one unit increase in the predictor variable. The results in Table 7 show that full time employees are likely to adopt eVisit later than other adopters; if a patient is a full time employee, the odds ratio of the patient being in a category of late adopters is 1.88 times higher than being in the early adopter category (the 1st column of Table 7). As the positive coefficient on age shows, the older the patient, the slower she/he adopts the service (the odds-ratio increases by 0.02 for every additional year of age). Interestingly, patients of the physician leader are less likely to adopt eVisit early. This may partly be due to the change in work balance because of physician leader's administrative role such as weekly meetings. Physician participation is 100 percent in the practice where physician leader is located (practice 2), and it also has the highest volume of eVisits and eVisit users. This implies that physician leader's influence on eVisit adoption can be observed in leading other physicians but not to individual patients.

Table 7 – Log-odds of being in slower adoption group

(Ordered logit regression results)

	Ordered Logit	
	K = 3	K = 4

Age	0.0221* (0.0103)	0.0196* (0.0099)
Female	0.0046 (0.2594)	-0.1108 (0.2515)
Married	-0.0502 (0.2654)	-0.1703 (0.2567)
Fulltime	0.6311** (0.2404)	0.5213* (0.2322)
White	-0.1218 (0.2344)	0.0101 (0.2286)
Cover	-0.1074 (0.2882)	0.0031 (0.279)
Problems	-0.0360 (0.0301)	-0.0381 (0.0284)
PCP.Female	0.3080 (0.3698)	0.3560 (0.3610)
PCP.Exper	-0.0317 (0.0220)	-0.0344 (0.0213)
PCP.Patients	0.0009 (0.0008)	0.0008 (0.0008)
PCP.Leader	1.8433* (0.7228)	1.7633** (0.6790)
Prob. > Chi^2	0.064	0.109
Observations	324	324
Pseudo R-squared	0.030	0.023

Standard errors in parentheses
* $p<0.05$, ** $p<0.01$, *** $p<0.001$

2.6 Discussion, Limitations and Conclusions

This study examines characteristics of online healthcare consumers to understand their patterns of adoption and usage of online clinical consultation services such as adoption time for portal users, whether adoption hazard changes over time, and what factors influence patients to become early/late adopters. Similar to observations in earlier studies of online health information seeking behavior, our analysis indicates that women are more likely to use the eVisit service despite the reported difference in online skills that favor men [5, 13, 20]. While the role of a female as the primary family caretaker has been the explanation of this finding in the context of tele-consultations [14], this explanation may not hold in our study because the study population does not include pediatrics, and patient account is strictly operated by the individual patient (no family accounts are allowed). Thus it is reasonable to assume that the people who submitted eVisit inquiries are the patients who needed the treatment. Thus our result supports prior studies regarding women being more likely to seek healthcare information and services. Furthermore, it also shows that even in actual service usage, women utilize online care delivery channels such as eVisit, but gender does not affect the decision regarding early/late adoption.

Contrary to earlier studies indicating that willingness to pay (WTP) for online medical service does not vary across age groups [18] but the motivation to use online consultation by elderly patients is higher [30], our study shows that older patients are less likely to use an online consultation service with an out-of-pocket payment requirement. The model results also reinforce that patient's age is a significant factor in the adoption decision, adoption hazard, and early vs. late adoption, particularly highlighting the discrepancy between the survey results of prior studies and actual usage in which patients face copayment for electronic visit. Since the study is limited to the patient population who are already online portal users, exposure to a new technology and computer skills is not a barrier to eVisit use.

An interesting group to examine is the retired population. There is a significant gap in their proportionate use of the patient portal vs. eVisits. The portal service provides personalized health information free of charge, thus using portal service may provide sufficient benefits to them. With more personal time and deeper health concerns, this group of patients is expected to use portal service frequently but not eVisit. However, the regression results with practice fixed effects indicates that while the patient populations differ across practices, this explanatory variable does not affect whether a portal user becomes an eVisit user.

Our findings also suggest that primary care practices need to expend significant additional effort to increase usage of the new service. There is value in educating older and retired patients, in particular, regarding the specific benefits of the eVisit service, especially as it expands to include management of chronic conditions and preventive care delivery. Outreach efforts must also target all patients newly enrolled in the patient portal because the hazard of adopting the service at any time decreases as the non-adoption period increases. Since patients' awareness has been observed to be a key ingredient in online consultation usage [30], healthcare providers need to focus on promoting the online service to their patients in order to increase the eVisit adoption and use.

This study has some limitations. The results may lack generalizability due to the small number of eVisit users compared to PP only users (446 out of 14,451), resulting in a skewed sample distribution. Secondly, we cannot identify which patients are lost to follow-up, for example, when patients switch to other clinics or move to other areas, so a patient's appearance in the visit records is based entirely on the patient's random and sparse health events. Third, the data do not provide sufficient information to reveal the relationships among patients, and thus network effects such as familial interactions on eVisit adoption cannot be estimated. Finally, time stamps are not available for diagnoses or medications, hence aggregate information is used in our analysis. Detailed, time-stamped historical records of eVisits may allow dynamic, time-varying analysis to produce more consistent, nuanced and rigorous survival analysis results [31].

Ongoing research proposes to examine the impact of detailed clinical history, prior user experiences, familiarity with the general structure of medical consultations, and substitutability of traditional office visit on eVisit use to provide new insights on the usefulness and effectiveness of this service. Unlike other online services and e-commerce transactions where trust and reputation based on other users' experiences play an important role [32], eVisit users are mostly aware of what to expect because they know the providers and their practices when such services are offered by their own primary care physicians. Thus patients' repeated eVisits should depend mostly on their own individual experiences rather than others' ratings. Therefore, a longitudinal study of the eVisit users to address their continuity of the service usage and estimating the impact of prior experiences, needs and familiarity on the subsequent service utilization is an important study, as is an examination of the effect of trial experience on the subsequent adoption of eVisit. With availability of physician response time and attributes such as diagnoses and prescribed medications, impact of individual and organizational learning that enhances service productivity and operational effectiveness is an ongoing investigation.

Finally, and most importantly, a rigorous evaluation of eVisit quality and outcomes is needed. Although it beyond the scope of this study, a preliminary examination of the number of eVisits where patients needed an office visit for the same condition within a week following eVisit submission indicates that only a very small fraction of the eVisits incurred office follow-ups (total of 10 cases or 1.7%). However, further comparisons of the re-visit rate and other outcome measures relevant to eVisits and office visits for the same conditions, depth of information and treatments associated with each delivery channel, and patient satisfaction and experience scores will provide greater insights into the current eVisit practice quality and outcomes.

Moving the venue of physician – patient encounter to online space will benefit many different patient groups. As addressed by a prior study [33], distance to the primary care practice is a deterrent to practice choice by patients. Thus, reducing travel time and cost via eVisit will provide greater convenience and access to care, especially for rural area residents and patients with disabilities. Also, the asynchronous delivery model of eVisit removes time constraints, hence busy patients can potentially receive timely treatments and feedback from physicians without much delay. Therefore, it is an important goal to promote and encourage both providers and patients to adopt the eVisit service.

With eVisit deployment extending currently to more than 100 practices, the rapidly growing eVisit service offers tremendous opportunities to develop and evaluate generalizable models of technology adoption and usage by both patients and providers and their implications for patient health outcomes, service provisioning, and organizational effectiveness.

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APPENDIX

A. Chow test results

Variable	Chi-square statistics (p-value)
Age	1.93 (0.5876)
Gender	6.65 (0.0838)
Portal	6.80 (0.0786)
Problems	1.28 (0.7348)
Cover	6.12 (0.1061)
PCP_eVisit	78.81 (0.0000)

B. Summary of patient demographics by practice

	eVisit patients				PP only patients			
Practice	Pra1	Pra2	Pra3	Pra4	Pra1	Pra2	Pra3	Pra4
Number of patients	67	355	16	8	6,516	5,655	998	836
Average age	42.2	45.3	55.0	46.3	47.6	50.1	54.4	49.9
Min (Max) age	20(69)	19(77)	26(78)	25(63)	18(96)	18(94)	19(94)	19(94)
Female (%)	80.6	74.4	56.3	75.0	62.5	58.1	68.1	47.6
Married (%)	55.2	69.6	68.8	37.5	58.7	73.0	70.3	69.9
Single (%)	35.8	19.4	25.0	50.0	32.7	17.6	21.5	23.7
Fulltime employed (%)	71.6	64.8	50.0	75.0	63.5	58.7	58.6	62.0
Retired (%)	1.5	5.4	18.8	12.5	9.8	14.0	20.4	17.5
Unemployed (%)	13.4	18.3	18.8	12.5	9.3	16.2	8.0	9.2
Student – Full time (%)	7.5	1.7	0	0	7.1	2.7	3.4	3.8
White (%)	61.2	54.6	81.3	75.0	64.8	54.6	72.1	64.1
Black (%)	9.0	0.6	6.3	0	5.5	0.4	3.9	3.3
With Insurance (%)	94.0	94.4	93.8	87.5	86.8	94.5	94.6	91.0
With eVisit coverage (%)	64.2	22.0	31.3	25.0	43.6	17.3	37.6	36.0
PCP participating (%)	40.3	100	87.5	100	33.4	100	74.3	100
Average # Problems	7.2	5.7	9.4	6.5	6.4	5.6	8.0	7.1
Average PP access volume	84.2	41.0	54.5	45.0	31.9	18.0	22.0	22.2

C. Definition of functions in Hazard model

(1) $h(t) = \lim_{\Delta t \to 0} \left(\frac{\Pr(t < T < t + \Delta t \mid T > t)}{\Delta t} \right) = \frac{f(t)}{S(t)}$

(2) $S(t) = 1 - F(t) = 1 - \Pr(x \leq t) = \int_0^t f(u)du$

(3) $f(t) = \frac{dF(t)}{dt} = \frac{d(1 - S(t))}{dt} = -S'(t)$

(4) $H(t) = \int_0^t h(u)du = \int_0^t \frac{f(u)}{S(u)}du = \int_0^t \frac{1}{S(u)} \left\{ \frac{dS(u)}{du} \right\} du = -\ln\{S(t)\}$

➔ $\ln(S(t)) = -H(t)$, thus

(5) $S(t) = e^{-H(t)}$

➔ $S(t, x, \beta) = e^{-r(x,\beta)H_0(t)}$ where r is a function of the parameter vector

➔ $r(x, \beta) = H(t, x, \beta)$

Proportional hazard function:

(6) $h(t, x) = h_0(t)e^{x'\beta}$

(7) $\frac{h(t)}{h_0(t)} = \exp(x'\beta) = e^{b_1x_1 + b_2x_2 + \cdots + b_px_p}$

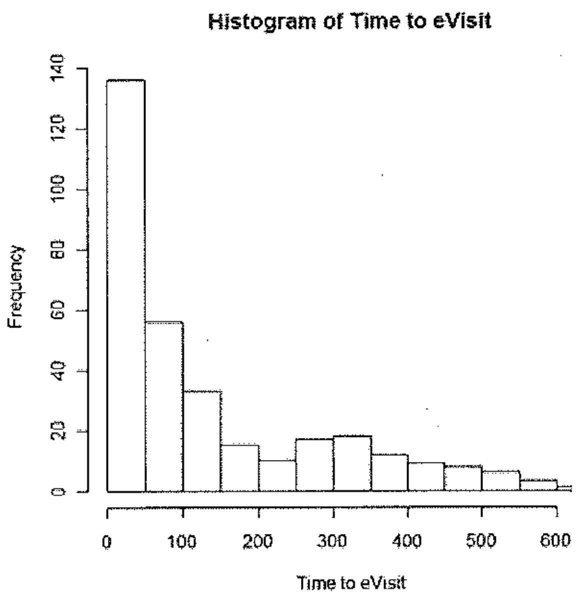
D. K-means clustering

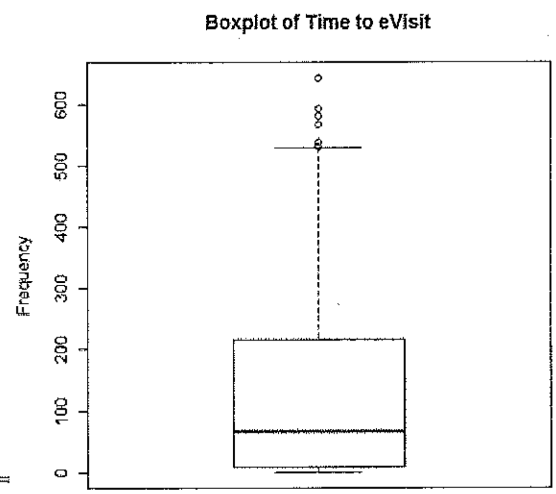
K	Between SS/ total SS	Min/Max (# obs. in groups)
2	79.8%	83 / 241
3	88.6% (+8.8)	65 / 190
4	94.5% (+5.9)	27 / 180
5	96.3% (+1.8)	26 / 118
6	97.5% (+1.2)	26 / 115

E. eVisit Summary by Subject

eVisit subject	Count	Proportion	Average volleys
Sinus/cold symptoms	223	37.2%	1.50
Cough	59	9.8%	2.08
Urinary symptoms	58	9.7%	1.26
Back pain	28	4.7%	1.93
Vaginal irritation/discharge	15	2.5%	1.40
Diarrhea	10	1.7%	1.60
Red eye	14	2.3%	1.07
Other	193	32.2%	1.63
Total	600	100%	1.59

F. Histogram and boxplot of 'days to eVisit from the first PP use'





G. Univariate analysis (Log-rank test of equality for categorical variables)

Variables	p-value
Gender	0.000
Ethnicity	0.533
Marital status	0.066
Employment	0.0000
Insurance	0.486
Age	0.000
Problem	0.807

Note: variable 'Ins. Cover' indicates whether a patient's payer covers eVisit

Chapter 3

3. Impact of Trialability on Patient Adoption of eVisit: Applying Diffusion of Innovation Theory to Online Clinical Consultations

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Abstract

Ongoing digital transformation of medical care delivery, particularly primary care, is being driven by the increasing gap between provider availability and patient demand for high quality, easily accessible care. Innovations in information and communication technologies are enabling a transformation from traditional, face-to-face encounters between clinicians and patients to online medical consultations. The growing interest in online medical consultation, or eVisit, is attributed to several factors such as immediacy of care, affordable cost, convenience, and efficient/flexible time management opportunities. Despite increasing attention, adoption of eVisit has been slow and little is known about the users of such digital services. In this study, we analyze the key features that distinguish early adopters of the service from patient portal consumers using data from a major healthcare provider in Western Pennsylvania. We find that eVisit users are younger, predominantly female, and fulltime employed. Furthermore, we test the impact of attributes of innovation diffusion theory on eVisit adoption employing actual usage data collected during a trial period and subsequent real use over 14 months. We consider two aspects of trialability – trial opportunity and actual trial experience – and their impact on patients' eVisit adoption. Furthermore, we compare the effect of resolved and unresolved trial experiences. Preliminary results indicate that if a portal user had trial opportunity, the odds of subsequent eVisit use increases by a factor of 1.8, and if a patient actually tried the service, the odds of adopting the service later increases significantly. Patients with positive trial experience are more likely to adopt the eVisit service later than patients whose health concerns were less satisfactorily resolved during the trial period. Further extensions of the theory and results have the potential to inform deployments of digital innovations in consumer healthcare delivery.

C. Jung, R. Padman, "Impact of Trialability on Patient Adoption of eVisit: Applying Diffusion of Innovation Theory of to Online Medical Consultations", under review with JAMIA.

3.1 Introduction

The growing interest in online medical consultation, referred to as eVisit, is attributed to several beneficial factors: ease of implementation and use, immediacy of care, freedom from scheduling conflicts, affordable cost, convenience, and efficient/flexible time management options for physicians (Liederman et al. 2004). Despite this, the rate of adoption has been slow (Mantzana et al. 2007; Zanaboni and Wootton, 2012) and there is little research investigating drivers of adoption of such services and facilitators of online care in order to improve awareness and adoption, especially from the patient perspective (Menachemi et al. 2004). In this paper, we explore a preliminary application of innovation diffusion theory to the field of online medical care to investigate whether strategic approaches to encourage adoption can potentially be developed and evaluated.

Many studies of adoption theories have tested an intention to use varied telemedicine innovations. However to the best of our knowledge, there is no empirical study of consumer adoption with real healthcare usage data that test the effect of the attributes from the theory on the actual adoption. At the same time, given the unique characteristics and challenges of the healthcare context, there is an opportunity to enrich the theory by developing new constructs that are particularly relevant to healthcare delivery. As a first step in this process, we analyze the effect of 'trialability' from Innovation Diffusion Theory (IDT) on real usage after the eVisit service is deployed because this attribute can be most clearly defined with the available retrospective data.

IDT has identified five characteristics that influence an individual's decision to adopt an innovation; relative advantage, compatibility, complexity, trialability, and observability (Rogers, 2003). Relative advantage is the degree to which the innovation is perceived to be more advantageous than what it supersedes. Compatibility is consistency with existing values. Complexity is reciprocal of ease of use, trialability is the degree to which the new innovation can be experimented with, and observability is the visibility of the innovation (Rogers, 2003). In the context of primary care delivery with the online medical consultation (eVisit) as a new innovation, we redefine the above five constructs as follows. Relative advantage of eVisit is the degree to which patients perceive that eVisit provides more benefits than traditional face-to-face visits. Compatibility is whether eVisit provides equal quality care as traditional clinic visits do to patients. Complexity is how difficult it is to use eVisit service, and trialability is the degree to which patients can explore and trial-use the eVisit service free of charge. Lastly, observability is the extent to which eVisit usage/results are visible to other users.

Many studies in information systems area have applied IDT in the e-commerce and digital services domains. Similar to online delivery of information goods, eVisit is an e-service product rather than a material product with higher levels of risk and uncertainty regarding the outcome. The adoption decision is more complex in the online service due to various reasons. First, the adoption initiates a new type of relationship between the consumer and service provider (Featherman and Pavlou, 2003). Second, the service product is often not returnable unlike material product when a consumer is dissatisfied or mistakenly purchased the service. Third, as a technology-based service innovation, online service is often restricted by accessibility (Lee et al. 2003). Fourth, for an interactive and knowledge-based service like eVisit, an organization needs an agreement from the individual service provider if it wants to provide try-out period for potential users. In an online shopping adoption study (Slyke et al, 2004), triability was dropped from the adoption analysis due to little variability in trialability; any potential customer can try out as long as he/she is computer and internet literate. In our context, the opportunity to experiment is available only when the medical practice of a patient's PCP provides a try-out option. Thus, our study site is a perfect setting to analyze the linkage between trialability and patients' adoption of the e-service.

In addition, the adoption decision of online healthcare service is even more complex and carefully made. The eVisit service is directly associated with a patient's health condition. It may make the situation worse if the service fails to resolve the patient's issue correctly. If a patient waits several days until she discovers she is not getting better after receiving eVisit consultation, she may then visit the clinic for in-person encounter, which delays the right time for the treatment. This may lead to a higher possibility of negative outcomes from trial experience, which is different from the known positive associations between trialability factor and decision on the innovation adoption in the literature (Rogers 2003; Ducharme et al. 2007). Therefore, revealing whether the trialability factor leads to higher adoption of online healthcare service and if so, whether positive experiences result in more adoption of the service will provide us the insights to understanding healthcare consumers' decision and furthermore strategy to increase awareness and adoption of the service, which ultimately increase the capacity of healthcare providers.

In many studies, system usage is operationalized via self-reported usage because objective usage metrics are often times not available although it is argued that self-reported metrics are not precise measures of actual usage (Davis et al. 1989). In this study, measurements are objective metrics since all data records are actual transactions of real patients and physicians, which provide insights into patients' real usage of the new innovation. Based on patients' real eVisit usage records, we explore the link between trailability of the service and patients' adoption behavior to generate managerial insights for improving eVisit adoption rate.

This paper is organized as follows. We describe the study site and eVisit service, including the trial environment, in the next section, and develop three hypotheses in section 3. Data and methods that are used in the study are detailed in sections 4 and 5, respectively. Section 6 discusses the results and we conclude with some limitations and extensions of this study in Section 7.

3.2 Patient Portal and eVisit of Study Sites

The primary care practices in this research allow patients to take a more active role in their own health by providing secure and convenient online access to their electronic health information via the patient portal. Users can review their clinical information such as health history, past visits and test results. Also patients perform appointment scheduling, pre-registration, and prescription renewal. The portal utilizes the underlying technical infrastructure and solutions offered by Epic Corporation and MyChart Patient Portal[1]. It has more than 100,000 current enrollees, and continues to grow along the two dimensions of users and services. The patient portal has been providing patients with online medical advice since 2003. Medical advice is a free service via the patient portal which is provided to all patients enrolled in the portal and whose practices are in Epic system[2]. This service is intended to reduce staff workload by encouraging patients to utilize the online route instead of telephone calls. As the purpose of the Medical advice is to replace telephone calls, the service is limited to only simple questions regarding previous visit, medications, follow-ups, updating patient condition after treatment, etc., which are answered mostly by nurses from the practice where the patient belongs to.

As an alternate channel for care delivery, a new service called eVisit was deployed within the portal in August 2008 as a trial service, providing patients the ability to request online consultations for acute, non-urgent conditions through a series of secure, structured message exchanges with a physician. Instead of free text messaging used in many other online medical messaging services, a standardized template is used for the eVisit of our sites, which creates formatted documentation for the consultation. Structured/standardized template means that patients' symptom reporting page is constructed as sequential questionnaire templates, which helps patients to report all the important and relevant information for physicians to assess patients' health condition. This template produces clear documentation for communication by capturing necessary information without unnecessary details. Thus it is easy to use for both patients and physicians and more efficient than free text entry. eVisit is integrated with practice workflow, and thus provides access to information that is stored in the practice's Electronic Medical Record (EMR). A successfully completed eVisit is finally documented in the EMR as well.

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[1] http://www.epic.com/software-phr.php (accessed on August 2, 2012)

[2] The healthcare center of this study has two different electronic healthcare systems, and one of them is developed based on Epic (www.epic.com).

The pilot system was deployed at a single primary care practice in August 2008, where all physicians participated in providing the service. During this trial period, the service was available free of charge. In April 2009, eVisit was formally rolled out, and deployed in three additional primary care practices (Figure 3.1). A few health plans started reimbursement for this service at the same time. Patients were charged $30 ($40 as of December 2013) or a co-pay amount, depending on their health insurance coverage policy for eVisit. A limited set of eight acute, non-urgent health conditions were handled via this initial eVisit service, which included sinus/cold, cough, back pain, diarrhea, urinary symptoms (UTI), red eye, vaginal irritation, as well as an 'other' category (this category allows free text entry). The set of conditions was expanded later to 22 conditions. The major difference between eVisit and Medical advice is that Medical advice does not deal with a new health concern, diagnosis or prescription, and is mostly answered by nurses whereas eVisit is strictly restricted to physicians, and is intended to handle limited, non-urgent, acute care visits that replace face-to-face visits by providing diagnoses, treatment guideline, and prescription order if needed.

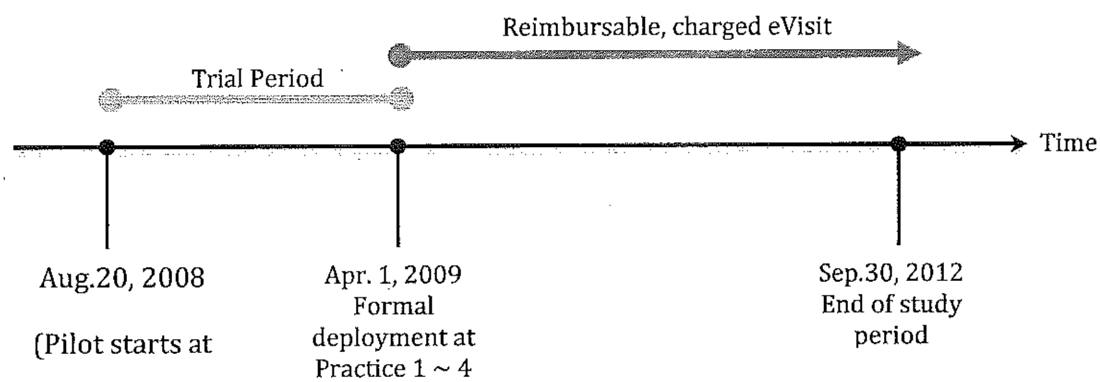

Figure 3.1. Timeline of eVisit service deployment

The eVisit health conditions and the assignment scheme for the responding physician remained unchanged until 2010, and later the number of conditions increased. Trial eVisit worked exactly the same as the formally deployed reimbursed service; patients were able to utilize the eVisit service for all seven symptoms plus 'other' option, send follow-up inquiries to the physician (as sequences to the original submission), and prescriptions were directly sent to the pharmacy of the patient's choice. This trial environment provided patients with the full experience instead of a limited version, thus reducing any uncertainty regarding the operation and potential value of the service.

