APPLICATIONS OF CONTINGENT VALUATION AND CONJOINT ANALYSIS IN MHEALTH: UNDERSTANDING THE WILLINGNESS TO PAY FOR HEALTHCARE SMARTPHONE APPLICATIONS

by

Thomas Robert Martin

A dissertation submitted to the Faculty of the University of Delaware in partial fulfillment of the requirements for the degree of Doctor of Philosophy in Urban Affairs and Public Policy

Spring 2014

APPPLICATIONS OF CONTINGENT VALUATION AND CONJOINT ANALYSIS IN MHEALTH: UNDERSTANDING THE WILLINGNESS TO PAY FOR HEALTHCARE SMARTPHONE APPLICATIONS

by

Thomas Robert Martin

Approved: ______________________________
Maria P. Aristigueta, D.P.A.
Chair of the School of Public Policy and Administration

Approved: ______________________________
George H. Watson, Ph.D.
Dean of the College of Arts and Sciences

Approved: ______________________________
James G. Richards, Ph.D.
Vice Provost for Graduate and Professional Education

I certify that I have read this dissertation and that in my opinion it meets the academic and professional standard required by the University as a dissertation for the degree of Doctor of Philosophy.

Signed: ______________________________

Paul Solano, Ph.D.
Professor in charge of dissertation

I certify that I have read this dissertation and that in my opinion it meets the academic and professional standard required by the University as a dissertation for the degree of Doctor of Philosophy.

Signed: ______________________________

John McNutt, Ph.D.
Member of dissertation committee

I certify that I have read this dissertation and that in my opinion it meets the academic and professional standard required by the University as a dissertation for the degree of Doctor of Philosophy.

Signed: ______________________________

Neal Sikka, M.D.
Member of dissertation committee

I certify that I have read this dissertation and that in my opinion it meets the academic and professional standard required by the University as a dissertation for the degree of Doctor of Philosophy.

Signed: ______________________________

William T. Riley, Ph.D.
Member of dissertation committee

ACKNOWLEDGMENTS

I would like to thank my entire family, academic community, and committee for their support over the years. Special acknowledgment is due to my committee chair Paul Solano for his wonderful ability to make complex problems simple. Paul is retiring soon. You have motivated countless students to ask critical questions and provided them the tools and resources to do so. Enjoy retirement! I received amazing support and time – no doubt taking away from other more pressing projects– by the other members of my committee, John McNutt, William Riley, and Neal Sikka. Thank you!

In addition, this work would not be possible without the support of numerous colleagues in the mHealth space. Your words of encouragement and actions to make this project possible will remain with me forever. To all of you I extend my gratitude and heartfelt thanks. Finally, I would like to thank my wife Maggie for her loving edits, proofing, and understanding. She is, and always will be, an inspiration for me to exceed the goals I set for myself.

TABLE OF CONTENTS

Appendix

LIST OF TABLES

LIST OF FIGURES

ABSTRACT

Increasingly, smartphones and the advanced features on these devices are used for the general provision of healthcare. Legislation associated with the American Recovery and Reinvestment Act provided incentives for the use of technology such as the electronic health record (EHR) to further the use of technology in healthcare. mHealth is a new term used to highlight the use of mobile technology in healthcare. No known studies have provided empirical evidence regarding the desire among healthcare providers to change or update existing policy to include technologies aside from EHRs. This includes broadening the scope of reimbursed technologies to include mobile applications or wireless devices. Recently, policy has focused on incentives associated with the use of desktop computers and electronic health records to facilitate more efficient healthcare. To provide policymakers and stakeholders with additional information, this dissertation examines current policy trends related to the use of mobile and wireless technology in healthcare. The study provides an assessment—within the theoretical framework of Diffusion of Innovation Theory and Utility Theory—of desirable attributes of mobile technology associated with the provision of healthcare via mobile devices. Within the aforementioned theoretical frameworks, attitudes towards changes in existing policy structures that impact the use of information technology in healthcare were observed and reported. Overall this study concludes that healthcare providers find changes to existing policy programs desirable which further expand the use of technology in health care settings. Certain attributes

of mobile applications stimulate a willingness to pay more so than others. Furthermore, inclusion or changes to existing policy structures exert a change in overall willingness to pay for a smartphone application related to the delivery of healthcare.

Chapter 1

INTRODUCTION

1.1 Purpose of Dissertation

The purpose of this dissertation is to conduct an assessment of attributes important to healthcare providers when downloading smartphone applications. In addition, I consider relevant policy implications that affect the use of new technology involved in the delivery of healthcare. Increasingly smartphones and the features on these devices are used for the general provision of healthcare. The adoption of new approaches of healthcare delivery—including new technology—remains heavily dependent on policies to increase the diffusion availability of technology. The use or purchase of technology or services at the organizational level in healthcare is ultimately a result of product attributes. Therefore, price and product attributes combine to stimulate a willingness to pay. As such, the purchase of mHealth technologies largely follows patterns of consumer demand. Any changes in policy exert impacts on consumers relative to the underlying attributes of a good or service (McIntosh, 2010).

Healthcare is a highly regulated industry with many policies impacting consumer behavior at the individual and firm level (Boardman, 2010; McIntosh, 2010) To date, most research has focused on current trends in adoption of mobile technologies with a small number of studies focusing on the use of mobile technology associated with improved outcomes in health status (Nilsen, 2012). A different perspective includes the assessment of technology in healthcare associated with incremental gains in efficiency within the provision of healthcare (Ryan, 1999). Researchers and healthcare providers remain interested in studies which demonstrate the incremental value associated with the use of technology in healthcare (Cocosila, 2008). While beyond the scope of this study, many of the methods described herein could be adapted to address issues associated with identifying these incremental benefits.

Few studies have tied provider adoption of mobile devices to existing policy initiatives such as the Meaningful Use program, discussed further in section 1.7. The Meaningful Use program represents the major vehicle to increase the use of electronic health records in healthcare delivery. An overall, disconnected policy initiative exists to directly support or further integrate the use of mobile devices into healthcare settings. With respect to the issue of support mechanisms provided by policymakers, a number of innovation grants and other funding mechanisms at the federal level provide funding to assess the impact of mobile devices in the delivery of healthcare. The results of recent studies—from the aforementioned grants from numerous federal agencies—have impact on the structure of future policy making and play an important additive role in provider selection of devices and software components to facilitate the provision of healthcare. The impact relevant to future policy making is twofold. First, policymakers recognize the significant ability for mobile devices to impact both the delivery of care from both a cost and quality perspective (Nilesn, 2012). Second, policymakers recognize the substantial diffusion of mobile devices into our daily lives but incorporation into existing policy frameworks remains challenging. mHealth studies conducted to date are principally in the form of research pilots that demonstrate efficacy in treatment or prevention and often lack significant focus on incremental economic benefits associated with use. Thus, many of these research pilots are narrow in scope or relevant only to a certain set of geographical or clinical stakeholders. It is also important to note that the Patient Protection and Affordable Care Act (PPACA) places significant emphasis on movement away from a fee for service model, choosing to focus on low cost yet high quality care. Mobile devices represent a potential conduit to achieve this policy objective (Atienza & Patrick, 2011). As a result, many mHealth initiatives to date are of limited utility in understanding how many diverse mHealth stakeholders and a myriad of regulatory bodies will impact the ultimate spread of mHealth as a means to deliver care. However, many stakeholders at the federal and legislative levels are seeking to move the issues of access to healthcare via mobile devices to the forefront of health and healthcare policymaking.

This dissertation provides applications of methods to study hypothetical responses in markets as a result of policy change that seeks to increase the use of mobile technology in the delivery of healthcare. To date, no known study has been conducted to assess what health care providers and hospital IT staff are willing to pay for a mobile application—more commonly referred to as apps—related to the provision of healthcare. In addition, no known studies exist that assess changes in willingness to pay for mobile applications as a result of an expansion of federal programs that provide incentives for the adoption of technology in the delivery of healthcare. Finally, no studies exist that assess demand for apps at the provider level or analyze the impact particular attributes have on provider willingness to pay for mHealth applications.