The process starts when a patient completes the relevant health condition questionnaire, submits eVisit on the patient portal, and the message goes to the support staff pool that forwards the eVisit to a participating physician. If primary care provider is unavailable, an assigned on-call physician takes the responsibility to act on the submission. Once the physician reviews and replies, the patient gets notification by email, checks the physician response via patient portal, and may choose to have further message exchanges before the physician closes the encounter. Once the encounter is closed, the support staff is notified and a claim is submitted for reimbursement. Further details of the process flow are found in the literature (Jung et al, 2011).

The physicians and staff at some of the practices encouraged their patients to sign up for portal access and use eVisits for treatment of the specified episodic illnesses. The use of the service was purely voluntary by patients and providers. In the next section, we draw on relevant theories to develop our study hypotheses.

3.3 Study Construct and Hypotheses Development

3.3.1 Study Construct

Factors contributing to *Relative Advantage of eVisit* are convenience, flexible time management, timely access to care, and lower cost which are the benefits provided due to the service delivery channel's unique characteristics. For example, busy patients may evaluate eVisit as advantageous since they can submit an eVisit at work if they have internet access and perform other activities while waiting for the response. Also, patients who are geographically distant from their primary care providers may believe that eVisit is advantageous for them as they do not need to travel to the physician office. *Compatibility of eVisit* is not immediately observable since objective outcome measures have yet to be defined, but it may depend on patients' demographic, socio-economic and health characteristics. Receiving treatments from a physician via an online channel may be well accepted by younger, more affluent, or educated population whereas it may be incompatible for older patients with low internet use and complex health conditions. *Complexity of eVisit* is the level of difficulty that patients encounter in submitting eVisits. This depends on patients' ability to use computers and internet, and prior experience with the patient portal site that provides access to the eVisit service. It is reasonable to assume that patients with frequent access to the patient portal are more familiar with the process of utilizing any service available via the portal site. eVisit is one of those services deployed within the patient portal, and thus more frequent users to the portal are likely to perceive that complexity level of eVisit use is low. *Trialability of eVisit* is the degree to which patients can try out the eVisit service. In fact, we choose trialability among the five attributes as the first step to study a link between actual e-health service adoption and innovation factors, for the following reasons; 1) it is a semi-unique feature that fits into the 'service' dimension due to the reasons detailed in the next paragraph, 2) it can be more objectively measured without estimating and translating potential adopters' level of perception, 3) retrospective data is available, and 4) due to the interactive feature in the service, the level of trial is controllable from the provider side who wants to encourage adoption, and thus it can be easily added into any interactive online service's marketing strategy. Lastly, *Observability of eVisit* is the degree to which patients see or hear about the eVisit use experience from others in the social system. Given that eVisit usage has been low, it is a software form of innovation which is less observable (Rogers, 2003), and there was no mobile-based service during the study period, there is limited opportunity to observe other patients' usage, especially the usage occurs only when there is an acute need. Thus, it is reasonable to assume that there is a negligible effect of this construct on the eVisit adoption decision.

3.3.2 Hypotheses Development

Trialability is the degree to which the innovation can be experimented with before committing to adoption (Rogers 2003). Many studies on IT innovation adoption indicate that trialability is positively associated with adoption of the innovation (Rogers 2003; Hsu et al. 2006; Zhou et al. 2010). Wilson et al. (2004) used IT acceptance models to predict patients' intention to use e-health. However, the majority of research on innovation adoption and technology adoption has been based on survey studies which are able to address the link between adoption attributes and intention to adopt rather than with consumers' actual adoption behavior. In fact, due to the discrepancy between stated preference (what people say they like) and revealed preference (what people actually chose), many researchers in various areas such as environmental or healthcare economics sector worked on combined model in early 2000s.

In order to test the impact of trialability on the actual adoption of a new innovation in primary care delivery, we define the eVisit service as an innovation as it is a new digital channel and product to deliver health care service to individual patients, the trialability as the trial opportunity of a new service delivery channel, eVisit, and substitute 'intention for use' with the actual usage, which leads us to uncover the effect of trialability on the patients' real adoption rather than hypothetical adoption. Thus,

- Hypothesis 1: Patients with eVisit trial opportunity are more likely to adopt the service

From utility theory, a rational patient will select a care delivery channel that provides higher utility. Let P_e be the probability of receiving the right diagnosis and medical consultation via eVisit, V be the value from getting the appropriate medical consultation which depends on patients' age, health complexity and current symptoms of inquiry, and C_e be the cost of receiving eVisit service, which consist of monetary value (copayment) and intangible cost such as time and convenience factors. Thus the expected utility of using eVisit is $U_e = P_eV - C_e$, and likewise utility from the offline/traditional clinic visit is $U_o = P_oV -$

C_o. This approach is similar to Kumar and Telang (2011), but in a different context and with different contents and interpretations. Then, a patient will choose eVisit if $U_e > U_o$.

In order for a patient to utilize eVisit, $C_e < C_o - (P_oV - P_eV)$ should be satisfied. Based on the reasonable assumption of $P_eV \leq P_oV$ and $C_e < C_0$, the condition requires 1) significantly lower cost for eVisit in comparison with offline visits if patients perceive P_e is much lower than P_o (this means patients hold high level of perceived risk on eVisits' performance) or 2) a patient values eVisit service as good as offline service ($P_oV - P_eV \approx 0$) or both 1 and 2.

In the primary care context, receiving trial care contributes to a change in intangible cost in the future by reducing the uncertainty in the probability of getting the right advice, which leads to increased value of the probability of receiving the right care (P_e). A large body of research in consumer behavior state that consumers' perceived risk is negatively associated with adoption of a new product or service. Perceived risk affects decisions on information systems adoption when there are uncertainties (Dowling and Staelin, 1994; Engel et al. 1986). Featherman et al. (2003) redefined the facets of perceived risk, in which performance risk is the baseline for all other risks, and proved that perceived risk reduces adoption intention. In other words, if the uncertainty in the probability of receiving appropriate care is reduced and in turn reduces patients' perceived risk, it will increase the adoption.

Likewise, trial experience reduces the realized cost of eVisit. Online banking literature suggests that customers with more experience with computer and the service are more efficient and profitable (Xue et al. 2007), and thus it is reasonable to assume that the opportunity cost of using eVisit decreases after trials due to established service experience, which then increases utility of using eVisit. Therefore, the chance for patients to adopt the service afterwards increases. Thus, patients' experiences from trial eVisit potentially have positive effect on the adoption of the service. We hypothesize the following relationship accordingly:

- Hypothesis 2: Patients who tried out eVisit service during trial period are more likely to adopt the service than patients without any eVisit trial experience

Hypothesis 2 is largely based on the belief that the eVisit service provides satisfactory health care, which is in fact supported by an earlier survey study (Albert et al. 2011) and prior study of the deployment of online medical consultation (Adamson and Bachman 2010). However, trial eVisit provides patients with the experience of new and unfamiliar medical service, from which patients either set their belief as eVisit is as good as offline visit or set P_e even lower than what they initially guessed if they regard eVisit as an unsatisfactory service. For example, if a patient had to visit the clinic because eVisit did not resolve his/her inquiry, then the patient may place P_e much lower ($P_e \ll P_o$), and otherwise, place P_e close to P_o. Thus, via the trial, patients are likely to use the service subsequently after the trial period if they received proper care, and we hypothesize as the following:

- Hypothesis 3: Patients who experienced appropriate medical care via eVisit trial are more likely to adopt the service than patients with unresolved care via eVisit trial

We conceptualize the association of trialability and innovation adoption in the following diagram (Figure 2).

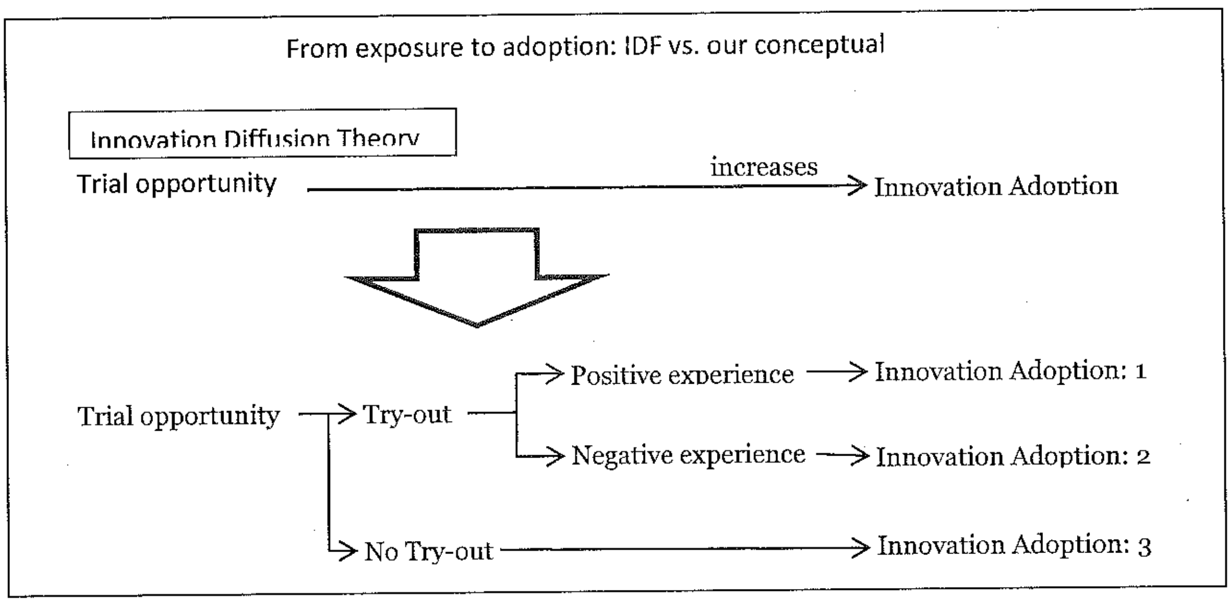

Figure 2. Conceptualization of innovation adoption process

3.4 Data

eVisit usage data, patient demographics, portal access data from August 20, 2008 to May 31, 2010 at four primary care practices are selected for the study. Practice 1 had a 7-month free trial period of eVisit, and the remaining practices (2–4) rolled out eVisit without a trial period. Other relevant information such as physician and payer information, offline clinic visits, call-in volumes, and patient health status are also obtained. The complexity of health condition is measured as the number of distinct comorbidities out of 19 conditions defined in Charlson Comorbidity Index (CCI) which includes myocardial infarction, congestive heart failure, peripheral vascular disease, diabetes, etc. (Charlson et al. 1987) Patient demographics include age, gender, ethnicity, marital and employment status.

We define 'patient population' as all patients of the study practice with portal access since August 2008. This is to minimize potential selection bias which may arise when targeting all patients regardless of their accessibility to computers and the Internet. All patients with active account in the patient portal have received announcement of eVisit service from the healthcare center, and thus it is reasonable to assume that these patients are all aware of the newly introduced service. Furthermore, we select patients whose PCP provides eVisit in order to suppress the impact of the difference in physician influence on patients' decision. It is expected that physicians willing to provide eVisit and those unwilling to do so may have largely different perspectives on the online consultation, and this difference would affect their patients' perception too.

In summary, 9,479 patients comprise the base population of the study; 413 trial eVisits were submitted by 304 unique patients during trial-period (hereafter, participants). A side-by-side comparison of the two groups (with trial opportunity and without the opportunity) is shown in Table 1 as well as participants' demographic summary in the last column.

Table 1. Demographic Comparison of Users

	with Trial opportunity	w/o Trial opportunity	p-value	Trial user
Number of patients	5,926	3,553	N/A	304
Avg. Offline visits	2.93	2.26	0.000	4.09
Avg. Offline visits to e-provider	2.17	0.98	0.000	3.09
Average age	49.9	48.2	0.000	46.9
Female (%)	59.2	57.6	0.119	73.7
Married (%)	72.9	62.1	0.000	73.7
Fulltime employed (%)	59.1	64.1	0.000	54.9
Retired (%)	13.5	12.6	0.229	8.9
Unemployed (%)	16.2	8.8	0.000	21.1
White (%)	91.8	84.6	0.000	94.1
Black (%)	0.7	7.1	0.000	0.3
Insurance w/ eVisit coverage (%)	17.6	42.1	0.000	20.7
Portal access before trial	1.1	3.0	0.000	5.0
Health complexity	0.46	0.44	0.302	0.49

Note: number of offline visits and portal access are counted for 12 months (2007/08 – 2008/07) prior to the trial period

There were 405 patients who adopted the eVisit service subsequently after the 7-month trial period, and they submitted 548 eVisits during 14 months of post-trial period. Table 2 summarizes the demographic comparison between participants (trial users) versus non-participants, and adopters versus non-adopters.

Table 2. Demographic Comparison of Adopters vs. Non-adopters

	Trial users	Non-Trial Users	Adopters	Non-Adopters
Number of patients	304	5,622	405	9,074
Avg. Offline visits	4.09	2.86	3.15	2.65
Avg. Offline visits to e-provider	3.09	2.12	2.40	1.69
Web Preference	0.064	0.019	0.033	0.021
Average age	46.9	50.0	45.3	49.4
Female (%)	73.7	58.4	74.3	57.9
Married (%)	73.7	72.8	67.4	68.9
Fulltime employed (%)	54.9	59.3	65.7	60.7
Retired (%)	8.9	13.7	5.7	13.5
Unemployed (%)	21.1	15.9	17.8	13.2
White (%)	94.1	91.7	95.1	88.8
Black (%)	0.3	0.7	1.5	3.2
Insurance w/ eVisit coverage (%)	20.7	17.4	24.7	26.9
Portal access before trial	5.0	1.0	1.9	1.9
Health complexity	0.50	0.46	0.41	0.46

Note: number of offline visits and portal access are counted for 12 months (2007/08 – 2008/07) prior to the trial period

3.5 Empirical Specifications

3.5.1 Dependent and Explanatory Variables

With each patient as a unit of analysis, the dependent variable is a dichotic value indicating the actual adoption of the user with value 1. If a patient submitted eVisit at least once after trial period ended, it is assumed that the patient adopted the eVisit service. As utilization of such healthcare service is a non-periodic, sparse, and need-base incident, it is unreasonable to define adoption as multiple uses of the service. Thus, we define adoption as at least one usage of the service by paying adequate amount of cost based on the patient's health insurance.

Explanatory variables are following: 1) *TrialOpp* indicates trial opportunity that is a binary value with a value of 1 if a patient's primary care practice provides trial service, and 0 if not, 2) *PortalAccess* is 12-month prior portal access frequency which partially explains each patient's perceived level of complexity on the new techy (the more access, the lower complexity), and this does not count portal access for the purpose of trial eVisit submission to eliminate confounding effect, 3) *WebPreference* is a proxy for the patient's web preference, which has a value of 1 for patients with more medical advice requests than telephone calls, 0.5 for patients who have the same volume of medical advice requests and calls, and zero is assigned to patients who have more telephone calls than medical advice or both volumes are zero, 4) *OfflineVisit* is 12-month prior offline clinic visit volume that is a proxy for the degree of patient's demand for medical attention.

Most variables are self-explanatory except *WebPreference*. It does not make sense to simply normalize the volume of medical advice to assess the preference because patients have different needs from their primary care practices at the first place. Also normalizing the differences between telephone calls and medical advices does not provide sensible value; we would expect to get 0.5 as an indifferent state of the preference, but we cannot generate the state with the extremely skewed data (larger call volumes than medical advice requests, and many people with phone calls only). Thus we assign the values to the variable as defined in the previous paragraph to provide simple yet sensible measure to the preference. As we explained in introductory section, medical advice functions as sending online messages to a patient's practice in order to obtain answers to minor questions that are traditionally handled via phone calls. By routing the patients' contacts to online venue, the healthcare center intended to reduce telephone call volume. Comparing medical advice volume and phone call volume by the same patient helps us assess each patient's web preference.

Other covariates are each patient's health complexity and demographics that consists of gender, age, employment, marital status, and ethnicity. As previously noted, health complexity is measured by the number of a patient's comorbidity conditions that are categorized in CCI. If fewer than three comorbidity conditions exist, the complexity score is the number comorbidity conditions; if three or greater comorbidity conditions exist, the complexity score is 3.

$$Health\ complexity = \begin{cases} x & if\ number\ of\ comorbidity\ codition\ x < 3 \\ 3 & if\ number\ of\ comorbidity\ condition\ x \geq 3 \end{cases}$$

We also include *Encounter* which is the number of offline encounters each patient had with eVisit providers 7-month prior to the formal deployment. This value implies the strength of the signal each patient received from the physicians regarding the availability and value of the eVisit service. Also, the variable accounts for the heterogeneity in patient-physician's dyad relationship. For trial participants, we counted the number of encounters until the first trial because encounters after the trial experience are no longer a signal or marketing effort that influences the patient's awareness of the new service.

3.5.2 Methods

First, we conduct logistic regression analysis to estimate the effect of the trial opportunity on the patients' actual eVisit adoption behavior. Since healthcare providers' readiness/attitude or recommendation have been shown to influence patients' adoption decision (Menachemi et al 2004), we add fixed effect for patients' PCPs with White cluster robust error for the physician identifier variable.

$$(1)\ Logit(P[eVisit\ adoption_i = 1]) \\ = \beta_0 + \beta_1 TrialOpp_i + \beta_2 PortalAccess_i + \beta_3 WebPreference_i + \beta_4 OfflineVisit_i \\ + \beta_5 HealthComplexity_i + \beta_6 Encounter_i + \gamma Demographics_i + \delta_j PCP_j + \varepsilon_i$$

(where i = patient index, j = physician index, $Demographics_i$ = a vector of patient i's demographic variable values, γ = a vector of coefficients for patients' demographic variables)

To test the second hypothesis, we compare the chances of adoption of patients with actual trial experience to patients without trial experience. We restrict the sample to patients from practice 1 where trial opportunity is given in order to reduce the biases from comparing patients with and without opportunity. However, this comparison still suffers serious self-selection bias due to the nature of observational study; those patients with trial experience self-selected to try out the new eVisit service unlike random assignment, and thus it is likely that the participants are systematically differ from the non-participants. To mitigate the issue, we conduct Propensity Score Matching (PSM) (Rosenbaum and Rubin, 1983) with nonparametric Kernel matching algorithm. Propensity score is the conditional probability of receiving treatment given pretreatment characteristics, and a useful non-experimental evaluation method that helps to assess the average treatment effect without counterfactuals. It uses pool of information from study units that participated or did not participate in the treatment (intervention) and generate one scalar value of score representing the probability of participation in the intervention, $P(D = 1|X)$. With the score, we can match the units in treatment group and control group without suffering from the problem of dimensionality, and these observationally similar units work as their own counterparts, which provide researchers a seemingly random experimental setting. For the validity of PSM application, the conditional independence and common support assumptions are checked in Appendix I.A and B. The dependent variable for computing propensity score is the trial experience, which is binary value 1 if a patient tried out the service during the trial period.

As earlier studies have proved that female users of the patient portal are more concerned and actively involved in taking charge of their own health condition, we include gender as our utmost important element that influence selection into the participation. Although all subjects of the study are web users as they are enrolled patients in the patient portal site, younger generation spends more time on the web compared to their parents' generation, and thus we include age in control variables. Other factors considered are insurance coverage, identifier for residing in the same zip code of their practice, the number of past medical advice requests, and the number of outpatient clinic visit within the past year of initial trial period. All variables included in selection model are pretreatment data, mostly time-invariant, observable, and measured in the same way for treated and untreated groups. To show if the balancing was successful between control and treated groups, the t-test for each covariate before and after matching are provided in Appendix I.C. Specifications of selection model (2.1) and impact model (2.2) are following, and the standard errors are obtained by using bootstrapping. Total 5,586 out of 5,622 non-participants from practice 1 are included in a control group.

$$(2.1)\quad P-score = Prob(Tryout_i = 1 | Demographics_i, Web.Pref_i, Same.Zip_i, \\ PP.Access_i, OfflineVisit_i, HealthComplexity_i)$$

$$(2.2)\quad P[eVisit\ adoption_i = 1] = \alpha_0 + \alpha_1 OfficeVisit.Pilot_i + \theta\lambda_i + Physician\ FE$$

(where i = patient index, $Demographics_i$ = a vector of patient i's demographic variable values),

Other possible options such as two-stage regression using Instrument Variable or Heckman two-step analysis (Heckman, 1976) to account for selection bias which may arise from having non-random sub-sample are not adequate since there is neither proper instrument nor exclusion that are observable due to extreme similarity between trial eVisit and actual eVisit. Also, Difference in Difference method, a common method when we have unobserved differences between treated and untreated groups, is not appropriate in our study since we do not have pretreatment outcome measure. Although using models other than OLS in the outcome equation is often taken place, it is erroneous (Bushway et al. 2007), and many studies addressed the serious collinearity issues as well as non-realistic assumptions underlying Heckman selection model, especially issues with exclusion restriction (Achen 1986). More importantly, if the same factors influence both selection and the outcome variable as our study, using a classic Heckman two-step model would cause a problem. Our selection is whether a patient decides to try out the service, and the outcome of interest is a decision on actual adoption of the very same service, and thus both involve similar decision process or goal as well as same cause, and finding an appropriate exclusion restriction is difficult. Therefore the situation obviously implies that same explanatory variables will affect the both, and any variable omitted in the two equations is likely to affect selection and outcome in a similar way.

Finally, we conduct the analysis based on specification (1) with a little adjustment to answer to hypothesis 3; the outcome of actual trial experience (whether the inquiry was resolved or not) is used in place of trial opportunity variable as a key explanatory variable. The analysis units are total 304 patients with trial experience. As explained in section 3, trial experience may add negativity to the patient's perception of eVisit in case they had to visit physician office after eVisit because the patients may believe that using eVisit is waste of money, unproductive, and only delays the treatment. As we do not have satisfaction survey reports for all eVisit users, and thus we assume the following after discussion with eVisit project team that includes physicians and eVisit Information System team. If a patient comes back for offline face-to-face visits within 7 days after the eVisit for the same symptom, we consider that the eVisit has failed to resolve the health issue for the patient, and thus provided negative experience. Thus we divide trial participants into two groups – no additional contact was made within 7 days (resolved group) and at least one office visit is made for the same reported symptoms (unresolved group, 42 patients). We added a binary variable 'Resolved' that represents the former group with a value of 1 if a patient is in resolved group. Total 72 patients from the two groups (304 trial participants) returned to utilize the eVisit service with co-payment or at full cost after the formal deployment. We drop variable 'Encounter' because all patients in this analysis have trial experience, and thus prior signal is ignored.

$$(3)\ Logit(P[eVisit\ adoption_i = 1]) = \beta_0 + \beta_1 Resolved_i + \beta_2 PortalAccess_i + \beta_3 WebPreference_i + \beta_4 OfflineVisit_i + \beta_5 HealthComplexity_i + \gamma Demographics_i + \delta_j PCP_j + \varepsilon_i$$

(where i = patient index, j = physician index, $Demographics_i$ = a vector of patient i's demographic variable values, γ = a vector of coefficients for patients' demographic variables)

3.6 Results

Logistic regression results of specification (1) and (3) are summarized in Table 3 columns 1 and 2, respectively. The results show that if a patient had a trial opportunity, the odds of using eVisit service in the subsequent periods increase by a factor of 1.5. This result supports the first hypothesis as well as the adoption theory with regard to the positive association of trialability with innovation adoption. In addition, actual trial experience by a patient has a significant influence on the adoption; patients with trial experience have on average 5 times higher odds of adoption (this is based on a separate regression with a variable Trial = 1 if a patient experienced trial regardless of the outcome). As expected, patients with unsatisfactorily resolved trial experience has lower odds of adoption (factor of 2.8) compared to non-participants than patients in resolved group (factor of 5.7), but note that even those who had to come in for offline clinic visit because initial eVisit treatment was presumably insufficient to handle their cases are more likely to adopt eVisit than those without a trial experience.