1.2 The Terminology of mHealth

This section provides an overview of the many terms used in this work and when appropriate provides clarification on the intent of the use of certain terms. mHealth, for the purpose of this study, is defined as access to, or the use of health information in a wireless environment. Many alterative terms for this access to health information exist, such as Digital Health and eHealth, but these terms cover a broader range of technologies and are not constrained to the mobile environment. Furthermore, in clinical care when certain reimbursement requirements are met, the term telemedicine is used, but this term also is not limited to consideration associated with mobile devices. For consistency and clarity in this study, mHealth is used to refer to patients or providers accessing health information via wireless or mobile devices for any purpose.

Numerous industry and academic reports show that the use of mobile technologies increasingly plays a role in the provision of, search for, and management of healthcare. This includes a focus on providing services to both providers and consumers or patients. In addition, mobile devices play a role in the creation of patient data for implementation back into a patient's medical record. Mobile devices encompass mobile phones, smartphones, tablet computers or other wireless devices which can accomplish the tasks of data search or data generation. The majority of these activities occur on smartphones which over the years have grown in popularity with industry reports stating between 72% to 96% adoption within the physician community (Epocrates, 2013). A number of challenges exist related to sampling bias and contextualization of questions presented to potential respondents (Herigon, 2011). Thus for the purpose of this study a "smartphone" is used to denote an advanced mobile telephone capable of executing complex tasks via software.

Tasks completed under the broad umbrella of mHealth in healthcare settings range from the use of texting to support of various public health initiatives, such as Text4Baby℠, to the use of video or images from mobile phone cameras to monitor or diagnose various observable diseases. For the purpose of this study, focus is placed on how providers approach the use and purchase of mHealth offerings, namely applications for smartphone devices. Apps—sophisticated programs or special applications designed for smartphones—are rapidly emerging as unique and effective sources of health information and patient self-management tools (Handel, 2011). The term "App" is used to refer to software written and intended for use on smartphones in this study. It is important to note that in the study, respondents were not directly asked to make tradeoffs in purchasing tendencies between smartphones or tablets. Furthermore respondents were constrained to certain models of payment which impact the analysis contained herein. This presents an area for further inquiry addressed further in the concluding remarks.

A number of reimbursement schemes exist that could impact or alter the adoption of mobile technologies. Many include codified legal terms such as telemedicine. Telemedicine is used to refer to specific programs that may intersect with the definition of mHealth, but have reimbursement implications associated with the use of the term "telemedicine". It is important to note that much of the thrust of current healthcare related technology policy is focused towards the adoption and use of the electronic health record (EHR) in clinical settings. The policy intersections of EHRs and mHealth are discussed later in section 1.7.

EHRs encompass electronic medical records or other digital health documents associated with the provision of care. These tools are often designed for a desktop environment but increasingly solutions specific for mobile devices are entering the marketplace. At this juncture it is important to note that a mobile device is largely a miniaturized desktop. Many of the capabilities available on desktop or laptop computers can be found in smartphones or tablets.

Finally, the Meaningful Use Program is a program funded, supported, and overseen by a number of federal agencies further outlined in section 1.7. The program provides incentives for the adoption of technology into the healthcare system largely focused on the use of an EHR. However, as discussed further in this work, opportunity exists to include other forms of technology within the scope of the program.

1.3 Overview of Chapter One

mHealth—as defined above—is a relatively new term in healthcare and presents an opportunity for the application of existing research methodologies to aid in understanding the use of technology in the healthcare system. There is an emerging argument for the creation of entirely new approaches to researching the topic of mHealth (Nilsen, 2012). While a number of research methodologies require optimization or retrenchment in light of the capabilities to collect both social and quantifiable data, a number of existing methodologies exist which can aid in the understanding of mHealth on a shorter time scale. This chapter is focused on providing an understanding of mHealth technology at a fundamental level and presents current approaches to policy aimed at increasing the overall use of technology within the healthcare sector.

Section 1.3 explores the role of mHealth in our current healthcare delivery system. Section 1.4 defines some of the problems that inhibit the adoption and use of mHealth technologies. Section 1.5 describes additional barriers beyond the scope of this study but provides an important background on the encumbrances of mHealth as a useful technology in today's healthcare system. Sections 1.5 and 1.6 explain existing programs to increase technology such as EHRs and how existing incentive frameworks could be expanded to include mHealth innovations. Section 1.7 provides an understanding of potential existing efforts or signals from policymakers to further the adoption of mobile technologies. Section 1.8 reviews major research questions outlined for the remainder of the study.

1.4 mHealth's Impact on Healthcare

The obvious goal of many healthcare related policy programs is to achieve cost savings and increase efficiency within the healthcare system. mHealth is used to describe the use of mobile or wireless technologies to access, create, or analyze health information. mHealth is often presented as a low cost option for communication between patients and providers, including the sharing of data, commonly referred to as protected health information (PHI). Furthermore, the integration of monitoring devices to achieve broad population health benefits and the potential to decrease or mitigate rising healthcare costs is an optimal outcome of the use of mHealth technologies (Dobkin & Dorsch, 2011).

Increasingly, physicians are turning to mobile devices as platforms for care delivery out of convenience or limited increases in productivity, and not because of direct financial incentives to embrace new technology (Norris, Stockdale & Sharma, 2009; Martin, 2012; Nilsen, 2012). Care providers cite improved access to patient data and the ability to review patient information from remote locations as the major benefit of utilizing mobile technologies (HIMSS Analytics, 2011). Care providers prefer mobile devices because the device allows for monitoring on information sourcing without being physically present before a patient or workstation—a big plus in the days of shrinking reimbursements (Larkin, 2011). While providers and healthcare professionals are increasingly using mobile devices to assist in the provision of care, numerous policies are working to at times encourage, and at other times discourage adoption. The result is a loose framework of stakeholders who at times seem at odds with obvious goals as outlined in section 1.6.

1.5 Defining the Problem

The overall adoption of technology in the healthcare sector has lagged behind other industry sectors such as banking, the government, or other professional services (BLS, 2003). Recent policy decisions in healthcare have sought to "build up" or increase the use of technology for the delivery of care in clinical settings (Martin, 2012). This section discusses current policy, existing barriers to further adoption of mHealth technologies, and introduces emerging questions surrounding research in the field of mHealth.

A number of individuals have pointed to uncertain benefits and questionable outcomes associated with the use of mobile technologies in healthcare (Nilsen, 2012). Other studies have found efficacious outcomes as the result of Simple Message Services (SMS) or text messaging (Stockwell, Kharbanda, Martinez, Vargas, Vawdrey & Camargo, 2012). Recent studies have evaluated the effectiveness of handheld computers for health care professionals focusing on four functions: patient documentation, patient care, information seeking, and professional work patterns (Mickan, Tilson, Atherton, Roberts & Heneghan, 2013). One of the biggest challenges in the creation of mHealth policies is to clearly define and articulate values and benefits associated with the use and the impacts of said benefits on society. Another challenge associated with research and observations on the use of technology, more specifically mobile devices, is the rate of technology change prevalent among the many devices available to consumers.

Overall there is a need for more clearly articulated mHealth policy to aid adoption. A number of researchers have pointed to exploring new methods of research to further understand the use of technology within the healthcare system (Atienza & Patrick, 2011). Historically, decisions to invest in healthcare technology are highly responsive to the extension of financial incentives; the understanding of characteristics that influence the purchasing decisions of healthcare providers is an appropriate first step to frame a policy discussion. In Section 1.6, I discuss various factors impacting policymaking outside the scope of this analysis such as privacy and security concerns that impact the use of mobile and wireless technology impacting the delivery of healthcare.

1.6 Additional Barriers to mHealth Adoption

A number of issues limit the impact of mHealth or present obstacles to the adoption of mobile related technology. Barriers to widespread adoption of mHealth include a lack of articulated policy among many stakeholders in the regulatory space. In addition, disjointed privacy and security frameworks commonly associated with broad interpretations of the Health Insurance Portability and Accountability Act (HIPAA) present challenges to the adoption of mobile technology. Furthermore, limited financial reimbursements for the use of mobile devices in care delivery contribute to hesitancy among providers and decision makers to further adopt technology.

For example, a recent release by the US Joint Commission for the Accreditation of Hospital Organizations (JCAHO) seeks to curb physician's use of unsecure texting to approve or initiate orders for patients (Joint Commission, 2011). However, computerized physician order entry (CPOE) represents a major tenant of meaningful use and existing polices to transition care delivery away from paper based model of order entry into electronic format. The Joint Commission states "It is not acceptable for physicians or licensed independent practitioners to text orders for patients to the hospital or other healthcare setting" (Jacson, 2011). The majority of aversions to mobile technology surround the protection of individual's privacy and security and limited incentives for use of mHealth technology (Karasz, 2013). Furthermore, a number of existing and common security measures would limit the impact of the Joint Commission's position. First, the majority of deployed wireless devices currently utilize passwords to limit security breaches. Second, a number of secure texting applications are available in the marketplace which, if included in the Meaningful Use program discussed below, could alleviate many concerns while increasing adoption of such services. Thus, in many IT environments, texting of orders represents a more secure method than that of traditional paper based order entry systems.

In addition, HIPAA[1] and general privacy and security aspects remain major obstacles to the integration of mHealth into the delivery of daily care. The regulatory discussion surrounding privacy and security issues in healthcare has led to the creation of fines resulting from the breach of patient data called disclosure penalties. A

[1] Passed in 1996 and re-enacted with updates in 2013.

number of survey respondents identified organizational policies as contributing factor to not downloading an app for the provision of healthcare before. Many organizations are looking to create IT environments which allow providers to bring devices into the healthcare environment.

The 2011 Benchmark Study on Patient Privacy and Data Security by the Ponemon Institute, now in its second year, found that health care organizations and their business associates are increasingly lax, if not sloppy, when it comes to personal health information (PHI) security (2009). The Ponemon Institute found that eighty-one percent (N=72) of healthcare organizations in the study reported that they use mobile devices to collect, store, and/or transmit some form of PHI. However, 49 percent of participants (N=72) admit their organizations do nothing to protect these devices. There are a number of emerging studies and frameworks which seek to reinvent or adapt existing privacy frameworks to fit the mHealth arena (Kotz, Avancha & Baxi, 2009). While no one specific security framework solves the overall complex nature of mHealth, the discussion is underway and as technology diffuses through society, aversion to the utilization of mobile devices in medical care should decrease over time. Care providers remain aware of the consequences of lax security within the confines of the hospital IT environment. Current hospital trends towards creating a "bring your own device or BYOD" environment can greatly impact perceptions surrounding the use of mobile devices in the delivery of clinical care. Given the risk and cost associated with data breaches and fines associated under HIPAA—the Ponemon study places the average reported breach at a cost of $2.2 million dollars—shifting the burden of protection of health information through mobile devices onto consumers makes at minimum financial sense for firms. As outlined later, methods associated with Cost Benefit Analysis could be leveraged to understand the impacts of combining, incentivizing, or requiring secure SMS text platforms as a component of federally directed EHR policymaking outlined in section 1.7. While examining the direct role of privacy and security policymaking is beyond the scope of this study, the methodologies deployed within this study could be adapted to meet the needs of assessing future changes to existing privacy and security policies.

1.7 Current Structures to Increase the Adoption of Technology in Healthcare (HITECH Act)

Policymakers and federal agencies within the United States continue to highlight the potential role mHealth plays in the delivery of healthcare (Nilsen, 2012). Programs and policies to increase the overall adoption of technology in healthcare included stimulus funds provided by the Health Information Technology for Economic and Clinical Health (HITECH) Act section of the American Recovery and Reinvestment Act (ARRA) passed in 2009. The HITECH Act includes many goals including the provision of incentives and disincentives associated with the Meaningful Use program. The Office of the National Coordinator for Health Information Technology (ONC) is responsible for oversight of the Meaningful Use program. The Meaningful use program includes payments via the Centers for Medicare & Medicaid Services (CMS) incentive programs for the use of electronic health records (EHRs). This payment system allows clinicians or providers and hospitals to earn incentive payments by meeting specific criteria.

In order to advance the rate of technological adoption of EHRs, various incentives to purchase or offset the cost of maintaining EHRs were enacted through legislation for both individual providers and hospital systems. The ARRA over time will provide up to twenty seven billion dollars to facilitate the adoption of EHRs in hospitals and represents the first substantial commitment of federal resources to support adoption of technology in hospitals (United States Department of Health and Human Services, 2010). The estimates of potential savings associated with the widespread adoption of EHR systems, including important health and safety benefits, through effective EHR implementation and advanced networking could eventually save more than $81 billion annually (Hillestad, Bigelow, Bower, Girosi, Meili, Scoville & Taylor, 2005). While the application of formal CBA is beyond the current scope of this dissertation, it is important to comment on the applicability of the CBA method as the program advances. In this study respondents are asked to evaluate use of mHealth technologies as a component of the meaningful use program and certain attributes such as increased privacy and security characteristics which may impact use in healthcare settings.

It is important to note the Meaningful Use program is currently structured in three major stages. The first stage accomplishes broad adoption of EHRs. The second stage advances the interoperability of EHRs and introduces reporting measures associated with quality initiatives and population health outreach. The third stage of meaningful use includes greater participation and engagement by patients. It is the third stage of meaningful use where mobile devices are often cited as playing the most important role for both patients and providers (Szolovits, 2011; Raths, 2012). It is also the third stage of meaningful use that also presents an opportunity to further include the use of mobile technologies as the ONC engages in implementation of the legislation associated with the HITECH Act. This is the result of using EHR technology to identify "at risk" populations as a result of syndromic surveillance.

However, the Meaningful Use program has limited delineation of programs providers should employ to address or serve these types of populations from a technological intervention perspective.

1.8 Policy Considerations and Impact on mHealth Adoption

The HITECH Act has not only provided the policy platform which could serve as the model or mechanism for incentivizing mHealth technologies, but the HITECH Act has also created the incentive structure that seeks to increase the overall utilization of technology in healthcare. This additional potential represents a major potential driver of mHealth recognized by many experts within the mHealth and Health Information Technology (HIT) arena. Recent federal rulemaking procedures, notably Request for Comment Regarding the Stage 3 Definition of Meaningful Use of EHRs[2] signals an opportunity for mHealth technologies to play a greater role as a component of an overall national strategy to increase the use of HIT in the provision of healthcare.

As noted earlier, there is no specified policy which captures the use of, or the provision of incentives for providers to use mobile devices in a meaningful way during care delivery, aside from certain existing telemedicine incentives. Nor is there a centralized agency that oversees the regulatory environment associated with mobile devices. Various aspects of mHealth are currently regulated by the Federal Communications Commission (FCC), the Food and Drug Administration (FDA),

---

[2] For full text see: Department of Health and Human Services Office of the National Coordinator for Health Information Technology Health Information Technology; HIT Policy Committee: Request for Comment Regarding the Stage 3 Definition of Meaningful Use of Electronic Health Records (EHRs)

Health and Human Services (HHS), the ONC and other federal agencies. All approach policymaking from differing perspectives.

The FCC regulates the use of radio frequency bands of the electromagnetic spectrum by a spectrum management process called frequency allocation (FCC, 2014). Spectrum represents a naturally occurring resource which enables the transmission of signals which enable the movement of data to wireless devices. The FDA regulates medical devices within the Center for Devices and Radiological Health. Recently, the FDA issued guidance on the agencies approach to regulation of mobile medical devices and apps.[3] This guidance provides developers with clarification on the oversight of the approach the FDA employs when assessing mobile apps and the intent of the app to diagnose or treat disease. Finally the ONC, located within HHS, is responsible for the oversight of the Meaningful Use program and while somewhat implied, writ large the overall advancement of technology in healthcare. Establishing a fast and effective framework for adoption of new mHealth technologies remains challenging (Nilsen, 2012). The diverse set of federal stakeholders representing various sub segments associated with the creation of articulate mHealth policy presents potential challenges. As discussed elsewhere in this study, certain policies at the federal level can, at times, compete with each other thus impacting adoption.