One additional encounter with their eVisit provider before eVisit service deployment increases the odds of adopting eVisit by 10 percent. This implies the importance of raising awareness amongst patients regarding the new innovation. There was no formal marketing effort until the trial period ended, and thus patients obtained information about eVisit through emails or from their eVisit providers. This is also a reason why we restrict our study population to those patients whose PCPs provide eVisit.

Regarding the demographics, gender, age, employment status affect adoption; younger, female, white, and fulltime employed have higher rate of adoption. Patients' health complexity, insurance coverage of eVisit, and marital status do not have significant effect on the adoption decision. Frequency of past portal access and office visit frequency do not have significant effect on the decision of adoption. Further analysis is needed to fully explain some of these findings.

Table 3. Estimates for Trial Opportunity and Trial Experience

	eVisit adoption with Trial opportunity		eVisit adoption by Trial experience	
Trial Opportunity	0.426***	(0.0468)		
Resolved (Trial)			1.741***	(0.142)
Portal Access	0.00192	(0.00253)	-0.00545	(0.00427)
Web Preference	0.442	(0.249)	0.310	(0.262)
Office Visit	0.00272	(0.00442)	0.00456	(0.0143)
Health Complexity	0.0173	(0.0870)	-0.00959	(0.100)
Female	0.664***	(0.146)	0.587**	(0.179)
Age	-0.0235***	(0.00356)	-0.0225***	(0.00469)
Fulltime	0.291*	(0.130)	0.333*	(0.162)
Married	0.0427	(0.142)	0.0430	(0.158)
White	0.825***	(0.244)	0.649*	(0.259)
Black	0.692	(0.472)	0.444	(0.920)
Cover	0.0996	(0.110)	0.101	(0.107)
Encounters with eVisit providers	0.0988***	(0.0217)	0.120***	(0.0219)
Constant	-3.738***	(0.331)	-3.387***	(0.307)
Observations	9269		5,926	
Pseudo R-squared	0.076		0.078	

Note: Robust standard errors in parentheses

+p<0.1, *p<0.05, **p<0.01, ***p<0.001

3.7 Conclusions and Limitations

For non-emergent acute conditions, our findings suggest that patients with an opportunity for experiencing a new service innovation in healthcare delivery are more likely to adopt it than patients without the opportunity when both groups are similar in internet usability and access. Stronger impact on adoption is achieved via actual trial experience. Our results support the hypotheses that trial opportunity and trial experience increase IT adoption, with a larger influence seen from actual trial experience. Fixed effect estimates for physicians are mostly significant (Jung et al. 2011). This indicates that primary care physician's influence is a very important determinant in encouraging patients to adopt/ re-use eVisit service.

Rogers (2003) asserts that trialability is perceived as more important by earlier adopters. There is no precedent for earlier adopters to follow whereas later adopters can use earlier adopters' experience as vicarious experience. Thus, for earlier adopters, trialability provides an opportunity to reduce uncertainty and learn by doing, which increases the odds of adopting the innovation. Our future study includes analyzing the effect of trialability on early adopters and later adopters using hazard analysis. Due to the demographic differences that are statistically significant between populations with trial opportunity and the rest, a study extension using propensity matching score may be a desirable approach.

A limitation of the study is the difficulty in tracking down all possible care delivery routes such as emergency department and retail clinic visits which may substitute for office visit in a similar manner as eVisit. These are currently being investigated. This study also does not incorporate individual patients' preference for web usage in the utility function, and instead simply assumes that cost of using office visit is the same for all patients vis-à-vis cost of using eVisit because the study population comprises only web-based, patient-portal users. Relaxing this assumption is also currently under investigation. Other extensions of this study include a multi-level regression analysis with physicians as higher level class and the construction and operationalization of other attributes of Innovation Diffusion Theory.

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APPENDIX I

A. Conditional independence assumption (CIA) means the outcomes of the treatment do not depend on treatment status once observable factors that influence selection into the treatment are controlled. When the potential outcome from non-treatment is Y_0 and that from treatment is Y_1 where treatment status is indicated as $D = 1$ being receiving treatment, this condition is written as follow:

$$P(Y_0, Y_1 \perp D|X)$$

B. Common support (or overlap) assumption is critical to apply PSM as it means that there are participants and nonparticipants with the same (or similar) values of X (explanatory variables). This can be written as follow:

$$0 < P(D = 1|X) < 1$$

The range of p-score supported by both participants and non-participants is 0.0168 to 0.3742, and the numbers of patients in each block from each group are provided in Table B.1.

Table B.1 P-score range and the number of subjects in commonly supported blocks

Block (p-score range)	Non-participants	Participants	Total
0.0168 – 0.05	3,058	97	3,155
0.05 – 0.1	2,361	183	2,544
0.1 – 0.2	157	21	178
0.2 – 0.3742	10	3	13
Total	5,586	304	5,890

We provide visual inspection that evidences overlap condition in our matching.

(Appendix C to be added)

Chapter 4

4. Volume Based Learning with Structured eVisits: Impact of Individual and Organizational Usage Experience on Service Efficiency

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Abstract

Online medical consultations or eVisits are a new delivery model for treating non-urgent, acute health conditions. eVisits are typically asynchronous; the patient submits the necessary information and the physician responds at some later point. The substitution of office visits by eVisits for minor illness may help address some of the growing demand for primary care and enable clinicians to care for a larger pool of patients. However, the growing use of eVisits will force physicians and practices to change their operational routines. How physicians adapt to using this new technology and how they integrate eVisits into existing operational routines is unknown. In this paper, we draw on theories of organizational learning to understand whether physicians develop efficiency gains as they provide more eVisits and variations among physicians in evaluating and responding to eVisits. We examine individual learning (increased efficiency for an individual physician as the physician provides more eVisits) from their individual experiences and organizational experiences. We analyzed 3,144 eVisits using 4 years of data from 22 physicians in 4 primary care practices in southwestern Pennsylvania. Our main outcome variable was physician evaluation time (time spent from opening eVisit to decision on treatment and response). The average time for physicians to evaluate and respond to eVisits was 7.5 minutes (standard deviation = 7.9) and patient wait time was 185 minutes. Using OLS and time series regression models, we find that physician evaluation time is greater when the physician does not have an ongoing primary-care-provider relationship with the patient, when the reason for the eVisit is ambiguous, and the patient has more complex illnesses. On average, there is a 1.3 percent decrease in physician evaluation time for 10 more eVisit experiences, and 0.85 percent decrease in evaluation time for 100 more organizational experiences. However, only marginal evidence supports that there is shared learning across physicians within a practice. Physicians without prior system knowledge shows higher rate of learning from their own experience, but the effect is marginal. These findings suggest that there are some gains in physician productivity as they learn this new care delivery model but very little knowledge sharing if exists. Individual physicians benefit from others' experience more when their own knowledge has accumulated to some level. Thus, training program before the new system installment or periodic discussion sessions may enhance overall productivity as well as strategic assignment of eVisits to physicians.

4.1 Introduction

Many sectors of the economy have benefited from digital innovation via online service delivery models for consumers, such as online education and financial management (Harasim 1996; Nightingale 2003). The ongoing digital transformation of the healthcare sector via electronic health records (EHR) and patient portals are shifting care from traditional face-to-face encounters to online consultations. One example of online consultations that is growing in popularity is eVisits. The growth of eVisits is driven by increasing consumer demand for improved access, anticipated increased demand due to health reform, availability of new technologies to deploy such services (Katz et al. 2004) and reimbursement by major payers (Padman et al. 2010; Adamson and Bachman 2010; Boehm et al. 2010). Deployment of patient portals has grown substantially, with 40 percent of physician practices reporting adoption, and the forecast is for continued growth until 2017.[3] Portals are the platform for providing eVisits, hence increasing portal use indicates great potential for eVisit adoption.

There are two types of online medical consultations. One is a simple online communication via message exchange or email between patients and physicians. It usually focuses on follow-up questions from a visit on issues such as laboratory tests. The other type is reimbursable medical consultation in which the patient initiates the encounter to address a new medical problem. Patients pay out-of-pocket for this type of service (defined as eVisit) if it is not covered by their health insurance and physicians are reimbursed for the service. The patients' payment for eVisit is typically lower than office visits, ranging from 35 to 45 dollars. The eVisit service provides patients with alternative for onsite office visits with the potential to increase the volume of patient access to providers (Jung et al. 2011; Zhou et al. 2007; Adamson and Bachman 2010).

Both models of online consultation service have been deployed in a few healthcare organizations, with some research on the first type (online communication) over the past decade including messaging content analysis (Roger et al. 2008; Sittig et al. 2001; White et al. 2004; Tang et al. 2006; Byrne et al. 2009), physician self-reported time taken to review and respond to free text messages by patients (Kummervold and Johnsen, 2011), impact on onsite visits and patient-physician relationship (Zhou et al. 2007; Palen et al. 2012; McGready et al. 2006), and eHealth adoption (Li et al. 2013). In contrast, there are few studies that have examined eVisit adoption and usage not to mention the physicians' adaptation to the service despite its importance in potentially substituting for current face-to-face visits.

Specifically, improvement in physician productivity is an important motivation for the deployment of information technology-enabled solutions. Prior studies have addressed the shortage of primary care

[3] U.S. Patient Portal Market for Hospitals and Physicians: Overview and Outlook, 2012–2017 http://www.frost.com/prod/servlet/svcg.pag/HCHL (accessed on October 29th, 2013)

physicians and therefore the lack of access to care by patients (Strunk and Cunningham 2002; MMS study 2013). While eVisit aims to provide better access to care for all patients, physician productivity is challenged by having to learn the new system (Goh et al. 2011). The ability to learn and adapt is a key component of the success of an organization (Argote and Miron-Spektor 2011). In other words, this can lead to successful eVisit provisioning, and therefore, to increased care delivery in the primary practices. Learning can be achieved by direct experience as well as knowledge sharing among users within an organization. Through accumulated experience, a change in organizational knowledge can take place, defined as organizational learning (Argote and Miron-Spektor 2011). Studies conclude that performance change is indicative of change in knowledge (Argote and Epple 1990) because objectively assessed, performance-based measures can capture both tacit and explicit knowledge (Argote and Miron-Spektor 2011). Productivity also improves as an individual and organization accumulate experience (Reagans et al. 2005; Pisano et al. 2001).

Therefore, individual physicians' learning associated with the deployment of new and challenging information technologies in the care delivery setting and their impact on performance is an important problem to investigate. This study presents empirical models and analyses focused on estimating the effect of learning-by-doing on eVisit service productivity in primary care practices in an attempt to find evidence of learning and knowledge sharing among individual physicians. The learning and adaption can be interpreted as improvement of physician eVisit service productivity in this study context. Individual physician's work proficiency is expected to improve as they accumulate more eVisit service experiences and they leverage knowledge from other members within the practice. Work coordination can also be improved as more efficient routines and work processes settle in the organization as learning in organization occurs (Epple et al. 1991), but it is beyond the scope of this study as there is hardly any group task in primary care practices. Ultimately, learning should reduce measurable cost - time taken by provider to respond to eVisit – which results in increased efficiency, with obvious and potentially significant implications for healthcare organizations in the process of deploying new information technologies in the clinical care setting.

4.2 Study Site

The structured online consultation, or eVisit, studied in this paper is a chargeable medical consultation provisioned through a series of structured and secure message exchanges between a physician and a patient using portal technologies and integrated with practice workflow and the clinic's Electronic

Medical Record (EMR). This service excludes simple communications which do not require physicians' direct attention, such as appointment requests, or do not involve patients' acute but non-urgent symptoms. For example, functionality such as renewing prescriptions, checking test results, and scheduling appointments that are provided via the patient portal free of charge are not considered as eVisits. Via the patient portal, users can review their clinical information and perform appointment scheduling, pre-registration, and prescription renewal.

Four practices affiliated with a large health system in Western Pennsylvania participated in providing reimbursable eVisit service beginning in April 2009. One of the four practices, named practice 1 for convenience, piloted the service for 7 months prior to April (trial period), at no cost to the patients. Unlike the remaining practices, practice 1 also had three locations with a total of twelve physicians, all participating in providing eVisits. The service was expanded to many more practices in September 2010. The population of patients eligible to submit eVisit was also expanded from patients within the eVisit practices only to any patient with office visit records in the health system within the most recent 3 years.

The eVisit service initially dealt with eight conditions - seven specific conditions, including sinus/cold, cough, back pain, diarrhea, urinary symptoms (UTI), red eye, vaginal irritation, plus an 'Other' category that patients chose when their current health condition was not found among the specific categories. The 'Other' category required patients to enter free text in response to a few data gathering questions, whereas the 7 specific condition categories relied on an average of twenty structured questions that are specific to the selected condition, with limited free text entry. These questions are intended to collect all necessary information of the patient's current condition to enable the physician to diagnose and treat the patient. The number of conditions increased to twenty two in early 2011.

As serving eVisit is voluntary for physicians in all practices, participation rate varies by practice. Considering only legitimate eVisit services (those that were responded to and have appropriate reimbursement codes), practice 1 achieved 100 percent participation by the first year after pilot deployment, while participation rate at other practices are 9.6 percent, 33 percent, and 28.6 percent for practice 2, 3, and 4, respectively. The main contributor to full participation in practice 1 is a physician champion who was part of the health system's eVisit project team and a member of the practice. The number of eVisits each physician handled during our study period ranged from 1 to over 500. Except one, all physicians in this study have over 7 years of tenure at their practices, identifying all were practicing at the current offices when eVisit and its relevant technology was first deployed.

4.2.1 The eVisit Service Constructs

In this study, we define three different time measurements; nurse triage time, physician evaluation time, and patient wait time. Among them, evaluation time represents individual physicians' eVisit service productivity as it includes time taken for each physician to review, evaluate, and respond to patients with diagnoses, treatment, and prescription order if needed. Figure 1 depicts a timeline associated with an eVisit and the three key time measurements.

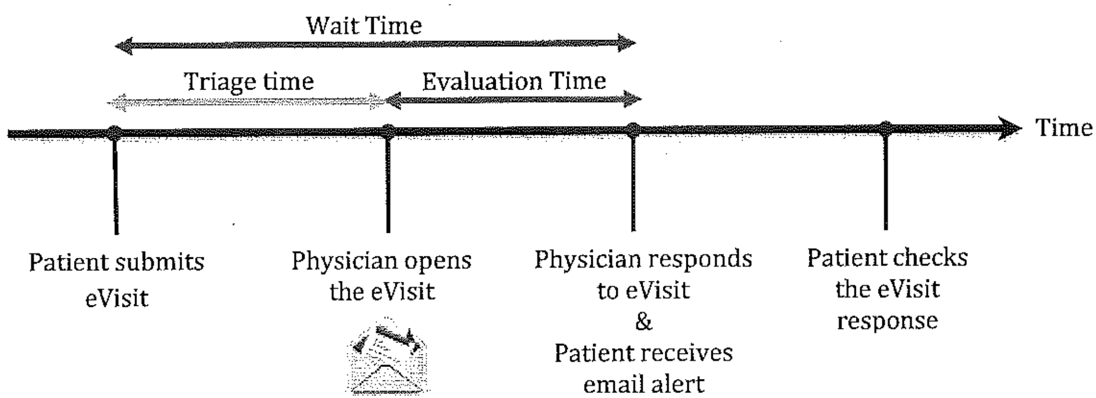

Figure 1. Simple depiction of three key time measurements in the study

As shown in Figure 1, '*Evaluation time*' indicates how quickly an individual physician processes eVisits and makes decisions about diagnosis and treatment. It is similar to face-to-face encounter time between physician and patient during office visits, but inclusive of the time taken for reviewing relevant patient information in the EHR such as medical history, medications, reason for visit, etc., documenting the care, informing the patient, as well as prescribing medications and ordering tests, if needed. '*Wait time*' computes the time from when a patient submits eVisit until he or she gets an alerting email that the eVisit has been answered by the physician. Patients can expect to receive a reply from physicians within 4 hours based on our data although there is no pressure for physicians as long as it is responded within 24 hours. This measure is different from what we conventionally call patient wait time, but in a virtual service environment where users are not aware of exactly when their inquiries are handled, the total time from eVisit submission to response alert can be considered as user wait time. It is consist of '*Evaluation time*', defined earlier, and '*Triage time*', the time taken until a physician attends to the submission. Both wait time and triage time are affected by coordination constraints in the practice (location if a practice has more than one office location), the location-level workload, culture of the practice, staff and physician's strategy for handling incoming eVisits, and all unobserved idiosyncrasy of the practice/location. The details of eVisit process are depicted in Figure 2, and the shaded area represents the initial message exchange; from a patient's eVisit submission to a physician' first response.

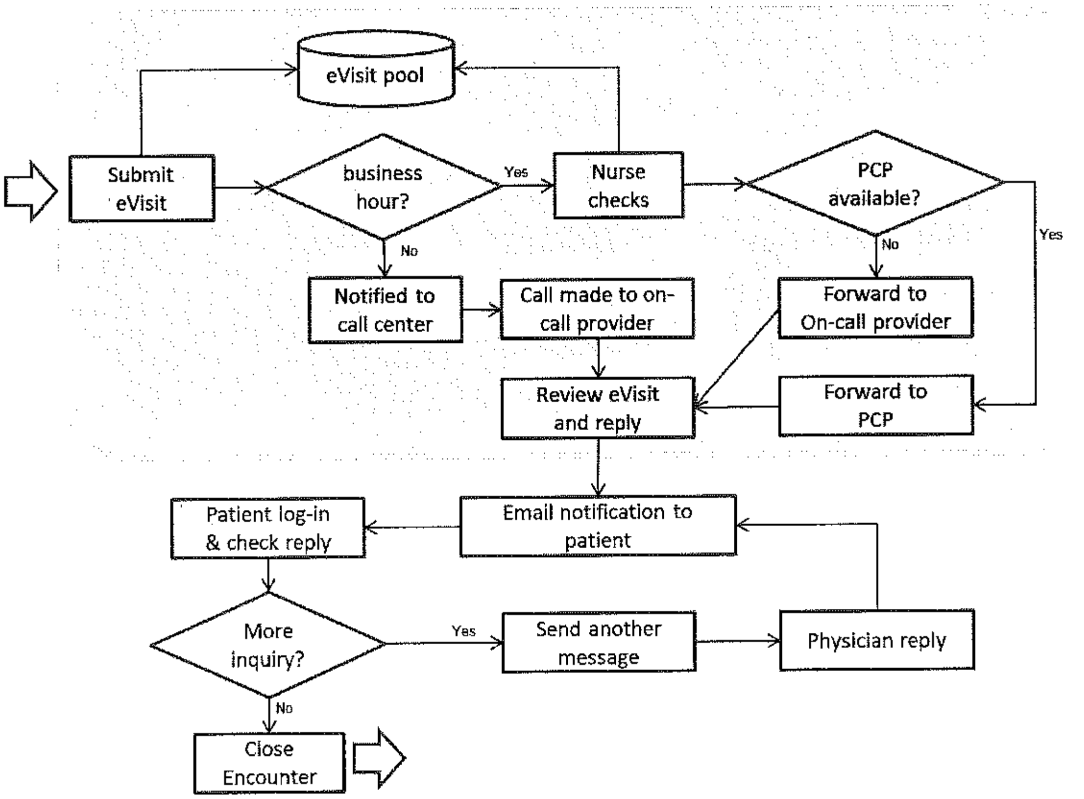

Figure 2. eVisit Process Flow

In the next section, we apply organizational learning theory to develop several hypotheses that relate the evaluation time to features of the eVisit service delivery process.

4.3 Hypotheses Development

4.3.1 Physician learning

As eVisit is a novel and innovative medical service channel for the health system with no physicians in its affiliated practices having any prior experience of eVisit when it was implemented, it is reasonable to assume that the productivity of eVisit service may have been low in the beginning. However, organizational learning theories have shown that an individual worker's proficiency is a function of the worker's cumulative experience on a given task (Argote et al. 2003; Reagans et al. 2005). Hence, we expect that a physician's productivity in handling eVisits improves as she or he experiences more eVisits over time. Likewise, the accumulated knowledge from other physicians in the practice may also enhance an individual physician's productivity. Physicians within the same practice have many chances to have face-to-face conversations and periodic staff meetings. Through these physical encounters, they have opportunity to share tacit and explicit knowledge (Olivera and Argote 1999), and via this knowledge sharing, individual physicians' task productivity can improve.

Thus, we hypothesize accordingly that:

- *Hypothesis 1a: As individual physicians accumulate experiences, the service productivity will improve (evaluation time will decrease).*
- *Hypothesis 1b: As organizational experience accumulates, the service productivity will improve (evaluation time will decrease).*

4.3.2 Stage of knowledge: Prior system knowledge

Given that the eVisit service is deployed within the existing patient portal solution, some physicians may have learned to use the portal and become familiar with it before eVisit deployment, particularly if they have responded to patients via the Medical Advice feature on the portal. This prior knowledge may lead to a different learning rate; prior studies have shown that people with higher previous expertise have lower learning rate (Shafer et al. 2001; Mukhopadhyay et al. 2011). For example, physician A, who has used Medical Advice frequently to communicate with patients and therefore has become an 'expert' of the system, may have less difficulty in adapting to a new service like eVisit than physicians who have not used Medical Advice. Physicians who are already proficient in usage of the system have less capacity to improve whereas physicians with little experience of Medical Advice have significantly greater opportunity to enhance their knowledge. Apart from system expertise, physicians with many years of expertise in practicing medicine are also likely to have a higher rate of learning. A similar argument can be made regarding physician experience of the eVisit task; as physicians accumulate more experience of eVisit, the exponential form of learning rate decreases.

- *Hypothesis 2: Physicians with lower prior usage of the system via Medical Advice service will have higher learning rates than those with higher prior experience.*

4.3.3 Complement / Substitution Effect of Individual and Organization experience

When an individual repeats a given task, the learning curve is likely to be steep in the early stages, but eventually this improvement levels off in later stages, which defines the basic shape of learning curve.

However, it is unclear which learning mechanism dominates or disappears as the learning from individual experience proceeds to later stages. Specifically, as individual experience accumulates further, organization experience may add more value to the learning, or work against the knowledge accumulation. In other words, organizational experience may reinforce or detract the effect of individual experience on eVisit service productivity. Bresman (2010) explains the reinforcing relationship based on 'absorptive capacity' (Cohen and Levinthal, 1990), in which individuals (or groups) benefit from others' experience (other groups' experiences) more when they accumulate more knowledge of their own. Especially, vicarious learning involves more procedural learning rather than fact-based learning compared to contextual learning. Vicarious learning is observational learning rather than having tutorial or slides to learn. With more procedural learning, the learning becomes more complex, and thus individual (group) needs to establish certain level of knowledge in order to understand and utilize others' experiences on their task.

On the other hand, others' experience may interfere learning from individuals' own experience. In Wong's study (2004), external learning could improve local's creative knowledge, but detract the focus of the group and therefore impedes the productivity. Therefore, others' accumulated knowledge negatively interact with individual knowledge, which means that individual experiences are less likely to have positive influence on service productivity improvement as their colleagues accumulate more experiences. This effect is called substitution effect of internal and external learning. Also, prior studies have shown that an individual tends to ignore others' knowledge as she accumulates experience of a given task (Weiss et al. 1999; Schwab 2007). Thus, physicians are more likely to learn from peers in the early stages of a new experience, rather than later stages where they will likely rely on their own experience.

- *Hypothesis 3: Individual and organization experience interact with each other to affect the service productivity. There are two competing hypotheses - complementary effect and substitutional effect:*

  3a: Individual and organization experience reinforce each other (complement effect).

  3b: As organization experience accumulates more, the individual learning is less likely to contribute to the service productivity improvement (substitution effect).

4.3.4 Task Complexity and Familiarity

While completing an eVisit submission, a patient can choose a specific condition included in the service, such as 'Red Eye', which leads to a series of structured questions requiring specific responses, or choose 'Other' category. Given the nature of free text responses to a few general questions in this category, the information is likely to be ambiguous and require additional clarifications by the physician. This ambiguity is a critical challenge in text-based environments that complicate communications (Derks and Bakker 2010). Hence, lack of clarity in the eVisit content may lead to longer evaluation time (physicians may search extensively within the patient's records for needed information or respond to patient with additional questions). In addition, patients with chronic health conditions add another level of complexity to their medical care (Wagner et al. 2001). This implies extra time required to review and respond to eVisits from such patients.