A number of questions and barriers remain to the further adoption of mHealth technologies in the healthcare setting. Necessary changes to existing policy architecture must accompany considerable changes in technology as a result of

---

[3] See website: http://www.fda.gov/medicaldevices/productsandmedicalprocedures/connectedhealth/mobilemedicalapplications/default.htm

rigorous analysis. An issue for analysts is the need to consider the impacts of mobile technology through the quantification of costs and benefits. This assessment of technology can be accomplished through existing theories surrounding diffusion of innovation, utility and welfare economics. Second, a discussion needs to begin surrounding changes to or the development of financial incentives for mHealth trends already in use, including changes to existing incentive structures to entice clinicians and hospitals to increase the utilization of mobile devices in the healthcare setting as a component of public programs. A number of tools exist for firms and policymakers to quantify the costs and benefits of potential mobile apps at both an organizational and national scale. Meaningful Use as a program has provided a platform to increase the adoption of technology in clinical environments. Since the inception of the HITECH Act over 144,000 payments totaling $6.9 billion between Medicaid payments and $11.9 billion in Medicare payments have already been issued to professionals and hospitals by the Centers for Medicare and Medicaid Services (CMS, 2013). As mentioned before, estimated savings associated with implementation of the Meaningful Use program should approach or exceed $81 billion.

In 2012, nearly three-quarters of office-based physicians 72 % had adopted any EHR system up from 57% in 2011 (ONC, 2013). However, the focus of certification programs and payments is directed largely at desktop computing environments which at times are difficult to optimize for mobile environments. Overall, the adoption rate for mobile technologies by providers far surpasses the adoption of desktop computing environments by providers (Mickan et al., 2013). However, access to various resources on mobile devices by providers remains diffuse.

mHealth represents an opportunity to engage in restructuring or further development of the meaningful use program, thus creating what can best be described as “Meaningful Use 2.0”. mHealth continues to challenge policymakers in the United States and throughout the world in terms of how to best manage privacy and security issues and extract utility from the use of technology in healthcare (Nguyen, 2012). A number of obstacles and issues surround the full adoption of mHealth including privacy and security concerns and a transition away from centralized care.

In addition, current telemedicine standards are not necessarily designed to include new technologies or advancements in digital image capture, data transmission, or improved voice connections via 3G or 4G networks (Choi, 2006). In the US, a limited number of consultations, office visits, or psychotherapy exams are reimbursable through the use of telemedicine largely a result of complex issues surrounding physician licensure (Siegal, 2012). The analysis of patient data or remote monitoring of patients is not fully optimized as a reimbursable provision of care as the HITECH Act currently stands. Provisions in the Patient Protection and Affordable Care Act require the Centers for Medicare and Medicaid Services to penalize hospitals for readmissions which occur within thirty days of discharge. Telehealth is widely identified as an appropriate means to address readmission rates, yet four in ten hospitals in the U.S. employ such technologies in practice (Adler-Milstein, 2014). Broad approaches to policymaking associated with the PPACA provide little definitive guidance on approaches to the use of technology to accomplish this task. This study asks providers whether the use of mobile technologies should be included as an attribute in the Meaningful Use attestation process and assesses changes in willingness to pay as a result of inclusion of mHealth type apps in the program. As noted previously, the use of incentives via the Meaningful Use program has shown impact on addressing structural issues associated with increasing the overall use of technology in the healthcare setting.

The ARRA and ONC provide input to the Certification Commission for Health Information Technology (CCHIT) which is responsible for certification of EHRs for providers and organizations attesting to receive Meaningful Use payments. The program is widely lauded for the process of certification which is largely focused on the certification of EHRs as a component of health information technology. While adoption rates of EHRs continues to rise (Jamoom, 2011) there is a need to explore other components of technology associated with the provision of healthcare.

1.9 Research Questions and Overview of Chapters

To date, no known analyses of attributes important to providers when downloading mobile apps in the healthcare delivery system exist that includes assessments of pricing for one time downloading of healthcare related apps. In addition, no known studies have evaluated the expansion of current incentive programs to adopt mHealth technology as a component of attestation for the Meaningful Use program. In general, the hypotheses fall into four generic questions; Do hospital and healthcare providers require incentives to increase the use of mobile devices in the healthcare setting? If so what level or structure of incentives is required to induce providers to increase the adoption or use of mobile devices? Is there a maximum personal willingness to pay for clinicians and providers to download "apps"? What are the attributes most important to providers when making a one-time purchase of a healthcare app?

There are many methodologies to understand consumer behavior at the individual and firm levels. Survey research is often utilized to gather data on the preferences of consumer's behavior towards price. Given the failure of the market system in health care to allocate resources optimally, there is a requirement for economic measures of value to guide policy making in the healthcare field (McIntosh, 2010). In the following chapters I will explore methodologies and theoretical frameworks widely used and accepted that provide empirical evidence to assist in the creation of future mHealth policy. The aim of this study is to provide an understanding of market drivers associated with characteristics of mHealth apps, the impacts of current programs on demand, while providing additional empirical support for future policy considerations. This work further examines the relationship between the adoption of a new technology, the relationship to the perceived utility of that innovation, and the interconnection between the two elements.

In Chapter 2, I discuss major theoretical frameworks used to assess mHealth technology in this analysis. In Chapter 3, I discuss the survey instrument created to evaluate the role of mHealth and potential sources of bias in the generalization of findings. In Chapter 4, I provide an overview of the surveyed population. In Chapter 5 I discuss Contingent Valuation (CV) results to aid with policy analysis and decision making. Contingent valuation is a useful technique to assess utility and pricing associated with non-market goods such as changes in policy. In Chapter 6 discussion on the applications of Conjoint Analysis (CA) is presented. Conjoint analysis is a technique used to understand attributes of apps important to healthcare providers. Chapter 7 provides concluding remarks, potential policy changes, and opportunities for future research.

Chapter 2

THEORETICAL FRAMEWORKS

The previous chapter defined mHealth and introduced policies attempting to increase the overall adoption of technology within the healthcare system. The instrument to achieve this was the HITECH Act which provides incentives related to the use of EHRs in hospital and "eligible" provider settings. In this chapter, I provide an overview of the major theoretical frameworks important to understanding the research approaches employed in this study. There are two major theoretical models which aid in assessing mHealth from a policy making perspective. The first theory, Rogers Theory of Diffusion of Innovation, is that innovative ideas move through society in certain ways (Rogers, 2003). Diffusion of Innovation theory holds that certain characteristics of a potential innovation affect its chances of achieving adoption by others. One such trait highlighted by Rogers is "relative advantage" which includes the use of incentives and mandates to further advance adoption rates of desirable innovations. This observation by Rogers provides a logical progression between diffusion of innovation theory creating a linkage to welfare economics and utility theory.

The second theory, Welfare Economics, is invoked since policymakers create policy based on the premise that scarce resources should be optimally allocated to enhance the benefit of society (McIntosh, 2010). While mobile devices themselves are not scarce resources, monetary funding for programs and projects is scarce in a challenged economic environment. Welfare of the society or group can best be understood by examining utility often measured in dollars or monetary units (Boardman, 2010). Utility is best described as attributes of a good or service can be measured to provide an understanding of consumer preference. Any changes in policy will exert an influence on an individual's desire to purchase goods or services (Ryan & Farrar, 2000). This desire is termed Willingness to Pay (WTP) which is discussed further in section 2.7. In this study the effect of policy change is examined or reflected in a change in price to download an app for the provision of healthcare at a clinical level.

2.1 Overview of Rogers Diffusion of Innovation Theory

Diffusion of innovation theory provides a useful framework for studying the adoption process of technology (Pankratz, Hallfors & Cho, 2002). Diffusion studies have found that the way targeted adopters perceive the attributes of an innovation is critical and these perception account for 49-87% of the variance in whether or not end users adopt (Rogers, 2003). Diffusion of innovation (DOI) theory suggests that a social system reflects ‘‘the structure of communities and organizations which can be thought of as a network of interconnected individuals’’ (Valente & Davis, 1999, p. 56). DOI has widespread applications. DOI is used to explain the development and adoption of ideas, products, and the ability to influence groups, communities, societies, and countries (Farr & Ames, 2008). Adoption is "a decision to make full use of an innovation as the best course of action available" (Rogers, 2003). Many aspects of Rogers work are applicable to the field of mHealth to understand trends among adopters no matter the stage of adoption outlined below.

mHealth represents a dynamic community with many facets including but not limited to a network of connected individuals. Like most technical innovations, the diffusion or take-up (Rogers, 2003) of mobile technologies begins with individual experts or enthusiasts (opinion leaders) who broadcast their endeavors to others who either quickly (early adopters) or more gradually (early and late majority) espouse and extend the technologies, and find new applications (Norris et al., 2009).