The relation of these moderating factors with the productivity is hypothesized as follows:

- *Hypothesis 4a: Lack of clarity (ambiguity) in service inquiry will negatively influence productivity.*
- *Hypothesis 4b: Increased complexity in patient's health condition will negatively affect service productivity*

We assume that a patient's primary care provider (PCP) is likely to know the patient's condition better than other on-call physicians, and thus is likely to take less time to respond to queries about the same condition. Likewise, if a physician has frequently encountered the eVisit patient in the past, the evaluation time may be reduced.

- *Hypothesis 5a: The eVisit service productivity is higher when physicians provide care to their own patients, or physicians have encountered the patients in the past.*
- *Hypothesis 5b: The intensity of patient familiarity positively influences individual productivity.*

4.4 Data

Our study data includes eVisit records, patient demographics and clinical data (diagnosis history of patients), physician demographic information, office visit records, and medical advice messages. A total of 3,144 eVisits are included in this study. More than thirty physicians from four practices participated in the eVisit service during nearly 4 years of the study period, with different physicians joining at different times. The number of eVisits handled by each physician ranges from 1 to 583.

Patients' history of health problems, recorded using ICD9 (International Classification of Diseases, 9th version) codes, is used to assess the complexity of patient health condition. The complexity is the same level as the number of a patient's comorbidity conditions that are categorized in Charlson Comorbidity Index (CCI) including myocardial infarction, congestive heart failure, peripheral vascular disease, diabetes, etc. (Charlson et al. 1987). If fewer than three comorbidity conditions exist, the complexity score is the number comorbidity conditions; if three or greater comorbidity conditions exist, the complexity score is 3.

$$complexity = \begin{cases} x & if\ number\ of\ comorbidity\ codition\ x < 3 \\ 3 & if\ number\ of\ comorbidity\ condition\ x \geq 3 \end{cases}$$

Physician information is collected from publically available sources. All physicians are either in internal medicine or family practice. Thus, we do not consider physician's specialty. Altogether, 33 physicians and one nurse practitioner completed at least one eVisit with legitimate CPT code and traceable response records. Among them, 22 physicians handled at least 10 eVisits, totaling 3,144 eVisits. We exclude physicians with less than 10 eVisits due to possible noise in the data.

In order to keep consistency in data regarding submitted conditions throughout study period, we compiled the various conditions into 15 categories; sinus/cold, urinary symptoms, back pain, rash/poison ivy, conjunctivitis, diarrhea, flu, vaginal irritation, birth control, erectile dysfunction, genital herpes, scabies, shingles, sore/strep throat, and other. Table 1 summarizes the number of eVisit submissions for each condition.

Table 1. eVisit submissions by condition

eVisit subject	eVisit count	Percentage
Sinus/cold	1517	48.3%
Other	727	23.1%
Urinary symptoms	300	9.5%
Sore/Strep throat	153	4.9%
Back pain	133	4.2%
Vaginal irritation	82	2.6%
Rash/Poison Ivy	68	2.2%
Conjunctivitis	67	2.1%
Diarrhea	39	1.2%
Flu	31	1.0%

Remaining conditions	27	0.9%
Total	3,144	100.0%

As previously noted, we use eVisit evaluation time as a measure of individual physician's service productivity. Evaluation time is the time taken by a physician to open the message, review and respond to it. We use eVisit audit records that capture the different status (message opened, replied, etc.) of each eVisit chronologically. The average evaluation time – averaged over every 50 eVisits sequentially – appears to slowly decrease over time (Figure 3) as eVisit experience accumulates across practices.

Descriptive statistics for other data attributes are found in Table 2. In Table 2, 'eVisit replied by PCP' computes the percentage of eVisits in which eVisit responders are the patient's primary care physician. Daily office encounter is the average number of office appointments for eVisit providers on the days when they handled eVisits. Patient age is the average age of the patients who submitted eVisit that are included in the study, and patient health complexity is the eVisit patients' average number of comorbidity conditions defined by CCI. eVisits resulting in prescription orders and test orders are the percentage of eVisits that included medication prescriptions to treat the condition and the percentage of eVisits that resulted in laboratory test orders, respectively. eVisits are associated with higher levels of prescription orders (89%) as indicated in a prior study (Mehrotra et al. 2013).

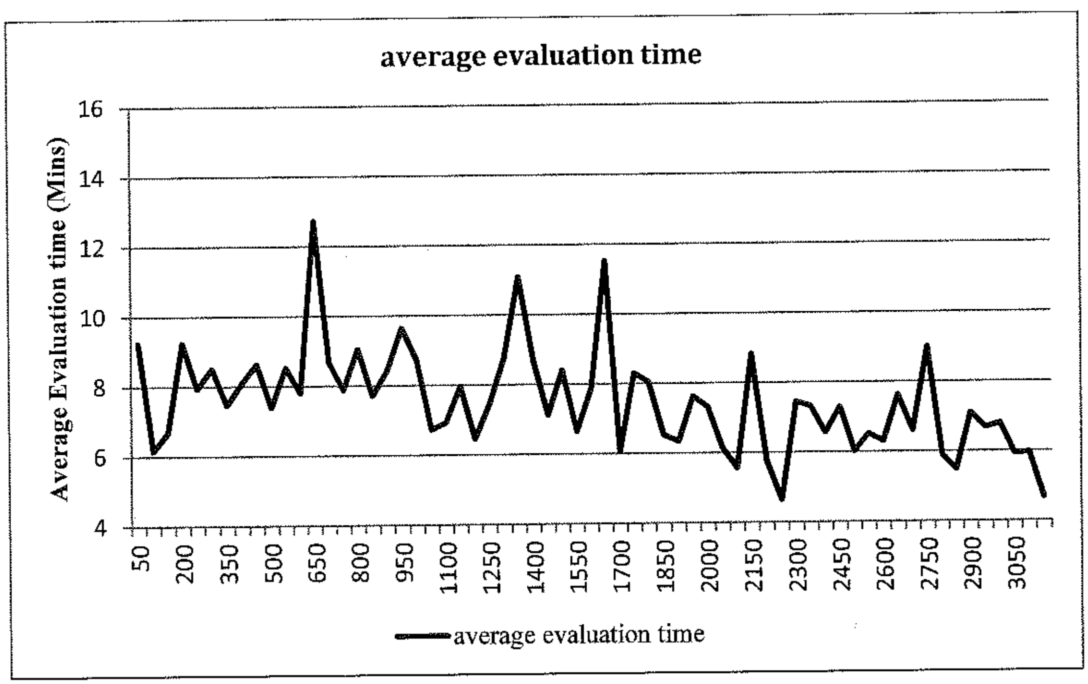

Figure 3. Average evaluation times for every 50 eVisits

Table 2. Descriptive statistics of main data attributes

	Mean	Standard Deviation
Evaluation time (in minutes)	7.54	7.94
Patient wait time (in minutes)	184.5	258.60
Physician age	50.1	6.40
Female physician (%)	24.5	n/a
eVisit replied by PCP (%)	39.2	n/a
Daily office encounters by eVisit provider per day	14.87	9.89
Patient age	46.6	12.60
Patient health complexity	0.50	0.76
eVisit resulting in prescription order (%)	89.0	n/a
eVisit resulting in lab order (%)	4.30	n/a

We only included in our analysis eVisits with CPT code '99444' (reimbursable online medical encounter). We discarded eVisits whose evaluation times are greater than 60 minutes since 96% of the evaluation time falls below 60 minutes and only sparse observations are found beyond the point (Figure 4). In fact, most eVisit evaluation times are less than 20 minutes. Also excluded are eVisits whose response records are untraceable, accounting for approximately 1% of the data. We include all eVisits regardless of whether they are submitted by repeat users. When patients submit eVisits multiple times for the same condition, it is possible that they may learn to answer the structured questions more clearly so that physicians can evaluate it more effectively. However, there are very few cases in our data in which patients request eVisit service for the same condition multiple times (Appendix I.A), thus we do not account for this issue in the current study.

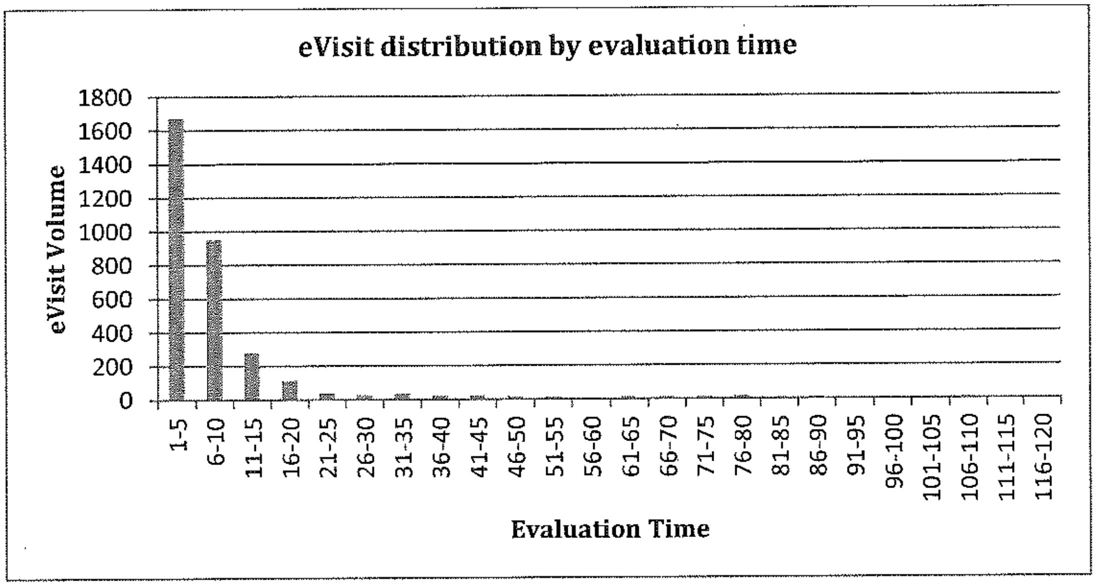

Figure 4. Distribution of eVisits by evaluation time

The next section develops specific empirical models that are relevant to the eVisit service delivery process from the individual learning perspectives in order to test the hypotheses described earlier.

4.5 Empirical Specifications

4.5.1 Dependent Variables

The unit of analysis is each eVisit record, and outcome variables are physicians' evaluation time (*Eval*) as a proxy for individual service proficiency. In many fields such as psychology and manufacturing, reduction in time required to perform a task has been considered as an indicator of learning (Carrillo and Gaimon 2000; Klein et al. 2001). Reduction in evaluation time indicates improved service productivity and physicians' acquired competence with the task. Thus, negative association between evaluation time and individual/organizational experience implies there is evidence of learning. We apply OLS coupled with various combinations of empirical specifications with physician fixed effects.

4.5.2 Explanatory Variables

For service productivity analysis, we regard each practice as an organization. Physicians in one practice do not cross over other practices in our study, and thus practice-level experience is used as organizational experiences. Thus, accumulated eVisit experiences of physician A and of other physicians within the practice are used as individual experience and organizational experience, respectively. The task performance can be improved by physicians' experiences and by knowledge sharing with other physicians they encounter. Within the same practice, physicians have opportunities for face-to-face communication. Although practice 1 has three locations, since physicians serve location 1 as well as locations 2 and 3, there are chances to discuss and share knowledge. A previous study by Huckman and Pisano (2006) showed that an individual's location specific knowledge significantly affects productivity, although the tasks they perform are the same type of surgeries across all locations. However, physicians in primary care practices do not require complex resources that are specific to the location unlike the surgeons, and the platform of eVisit is exactly the same across the practices. Thus, we use practice-level experience rather than location-specific experience of individual physicians and that of other physicians within the location as the variables of cumulative eVisit experience.

We compute the number of eVisits each physician experienced up to the physician's previous eVisit and the number eVisit experiences by other physicians within the practice, termed *Inv.exper* and *Pra.Exper,* respectively. $Inv.exper_{jk-1}$ is a physician j's cumulative eVisit experience until the $(k-1)^{th}$ eVisit, and $Pra.exper_{ijk-1}$ means the cumulative number of eVisits served in practice i until the $(k-1)^{th}$ eVisit by physicians other than physician j.

An explicit physician-patient relationship is identified by using a binary indicator variable *PCP,* which indicates whether the eVisit was handled by the patient's PCP. We also sum the number of office encounters between the patient and the physician prior to the eVisit within recent 3 years, *Pt.Phy.enc*, in order to understand the effect of relationship intensity on productivity. We identify potential lack of clarity in eVisit contents using identifier variable *Other*, indicating whether the condition is chosen as 'other' by the patient. Another factor that adds complexity to eVisit evaluation is the patient's overall health condition. *Complexity* indicates the patient's health condition as described in the Data section. We conduct sensitivity analysis for this variable by changing the threshold number of conditions to 2 and 4 (3 is used in the study). Phy_load_{jk} is a workload variable of physician j on the day when k^{th} eVisit is submitted and counted as the number of scheduled office visits handled by physician j. $Physician_j$ is identifier variable for physician j.

We take into account each eVisit's specific characteristics; if medication was prescribed for the eVisit, variable $Med = 1$ and if laboratory test order was placed, variable $Lab = 1$ otherwise 0. It is reasonable to assume that medications are prescribed when the physician is confident about the diagnosis associated with the eVisit whereas a laboratory test is ordered when further information or assurance is needed. Thus, these two variables are likely to be associated with the evaluation time, and therefore are included in the model.

We also control for year, day of the week, and submission time. Physicians' actual and mental workload and other unobservable factors may affect their productivity differently by time of the day or day of the week. In fact, eVisits are mostly submitted during weekdays, and the volume decreases as it nears the weekend (Figure 5). Also, the environmental and technological factors such as advanced computing power that are correlated with the service productivity may change over time, and thus we need to isolate effect of experience from other time-variant unobservable elements (Argote 2013; Solow 1957).

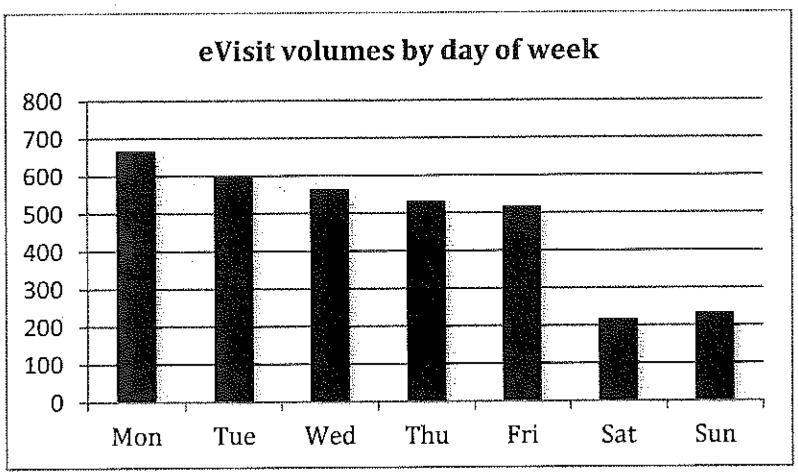

Figure 5. eVisit volumes by day of week

4.5.3 Empirical Models and Strategy

The classic learning curve function is a relation between productivity (or other measures such as defective units) and power function of experience (production output measure) for which cumulative units produced or service delivered are used as a standard measure (Argote 2013). We base our empirical model on an alternative learning curve function in which the relationship is expressed in exponential form, defined as 'adaptation curve' (Levy 1965), rather than power function form. The shortcomings of power form have been addressed by many scholars (Lapré et al. 2000). In addition to the theoretical justification, the exponential function provides benefits in estimation of learning rate, especially when initial experience is not observable since omitting prior experience leads to biased estimation of learning rate (Lapré 2000; Lapré and Tsikriktsis 2006; Clark et al. 2013). In our study, the initial two months of eVisit records are not included in this study due to inadequate information to trace evaluation times and non-standardized use of the eVisit service. Thus, we assess the learning rate (change in productivity via accumulated experience) using the exponential form.

To test hypothesis 1a and 1b, the empirical model is as follows:

$$(1)\ \log(\boldsymbol{Eval}_{ijk}) = \boldsymbol{\beta}_0 + \boldsymbol{\beta}_1\boldsymbol{Ind.exper}_{ijk-1} + \boldsymbol{\beta}_2\boldsymbol{Pra.exper}_{ijk-1} + \boldsymbol{\varphi}_j\boldsymbol{Physician}_j + \boldsymbol{\varepsilon}_k$$

(where i = practice, j = physician index, k = eVisit index)

We expect both β_1 and β_2 to be negative since negative influence means that the time taken to finish evaluation and response diminishes as experience increases. Negative and significant β_1 indicates physicians learn from their own experiences and negative and significant β_2 indicates physicians also learn from their peers (knowledge sharing).

Addressing hypothesis 2 requires categorization of physicians into two groups: non-expert (of the technology) and expert. The differentiation is based on the usage of Medical Advice (MA) prior to eVisit deployment. Medical advice feature on the patient portal allows patients to ask simple questions such as medication dosage and mostly answered by nurses. Although MA is different from eVisit, experience in MA would have helped physicians to be exposed to the portal technology. Non-expert group consists of physicians with lower pre-MA usage, and expert group is composed of physicians with frequent pre-MA usage. To obtain the threshold for categorization, we count the number of Medical advice messages answered by each physician within 1 year prior to their formal eVisit rollout, and identify the 25th and 75th percentile of usage levels. Based on the data, we thus group physicians with no more than 15 MA messages into low-user group (non-expert), and physicians with at least 185 messages into high-user group (system expert). We conduct the regression (2) for all physicians (including physicians neither in non-expert group nor in expert group), and hypothesis 2 is supported if $\beta_3 < 0$.

$$\begin{aligned}(2)\ \log(\boldsymbol{Eval}_{ijk}) \\ &= \boldsymbol{\beta}_0 + \boldsymbol{\beta}_1\boldsymbol{Ind.exper}_{ijk-1} + \boldsymbol{\beta}_2\boldsymbol{Pra.exper}_{ijk-1} + \boldsymbol{\beta}_3\boldsymbol{NonExpert}_j \\ &\times \boldsymbol{Ind.exper}_{ijk-1} + \boldsymbol{\beta}_4\boldsymbol{MidExpert}_j \times \boldsymbol{Ind.exper}_{ijk-1} + \boldsymbol{\varphi}_j\boldsymbol{Physician}_j + \boldsymbol{\varepsilon}_k\end{aligned}$$

(where i = practice, j = physician index, k = eVisit index)

To test hypothesis 3 with two competing directions of the relation between individuals and others' experience, we added the interaction term between the two different experiences. If the relation is complementary, we expect $\beta_3 < 0$, or $\beta_3 > 0$ if it is substitutive relation.

$$\begin{aligned}(3)\ \log(\boldsymbol{Eval}_{ijk}) &= \boldsymbol{\beta}_0 + \boldsymbol{\beta}_1\boldsymbol{Ind.exper}_{ijk-1} + \boldsymbol{\beta}_2\boldsymbol{Pra.exper}_{ijk-1} \\ &+ \boldsymbol{\beta}_3\boldsymbol{Ind.exper}_{ijk-1} \times \boldsymbol{Pra.exper}_{ijk-1} + \boldsymbol{\varphi}_j\boldsymbol{Physician}_j + \boldsymbol{\varepsilon}_k\end{aligned}$$

(where i = practice, j = physician index, k = eVisit index)

The effect of ambiguous eVisit contents are assessed by estimating effects of two added explanatory variables – *Other.condition* and *Complexity*. We add these variables to (1) resulting in (4). If less clear contents and more complex patients' health condition affect the physician's productivity negatively, we expect both θ_1 and θ_2 to be positive as increase in time to finish the task is an indicative of lower productivity.

$$\begin{aligned}(4)\ \log(\boldsymbol{Eval_{ijk}}) &= \boldsymbol{\beta_0 + \beta_1 Ind.exper_{ijk-1} + \beta_2 Pra.exper_{ijk-1} + \theta_1 Other.condition_k} \\ &\quad \boldsymbol{+ \theta_2 Complexity_k + \varphi_j Physician_j + \varepsilon_k}\end{aligned}$$

(where i = practice, n = physician index, k = eVisit index)

Explicit physician-patient relation and intensity of patient familiarity, variable PCP and $Pt.Phy.enc$ respectively, are expected to have positive effect on the eVisit productivity. We add the variables to (1) to have (5) as below. The expected outcomes are that both $\boldsymbol{\delta_1}$ and $\boldsymbol{\delta_2}$ are significantly negative; physicians' familiarity to patients boosts physician productivity on evaluating and responding to eVisit.

$$\begin{aligned}(5)\ \log(\boldsymbol{Eval_{ijk}}) &= \boldsymbol{\beta_0 + \beta_1 Ind.exper_{ijk-1} + \beta_2 Pra.exper_{ijk-1} + \delta_1 PCP_{jk} + \delta_2 Pt.Phy.enc_{jk}} \\ &\quad \boldsymbol{+ \varphi_j Physician_j + \varepsilon_k}\end{aligned}$$

(where i = practice, n = physician index, k = eVisit index)

Throughout the analysis on individual service productivity, we do not consider multilevel regression model (hierarchical model) although the physicians are nested in the practices. First, macro level (practice) has only four units, which is not a sufficient number to estimate parameters without biases (Maas and Hox 2005; Van der Meer et al. 2010). Secondly, the selection of practices is not random, and lastly, omitted variable bias is likely to occur as we do not have sufficient information on each practice. Thus, we apply fixed effect of physicians rather than apply multilevel model.

4.5.4 Time Series Analysis

Although, only 2.2 eVisits are submitted per day on average, which implies that the time intervals between submissions presumptively are not small enough to affect performance of the next eVisit submission, we cannot ignore the potential serial correlation between adjacent eVisit services. Since a goal of the study is to find a potential change in the time to handle eVisit service over time as they accumulate experiences, if simply illustrated, we should not overlook time series aspect of the data analysis. To account for this possibility, we re-structured our dataset for time series analysis by generating monthly and weekly level of eVisit data. In order to sufficiently control for variations incurred due to differences in practices as well as smaller number of eVisits from the three practices, we exclude those 3 practices which started eVisit service later from the time series analysis. Aggregate-level data are easily affected by extreme values, and thus we focus on the primary care practice that handles majority of eVists.

Explanatory Variables for ARMA regression: The variables of interest is log of average evaluation time by week (month for monthly data). *Cum.eVisit* is our main variable of interest in time series analysis. It is cumulative number of eVisits up to the past week. *Office* is the total number of office visits to the practice during that week. *Phy.count* is the number of physicians who were available in week *t*, *Complex* is the average number of chronic conditions in CCI of eVisit patients after converting the number such that 0 is mapped to 0, 1 to 1, 2 to 2, and 3 or more to 3. *Phy.Um* is the weekly average number of user messages that the eVisit provider responded to on days when eVisits are submitted, and *Med.Lab* is the number of eVisits during the week that included medication prescriptions or lab tests.

Weekly-level data are serially correlated when tested using Durbin-Watson and Lagrange Multiplier tests, but do not show any trend as revealed from both graphical (Appendix II.A) and statistical tests – augmented Dickey-Fuller unit root test (Said and Dickey, 1984) and Phillips-Perron unit root test (Phillips and Perron, 1988). We apply Autoregressive Moving Average model (ARMA) (Box and Jenkins, 1970) with autoregressive order of 1 and moving average order of 1, after checking autocorrelation function (ACF) and partial autocorrelation function (PACF) of log of average evaluation time and average wait time (Appendix II.B, C). We do not include lags of exogenous variables in the model as it is a reasonable assumption that physician workload, patient information, and characteristics of eVisits in different weeks are independent of each other, respectively, and it is evidenced by cross correlation of residuals from univariate (evaluation time or wait time) ARMA(1,1) and exogenous variables. The correlograms between residuals from ARMA(1,1) regression and cumulative eVisit are included in Appendix II.D . The empirical specification follows as:

$$(6)\ \log(Avg.Eval_t) = \beta_0 + \beta_1 Cum.eVisit_{t-1} + \beta_2 Office_t + \beta_3 Phy.count_t + \beta_4 Complex_t + \beta_5 Phy.Um_t + \beta_6 Med.Lab_t + \varphi Log(Avg.Resp_{t-1}) + \varepsilon_t + \theta\varepsilon_{t-1}$$

(*where t = week (or month for monthly-level data)*)

Monthly-level records do not appear to have a serial correlation based on the results from Durbin-Watson and Lagrange Multiplier tests for serial correlation, and thus the monthly-level data are analyzed with simple OLS with robust standard errors.

4.6 Results

4.6.1 Effect of individual and organizational learning

Table 3 summarizes results of regressing log of evaluation time on the cumulative eVisit experience to test hypotheses 1a through 3. Findings (Table 3, column 1) indicate that, on average, evaluation time decreases by 1.3% with 10 additional individual physicians' eVisit experience. A physician with an average evaluation time may reduce his/her eVisit service time by 6 seconds after accumulating 10 more eVisit experiences. Compared to individual experience, influence from other physicians' experience on evaluation time is very small in magnitude and only marginally significant (both Hypothesis 1a and 1b are statistically supported but H1b has weak support at 0.1). This means that almost negligible knowledge sharing takes place within these practices. Unlike surgical procedures and machinery buildings, primary healthcare delivery does not necessarily require cooperation and coordination among physicians. In particular, there is little conversation or learning from each other once the process of evaluating a particular patient begins. Thus, it is reasonable to observe little knowledge sharing within a practice in the individual eVisit service productivity metric, measured by individual physician's evaluation time.

4.6.2 Learning rates by stage of knowledge

Table 3 also shows that physicians who are non-experts on the new technology actively learn from their own experience and others' expertise whereas expert group of physicians do not exhibit statistically significant evidence of learning from their own experience. Also, the magnitude of productivity improvement via knowledge sharing is larger in the non-expert group. Physicians who lack previous knowledge regarding the system learn more from their subsequent usage of system while physicians who have already explored the system through prior usage have little room to improve. The average evaluation time by non-expert group decreased by more than 6 minutes (12.6 minutes to 5.8 minutes), but the decrease in evaluation time by expert group is negligible (from 9.8 minutes to 9.2 minutes) when compared the first five eVisits and the last five eVisits by each group. Although this result is partly due to the higher volulme of eVisits that non-expert group served during the same period, the reduction in evaluation time is far greater for the non-expert group even when accounting for the volume. This supports hypothesis 2.

The individual and organization experiences found to have a marginal complementary relationship although the magnitude of the effect is small. This finding is reasonable under the study setting. There was neither formal training nor education session for the physicians before starting the eVisit service, and thus physicians learned to use the eVisit in ad-hoc basis. Therefore, learning how to use eVisit can be considered as vicarious learning (observational learning), which is more complex than contextual learning. In order to absorb complex learning, individuals need to have accumulated knowledge. Since vicarious learning involves more procedural learning, it is relatively difficult to benefit from others' experience when the individuals are still in their early stage of the focal task. In our study context, physicians may need to establish some individual experience in order to understand others' experience. In other words, physicians learn from others' experience better when they accumulate the knowledge more.

Another reason for the finding might be that physicians may ask other experienced physicians while handling eVisit when their own experience is in early stage in order to learn from their peers within the same practice. The questions and interactions would not take place if no one else experienced the service. Thus, during the early stage, physicians take more time in evaluating to ask questions in order to learn from others' experiences. This was observed in one of the practices in this study where the clinic set up a separate computer station for physicians to handle their eVisis. Thus, it is likely that when two physicians interact at the workstation, the eVisit provider may start discussion regarding many aspects of eVisit service to learn from more experienced peers, but their ability to utilize others' experience is lower in the early stage.

4.6.3 Effect of task complexity and familiarity

Table 4 shows regression results to test hypotheses 4a through 5b. We hypothesized that 'Other' condition is linked to ambiguity of the eVisit contents and therefore may lead to delayed evaluation time. Supporting hypothesis 4a, we observe the positive effect of 'Other' condition (Table 4, column 1). Although we cannot observe the actual text contents in each eVisit submission or the responses from physicians, it is also possible that physicians may respond faster to obtain further information from patients when the actual content is ambiguous to them, resulting in more messages being exchanged. To address this issue, we discard all eVisits with more than one pair of message exchanges and repeat the analysis. The result of the impact of ambiguity, with all other factors controlled in the last column (7) of Table 4, remains unchanged. Productivity is also negatively affected (evaluation time is positively affected) when the eVisit patient has complex health conditions (Table 4 column 1). Thus, both hypothesis 4a and 4b are supported. The eVisit submission of 'Other' condition delays evaluation by about 12 percent, on average. For a patient with less than 3 comorbid conditions (based on CCI), adding one more chronic condition to the existing list will result in 5 percent increase in evaluation time. Sensitivity analysis (Appendix I.B) with varying thresholds for the complexity index further supports this finding.

Regarding physician-patient relationship, when primary care physician responds to an eVisit, on average, the evaluation time is decreased by 6%. For example, when physician A is responding to his/her own patients, the time taken to evaluate and respond to the eVisit is nearly 29 seconds faster than responding to patients of other physicians, if it normally takes about 8 minutes. This supports our hypothesis about the positive influence of patient familiarity on service productivity (hypothesis 5a). However, the intensity of the relationship, approximated by the number of encounters between the patient and physician does not have any significant influence on the productivity. It is reasonable to conclude that encountering patient B twice over the course of 3 year-time window will not make a difference given the daily physician workload.

Physicians do not speed up eVisit evaluation and response process based on the scheduled office visit appointments in this study. The number of office visits a physician has on a given day does not influence the amount of time the physician spends on handling eVisits. This finding is different from previous study of Intensive Care Unit (ICU) by KC and Terwiesch (2009; 2011) and goal setting theory (Locke 1968; Latham and Locke, 1979; Bendoly 2011; Deci et al. 1989). One reason could be that the eVisit task by primary care practice physicians are not for urgent condition, and is less time sensitive than ICU. Secondly, the task about which we are measuring productivity (eVisit) is not exactly same as the task about which we measure the workload (office encounter) although the cognitive process to perform the task is similar. Nevertheless, it is an interesting finding since it indicates that physicians take the necessary amount of time to handle each eVisit rather than addressing it quickly to remove it from his or her task list, thus providing unbiased care to eVisit patients.

Table 3. Effect of individual/organizational experience on the eVisit service productivity

$y = \log(evaluation\ time)$	H1	H2	H3

	(1)	(2)	(3)
Individual experience	-0.00129*** (0.000255)	-0.000481+ (0.000267)	-0.000193 (0.000584)
Other physicians experience	-0.0000847+ (0.0000481)	-0.0000887+ (0.0000440)	-0.0000385 (0.0000478)
Non-expert * Individual experience		-0.000328+ (0.000177)	
Mid-expert * Individual experience		-0.00100*** (0.000159)	
Individual experience * Others' experience			-0.000000512+ (0.000000262)
Medication order = 'yes'	-0.145** (0.0394)	-0.0994* (0.0442)	-0.101* (0.0419)
Lab test order = 'yes'	0.270*** (0.0633)	0.268*** (0.0589)	0.261*** (0.0599)
Constant	2.017*** (0.0562)	1.933*** (0.0810)	1.909*** (0.0768)
Physician workload, Submission time, day of the week, year, physician FE are controlled			
Observations	3144	3144	3144
Adjusted R-squared	0.062	0.064	0.063

Note: Robust clustered standard errors in parentheses

+p<0.1, *p<0.05, **p<0.01, ***p<0.001

Table 4. Effect of eVisit content, patient familiarity, and pre-determined workload on eVisit efficiency

$y =$ $\log(evaluation\ time)$	Content (H4)	Familiarity (H5)	All control (6)	1 set of message exchange (7)
Individual experience	-0.00131*** (0.000251)	-0.00128*** (0.000260)	-0.00129*** (0.000256)	-0.00121*** (.000304)
Other physicians experience	-0.0000853+ (0.0000480)	-0.0000905+ (0.0000482)	-0.0000918+ (0.0000482)	-0.000111* (.0000510)
Condition = 'Other'	0.118* (0.0488)		0.119* (0.0476)	0.120* (0.0459)
Patient Health Complexity	0.0512*** (0.0122)		0.0539*** (0.0141)	0.0620*** (0.0143)
PCP = 'yes'		-0.0689* (0.0286)	-0.0565+ (0.0277)	-0.0741** (0.0246)
Patient-physician encounter		-0.00306	-0.00494	-0.00274

		(0.00302)	(0.00337)	(0.00257)
Medication order = 'yes'	-0.0989*	-0.145**	-0.0988*	-0.0951+
	(0.0421)	(0.0405)	(0.0427)	(0.0508)
Lab test order = 'yes'	0.255***	0.274***	0.259***	0.243*
	(0.0587)	(0.0649)	(0.0603)	(0.0905)
Constant	1.916***	2.049***	1.945***	1.930***
	(0.0679)	(0.0553)	(0.0700)	(0.0730)
Physician workload, Submission time, day of the week, year, physician FE are controlled				
Observations	3144	3144	3144	2761
Adjusted R-squared	0.059	0.054	0.062	0.064

Note: Robust clustered standard errors in parentheses

+p<0.1, *p<0.05, **p<0.01, ***p<0.001

Time series analysis results from ARMA (1, 1) agree with the previous OLS results on the significant effect of eVisit experience on the individual service productivity (Table 5).

Table 5. Results of ARMA (1, 1) regression of evaluation time

$y = \log(evaluation\ time)$	coefficient	p-value
Cumulative evisit	-0.0002658***	0.000
Office encounter volume	0.0010216*	0.030
call_volume	-0.0004823	0.629
phy_count	-0.0224696	0.505
phy_um	0.0948527	0.111
pt_other	0.0063062	0.827
complex	-0.2144246	0.192
medlab	-0.0004262	0.967
Observation	246	

***p<0.05, **p<0.01, ***p<0.001**

4.7 Discussion and Conclusion

From these four practices pioneering the eVisit service, we find the evidence of learning via individual experience and knowledge sharing in physician eVisit service productivity. Note that we observed marginal effect of learning from others on the service productivity, indicating that physicians' eVisit productivity gain is mainly attributed to individual experience rather than knowledge sharing. This finding is partly due to the characteristics of primary care practices where physicians work at the same place, but do not work as a team unlike more complex procedures such as cardiac surgeries which require a team of surgeons. In order to increase the level of knowledge sharing, it is suggestive that primary care practices set up regularly meetings that encourage physicians to exchange their uptake of the eVisit.

4.7.1 Different learning process by stage of knowledge

Physicians with less exposure to similar technologies in the past showed to have higher rate of learning from their own experience compared to the physicians with high-level of knowledge in such applications. The number of eVisits handled by non-expert group is greater than the one by expert group, and thus the magnitude of the average additional learning rate of the non-expert group might be underestimated. The higher rate of learning and greater volume of eVisit by non-expert group implies that expert group is generally less motivated to improve their productivity further, and may have less interest in serving eVisit. In order to prevent the expert group from eventually performing worse than non-expert group, as evidenced from our data, it is important for the practices to encourage physicians with system expertise to actively participate in serving eVisit, which leads to the higher productivity. If lower interest in the eVisit among expert group is prevalent, it is recommended that healthcare organizations gather the physicians' feedbacks on the prior system experience in order to address the root reasons such as unintuitive system design, uncooperative technical experts.

Interestingly, mid-level expertise in the similar system prior to the eVisit deployment seems to have the highest learning rate from individual experience. This indicates that physicians with moderate amount of familiarity with the system performs best regarding the productivity among others when a new technology-based service is introduced. The idea of moderate system expertise boosting the learning the best implies the importance of formal training / education phase before the installment of the new system. By the training, practices can increase the number of physicians with mid-level expertise in the new system, which in turn may increase the overall productivity of serving eVisit.

4.7.2 Relationship between individual and others' experiences

From the relationship between individual experience and others' experience, we found a marginal effect of those two experiences reinforcing each other. In the early stage of the focal task experience, physicians may have higher productivity improvement for each additional eVisit experience of their own, but less likely to be productive in learning from peers, whereas such knowledge sharing plays more important role in later stages. When a physician is in earlier stage of providing eVisit service, he/she may speak to a limited pool of physicians within the same practice due to the inability to understand highly skilled phsyicians in the eVisit. After achieving higher level of knowledge in the focal task, physicians may start to communicate actively and share their knowledge frequently. At this point, skilled physicians understand others' experience, and thus are able to benefit from others. With an adequate training prior to the eVisit deployment and regular discussion session among peers, practices can accelerate the physicians' learning process early on. Through discussion, physicians in later stage of task experience will transfer their knowledge to other members in the practice, leading to boosting early stage physicians learning and reinforcing other later stage physicians' knowledge. If then, physicians in initial stage of knowledge may learn from others, which will add more improvement in their service productivity early on.

4.7.3 Task complexity, Patient familiarity, and others

Patient familiarity by physicians reduces individual eVisit service time, which implies positive effect on individual service productivity. On the other hand, eVisit content ambiguity, identified by 'Other' condition, and complex patient health condition interferes with service productivity. This finding suggests that adding more specific questions and reducing free text entry during eVisit submission may capture necessary detailed information for reducing uncertainty and therefore improve service productivity. For patients with higher comorbidity, it may be more efficient and effective to assign the patient's PCP to handle the eVisit if the provider is participating in providing eVisit service. By doing so, the positive effect from patient familiarity by the physician may potentially offset the negative effect of the patient's complex health condition.

In this study setting, we do not observe any goal setting behavior by physicians in handling eVisits, perhaps due to factors such as self-efficacy, or the random arrivals of limited eVisits per day. It is possible that physicians' goal setting behavior may be observed in office encounters because the focal task is the same in that setting; what they observe beforehand is the number of scheduled office visit appointments, and thus they may try to manage office visits based on their mental goal rather than random tasks such as medical advice messages and eVisits. However, it has also been observed that higher workload leads to faster turnover (shorter patient wait time). The different behavior captured in evaluation time and patient wait time implies that physicians take necessary amount of time to evaluate each eVisit regardless of their workload while try to take on the eVisit task sooner when more work in the location is observed. This reinsures that patients receive consistent service quality because physicians handle all eVisits equivalently and make sure patients receive the care in time.

4.8 Discussion

Future research regarding learning in eVisit service provisioning may address the perspective of patients. In this context, learning may mean whether a patient becomes a frequent eVisit user after the first service experience, and make less eVisit subsmissions that end up being categorized as non-qualified eVisit or being called in to the physician's office. However, unlike consumer learning in marketing literature, frequent purchase behavior of healthcare service is not observable because consumers seek medical care only if they have health problems. The sporadic observation limits the study on patient-side, but it might be addressed as additional control to the model. While our results may provide preliminary insights into eVisit service productivity, this does not define overall performance of the online medical consultation service as the eVisit service is technology-specific, which is usually customized for the healthcare delivery setting. The impact of this new channel of healthcare delivery on health outcomes for patients is another avenue for ongoing investigations.

As organizations gain experience and obtain feedback about outcomes, organizations develop routines (Levitt and March 1988). These routines are capable of endogenous change (Feldman and Pentland 2003), enabling more efficient operation. As eVisit is a new addition to the existing medical care delivery within the practices, it is meaningful to address the operational efficiency gain as practices accumulate more eVisit knowledge. In this study, we do not observe pre-determined workloads and physician assignment rules in each location and practice. It is important to learn the details of routines beyond the current ad-hoc level. As additional data becomes available, both OLS regressions and time series analysis may provide new insights into the challenges of routinization and its impact on eVisit operational efficiency. Using patient wait time (turnaround time) that adds wait time in queue and service time as a measure of efficiency in eVisit operation management may be a reasonable approach to address operational efficiency gain.

The current practice of providing eVisit service is not optimized in a way to provide faster service; instead it appears that many eVisits are handled within office hours especially during the morning hours and early afternoon (Figure 6). The wait time is heavily dependent on submission time whereas evaluation time is fairly similar across the day. As physicians respond in the early morning to eVisits that have queued up overnight, the wait time plummets. As eVisit submissions increase during the day wait time slowly grows. This may imply that practices adjust the eVisit provision strategy in the early morning for better efficiency, but do not have a consistent strategy for the rest of the day. Thus the study of optimal eVisit service provisioning may provide valuable insights and guidance for primary care practices that are considering deployment of online medical consultation, and it is an area for future research.

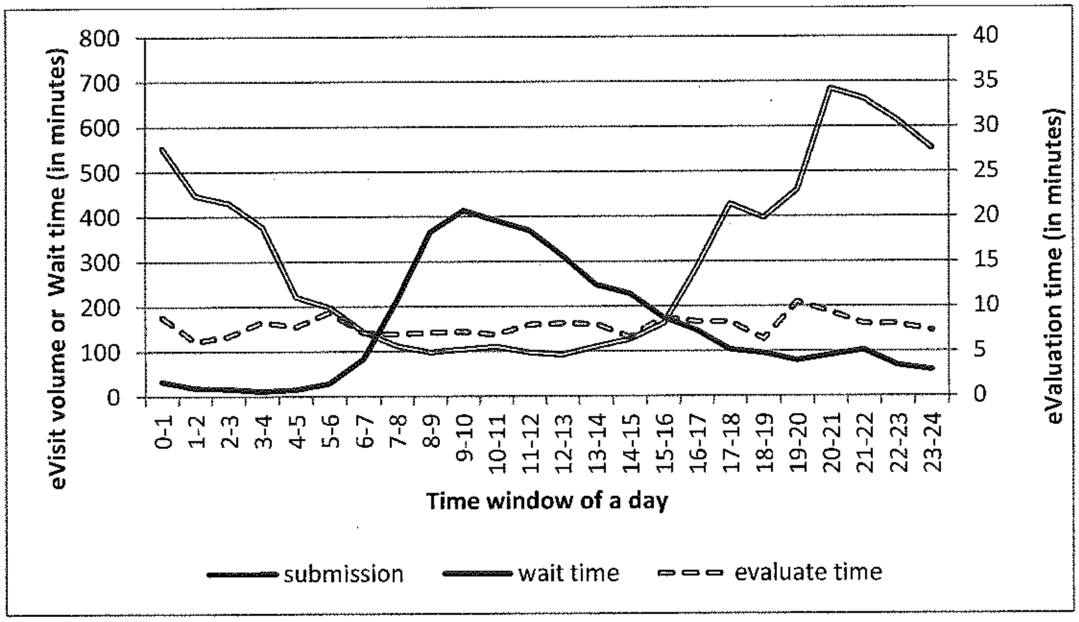

Figure 6. Distribution of eVisit submission and evaluation by time of day

Finally, practices which rolled out the eVisit service 7 months after the first practice piloted it are likely to have acquired knowledge regarding the service from practice 1. However, this transactive memory could have faded away a few months after system deployment as they develop their own knowledge via accumulated experience (Darr et al. 1995). Measuring the intensity, duration and impact of this transactive memory effect among the practices that subsequently adopt the service may be useful to the health system to understand the mechanisms of knowledge transfer, duration of knowledge retention, and its value in speeding up adoption to improve productivity.

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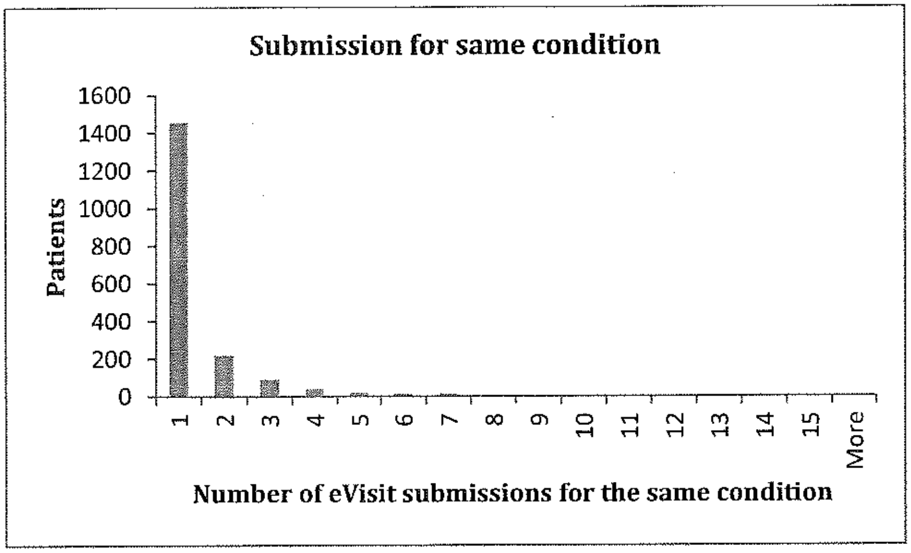
APPENDIX I.

A. Distribution of patients by the number of eVisit submissions for the same condition



B. Effect on eVisit efficiency by varying the criterion on patient health complexity

$y = \log(evaluation\ time)$	Cutoff = 2 (1)	Cutoff = 3 (2)	Cutoff = 4 (3)
Individual experience	-0.00129***	-0.00129***	-0.00129***
	(0.000254)	(0.000256)	(0.000257)
Other physicians experience	-0.0000921+	-0.0000918+	-0.0000919+
	(0.0000482)	(0.0000482)	(0.0000482)
Condition = 'Other'	0.119*	0.119*	0.119*
	(0.0478)	(0.0476)	(0.0474)
Patient Health Complexity	0.0581***	0.0539***	0.0525***
	(0.0152)	(0.0141)	(0.0135)
PCP = 'yes'	-0.0568+	-0.0565+	-0.0563+
	(0.0276)	(0.0277)	(0.0277)
Patient-physician encounter	-0.00491	-0.00494	-0.00500

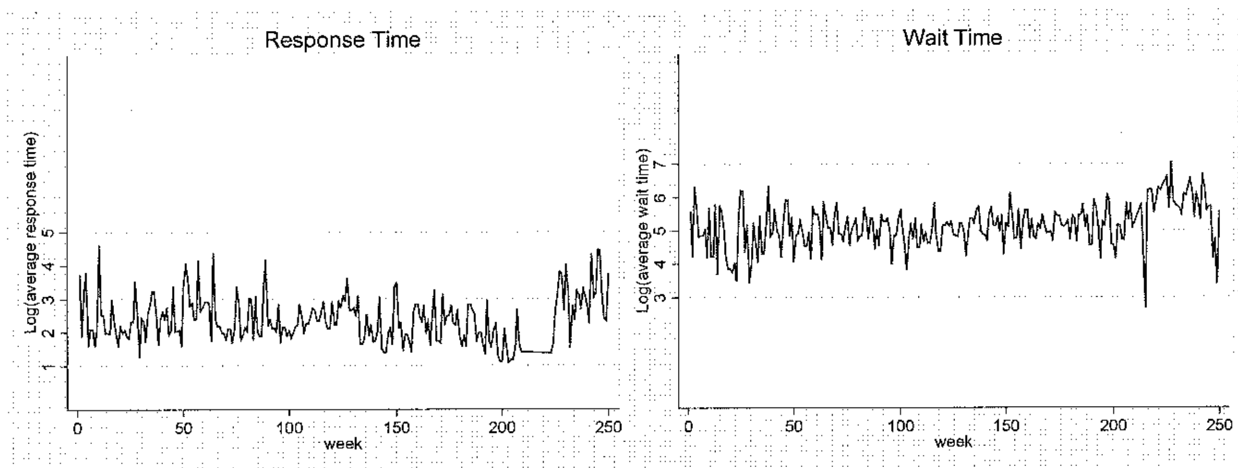
	(0.00336)	(0.00337)	(0.00339)
Physician workload	-0.000740	-0.000757	-0.000750
	(0.00260)	(0.00262)	(0.00261)
Test order, Medication order, Submission time, day of the week, year, physician FE are controlled			
Observations	3144	3144	3144
Adjusted R-squared	0.062	0.062	0.062