2.2 Examples of Rogers Theory in Healthcare and Impacts on mHealth Adoption

We have a considerable body of research based literature that illuminates the adoption of technology based tools in healthcare (Benjamini,1986; Geibert, 2006; Ford, Rainer, Cegielski, Weigel & Hazen, 2012) and a substantial number of other arenas including agriculture, public policy and education (Rogers, 2003). Rogers Diffusion of Innovation theory is widely used as it is a "frequently-studied and widely-accepted theory" (Ford, 2012). Examples of the application of Rogers theory in healthcare span from advancements in cancer screenings (Hahm Mi, 2011) to understanding barriers of early adopters of technology in the field of healthcare (Barnett, 2011). Increasingly, Rogers theory is used in the field of nursing and medical informatics (Hilz, 2000; Weigel, 2012) with regards to the evaluation of the adoption of information technology (Geibert, 2006). As discussed in Chapter one, current polices have focused largely on the adoption of the EHR over other "ancillary" technologies in the healthcare field. Work by R.C. Giebert has evaluated diffusion of innovation theory associated with EHRs and serves as an excellent model to further assess mHealth (Geibert, 2006). Rogers (2003) argues that relative advantage, compatibility, complexity, trialbility, and obeservability are the characteristics that influence adoption of an innovation. This is discussed further in the following sections with commentary on their relationship to mHealth.

2.2.1 Relative Advantage

The first major attribute Rogers highlights is that the idea or innovation needs to serve as an improvement over existing technologies or methods. Relative advantage is the degree to which an innovation is perceived as being "better" than the idea it replaces (Rogers, 2003). With respect to mHealth, advantages include increased usability and portability. Furthermore, the convergence of many medical devices into one common platform represents a major advantage. Many of these advantages associated with mHealth assist with mHealth being readily deployed in the developing world, especially for workers providing health services in remote or underserved clinics (Desai, 2011; Lund, 2012) .

Economic factors also impact adoption rates of technology (Rogers, 2003). As Rogers highlights in his book "Diffusion of Innovations", the pricing of technology plays an important factor in facilitating the movement of technology into society. From an mHealth perspective, economic drivers and other characteristics play an important role in driving technology adoption. Rogers also highlights the need for early adopters to receive confirmation or information which demonstrates the advantage of new technology (Rogers, 2003).

Rogers further defines preventative initiatives as a potential component to the use of mHealth technologies in the delivery of healthcare either by prevention or an optimal change in health status. Rogers also highlights that preventative initiatives -or in this instance technologies- which lower the probability of an unwanted event are both challenging to diffuse and sometimes complex to prove (Rogers, 2003). For example, many of the benefits associated with the use of mobile devices to integrate with an EHR would be difficult to isolate within a scientific method framework. Many of the challenges in determining optimal outcomes associated with adoption are discussed further in context with welfare economics which seeks to increase societal welfare.

Finally, Rogers highlights the role of mandates and incentives as a component of advantages to drive adoption or diffusion of technology. A recent and directly applicable example of the use of incentives is the Meaningful Use program designed to increase the use of EHRs in healthcare. Many initiatives are underway which support the growth of evidence of the use of mHealth technologies in the healthcare setting which will further confirm the need to adopt such technology. In addition, this study provides examples of incentives and mandates which could prove useful to further drive adoption of mobile or mHealth focused interventions.

2.2.2 Compatibility

Compatibility is the degree to which an innovation is perceived as consistent with the existing ideals and values within a society (Rogers, 2003). The idea needs to be acceptable to existing social structures or technological frameworks. mHealth apps for the provision of care are being included in some platforms but are somewhat disruptive to the status quo. Rogers highlights to key elements of compatibility that are relevant to the adoption of mHealth technologies. The first is compatibility with previously introduced ideas (Rogers, 2003). From a policy perspective -pertaining to the adoption of technology into the healthcare setting- mobile apps present a logical transition for many of the EHR vendors currently operating. However, at the current time no components of attestation of compliance associated with the Meaningful Use program specify the use of mobile technology within the program.

The second element Rogers highlights is compatibility with needs. As this study provides in later chapters, the need for compatibility at both a policy level and technological perspective is quite high among providers (See Table 4.5.2 and Table 5.3). Finally, with respect to compatibility with needs, Rogers highlights that when needs of compatibility are met, a faster rate of adoption occurs (Rogers, 2003). With respect to need of mHealth, survey respondents highlighted the need for the ability to interface with an EHR.

2.2.3 Complexity

Rogers defines complexity as the degree to which an innovation is perceived as difficult to understand or use (Rogers, 2003). The ability for individuals or groups to understand an idea or gain skills for use is an important component of technology adoption. The use of smartphone applications in healthcare, while still complex in nature, pales in comparison to EHRs. Dissatisfaction with EHRs among providers remains high (Dolan, 2013). By 2014, nine out of 10 physicians are expected to use a mobile device for the delivery of healthcare (Epocrates, 2013). As highlighted elsewhere in this study, providers overwhelmingly point towards mobile devices as highly "usable" device when integrated with an EHR which serves a major reason to adopt (See Table 4.3.2).

2.2.4 Trialability

Trialibility is the ability to "test" innovation without significant "risk" to the user (Rogers, 2003). One of the major advantages of mHealth is the rapid development of both devices as platforms, accessory hardware, and software applications. Many users of mHealth apps can download a trial version or limited feature version. Trialbility represents a major challenge to this work. Since many of the advanced apps associated with an EHR follow a "software as a service" model with licensing fees. This model includes the purchase for seat license of a specific number of "access points" as opposed to the one time download fee probed in the survey tool.[4]

2.2.5 Obeservability

Results of innovations need to be "visible" by other members within the society or organization. Rogers reports that the more visible an innovation is to society, the more likely an individual or organization is to adopt. Currently, the observability of mHealth innovations is under question with a focus on providing additional avenues to increase observability (Nilsen, 2012). While diffusion of technology takes time, the number of mobile apps for the provision of healthcare continues to grow. At the current time of writing over 100 FDA regulated mobile apps and even more that fall outside the oversight of the FDA (FDA, 2013). A large number of pilot studies exist which impacts the adoption of the space. While commenting further on issues of oberservablity is beyond the scope, additional inquiry is needed to further assess the awareness of mobile health tools among providers.

2.3 Further Refinements of Rogers Theory in mHealth

To assess the diffusion of mHealth technology, respondents could be directly asked to rate the following attributes associated with DOI theory: relative advantage, comparability, complexity, observability, and trialability. However, the examined attributes of mHealth must be mutually exclusive. In the context of mHealth, attributes

[4] The term "seat license" is used to refer to models based on access for a certain number of individuals to a software platform.

such as relative advantage and complexity could be misconstrued by respondents. The intent of the questions contained in the survey instrument must be clear to the respondent. The use of certain terms in a survey may add confusion or fail to convey necessary information to the respondent.

Furthermore, the potential uses of "apps" in care delivery settings can vary widely based on personal preference or organizational policy. Broad interpretation of Rogers's characteristics could lead to unintentional bias of responses, either by failure to recognize and apply the attribute to the good or service in question or the potential for overlap of the attributes.

For the purpose of this study I will evaluate approaches to decision making and preference surrounding mHealth innovation, established by Rogers, which highlight characteristics recognizable by adopters of mHealth. For example, "Usablity" is a widespread topic of discussion and broadly understood within the healthcare field. This term is comparable to the terms "complexity" or "compatability" introduced by Rogers and discussed in depth in Chapter 3.

2.4 Rogers Diffusion of Innovation and Decision Making

The diffusion of medical technology and its effect on the modern hospital is an issue which receives considerable attention from economists and policy analysts (Benjamini, 1986). From a theoretical perspective, understanding social channels for the uptake of a technology should represent an important step for policymakers when crafting policy initiatives. Innovation-diffusion theory involves the examination and appreciation of the process by which an innovation is communicated through social channels in a particular group or organization over time (Rogers, 2003). Decision making phases associated with DOI theory include the knowledge phase, the persuasion phase, the decision phase, the implementation phase and the confirmation phase.

With respect to the knowledge state, Rogers asks the question "whether need or awareness drives adoption". From a mHealth perspective, much of the adoption surrounds awareness of the platform and that mobile applications *could* play a greater role in the provision of care. However, as indicated earlier, healthcare remains a highly regulated industry. Much of the innovative technology associated with healthcare is adopted and generated under a dominant regulatory force. While necessary to ensure public safety associated with the creation and use of new technologies, much can be done on a small scale to improve or highlight the needs associated with mHealth technologies.

The persuasion state of decision making within healthcare is closely tied to the relative advantages of technology highlighted earlier. As Rogers noted, incentives and mandates play an important role in the adoption of technology (Rogers, 2003). From a policy perspective, mandates and incentives within the healthcare sector often exert more influence on the diffusion of new technologies than the other attributes outlined by Rogers (O'Neill, 2009). Thus, persuasion in healthcare is almost directly driven by advantages associated with incentives or mandates. With respect to the persuasion to adopt EHRs, one needs to look no further than the Meaningful Use program to witness the impacts and persuasive nature created by a policy framework overseen by the ONC.

Prior to the implementation of the Meaningful Use program approximately 9.4% of United States hospitals employed an EHR (Charles, 2013). As of 2012, 44% of hospitals in the United States reported at least a basic EHR for the use of clinical documentation (Charles, 2013). This rate of adoption highlights the importance of incentives in the health care space to urge providers to adopt technology.

For the purpose of this study and in relationship to the theoretical framework presented by Rogers, the first three phases of Rogers work are considered. These include the knowledge, persuasion, and decision phases within this analysis of responses. The implementation and confirmation phases are not considered in depth in this study because they remain unclear under the current regulatory framework and temporal progression of the Meaningful Use program.

2.5 Evolution of Knowledge Surrounding mHealth Innovation

The first stage of [technology adoption/diffusion of innovation] the knowledge stage, involves the initial exposure to the innovation (Hilz, 2000). As noted above, there are multiple stages by which an innovation moves through social channels in addition to attributes important to the adoption of a technology. In this study I will assess components of DOI theory which reflect how adopters acquire information about and decide which mHealth technologies to adopt. The persuasion stage is characterized by the individual's integration of knowledge and development of an attitude toward the innovation (Hilz, 2000). Policymakers at both the organizational and governmental levels play a role in persuasion for the use of technology in healthcare. The Meaningful Use program represents an excellent example of persuasion to adopt technology. The decision phase provides an opportunity to reflect on acceptance or rejection, in essence trialablity without significant risk of failure would exert positive influences on the adoption of a technology.

2.6 Innovation in Organizations

The discussion above surrounding Rogers DOI theory is largely predicated on individual perspectives and approaches surrounding the adoption of innovations within a society or organization. Rogers also notes the importance of large networks of individuals called organizations with respect to the ability to adopt new technologies. Rogers defines organizations as a stable social structure of individuals working together to achieve common goals (Rogers, 2003). A number of organizational structures exist across the mHealth community which aid in further adoption or mHealth innovations. These include regulatory or advocacy coalitions, international efforts in the mHealth space, and other types of organizations discussed in previous sections within the framework associated with Rogers definitions of organizations.

Rogers highlights that in many instances individuals lack the authority to advance new innovations (Rogers, 2003) which makes collective decision making beneficial to the adoption of new ideas or innovations. Rogers highlights four types of innovation decisions. These include optional, collective, authority/authoritarian, and contingent innovation-decisions. With respect to mHealth, a number of types of innovation-driven organizations that impact decisions are present.

2.6.1 Optional Innovation Decisions

Rogers defines optional innovation decisions as an individual's decision to adopt a technology independent of others choices to adopt within a loose framework of a defined organization (Rogers, 2003). As it relates to the adoption of mHealth and this study, the decision to adopt mHealth technologies ultimately varies by individual. This variation is minimized by the choices a respondent is presented in the survey tool. However, the respondent is prompted to provide additional examples of mobile related apps used in the delivery of care. Further analysis of the free text entries could provide insight in to optional choices in the use of mobile applications for the delivery of healthcare. Examples include differences between integrated delivery networks or large institutions which broadly embrace technology to smaller organizations where differences in adoption or availability of technology exist. It is also important to note that the aggregation of individual decisions to adopt can provide support for optimized policy making associated with the other elements of organizational innovation decision making.

2.6.2 Collective Innovation-Decisions

Collective innovation decisions require consensus among members of an organization to advance an innovation (Rogers, 2003). Elements of the study which assess collective mHealth innovation decisions include the role of certification or accreditation bodies associated with existing organizational structures. These collective organizational structures include Medical Colleges or associations and the emergence of new accreditation bodies such as Happtique™. Happtique™ provides a cursory review of mHealth apps for content validity, review for privacy and security issues, and code evaluation to assess the potential for malicious software attacks when a user downloads an app. When consensus decisions from non-authoritarian sources fail, decision making to adopt an innovation is largely left to authoritarian organizations. The potential exists for the uptake of mHealth to be impacted by a lack of consensus to advance innovation adoption.

2.6.3 Authority Innovation-Decisions

Rogers also notes the role of authority figures to enable the adoption of an innovation without regard to broad consensus or optional adoption of an innovation (Rogers, 2003). In the context of mHealth policy creation, the vast majority of the authoritarian efforts to increase adoption operate within the jurisdiction of a federal government. Specific to mHealth, policymaking to date has largely deferred action of organizational decisions in favor of adoption by optional or consensus decision making. However, a number of legislative efforts are underway to align formal governmental oversight with the consensus of organizations or citizens. These efforts are not exclusive to the United States, with a number of governments advancing consensus decisions to adopt mHealth innovations. With respect to observational information collected in the study, survey respondents are probed regarding the support for policy changes driven by authoritarian type decisions to adopt. As noted earlier, the use of incentives in healthcare are largely employed to minimize dissent resulting from authoritarian decisions to adopt innovations.

2.6.4 Contingent Innovation-Decisions

Rogers also discusses the importance of “chained” events associated with the innovation decision making process. When the decision to adopt is based on a prior innovation decision, Rogers uses the term “contingent innovation decisions” (Rogers, 2003). Within the framework presented in this study, the decision to adopt mHealth innovations is at times coupled with adoption of other innovations. For example, the need to access an EHR from a mobile device is largely dependent on a decision to implement an EHR. However, at the time of writing there is no certification requirement for EHR manufactures to provide mobile access as a component of basic

EHR technology. Overall, one of the major challenges presented by mHealth is the need for multiple contingent decisions to advance the use of mHealth solutions in healthcare. For example, there is a converging need for policy making at both authoritarian levels and collective levels. Many of these decisions impact the overall utility of mHealth solutions adopted with the healthcare system discussed further in the next section.

2.7 Welfare Economics and Utility Theory

Normative or welfare economics is concerned with evaluating the consequences of policy change and coming to a conclusion regarding the impact of a particular change or policies measured in terms of the improvement in societal welfare (Drummond 2010; McIntosh, 2010). For healthcare, welfare economics would involve the investigation of methods of individuals' preferences for a good, service, or change in health status (McIntosh, 2010). Utility is the value of preferences that consumers have for a good or service expressed through consumption patterns. One of the easiest ways to study the impact of preference is to assess utility from the perspective of monetary valuations i.e. dollars. Economists often refer to household production models when assessing utility and preference can be identified via an observation of the value an individual places on an item (Boardman, 2010). It is widely understood that consumers exhibit preference for goods and services as a result of the underlying utility of that good or service (Boardman, 2010).

As viewed in the economics literature, Cost Benefit Analysis (CBA) is a comprehensive research method intended for assessing of whether proposed public policy, program, project would enhance societal welfare. This objective is to be achieved by comparing (a) the value of all consequences for societal members impacted by the initiative that are quantified in monetary terms to measure benefits with (b) all the financial cost incurred as well as the social (non-market) costs associated with initiative both of which are measured in monetary terms (Boardman, 2010). If benefits are greater than costs, then society realizes a gain in economic efficiency or societal welfare, or within the context of mHealth utilization, a net improvement in health care with a potential decrease in effort or monetary expenditure. While designed for public policy analysis, CBA has applicability and can be expanded to include approaches to decision making in for profit arenas. In a very general way, studies in the for-profit sector would focus on increased productivity or aid in determining consumer preference to maximize firm profitability.