Note: Robust standard errors in parentheses

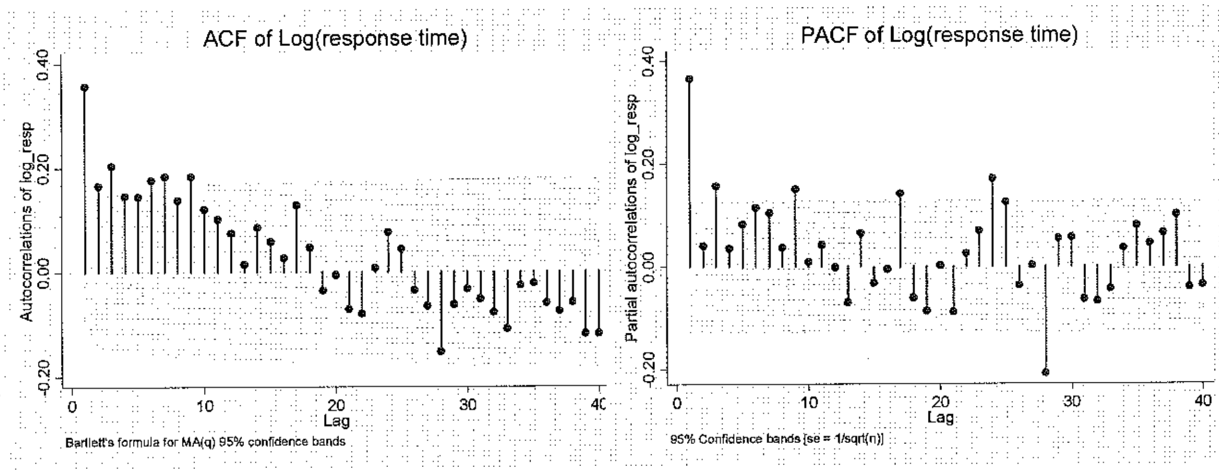
+p<0.1, *p<0.05, **p<0.01, ***p<0.001

APPENDIX II

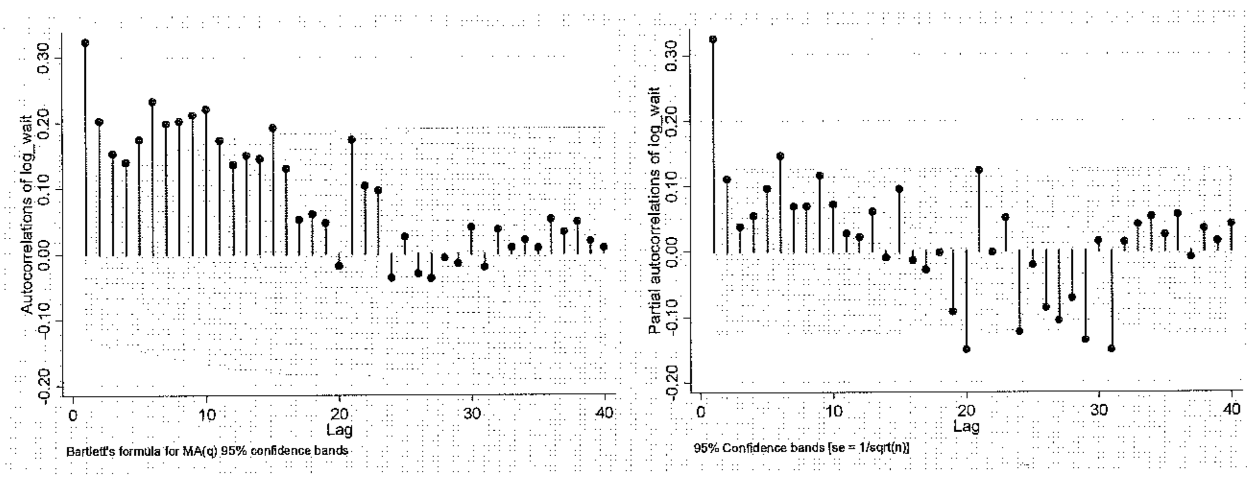
A. Line graph of log (average response time) and log (average wait time) from weekly data



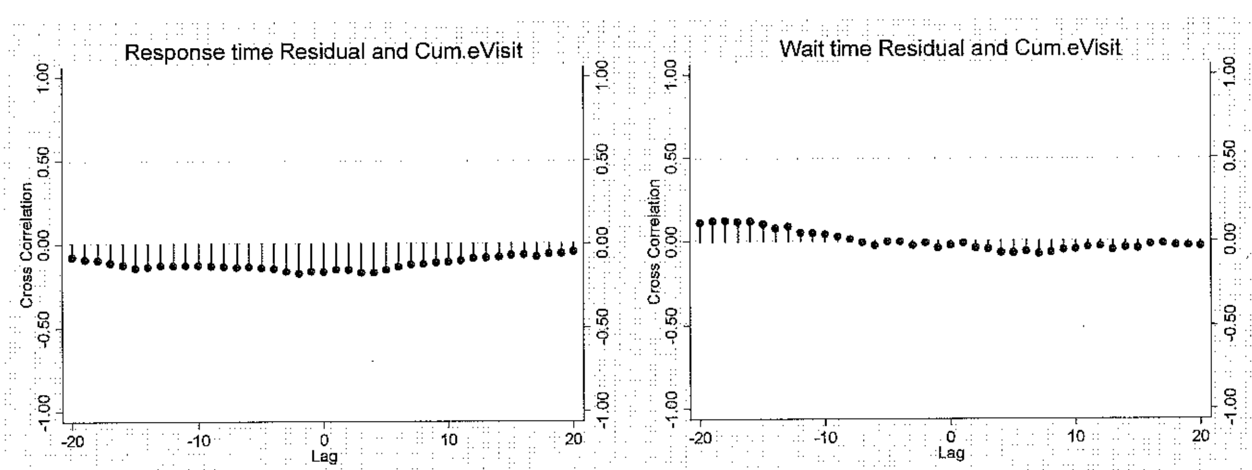
B. ACF and PACF of Log Response time



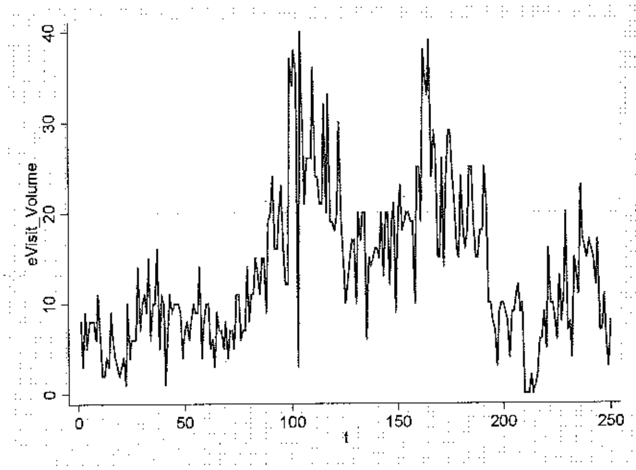
C. ACF and PACF of Log Wait time



D. Cross-Correlogram of residuals from ARMA (1, 1) with single variable (response time) and Cumulative eVisit



E. Weekly eVisit submission volume



Chapter 5

5. eVisit Operational Efficiency: Effect of the New Service Channel on Operational Efficiency

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5.1 Introduction

Many studies have examined how to accommodate patients' needs to schedule an encounter with their physicians: after-hour walk-ins or same-day scheduling for clinic visits (Jones 2000); online medical consultations for a fee (Jung et al. 2011; Adamson and Bachman 2010); and premier membership care for a monthly fee (Davis et al. 2005), among others. These offerings all have the potential to reduce unnecessary visits to an emergency department, representing 'inappropriate use' of its resources (Philips et al. 2010), and ultimately reach the goal of patient-centered care (Davis et al. 2005). Other options exist as substitutes for primary care visits, including using outside care such as retail clinics or walk-in centers (Minute Clinics, Med Express, etc.). However, these options are likely to interfere with the continuity of patient care (Jones 2000; Reid et al. 2013), which may produce inferior outcomes for patients (Lambrew et al. 1996). Thus, it is recommended that patients be seen by the same pool of physicians or at least by the same healthcare organization where they are regularly treated. Retaining patients in a practice is an important topic to investigate not only because of competition with retail clinics, but also to ensure continuity of care, which results in better patient outcomes. Therefore, offering timely access to care is a critical issue for primary care practices, and is seen as a key attribute of patient-centered primary care delivery (Davis et al. 2005). Increasing the number of care delivery channels in primary care practices offers different options to meet patient needs, with the potential to improve the overall healthcare of patients. Furthermore, a body of literature addresses the willingness of patients to utilize the additional channels of primary care services other than pre-scheduled office visits (Adler 2006; Boehm et al. 2010); indeed, a prior study found that patients are willing to pay extra $7 for flexibility in appointment times (Cheraghi-Sohi et al. 2008).

Although many studies have been conducted on Healthcare Information Technology, mostly regarding the digitization of core work processes via EMR (Electronic Medical Records), research has not yet examined how a newly installed service channel is adapted and routinized over time and how it is integrated with pre-existing service channels in primary care practice settings. Most practices offer multiple channels for patients to receive direct care from their physicians. Patients can try out other routes of service within the available options offered by their primary care practices, and can return to the pre-existing service if they have to wait longer than expected to get answers, or even migrate to other healthcare organizations or select off-practice options if the overall efficiency in the system becomes worse after the introduction of the new service.

One of the biggest barriers to the adoption of such technologies is the loss of productivity that results from the disruption caused by introducing newer technologies (Scott et al. 2005). Indeed, the introduction of new healthcare technologies can disrupt the existing routines in healthcare settings (Barley 1986; Edmondson et al. 2001). Failures in implementation of the new technologies are mostly due to challenges in integrating the technology into the existing workflows (Simon et al. 2007; DesRoches et al. 2008). Typically, when an additional channel for self-service is introduced, such as online banking, it does not raise concerns in operations because the service system is automated, and does not require involvement from bank tellers; however, online medical consultation or any service that is based on interactive communication can interfere with current operations because the existing staff on the front lines of the service need to serve an extra service channel. Thus, it is important to understand the operational efficiency of a newly-deployed service.

Since one of the biggest challenges in adopting and deploying a new service channel is service productivity, in this chapter, we address the impact of learning on eVisit operational efficiency of the participating practices based on both patients' turnaround time and work coordination among the members within a practice. We measure this efficiency using patient wait time as the evaluation metric, which is defined as the time between the submission of an eVisit and physician response to the eVisit. It is reasonable to expect that eVisits' turnaround time is longer than that of office visits, as face-to-face visits are higher in priority than eVisits during the clinic's business hours. If eVisits' turnaround time is not dramatically longer than the turnaround time of office visits, eVisits still offer added convenience for patients since office-visits' turnaround time does not account for preparation and travel time to a clinic and the opportunity cost of waiting in the clinic is high whereas this waiting time can be productively utilized for an eVisit.

We expect that operational efficiency improves as experience with the eVisit service accumulates. As organizations accumulate experience, they develop routines and practices that enable them to coordinate more effectively (Epple et al. 1991). The organizational learning and adaptation can be interpreted as improvement in the operational efficiency of the eVisit service. In this study, the change in patient turnaround time (patient wait time) indicates how effectively eVisit practices adapt; we may find a negative effect of eVisit experience on the service turnaround time if members of the organization resist or cannot find a way to coordinate the new service with existing services, or a positive effect if the members establish more efficient ways of working with the eVisit service. We address these questions regarding potential efficiency gains based on organizational learning theory. Ultimately, learning should reduce measurable cost, including both the wait time required by patients and the resource utilization in the eVisit practices.

The study environment is distinguished from previous literature where organizational learning theory is explored. Many studies have found evidence of learning in manufacturing plants, surgical teams, etc. where focal tasks and procedures can be defined precisely and have readily available solutions for the tasks. This kind of job or process is regarded as a value-added process delivery whereas tasks that provide solutions are regarded as a solution shop, such as providing diagnosis and consultation (Christensen 2009). Value-added process delivery is defined as taking on a similar job repeatedly, and thus the variation of the outcome decreases over time and increases the efficiency at the same time. On the other hand, solution shop is a place where each job differs, and may require customization on many different levels. Primary care practices have been considered as a solution shop since the most important task is providing the right diagnosis, and caring for patients under varying conditions. Surgical hospitals are considered to provide value-added process delivery. Under this definition, primary care has more uncertainty in work process, and the time to take on and process eVisits is not as precisely scheduled as operating time in surgical hospitals or manufacturing processes. Thus, finding any evidence of learning in this study setting would be a significant contribution to the current stream of organizational learning literature.

The findings have important implications for healthcare organizations in the process of deploying new information technologies in the clinical care setting. As medical practices actively participate in the eVisit service, efficiency gains can be achieved more quickly and require less activity by multiple members of the organization; consequently, the service provision will require fewer human resources as the organization routinizes the work process and better aligns the workflows with the required tasks.

5.2 The eVisit Service Constructs

5.2.1 Service Operational Efficiency

Many studies have used a firm's resources such as labor, material resources, space, etc. as inputs to measure operational efficiency (Sarkis 2000; Suteriou and Zenios 1999; Oral and Yolalan 1990). The majority of the service operations literature comes from the banking industry, and thus includes in the analyses such inputs as employees, branch space, types of accounts and customers. In the healthcare context, Lu and Wedig (2013) examined the operating efficiency of nursing home chains by using labor, material resources, geographic proximity of the nursing home chains, and patients' initial health conditions as inputs, and deficiency citations as an output. Also, a prior study on efficiency in primary care practices uses personnel and physical space as inputs (Andres et al. 2002). Overall, studies in operating efficiency commonly use two elements as inputs: human resources and material resources/physical space. Frequently used outputs are measurable outcomes, which are the results of the service, such as total service time (Soteriou and Zenios 1999; Oral and Yolalan 1990), number of customers serviced or number of services provided (Sherman and Gold 1985), sales (Banker and Morey 1986), or reduced waste (Banker et al. 1990). Other studies include additional factors such as the age of the store branch, and marketing expenditures (Banker and Morey 1986). When we examine operating efficiency in online services, these elements need to be redefined. There is no physical space that restricts the number of customers waiting in queue in online services (e.g. number of beds in an intensive care unit, number of chairs/space in the primary care practices). Also, which material resources should be included as inputs in online consultation service efficiency study is controversial as there are no particular materialistic inputs required other than computer monitors, which are already in place. There is a lack of literature on online service operations, and no study that defines the elements needed to analyze operational efficiency in providing online services / consultation.

In addition, no study has addressed operational efficiency in the provision of online medical consultation. Most studies in a similar context have examined the efficiency of patient portals, while others have examined the association between the utilization of patient portals by chronic patients with ED visits (Ross et al. 2004), other types of physician visits (Ralston et al. 2009), or with the usage of web/telephone calls (Green et al. 2008). Greater detail and information about specific papers are available in a review paper by Goldzweig et al. (2013).

5.2.2 The Case of eVisit Service

In this study, we present two different outcome measures that capture operational efficiency in serving eVisits. The first measure is patients' wait time (hereafter, wait time or patient wait time), which represents turnaround time with an eVisit submission. We focus on wait time to capture operational efficiency due to the following reasons. First, members of an office need to coordinate efficiently, so that physicians receive notification of eVisit arrival in a timely manner. If there was little coordination, staff members will neither monitor eVisit arrivals regularly nor notify physicians responsible for the eVisit processing. When there is a delay in this process, patient wait time becomes longer, and this indicates that office members need to improve their work process around eVisits. Second, eVisit assignment may be an ad hoc process; there may be no dedicated eVisit provider of the day or week, and no formal rules of assignment. Thus, when staff members assign eVisits to physicians with a long queue of patients waiting in the office, the eVisit is likely to take longer. Thus, efficient assignment of eVisits may result in reduced wait time. Third, it is beneficial for the healthcare organization to control the patient wait time in order to incentivize eVisit patients by providing healthcare service in a timely manner. If patients must wait for eVisit response far longer than traveling to physician's office, the advantages of eVisit are significantly diminished, and may discourage patients from utilizing the service altogether. The under-utilization of eVisits by patients may thus undermine the organization's intention to deploy the service by moving acute, non-urgent patients with minor symptoms to an online care delivery mode. Therefore, less wait time implies more efficiency in the office operations and coordination in addition to enabling the healthcare organization to achieve their goals around patient care more efficiently.

Figure 5.1 depicts the timeline associated with an eVisit with the wait time measurement. Patient wait time is translated as patient turnaround time, which is often used as the efficiency measure in healthcare.

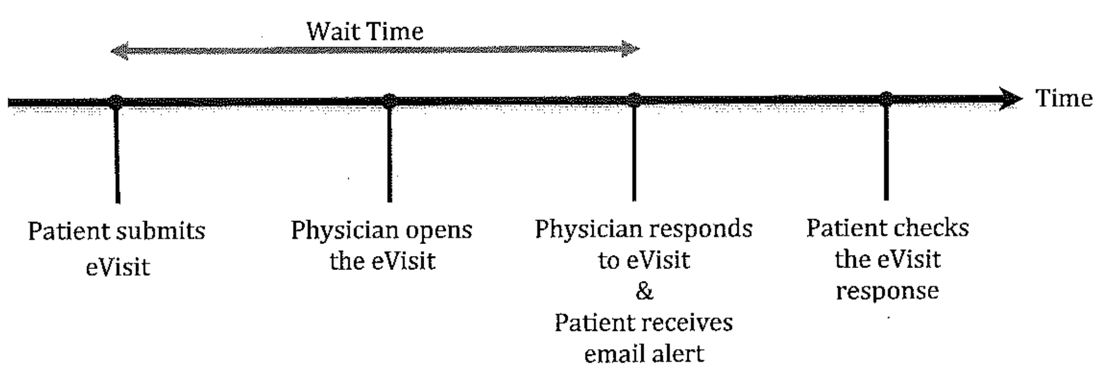


Figure 5.1. Simple depiction of the key time measurements in the study

'*Wait time*' computes the time from when a patient submits an eVisit until he or she receives a notification email that the eVisit has been answered by the physician. This measure is different from what we conventionally call patient wait time, which is the time spent in the reception area of the clinic plus waiting time in the exam room. However, in a virtual service environment, users are not aware of the exact time physicians attend to their submitted eVisit. In this sense, the total time from eVisit submission to receiving a response alert can be considered to be patient wait time; wait time is affected by coordination constraints in the practice, workload, as well as the clinic strategy for handling incoming eVisits.

The second outcome of interest is the non-value-added activities in eVisits. When communication among the members within an office is not efficient or is frequently disrupted, miscommunication occurs, which then may lead to unnecessary additional work in the office. In our study setting, confusion in communication or work assignments may lead physicians or staff members to open the eVisit or forward the message multiple times before the eVisit provider finally opens and evaluates the eVisit. Using eVisit audit records, we were able to compute the number of such activities engaged in by members of the organization other than the eVisit provider, which serves as a proxy for communication/coordination confusion and redundancy. When an organization has a higher number of non-value-added activities due to miscommunication or failed coordination, the overall operational efficiency of the organization decreases because the resource (members' labor) could have been used for other work. In addition, the members who conducted those unnecessary activities are likely to be distracted from their focal task. Thus, it is reasonable to consider others' (non-eVisit providers) engagement with eVisits as a measure of confusion/coordination issues, which lowers operational productivity.

In the next section, we apply organizational learning theory to develop several hypotheses that relate to these two key measurements to elements of the eVisit operational process.

5.3 Hypotheses Development

Patients with scheduled office visits typically receive more immediate attention than those awaiting eVisits since they are physically present in the clinic for the scheduled appointment. Thus, it is difficult to reply to all eVisits as soon as new submissions are acknowledged. In addition, eVisits are submitted throughout the day without scheduling, and thus the service operation is likely to have a large variation, which makes it harder for the members of the healthcare organization to set up a precise and specified routine. On the other hand, prolonged delays in eVisits may discourage patients from utilizing the service again in the future, which is not desirable for practices that are trying to efficiently manage care delivery by routing patients with non-urgent, acute conditions to online encounters.

5.3.1 Effect of Learning by Doing on eVisit Wait Time

As previously noted, we use patient wait time (turnaround time) as one of the measures of efficiency in eVisit operational management. Patient wait time is likely to be high during the eVisit inception period due to inexperience and potential resistance among staff and physicians. As organizations gain experience and obtain feedback, organizations develop routines (Levitt and March 1988). These routines are capable of creating endogenous change (Feldman and Pentland 2003) such as adjustments in operating speed or accuracy, which indicates that organizational learning took place (Dutton and Thomas 1984; Argote et al. 1990), which in turn leads to more efficient operations. Thus, we expect that as the primary care practices acquire more eVisit experiences, they will learn how to engage in eVisit service operation to establish a well-organized routine. Consequently, it may also be likely that patient wait time will decrease as a result. Also, experience acquired by other practices may bring about a positive influence through knowledge transfer, as explained earlier.

Thus, we hypothesize the following:

- *Hypothesis 1.a: eVisit operational time efficiency will improve as a practice gains more practice-level eVisit experience (wait time will decrease as a practice accumulates more eVisit experience).*
- *Hypothesis 1.b: eVisit operational time efficiency will improve in a decreasing manner as a practice gains more eVisit experience.*

5.3.2 Effect of "Learning by Doing" on eVisit Processing

If the physician assignment rule and eVisit work process flow are well defined and the members follow the protocol, fewer activities are completed by "middle men" (e.g. other physicians or nurses) who open, forward, or check off the eVisit from the eVisit pool. The ideal sequence of handling eVisits provided by the healthcare organization includes the following tasks: 1) nurse opens eVisit to make a judgment on the legitimacy of the eVisit (whether it is an eVisit, or can be handled via a simple response, or the patient must come in); 2) the nurse forwards the eVisit to the appropriate physician; 3) the physician opens and reads the eVisit to evaluate the patient's condition; 4) the physician makes a diagnosis and prescribes medication if necessary, and replies back to the patient. When there is uncertainty about the assignment of the work or triaging scheme, more people may take action on the eVisit than necessary; a physician who received the message may open the eVisit and check it off after realizing the eVisit is not for him or her, then forward it to someone else who can handle the request more appropriately. It is likely that the ideal process can be achieved with more experience: as the members of a practice acquire more experience, they will learn who can handle particular eVisits better, to whom each eVisit must be assigned, and generally what to do in various situations that arise. Broadly, this type of knowledge acquisition is called Transactive Memory (Liang et al. 1995). A transactive memory system (TMS) is developed when individuals work as a group, and by these mechanisms, members in the group encode, store, and retrieve the knowledge (Wegner et al. 1985; Wegner 1986). As a practice gains more experience, members learn who is good at what and assign tasks to the most qualified members. TMS has been shown to improve team performance (Ren and Argote, 2011). Thus, it is likely that the number of other members' activities (NVAA) in response to eVisits may decrease as the practice acquires more knowledge regarding eVisit coordination and assignment. Decreasing NVAA is regarded as an indicator of the existence of TMS in a practice.

- *Hypothesis 2: The number of NVAA in processing eVisits decreases as a practice gains more eVisit experience (reduced extra activities on eVisits by Transactive Memory System development)*

5.3.3 Knowledge Transfer across Subunits within an Organization

As each practice has different characteristics that affect its productivity, there could be a difference in learning rates across the practices. Hayes and Clark (1986) addressed the varying learning curves across subunits of an organization, and Pisano et al. (2001) revealed that learning rates in cardiac surgery differ across healthcare organizations. However, as these practices are under the same healthcare organization, the practice may learn by observing the trials and errors of other practices, acquiring knowledge from others. This is called knowledge transfer (Argote and Ingram, 2000). Researchers have theorized and revealed the differences between intra-organizational relationships and inter-organizational relationships between independent organizations (Tushman 1977; Tichy et al. 1979). Since subunits of the same organization share more commonalities, regular communication, and personal acquaintances, which are mechanisms for knowledge transfer (Tushman 1977; Huberman 1983; Darr et al. 1995), the intra-organizational units have higher rates of knowledge transfer when compared to inter-organizational relationships. Based on this theory, four practices within the same organization are likely to set up an efficient way of providing eVisit services by learning from other practices' experiences. However, there has been no recorded organizational effort to create central channels to share experiences and feedback across practices, and thus it is difficult to predict the effects of knowledge sharing (Dutton and Starbuck 1978). If each practice acts independently of one another, it would be difficult to find any evidence of knowledge transfer. Darr et al. (1995) found evidence of knowledge transfer among fast food stores owned by the same – but not different – franchisees. Based on prior studies in organizational learning, we hypothesize the following:

- *Hypothesis 3.a: The eVisit patient wait time will improve as other practices accumulate more eVisit experience (Knowledge Transfer exists).*
- *Hypothesis 3.b: The number of NVAA in processing eVisits decreases as other practices within the organization gain more eVisit experience (reduced extra activities on eVisits by Knowledge Transfer)*

5.4 Data

Our study data includes eVisit records, patient demographics and clinical data (diagnosis history of patients), physician information, office visit records, and medical advice records. The eVisit and office visit records included in the study are restricted to the visits made during office hours (from 8 am to 4 pm), and we discarded eVisits with more than 1440 minutes (24 hours) of patient wait time as the healthcare organization internally regulated that all eVisits to be answered within 24 hours. Also, eVisits that were answered the next day were discarded as it was presumed that those eVisis were left unattended (or forgotten) and thus this random incident hardly explains work coordination or operation within a practice. As a result, a total of 1,977 eVisits submitted by 1,303 unique patients during a 47-month period are included in this study, and 29 physicians from four practices provided eVisit services. The number of eVisits handled by each physician ranges from 1 to 342. The average number of physicians available for face-to-face encounters each day is 33 from all participating locations and these physicians encountered a total of 347 outpatients on an average day during office hours. The average number of patients that each physician encountered per day is 16 at three primary care community practices in the study, and 6 at an academic practice (Practice 2). The average patient turnaround time for office visits and for eVisits are 127 minutes and 94 minutes, respectively.

Patients' histories of health problems, recorded using ICD9 (International Classification of Diseases, 9th version) codes, are used to assess the complexity of their health conditions. The complexity is defined by using the number of a patient's comorbidity conditions that are categorized in the Charlson Comorbidity Index (CCI) including myocardial infarction, congestive heart failure, peripheral vascular disease, diabetes, etc. (Charlson et al. 1987). If fewer than three comorbidity conditions exist, the complexity score is the number of comorbidity conditions; if three or greater comorbidity conditions exist, the complexity score is set to 3.

$$complexity = \begin{cases} x & if\ number\ of\ comorbidity\ codition\ x < 3 \\ 3 & if\ number\ of\ comorbidity\ condition\ x \geq 3 \end{cases}$$

Physician information is collected from publically available sources. All physicians work in either internal medicine or family practice. Thus, we do not consider a physician's specialty/degree. Altogether, 29 physicians completed at least one eVisit with legitimate CPT codes and traceable response records.

In order to maintain consistency in data regarding submitted conditions throughout the study period, we compiled the various conditions into 15 categories: sinus/cold, urinary symptoms, back pain, rash/poison ivy, conjunctivitis, diarrhea, flu, vaginal irritation, birth control, erectile dysfunction, genital herpes, scabies, shingles, sore/strep throat, and other. Table 1 summarizes the number of eVisit submissions for each condition. The 'other' category is assigned when a patient cannot find any category where his or her ailment fits. The subject does not provide specific subsequent questions as the rest of the subjects do, and thus it may involve higher level of ambiguity and physicians' reluctance to take on the task.

Table 1. eVisit submissions by condition

eVisit subject	eVisit count	Percentage
Sinus/cold/bronchitis/pneumonia	1,013	51.2%
Urinary symptoms	177	9.0%
Sore/Strep throat	81	4.1%
Back pain	75	3.8%
Vaginal irritation/discharge	49	2.5%
Rash/Poison ivy	44	2.2%
Conjunctivitis	38	1.9%
Diarrhea	22	1.1%
Flu	10	0.5%
Erectile dysfunction	7	0.4%
Remaining conditions	8	0.4%
Other	453	22.9%
Total	1,977	100%

Remaining conditions: Shingles, Scabies, and Genital herpes

As the study addresses the effect of NVAA by staff and/or other physicians within a practice on patient wait time, a descriptive summary is provided in Table 2. With the exception of zero NVAA, there is a positive relationship between the level of NVAAs and patient wait time. However, this exception simply comes from one of the practices having an exceptionally higher case of zero NVAA. This practice is a part of a larger academic facility within the organization, and thus physician schedules and work patterns with the other members in the clinic are different than the rest of the practices. This particular practice has almost twice the wait time of Practice 1, where the majority of eVisits are served. Detailed information by practice is shown in Table 3 and Figure 2. Overall, if the number of steps before reaching the final physician increases, the patient wait time gets longer.

Table 2. Descriptive Statistics of non-value added activities on eVisits

Number of Interrupters	eVisit count	Average wait time (mins)	Standard Deviation wait time (mins)
0	209	155.2	202.9
1	1,557	78.9	119.2
2	196	144.8	231.4
3	14	180.4	292.2
4	1	138	N/A
Total	1,977	94.3	149.2

Table 3. Descriptive Statistics by Practices

	eVisits	Avg. wait	StDev. wait	Avg. NVAA	StDev. NVAA
Practice 1	1,725	83.13	137.9	1.11	0.39
Practice 2	206	162.1	193.7	0.16	0.38
Practice 3	12	112.1	89.85	1.08	0.51
Practice 4	34	241.5	213.5	1	0.25
Total	1,977	94.3	149.2	1.01	0.49

Figure 2. Average Patient Wait time for every 50 eVisits

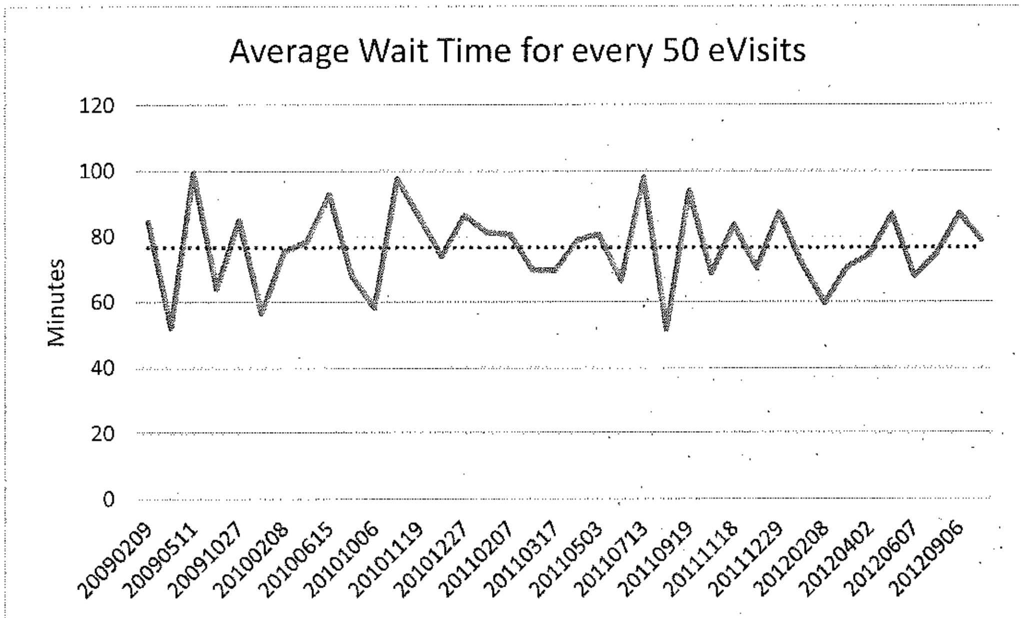
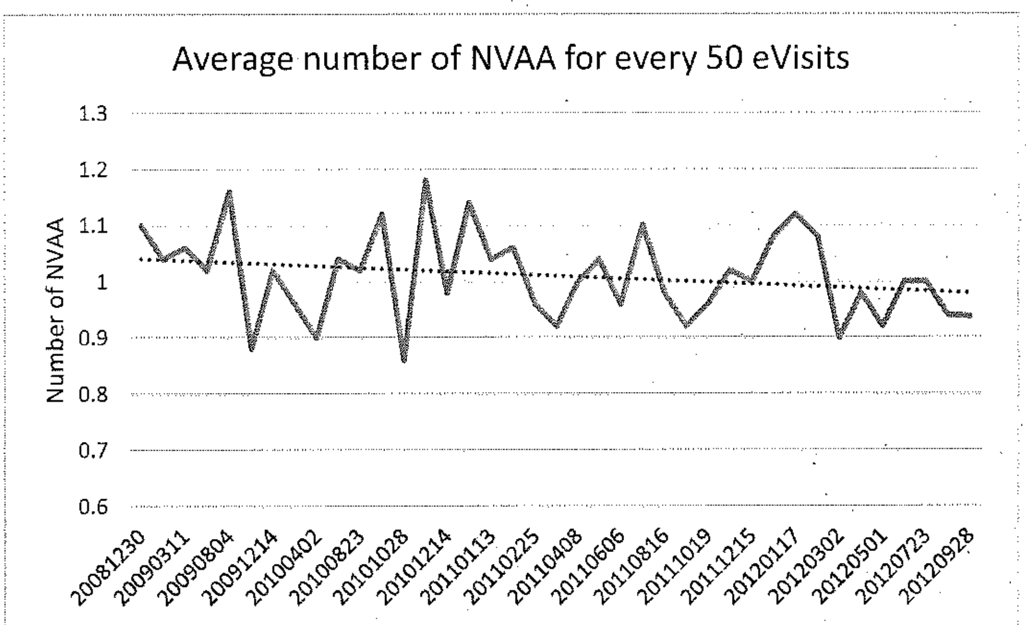


Figure 3. Average Patient Wait time for every 50 eVisits



5.5 Empirical Specifications

5.5.1 Dependent Variables

The unit of analysis for eVisit operation is each eVisit record, and outcome variables are patient wait time (*Wait*) as indicators of operational productivity in addressing an eVisit. In many fields ranging from psychology and manufacturing, reductions in time required to perform a task or produce an outcome associated with experience have been utilized as indicators of learning (Carrillo and Gaimon 2000; Klein et al. 2001). Reduction in patient wait time in providing the eVisit service indicates improved service coordination, increased acquired competence with the task among group members, and the establishment of routines to provide the new service. Thus, negative association between wait time and group experience (practice-level experience) serves as evidence of learning.

Another outcome of interest is the level of NVAA in the eVisit service, which is measured by counting the number of distinct members of the practice other than the final responder who took an action on the eVisit. These members include staff, nurses, and/or physicians. We are able to capture activity on eVisits--such as opening a message or forwarding it--which take place for several reasons. First, the staff members may be triaging eVisits to physicians; secondly, a physician who opened a newly arrived eVisit may be unsure as to whether s/he can take on the task; and thirdly, the eVisit may be assigned to the wrong person. The first case can be regarded as a normal step, as a best practice within the process is to have a staff member or nurse preview the eVisit and forward it to an appropriate physician. However, it is possible that a physician simply opens up an eVisit without being notified and handles the eVisit accordingly. This is a case where we do not observe any middle person within the eVisit handling. When there is confusion in the eVisit assignment, or physicians are unable to answer the eVisit for one reason or another, more than 1 middle person is observed in the eVisit logs. We use the number of distinct personnel who took at least one non-value-added activity on the eVisit before the final responder opens up the eVisit as the second measure of operational efficiency. It is expected that the higher the number, the lower the operational efficiency, and thus we use this measure to assess the operational inefficiency of eVisit service. As group members are more experienced with the service and adapt to the new routine, the operational inefficiency level will decrease; however, having one middle person cannot be regarded as inefficient in comparison with the zero case, since having the first middle man triaging to the next is the protocol of the service. In fact, the case of having no middle person is different from other procedures as it does not follow the protocol to begin with. Thus, we consider that the mechanism by which zero NVAA is observed is systematically different than the rest, and apply the Poisson-Hurdle model accordingly to analyze learning effects on operational inefficiency.

5.5.2 Explanatory Variables

As a measure of practice-level experience, we count cumulative eVisit experience up to the last eVisit by practice. In order to test knowledge-sharing among practices (inter-practice), we captured the number of eVisit experience by other practices up to the most recent eVisit within the healthcare organization. Many studies in the organizational learning literature find that the cumulative experience from other groups within same organization brings more knowledge to the group (i.e. knowledge-sharing), and thus the group may achieve a higher learning rate by indirect experience (Argote, 2012). For organization-level experience, we counted cumulative eVisit experience up until the last eVisit by other practices, excluding the current eVisit practice. Specifically, we computed the number of eVisits each practice served up until the practice's previous eVisit, and the number of eVisit experiences by other practices within the healthcare organization, termed *Pra.Exper* and *Org.Exper,* respectively. $Pra.Exper_{jk-1}$ is a practice j's cumulative eVisit experience until the $(k-1)^{th}$ eVisit, and $Org.Exper_{jk-1}$ refers to the cumulative number of eVisits served until the $(k-1)^{th}$ eVisit by practices other than practice j. Since we expect the cumulative eVisit experience to negatively affect patient wait time, but in a decreasing magnitude, the association between the experience and wait time may form a convex curvature. Thus we add a quadratic term of the practice-level experience, and denote $Pra.Exper_{jk-1}{}^{2}$.

Other factors that may interfere with the workflow, or de-motivate members to proceed with the work, are work complexity and uncertainty. We identify potential lack of clarity in eVisit content using identifier variable *Other*, indicating whether the condition is chosen as 'other' by the patient. When the submitted condition is not clear up front, it may take a longer time for nurses to forward the eVisit to physicians, as the nurses work as gatekeepers of the eVisit. Also, when a patient submits 'other' as the condition, it is harder for a physician to clearly understand the problem up front, which then might result in his/her unwillingness to take care of the eVisit unless he/she is a PCP and creates one more forwarding step.

To capture the task familiarity/ease, we sum the number of eVisit encounters between the particular patient and physician (*Pt.Phy.Enc*). We have observed that the same physician is likely to handle the eVisit for the same patient who previously had an eVisit response from the physician. More explicit physician-patient relationships are identified by using a binary indicator variable *PCP,* which indicates whether the eVisit was handled by the patient's PCP. We also identify whether the patient belongs to another practice by using a binary variable *Pt.Other,* which is 1 when the patient comes from outside and zero when the patient belongs to the practice. These variables will help us to understand the effect of patient familiarity on operation productivity. Another factor that adds complexity to the eVisit assignment is the patient's overall health condition. *Complexity* indicates the patient's health as described in the Data section. We conduct sensitivity analysis for this variable by changing the threshold of the number of conditions to 2 and 4 (3 is the baseline).

Operational efficiency is affected not only by knowledge accumulation and task complexity, but also by other factors such as resource availability (available number of physicians), workload in each specific practice (number of office visits), as well as the work routine by which members of the organization coordinate to efficiently handle a task. Taking other factors into account, we introduce additional explanatory variables that are relevant to the workload and resource. $Pra.load.bf_{jk}$ represents pre-workload variable of practice j prior to the submission of the k^{th} eVisit, and is the number of scheduled office visits to practice j during the 2-hour period before the eVisit's arrival. Likewise, $Pra.load.af_{jk}$ is a workload of practice j after the submission of the k^{th} eVisit, and is measured by the number of scheduled office visits to practice j during the 2-hour period after the eVisit. We also include *Pra.UM,* the number of user messages submitted to the practice on the day of eVisit submission, which the captures additional workload related to monitoring online requests by patients. For resource availability, the most relevant factor in this study is the availability of eVisit providers. Assuming other workloads are the same, if there is only one eVisit provider available on a particular day, the task assignment and forwarding of the message is straightforward. When the number grows, the way members in a practice work might differ. Thus we include a variable, *Pra.ePhy.Count*, which is the number of eVisit providers available on the day of the eVisit submission.

We include a variable for practice fixed effect, $Practice_j$, which is an identifier variable for practice *i*. As descriptive statistics by practices show, patient wait time and the average number of NVAA differ across practices. Thus, we include practice identifiers and calculate practice-level clustered standard errors in the analysis.

We also control for submission time, day of the week, month, and year. Group members' actual and mental workloads and other unobservable factors may affect their productivity differently by the time of day or day of the week. In fact, the average volume of eVisits decreases as we move from Monday to Friday (Figure 3). Also, environmental and technological factors that are correlated with service productivity, such as advanced computing power, and members' competency with the technology may change over time, and thus we need to isolate effect of experience from other time-varying unobservable elements (Argote 2013; Solow 1957). We apply OLS coupled with various combinations of empirical specifications with practice fixed effects.

5.5.3 Empirical Models and Strategy

We base our empirical model on an alternative learning curve function in which the relationship between output (productivity measure) and experience is expressed in exponential form, defined as the 'adaptation curve' (Levy 1965), rather than power function form. In this study, the initial two months of eVisit records are not included due to inadequate information availability to trace patient wait time. Thus, we assess the learning rate (change in productivity via accumulated experience) using the exponential form.

To test hypothesis 1, in which we estimate the learning from practicing specific experiences, and the knowledge transfer across practices, we conduct regression (1). If there is productivity gain in eVisit operation as practices accumulate more experience, evidence exists of learning in the operational management of eVisit. In other words, if learning in eVisit operation occurs, we will be able to observe reduction in triage time as the offices' cumulative eVisit experience increases. Thus we expect to find $\beta_1 < 0$ and $\beta_2 > 0$.

$$(1)\ \log(Wait_{ijk}) = \beta_0 + \beta_1 Pra.Exper_{jk-1} + \beta_2 Pra.Exper_{jk-1}^2 + \beta_3 Org.Exper_{jk-1} + \varphi_j Practice_j + \theta TASK_k + \rho LOAD_k + \varepsilon_k$$

(where j = practice index, k = eVisit index, θ=vector of coefficients of Task related variables, ρ=verctor coefficients of workload related variables)

The measure of efficiency of eVisit operations is the level of other group members' actions (handoffs) on each eVisit. This measure accounts for actions such as read and forward, which are performed by other members of the practice. We name this measure NVAA and it approximates operational inefficiency as the increment in this measure indicates confusion in work coordination. The higher the number in this measure, the lower the productivity in serving eVisits as well as face-to-face office visits because more staff resources are unnecessarily involved and used to handle one eVisit. In addition, these activities can distract those members from the focus on other tasks. Thus, we expect to find a decrease in this operational inefficiency measure as a practice experiences more eVisits. To test hypothesis 3, we conduct the Poisson-Hurdle analysis with the NVAA as the outcome measure. Poisson-Hurdle is an appropriate model when the mechanism that generates a zero value for the outcome is systematically different than one generating non-zero outcomes, and non-zero outcomes are positive countable measures. The model contains two parts of analysis: the first is logistic regression where it defines all non-zero outcomes as 1, while the second part of the analysis is a zero-truncated Poisson regression in which the analysis drops zero values and conducts the Poisson regression with non-zero values only. The followings (2 – 6) describe the model; starts with the binomial process, and then applies the Poisson after it truncates the zeros.

$$(2)\ \Pr(Y = y) = \begin{cases} \alpha & y = 0 \\ 1 - \alpha & y = 1, 2, 3, \ldots \end{cases}$$

$$(3)\ \Pr(Y = y | Y \neq 0) = \begin{cases} 0, & otherwise \\ \dfrac{\lambda^y}{(e^{\lambda} - 1)y!}, & y = 1, 2, 3, \ldots \end{cases}$$

Thus, combining (2) and (3) will produce the following.

$$(4)\ \Pr(Y = y) = \begin{cases} \alpha, & y = 0 \\ (1 - \alpha)\dfrac{\lambda^y}{(e^{\lambda} - 1)y!}, & y = 1, 2, 3, \ldots \end{cases}$$

The regression model for the first process, binary logistic regression is the following.

$$(5)\ Ln\left(\frac{P(NVAA_k > 0)}{1 - P(NVAA_k > 0)}\right) = \beta_0 + \beta_1 Pra.exper_{jk-1} + \beta_2 Org.exper_{jk-1} + \varphi_j Practice_j + \varepsilon_k$$

The regression model for the zero-truncated Poisson model is the following:

$$(6)\ \ Ln(E[NVAA | NVAA_k > 0]) = \beta_0 + \beta_1 Pra.exper_{jk-1} + \beta_2 Org.exper_{jk-1} + \varphi_j Practice_j + \varepsilon_k$$

(where j = practice index, k = eVisit index)

Although not included in this study in detail, we check the change in operational efficiency of existing service (face-to-face visits) by comparing office-visit patients' turnaround time at the clinics before and after the eVisit implementation. The approach attempts to verify whether eVisits have an interruptive effect on office visits. A newly introduced service has the potential to negatively affect the performance of the existing service as the two different services share the same resource. In this test, the unit of analysis is each office visit record, and the Difference-in-Difference method is applied. The outcome variable of interest is patients' turnaround time, measured by the difference between the check-in and check-out times of the patients in the study locations. We found no evidence of a change in office visit turnaround time.

5.6 Results

As expected, the patients' wait time improves as the practices accumulate more eVisit experiences (Table 4, column (1) to (3)). With or without other controls such as the complexity of patients' health conditions, prior encounters via eVisit between the particular patient and the physician, practice workload, etc., the results are consistent (see column (1) and (2) in Table 4), although the magnitude of the effect increases when other explanatory variables are considered. The patient wait time on average reduces at a decreasing rate as a practice accumulates more eVisit experience (the quadratic term of practice-level experience is significant in positive terms). When a practice accumulates 10 additional eVisit experiences, it is expected that the patient wait time decreases by 1 minute at the beginning of the service implementation, but the reduction in wait time decreases to 51 seconds from the same 10 additional eVisit volume when the practice already has 100 cumulative eVisit experiences. However, it is interesting to note that the patient wait time does not benefit from other practices' eVisit experience. In other words, we do not observe evidence of knowledge-sharing with regard to the patient wait-time measure. The practices in the study certainly did share their experiences with the eVisit service with other practices based on the authors' discussion with the eHealth team of the organization; in fact, physician "champions" visited other practices to help them with the eVisit process, share tips, and motivate participation. Also periodic meetings were held to discuss the feedback from each practice and address the complaints and best practices. Despite the effort, we found an insignificant effect of other practices' experience on patient wait time, and details will be discussed in the next section.

Table 4. Effect of practice/organizational-level experience on eVisit operation efficiency

$y = log(wait\ time)$	(1)	(2) with other's experience	(3) with all controls
Practice-level experience	-0.00107*** (0.0000230)	-0.000985*** (0.0000306)	-0.00107** (0.0000901)
Practice-level experience^2	0.000000363** (3.16e-08)	0.000000378** (3.67e-08)	0.000000436** (3.96e-08)
Others practices' experience		0.000158 (0.0000984)	0.000125 (0.000175)
Patient from other practice			0.409** (0.0539)
'Other' subject			0.147** (0.0238)
Patient-physician encounters			-0.00485* (0.00150)
Patient health complexity			0.0593+ (0.0219)

# Available eVisit provider			-0.0519* (0.00943)
Office visit volume prior 2hr			-0.00341 (0.000448)
Office visit volumn after 2hr			-0.00357* (0.000670)
User message volume			-0.000148 (0.00883)
Telephone Call volume			0.00151 (0.00119)
PCP, Patient age, # physician available in the office, eVisit load, physician workload, eVisit interval, Practice FE, eVisit Submission time, day of the week, month, and year are controlled			
Constant	4.123*** (0.0187)	4.131*** (0.0211)	4.609*** (0.230)
Observations	1,977	1,977	1977
Adjusted R-squared	0.015	0.015	0.052

Note: Robust clustered standard errors in parentheses

+p<0.1, *p<0.05, **p<0.01, ***p<0.001

When patients have obscure conditions (other_condition = 1), the eVisit wait time increases by 16 percent on (geometric) average. This is a reasonable finding as the members in a clinic might be less willing to take on a task when the task is less familiar or accompanies a more complex situation, and thus is likely to delay the work assignment. The same explanation can be used for *'patient health complexity'* and *'patient from other practice'*. When the patient has higher comorbidity status, healthcare providers are likely to be more careful in treatment process and thus it may cause delay in job assignment and job itself. Likewise when the patient belongs to another practice, the work assignment is less clear, and physicians might be hesitant to take on the job immediately. This result is consistent with a sensitivity analysis with other levels of patients' health complexity measures with varying cut-off points (2 and 4, the study used 3) (see Appendix A.3). When a patient and a physician have had face-to-face encounters prior to the current eVisit (*Patient-physician encounters*), then our data indicates a high likelihood of the same physician serving the same patient on the current eVisit. This fact implies that it is less complicated to assign an eVisit when a patient and a physician have an established relationship.

It seems that a practice speeds up eVisit process when a practice has a higher expected workload (scheduled patient office visits) after eVisit's arrival, but most other workloads such as the volume of user message, telephone calls, eVisits, and physician's individual workload do not affect the patient wait time. The results are partially aligned with the much-studied goal setting theory, in which goals that are difficult to achieve tend to increase organizational performance (Locke and Latham, 1990). When a practice has more patients in the office, it is harder to meet the goal, which is to process patients' records, encounter patients, and take necessary steps for patients' treatment. Details of the regression result are found in Appendix A.4.

To assess the multicollinearity issue among explanatory variables, we checked Variance Inflation Factor (VIF) (Green 2011), from which a value greater than 10 indicates a multicollinearity problem among the explanatory variables (Wooldridge 2012). All of the independent variables have VIF values ranging from 1.01 to 1.51. In addition, as it is reasonable to believe that the staff members take care of the eVisits that are submitted even after the office hour (by 4pm) while they work on documentation and other miscellaneous tasks, the authors conducted the test on the extended dataset; eVisits submitted from 8am to 5pm. The results are consistent in that the patient wait time decreases in a decreasing manner as the eVisit experience of the practice increases, and there is no evidence of knowledge transfer from other practices.