Despite their differences in goal maximization, a fundamental CBA concept common to both private sector and public sector decision makers and analysts is an understanding of market demand for mHealth devices that can be the source of sale and purchases of mHealth technology and thus could generate welfare gain or profits. Market demand for a mHealth device is derived from four factors: (a) the financial cost of the device to the buyer/use which would be equal to the price paid offset by any financial subsidies received by the buyer, (b) the actual and desirable attributes of a device that is consistent with potential users' preferences, (c) potential purchasers' income that indicates the ability to pay for a device, and (d) the value that the user could yield in health care improvements with the device. Together all four factors stimulate a consumer's willingness to pay (WTP) for the technology. An individual's WTP is the monetary amount (or actual net price paid) that a potential user would give up to purchase a device. When sales and purchases of mHealth are realized through the understanding of consumers' demand, social value in the form of societal welfare enhancement and private sector profit could be determined. In the following chapters I describe the use of CBA to measure WTP from which consumer demand can be derived with a focus on mHealth technologies for the provision of healthcare.

2.7.1 Utility Theory

As discussed above, utility cannot be measured directly but is rather inferred from observable attributes of a good or product resulting in a preference to purchase or engage in trialiablity (McIntosh, 2010). [5] There is a growing volume of literature aimed at determining the elicitation and application of citizens' preferences in healthcare in relationship to changes in outcomes (Wiseman, 2004). As noted in Chapter one, preference and intended use is increasingly incorporated into the policy making process to determine optimal policy solutions. Discrete choice experiments (DCEs) are regularly used in health economics to elicit preferences for healthcare products and programs (Lancsar, 2008). DCEs involve respondents making tradeoffs between a good, product or service. Simply stated DCEs focus on consumer selecting an optimal solution when presented with a choice. This includes products which may or may not have ties to changes in policymaking. For many products in healthcare, market success not only relates to end users of the product, it also relies on key decision makers (Whitty, 2012) and policymaking by these decision makers. Many of the DCEs presented in this work involve inferences in hypothetical changes to the

[5] As a general note, a number of business models exist for smartphone apps. Single fee downloads, licensing outside of mobile marketplaces, and “freemium” models are representative of approaches to pricing and monetizing mobile apps. For the purpose of this dissertation only one time download fees are considered and presented to survey respondents.

Meaningful Use program. As noted in Rogers Diffusion of Innovation Theory decision making types will no doubt place great emphasis on product attributes. As such, this study is predicated on the idea that policymakers will seek to understand provider preference when evaluating existing policies and in the planning for future programs.

The use of a Random Utility Model provides a behavioral-theoretical basis by which one can formulate and test many statistical preference models (McIntosh, 2010). Utility is represented by the following equation

$$U_{ij} = V_{ij} + \epsilon_{ij}$$

Where is U_{ij} the utility associated with the attribute in question, V_{ij} is the observable component of utility, and ϵ_{ij} the unexplainable component of utility (McIntosh, 2010). The Conjoint Analysis (CA) used in this study assess the stated individuals valuation of broad attributes of mHealth apps to measure individual preference (San Miguel, 2000). The Contingent Valuation (CV or CVM) is a method of economic analysis, employed in this study, that utilizes survey research to compile predictions resulting from various hypothetical interventions or policy alternatives (Drummond, 2010). This is conducted in the context an individual's ability to participate in a market for any good, service, or program. Since no incentives currently exist for the direct use of "apps" in healthcare, an ex-ante approach is implied. Within the context of this mHealth study, compensating variations involves the value of an individual's WTP at least equal to their gain in utility from the purchase so that their payment would not make them worse off after the purchase. When an ex-ante perspective is taken, WTP is elicited prior to the event happening

(McIntosh, 2010). Also, with no incentive at the current time of writing, compensating variation is also implied.

Furthermore, additional work is needed to refine the CBA method. The ancillary use of technology in the delivery of healthcare is of interest to a number of individuals in the healthcare stakeholder landscape. Policymakers continue to search for assessments associated with the benefit of using technology in an ancillary manner to provide healthcare. This includes assessments ranging from improvements of organizational or firm efficiencies to exploration of the method to directly observe and quantify improvements in health status (Ryan, 1999). Wide deployment of CBA is one such method to achieve this but beyond the scope of this work.

2.7.2 mHealth Focused Applications of Utility Theory

In this analysis, the willingness to pay for apps before and after a hypothetical policy intervention is considered. It is assumed that utility of app is increased provided it is incentivized properly. WTP is a measurement technique that assesses the maximum an individual or agent is willing to pay for a certain program or benefit (Drummond, 2010). In this instance the potential to reimburse physicians for the use of mobile "apps" in the delivery of care and incentivized as a core objective of meaningful use policies described above. As noted earlier, within the context of DOI theory, incentives and mandates represent a critical component of policy frameworks within the healthcare sector.

The healthcare industry is a heavily regulated industry and it's plausible that regulations or policies may affect an individual's willingness to pay for technological innovations that may cost too much early on in the adoption process. Previous examples of incentives to utilize technology include the provision of financial incentives for the purchase and meaningful use of EHRs in the healthcare setting through the passage of the HITECH Act in 2009. In this study the hypothetical suggestion is that policymakers would seek to increase the adoption of mobile devices in the healthcare setting through the provision of financial incentives to adopt and use mobile technology in way that is meaningful and that creates value for individuals and society.

Future changes to policy may result from the need to accelerate the use mobile devices in care settings; through the provision of incentives in order to optimize access to care; or the involvement of new technologies into existing programs like Meaningful Use. Previous changes to incentive structures have focused on expanding the eligibility the physician, the hospital, and other care providers such as physician's assistants by the Office of the National Coordinator. For the purpose of this study the survey is focused towards the potential need to incentivize apps among physicians and other providers in the healthcare delivery system. Many of these decisions are made by authoritarian policy making organizations described above.

In addition to the location of preference there is an issue of the type of apps firms or individuals would seek to utilize in care delivery settings and the importance of attributes associated with utility gains associated with use. There is also a need to elicit preference for specific attribute and the importance of these attributes when considering potential future polices. In recent years there has been rapid growth in the number of contingent valuation studies published in the health care literature (Drummond, 2010). The CA/CV methods are gaining acceptance as stepping stone for the design of future policy because of the need to assess and analyze the behaviors of consumers-in this instance physicians and providers- in the healthcare setting. The following chapter provides an over view of the creation of a survey tool to understand respondents understanding of current policy programs, assess gains in utility from changes in the existing meaningful use program, and collect information relevant to characteristics which impact decisions to purchase services.

2.8 Relationship between Utility Theory and Rogers Diffusion of Innovation Theory

Relatively little is written with regards to the relationship between Utility Theory and Rogers DOI theory. The challenge remains establishing a focused framework for the quantification and measurement of attributes identified by Rogers. More work is needed to further assess the relationship and overlap between these two important theoretical frameworks. Arguably, cost and pricing represent major characteristics of innovations which impart substantial impacts on adoption. Rogers provides minimal relationship between cost structures and decisions to adopt an innovation. Rogers intonates towards the need to conduct market research in order to properly position an innovation (Rogers, 2003). This same need is present in the field of mHealth. While not identified directly in the work of Rogers, the methods of conjoint analysis permit a further assessment of certain attributes with the context of willingness to pay as an observed and quantifiable indicator of a decision to adopt. Contingent valuation methods allow for the assessment of positioning relative to potential or hypothetical changes in policymaking.

One could argue that exhibiting a willingness to pay also indicates a willingness to adopt. This is to say that an individual is willing to adopt and would pay, but has not yet engaged in an act of commerce. However, a decision to adopt a technology may not manifest itself simply by exhibiting a willingness to pay.

Conversely, the establishment of policy which incorporates subsidies to adopt renders challenges in observing an unbiased elicitation of willingness to pay. The shortcomings of DOI theory and the impact of attributes and policymaking are discussed within the context of conjoint analysis and contingent valuation in Section 3.6 , Chapter 5, and Chapter 6 respectively.