It is reasonable to believe that each practice wants to reduce the number of people involved in one eVisit service in order to maximize its human resource utilization. As the number of eVisit experiences accumulates, the members of a practice may develop a transactive memory system by learning how to assign and distribute the eVisit submission to the right personnel, as well as how to routinely monitor eVisit arrivals and effectively triage the eVisits to the physicians. Thus, we conducted an analysis of the NVAA on the practice/organization-level eVisit experience and other control variables by applying the Poisson-Hurdle regression model. The first column in Table 5 is the result of Logit regression as a part of the Poisson-Hurdle analysis, which defines the outcome variable as zero when the number of NVAA is zero, and as 1 otherwise. The second column of Table 5 shows the Poisson regression result for outcome values 1 through 4.

Table 5. Poisson-Hurdle Regression Results of NVAA on Practice/Organization-level experience

$y = NVAAs$				
Hurdle (Logistic regression on 0 vs. others)			Zero Truncated Poisson	
Practice-level experience	0.00339*** (0.00100)		Practice-level experience	-0.00129*** (0.0000338)
Organizational-level experience	0.00192 (0.00127)		Organizational-level experience	-0.00195*** (0.000408)
Patient-Physician encounters	-0.0375*** (0.00384)		Patient-Physician encounters	-0.0111*** (0.00125)
# Available eVisit providers	-0.0286 (0.0332)		# Available eVisit providers	0.112 (0.114)
Patient health complexity	-0.301		Patient health complexity	0.117***

	(0.255)			(0.00644)
PCP handled eVisit	2.156*** (0.217)		PCP handled eVisit	-0.185*** (0.0263)
Patient from other practice	-0.408*** (0.0611)		Patient from other practice	0.486*** (0.0103)
'Other' subject	-0.0745 (0.205)		'Other' subject	0.164*** (0.0151)
Office visit volume prior 2hr	-0.0184 (0.0120)		Office visit volume prior 2hr	0.0184*** (0.000994)
Office visit volume after 2hr	0.0118 (0.0151)		Office visit volume after 2hr	-0.00591*** (0.000857)
User Message volume	-0.0197 (0.0312)		User Message volume	0.0584*** (0.00504)
Telephone call volume	-0.00125 (0.00208)		Telephone call volume	0.00110 (0.00277)
eVisit interval	0.0263 (0.0307)		eVisit interval	-0.0201 (0.0426)
Constant	-1.645** (0.627)		Constant	-0.559 (1.934)
Observations	1,977		Observations	1,977
Available physicians, eVisit volume, Physician workload, Practice FE, eVisit submission hour, day of the week, month, and year are controlled.				

6 *Note: Robust clustered standard errors in parentheses*

7 **+p<0.1, *p<0.05, **p<0.01, ***p<0.001**

As displayed in Table 5, the NVAA is also reduced by increase in the practice-level experience once triage takes place (see column 2). Unlike patient wait time, the number of NVAAs is also affected by organizational experience. As other practices accumulate more eVisit experiences, eVisits handled in a focal practice have fewer additional activities. The accumulated experience is not a significant factor in the decision of utilizing triage or not (first column). These findings unveil the triaging routine, which is consistent with the health system's set process. When PCP is available, eVisits are directed to the PCPs, otherwise, they are forwarded to other physicians. As we can see from the results, as the number of NVAAs increases from one to two, and two to three, the likelihood of receiving care from a PCP decreases; this indicates that if there is a PCP readily available, the request is forwarded at once and is mostly handled by the PCP, and that there is a very low probability of the PCP forwarding his/her patients to other physicians.

5.7 Conclusion and Discussion

We found evidence of learning by practice-level experience in eVisit operational efficiency, measured by patient wait time. The magnitude of the learning rate seems to be small, but as the study is based on practice-level experience, the cumulative experience grows faster in aggregate as long as a practice gains higher physician participation. The rate of learning increases at a decreasing rate, which implies that patient wait time might reach a saturation point (close to the minimal point) after accumulating more eVisit experience. We were able to find an evidence of knowledge-sharing among the practices in routinizing the eVisit process (measured by the number of NVAA), but the same evidence was not found in patient wait time. The finding is understandable in this particular study context, or even in general healthcare settings where many community practices are affiliated with a large hospital.

5.7.1. Practice-level learning and Knowledge-sharing across practices

Since we found that a practice's eVisit patient wait time improves as its eVisit experience accumulates, the healthcare organization may want to promote practices to actively participate in the service. The greater the amount of participation achieved, the faster their eVisit operation becomes efficient.

It is interesting to find that there is significant evidence of knowledge-sharing across the practices in reducing NVAA but no evidence of knowledge-sharing in patient wait time. Through the meetings and discussions, the practices shared the experience of their daily routine on the focal task, and the best practice to provide the eVisit service as well as collecting feedback. The knowledge on the eVisit process including how to run the service, the best sequence of the work, best way of eVisit assignment, etc. is shared among the practices, and our results show that each practice benefits from others' experience in improving the unnecessary involvement by multiple members.

Regarding the patient wait time, one of the authors discussed the finding with the CIO of the healthcare organization and his eHealth team, and learned the organization's thoughts on the insignificant effect of others' experience on the wait time. During the study period, there was no status quo for online medical service regarding patient response time. Also, there was lack of competition in the service because only a handful of organizations were capable of providing a similar service. Even among them, this particular organization had one of the most advanced eVisit systems. Thus, the organization's initial target was to promote the adoption of eVisit by physicians and patients rather than regulating and promoting shorter patient wait time although it is rational that faster turnaround time will help promoting the service adoption. Therefore, as long as an eVisit was addressed within 24 hours, no other intervention (alert) was triggered. In addition, stressing eVisit wait time might distract members of the practice from the existing office operation, which might result in members' resistance to the eVisit service. For these reasons, it was an unsurprising finding to the organization. The finding that the practice-level experience contributes to the reduction in patient wait time serves as definitive evidence of practice-level learning by doing. In other words, the staff members and physicians within a practice work around the eVisit service in a manner that routinizes the operation, which leads to improvement in its efficiency.

Based on prior literature, it is likely that subunits within an organization tend to improve their productivity by learning from their peers as well as from their own experience. However, organizational context differs by industry, and by characteristics of the subunits. Many studies have found knowledge-sharing within healthcare organizations when utilizing total time spent on the task as a measure, but the study settings were about surgical operations in which many parties were involved and the intensity of the task importance or the knowledge importance is higher than primary care practices. Multi-physician primary care practices usually hold regular meetings within the practice, but rarely do so with other practices that are affiliated with the same healthcare organization. From other service industries and the healthcare context, it is clear that subunits of an organization benefit from other subunits, and it is likely that primary care practices may also benefit from other practices' accumulated knowledge on a particular task that is newly introduced. Thus, it is important to establish a mechanism by which members of the organization can benefit from indirect experience (i.e. others' experience). There are multiple ways to do so such as creating a centralized channel that enables all of the members of the organization to exchange their ideas, and having physician "champions" visit other practices to discuss a pioneering practice's experience.

5.7.2. Task and workload effect on the eVisit operation

When an eVisit patient comes from another practice, we found the patient's wait time is longer than the wait time for patients belonging to the practice. In order to regulate overall patient wait time in the eVisit service, the organization may need to set an explicit task assignment rule for varying cases so that less confusion or reluctance occurs when such eVisits are submitted. Also we observe that 'other' subject categorization tends to increase patient wait time as well as NVAA. This implies that task complexity increases staff and physicians' inability to follow the protocol and reluctance to take on the job. We suggest that training one or two gatekeepers who preview the eVisit to filter and assign the work to physicians could mitigate this outcome. When the similar task is performed repeatedly, the performance improves in general. For example, if one or two nurses always monitor the eVisits, then the high level of performance by these nurses will be achieved early on, and they are likely to sense an actual category to which the patient's ailment belongs. Not surprisingly, patients' health complexity (measured using comorbidity level) is a significant factor in both patient wait time and NVAA. This means that the work assignment and decision of taking the job depends on the submitted context (ailment subject) and patients' history of illness as well as physician and patient's familiarity level. The magnitude of the effect by patient health condition is much smaller than the effect by 'other' condition in patient wait time. This indicates that patients' health history is less likely to be checked when the task is assigned, which makes sense as the gatekeepers' job is to filter whether the submission is a legitimate eVisit or not, and thus they are less likely to click through to the patients' EMR.

5.7.3. Effect on Non-Value Added Activity

It is important to note that coordination problem, which is measured by NVAA, improves with both practice-level and organization-level experience. This indicates that a practice's operational efficiency in eVisit process can be improved as other practices accumulate their own eVisit experience, which was not the case for patient wait time. The finding is contributed by the effort of setting up and following the protocol of the eVisit service provision. The practices were able to learn from others' experience as the better/worse work process is discussed in their meetings. Thus, we need to emphasize communication among the practices in order to develop the routine and provide service more efficiently when a new service is introduced.

5.7.4. Discussion and Limitation

In this study, we were able to capture the eVisit work structure of each practice despite many ad-hoc practices and uncertainties in place. The authors have learned that each practice operates eVisits on an ad-hoc basis initially, and no structured format about who assigns or distributes the workload regarding eVisits existed despite the given protocol during the inception period. Thus, when authors questioned staff regarding the process, no one in the organization was able to provide definitive answers. It is likely that each practice has established tacit knowledge of the eVisit service operation, as it accumulates greater eVisit volume. For example, having a particular nurse dedicated to monitor the arrival of an eVisit, check its validity, triage to a physician, and inform the assigned physician of the pending eVisit results in a better work flow. In order to understand the work procedure more precisely, the authors have observed how eVisits are handled in one of the practices.

In addition, there is a notable gap in the physician adoption rate as well as the eVisit volume across the practices. Practice 1 handles the most eVisits (more than 80 percent) whereas the rest handle only a small proportion. This phenomenon can be attributed to the fact that practice 1 started the eVisit service first as the organization initiated pilot service in that practice, and elected a physician champion from the practice. Throughout the study, we control for unobservable differences between practices by including practice-level fixed effect to mitigate these concerns.

Finally, the study is limited in addressing the overall performance of the eVisit service. Generally, performance in service operation should consist of multiple facets: internal efficiency (operational efficiency); external efficiency (customer satisfaction) which is related to service quality; and profit efficiency (Soteriou and Zenios, 1999). It is very difficult to discuss efficiency in healthcare organization in terms of profitability although it is certainly an important factor for the organization's sustainability. Also, the eVisit operation is an additional service on top of the current operation that requires additional information system support, and thus the financial efficiency should be measured with regard to the information system's value. The service quality of eVisits is addressed in the organization's internal survey study, and it received a high level of patient satisfaction. Also, we compared the return visit rate to the office with that of the eVisit patients for the same ailment within a week, and found that only 10 patients had come in during the entire study period. Additionally, this return event did not stop the patient from using the eVisit service in the future. Further examination regarding other elements is ongoing.

For future study, it would be interesting to explore whether organizational forgetting is found in the primary care practice environment. The employee turnover rate is known to affect organizational learning and forgetting (Argote 2012; Argote et al. 1997; David and Brachet 2011; Engestrom et al. 1990), as it is generally agreed that organizational knowledge resides in elements such as individuals within the organization (Argote 2012). Thus, if information about office staff members' departure or the arrival of new members is obtained, further extension of the study might be able to address the knowledge depreciation due to the change in the membership. From various study settings, researchers found that employee turnover has more of a negative impact on organizational learning when the task is more complex (Argote et al. 1995), or brings even positive effects on organizational learning when the task requires creativity and innovations (Wells and Pelz 1966; Virany et al. 1992). In either case, the task is relatively complicated as more distinct skillsets are held by the employees in the study, such as scientists and executives in the computer industry. Nurses and medical assistants are also distinguished from regular production line workers as they have specific knowledge and skillsets. Thus there might be little disadvantage in eVisit operation from employee turnover, if there is any. This will be included in our future study.

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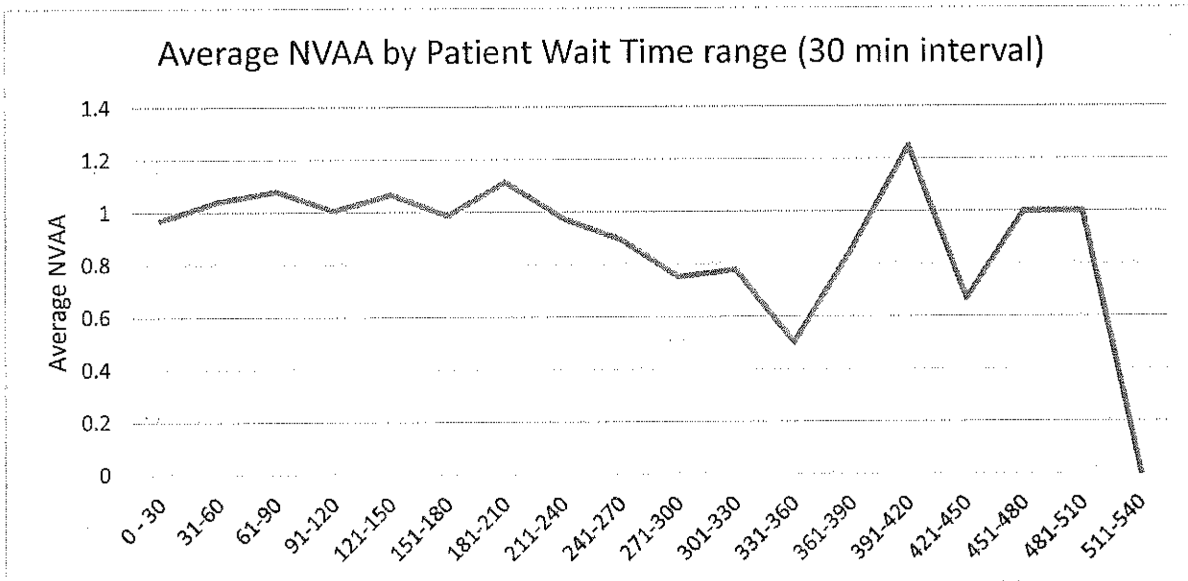
Appendix.

A.1 Average NVAA level by patient wait-time level (30-minute range)



A.2 Average patient wait time difference between office hours vs. non-office hours (in minutes)

	eVisits submitted during office hour (non-holiday week days)	eVisits submitted after office hour (non-holiday week days)	eVisits submitted during weekends and holiday
Avg. Wait time	94.3	371.7	276.4
Avg. NVAA	1.00	0.78	0.20
eVisit Count	1,977	828	493

A.3. Sensitivity analysis with varying cut-off criteria of patient health complex measure

	Cutoff = 2	Cutoff = 3	Cutoff = 4
Practice-level experience	-0.00106** (0.0000883)	-0.00107** (0.0000901)	-0.00107** (0.0000899)
Practice-level experience^2	0.000000431** (4.20e-08)	0.000000436** (3.96e-08)	0.000000436** (3.99e-08)
Others' experience	0.000125 (0.000176)	0.000125 (0.000175)	0.000124 (0.000175)
Patient health complexity (2)	0.0603+ (0.0196)		
Patient health complexity (3)		0.0596+ (0.0193)	
Patient health complexity (4)			0.0596* (0.0181)
Patient's age	-0.0000326 (0.00120)	-0.0000908 (0.00117)	-0.000102 (0.00118)
'Other' subject	0.148* (0.0275)	0.149* (0.0275)	0.149* (0.0274)
PCP handled eVisit	0.0423 (0.0230)	0.0435 (0.0236)	0.0439 (0.0234)
Patient from other practice	0.438*** (0.0323)	0.438*** (0.0322)	0.438*** (0.0322)
Patient-physician encounter	-0.00569* (0.00136)	-0.00584* (0.00142)	-0.00597* (0.00142)
# Available eVisit provider	-0.0551* (0.00966)	-0.0556** (0.00941)	-0.0556** (0.00947)
# Available providers	0.00186 (0.00366)	0.00199 (0.00367)	0.00199 (0.00364)
Office visit volume prior 2hr	-0.000253 (0.000331)	-0.000199 (0.000304)	-0.000189 (0.000306)
Office visit volumn after 2hr	-0.00404** (0.000669)	-0.00404** (0.000658)	-0.00404** (0.000657)
eVisit voloume	0.000999*** (0.0000480)	0.00100*** (0.0000482)	0.00100*** (0.0000482)
Physician workload	-0.00883** (0.00139)	-0.00887** (0.00140)	-0.00887** (0.00140)
User Message volume	0.000278 (0.00887)	0.000167 (0.00877)	0.000150 (0.00877)
Telephone call volume	0.00166 (0.00118)	0.00166 (0.00118)	0.00166 (0.00118)
Patient called in	0.187 (0.183)	0.189 (0.184)	0.189 (0.184)
eVisit arrival interval	-0.00267 (0.00280)	-0.00262 (0.00282)	-0.00263 (0.00281)
Constant	4.605*** (0.289)	4.611*** (0.286)	4.612*** (0.286)
Observations	1977	1977	1977
Adjusted R-squared	0.060	0.061	0.061

A.4. Effect on patient wait time by varying compositions of explanatory variables

	(1)	(2)	(3)	(4)	(5)	
Practice-level experience	-0.000318** (0.0000300)	-0.00107*** (0.0000230)	-0.000985*** (0.0000306)	-0.00114*** (0.0000338)	-0.00107** (0.0000921)	-0.001 (0.000
Practice-level experience^2		3.63e-07** (3.16e-08)	3.78e-07** (3.67e-08)	4.53e-07** (4.46e-08)	4.38e-07** (3.92e-08)	4.36e- (3.96
Others' experience			0.000159 (0.0000984)	0.000164 (0.000106)	0.000133 (0.000175)	0.000 (0.000
Patient health condition				0.0506 (0.0220)	0.0595+ (0.0192)	0.059 (0.019
Patient's age				-0.000297 (0.00122)	-0.0000457 (0.00118)	-0.000 (0.001
'Other' subject				0.159* (0.0286)	0.149* (0.0275)	0.149 (0.027
PCP handled eVisit				0.0731* (0.0168)	0.0442 (0.0236)	0.043 (0.023
Patient from others				0.414** (0.0460)	0.439*** (0.0323)	0.438 (0.032
Pat-Phy encounters				-0.00372+ (0.00137)	-0.00577* (0.00138)	-0.005 (0.001
# Available eVisit phys.					-0.0555** (0.00940)	-0.055 (0.009
# Available physicians					0.00184 (0.00370)	0.001 (0.003
Office volume 2hr prior					-0.000180 (0.000315)	-0.000 (0.000
Office volume 2hr post					-0.00400* (0.000690)	-0.004 (0.000
eVisit volume					0.00100*** (0.0000485)	0.001 (0.000
Physician workload					-0.00889** (0.00143)	-0.008 (0.001
User message volume					0.000203 (0.00877)	0.000 (0.008
Telephone call volume					0.00167 (0.00117)	0.001 (0.001
Patient called in						0.189 (0.184
eVisit arrival interval						-0.002 (0.002
Constant	4.025***	4.123***	4.131***	4.069***	4.603***	4.611
	(0.0210)	(0.0187)	(0.0211)	(0.0726)	(0.283)	(0.286
Observations	1977	1977	1977	1977	1977	1977
Adjusted R-squared	0.014	0.015	0.015	0.037	0.061	0.061

A.5. Effect on patient wait time (with eVisits submitted from 8am to 5pm)

Explanatory variables	Effect size on the patient wait time	
Practice-level experience	-0.000768*	(0.000249)
Practice-level experience^2	0.000000290*	(8.69e-08)
Others' experience	-0.0000916	(0.000195)
Patient health condition, age, eVisit subject, PCP handling, Patient-physician encounters, the number of available physicians and eVisit providers, office visit volume, eVisit, user message, and telephone volume, eVisit arrival intervals are controlled		
Constant	4.166***	(0.298)
Observations	2480	
Adjusted R-squared	0.044	

A.6 Descriptive statistics of the variables

Variables	Average value	Standard deviation
Patient wait time (minutes)	94.3	149.2
NVAA	1.01	0.49
PCP handled eVisit (%)	49.2	N/A
Patient from other practice (%)	13.9	N/A
'Other' subject (%)	22.9	N/A
Patient health complexity	0.49	0.75
Patient age	47.4	12.3
Patient-Physician encounters	3.48	5.09
Office visit volume 2hr prior	31.95	13.57
Office visit volume 2hr post	34.13	11.96
Available number of eVisit providers	9.05	2.43
Available number of physicians	11.7	5.69
User message volume	15.9	6.14
Telephone call volume	37.7	49.1
Patient called in (%)	0.51	N/A
eVisit arrival interval (days)	1.12	3.82

6. Conclusion

The studies in this dissertation are the first systematic approach to understand online medical consultation, or eVisit, from multiple perspectives. With a unique, longitudinal dataset, I draw on Innovation Diffusion theory and Organizational Learning theory to investigate patient-side adoption of the eVisit service, physicians' individual learning and the moderating effects of existing skill level and other physicians' experience on eVisit evaluation efficiency, and finally, the impact of practice operations on the service response time associated with eVisits.

From the patients' perspective, the eVisit service is a new, uncertain, and perhaps risky product to adopt. However, a feasible mechanism to minimize the uncertainty may be to allow patients to try the service at no additional cost. In my analysis, I find that after being provided a trial opportunity, patients are more likely to adopt the eVisit once it is formally deployed. Having actual eVisit experience during the trial opportunity increases the likelihood of subsequent adoption by patients. As expected, the adoption rate by patients whose eVisit condition was successfully resolved is higher than the patients for whom the eVisit resulted in follow-ups at the office.

Physicians' resistance to providing the service due to concerns about learning a new technology, inefficient service provisioning, and increased workload is an important challenge to address. Chapter 4 addresses this issue by analyzing the impact of physicians' individual learning in providing the eVisit service. The service efficiency by individual physicians is captured by physicians' evaluation time on each eVisit. The findings indicate evidence of physicians' learning and even knowledge sharing among colleagues within the same practice. There is a marginal, but complementary, effect of colleagues' experience and individuals' experience, which indicates that physicians benefit from other colleagues' experience even more when they accumulate their own experience. Physician's familiarity with the patient works as a positive factor in improving evaluation time. However, patient complexity, such as higher morbidity conditions and ambiguous contents of eVisit tend to be an obstacle. Overall, I suggest that assigning an eVisit in a strategic way (for example, assign patients with complex conditions to PCP only) may enhance physician evaluation time even further. An interesting finding is that medium-skilled physicians (with regard to technology skills) have a higher rate of learning than highly-skilled and lower-skilled physicians. This suggests that healthcare organizations need to provide organized training before such services are launched so that the physicians are equipped with a proper level of knowledge about the new technology.

Chapter 5 explores operational efficiency in the context of using the online channel. I introduce two operational efficiency measures – patients' waiting time (response time) and NVAA (Non-value added activities) which represents coordination problems amongst care delivery team members. As the members in a practice collectively learn and gain knowledge regarding a new service, they not only routinize the work, but also develop knowledge of who knows what, and what to do in specific situations, called transactive memory. Thus, as each practice accumulates more eVisit experience, their response time is likely to decrease if learning occurs, and the number of interventions or handoffs by care team members, other than final physician responder, is likely to decrease if transactive memory develops. I found evidence of organizational learning and transactive memory development in reducing response time and improving coordination problems, but knowledge transfer is observed only in the work coordination measure. This difference in the findings implies that the practices may benefit from other practices when they develop more efficient work sequences and proper task assignment protocol, but the benefit does not necessarily transfer to patient waiting time because each practice runs its operations independently and in their own unique way.

This study environment is clearly distinct from prior studies in the literature where organizational learning theory has been explored. Evidence of learning have been determined in studies of manufacturing plants, surgical teams, and so on, where the work is precisely defined and can be regarded as value-added-process rather than solution shop (Christensen 2012). Value-added process delivery is mostly defined as taking on a similar job repeatedly, thus decreasing variations in outcome over time and increasing efficiency. On the other hand, the solution shop is an environment where each job differs, and may require customizations on many different levels. Primary care practices have been considered as a solution shop in which the most important tasks are to provide the right diagnosis and care for varying conditions, whereas surgical hospitals are considered to provide value-added process delivery. Under this definition, primary care has more uncertainty in work process, and the time to take on and process eVisits is not as precisely scheduled as operating time in surgical hospitals. Thus, finding an evidence of learning in this study setting is remarkable and adds an important contribution to the current stream of literature.

The studies summarized here have some limitations. They are based on data and eVisit experiences from only one healthcare provider organization – all the practices in the study are affiliated with the organization. This may limit the overall generalizability of the studies. Furthermore, there is no data that captures the interactions between practices that may enable us to explore the effect of knowledge transfer at a micro-level; higher level of interactions between two particular practices and the type of meetings/venue allow us to address the direction of knowledge transfer.

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