Chapter 3

RESEARCH METHODS AND DATA COLLECTION

The previous chapters presented an overview of mHealth, theoretical frameworks for assessing utility, and a theoretical framework for how innovative ideas moves through society. The purpose of this chapter is to review empirical methods for observing and modeling attributes important to users, discuss the sample used to create and test the model. In addition this section discusses pilot testing, cognitive effort assessments and modifications to the survey instrument. Finally this chapter seeks to identify potential areas of bias associated with data collection process and steps taken to mitigate the impacts on this study.

3.1 Contingent Valuation Experiments in Healthcare

In a contingent valuation surveys consumers are asked to consider a hypothetical scenario where a market exists in relationship to a public program with benefits for evaluation (Diener, O'Brien & Gafni, 1998). In certain instances, associated costs accompany participation in a program or project. In this study changes to the Meaningful Use program is presented to the respondent. Contingent valuation surveys provide useful information to analysts by having respondents place monetary values on non-market goods and amenities (Howe, Lee Lee & Bennett, 1994). In many instances some goods are difficult to quantify (McIntosh, 2010). A number of researchers have applied the contingent valuation method (CVM) in healthcare settings to further the understanding of pricing related to initiatives or services. The number of health care CVM studies is growing rapidly and the majority are done in the context of CBA (Boardman, 2010). Many studies assess the impact on improvements in health outcomes. However, a growing need is to use the CVM to assess the impacts of technology without a focus on non-health outcomes (Ryan, 1999). This includes expansion of the method to assess the partial or ancillary benefits of new technologies.

There is wide variation among health care CVM studies in terms of the types of questions being posed and the elicitation formats being used including the classification and appraisal of the literature is difficult because reporting of methods and researcher relationship with the conceptual framework of CBA being classified as poor (Diener et al., 1998). Several types of contingent valuation models exist; all seek to estimate an individual's WTP for a good or service. For the purpose of this analysis the contingent ranking method, and the dichotomous choice (referendum) methods are used. CV modeling is useful since the population sample includes both qualitative and quantitative dimensions in the hopes to reduce the bias in the study. Irrespective of the particular elicitation format, CV modeling is useful since the population sample includes both qualitative and quantitative dimensions in the hopes to reduce the bias in the study. The former entails the scenario that provides a description of the factors encompassed by the policy change. The quantitative dimension includes the way in which the WTP value is elicited. In this study, follow up questions included further probing of input on job types and lack of a previous history of payment for a mobile application to further assess the bases of individuals' WTP. For example, revealing a preference for incentives to cover the cost of incentivized apps by clinicians' providers, or managers within an organization would yield both a binary response (qualitative) combined with stated WTP values (quantitative). Respondents are merely asked what price they are willing to pay to obtain a good or policy (Boardman, 2010). Open ended choices with follow-up questions are incorporated into the survey and can be found in Appendix B. Iterative bid questions are also incorporated in the survey tool and provide an opportunity to further correlate the validity of open ended solicitations of WTP. Follow up questions included areas of free text to solicit input from respondent. Follow up questions included further probing of input on job types and lack of a previous history of payment for a mobile application. In dichotomous choice sets respondents are asked whether they are willing to pay a particular price to obtain a good or advance a policy (Boardman, 2010). There is an emerging practice of utilizing advanced statistical models with combined mixed methods for the analysis of CV surveys. These include the use of the Pearson Test and Ordinary Least Squares Regression (Günther, 2006).

As a method, CVM is useful to frame a valuation study but often lacks sufficient rigor with respect to heterogeneous application of the method. That is, CVM proves useful for assessing at a fundamental level the potential impacts of changes in policy. However, the aggregated impact of the study and the ability to centralize a general framework as "acceptable" for all models and applications is difficult. This is true for applications in mHealth due to the large variation of characteristics of potential apps for purchase and study. Furthermore, the use of all healthcare related applications may not represent the criteria of "meaningful use" of technology as defined by the ONC. In addition, this chapter explores the impact of polices and tradeoffs consumers are willing to undertake when making a purchase with conjoint analysis.

3.2 Expansion of Discrete Choice Experiments

Discrete choice experiments are an attribute based measure of benefit (Ryan, 2003). DCEs make the assumption that healthcare interventions, services, or policies can be described by their characteristics (or attributes) and secondly, an individual's valuation depends on the levels of these characteristics (Ryan, 2004). Many discussions in the HIT policy space have focused on results outside the quality adjusted life year (QALY) methodology or other studies focused predominantly on clinical tradeoffs between treatment plans. There has been an assumption in the health economics literature that health outcomes are all that need to be considered when attempting to measure the benefits from health care interventions (Ryan, 1999). With the increased use of technology within the healthcare system, normative questions around utility increasingly turn to ancillary benefits associated with the use of technology. Benefits associated with the use of technology in healthcare often extend beyond per patient improvements in care. Many of the factors identified as non-health outcomes and process attributes are capable of being directly influenced by policymakers (Ryan, 1999). Increasingly other benefits such as access to information or preference for access to providers are examined using discrete choice experiments.

At the methodological level, studies find that respondents will complete discrete choice experiments in an internally valid and consistent manner (Ryan, 2001; Ryan, 2004; Lancsar, 2008). Furthermore, DCEs are increasingly used in health policy analysis (Viney, 2002; Ryan, 2004; Promberger, 2012) and in the creation agricultural and environmental policy (Broch, 2012). Optimizing the design of DCEs involves maximizing not only the statistical efficiency, but also how the nature and complexity of the experiment itself affects model parameters and variance (Bech, 2011). As used in the present study, conjoint analysis is merely a particular application of a discrete choice experiment.

The essence of survey research is eliciting information about a population from a small sample drawn from that population (Boardman, 2010). Sample sizes for DCEs vary widely and are largely dependent on an analysts understanding of tradeoffs associated with study design and statistical modeling. A selection of DCE survey populations is provided to highlight the varying population samples associated with DCEs.

N=103 (Carroll, Al-Janabi et al. 2013) A study of Prenatal Down's Syndrome Screening

N=254 (Bonnichsen, 2011) A study of Ostomy Pouch Preference

N=81 and N=101 (Promberger, 2012) A study of Incentives to Change Behavior

Hensher, Stopher, and Louviere (2001) found that the number of choices had little impact on response rate, no impact on respondent fatigue and simplification of response strategies, minimal impact on the goodness of-fit statistics, and finally, little impact on the mean WTP estimates. An increase in the number of choice sets presented to each respondent provides more observations, lowering the costs of data collection (Bech, 2011). The researcher's decision regarding the number of choice sets per respondent is indeed non-trivial and involves a trade-off between factors such as design efficiency and cognitive burden (Dobkin & Dorsch, 2011). To minimize exhaustion of respondents, the survey was designed with multiple generalizable characteristics of mobile app use and attributes associated with healthcare related mobile applications at the time of writing.

There is an emerging body of evidence placing more emphasis on the number of choice sets provided to respondents over drawing large sample sizes (Bech, 2011). In addition to choice sets, the determination of confidence intervals is highly dependent on a researchers approach to risk in making probabilistic statements (McIntosh, 2010). The discussion on the number of choice sets, total observations, and survey sample size is beyond the scope of this work.

3.3 Conjoint Analysis

Conjoint analysis (CA) is "based on the premises that any good or service can be described by its characteristics (or attributes) and that the extent to which an individual values a good or service depends on the levels of these characteristics" (Ryan & Farrar, 2000). CA studies seek to assess changes in policy by determining an increase in societal welfare via empirical research and determination of value associated with tradeoffs of attributes and their values that pertain of attributes to decisions related to policy.

However, the determination of benefits associated with the use of apps in a healthcare setting is challenging. Researchers in medicine, healthcare economics, and health policy have discovered the value of this methodology in determining treatment preferences, resource allocation, and willingness to pay (Mele, 2008). Decision makers in organizational and governmental roles must also be concerned with the expected costs as well as the potential gain from mHealth technology, a result that can be appraised by quantifying the benefits of such technology.

In a typical CA study individuals are presented with hypothetical scenarios involving different levels of various attributes which have been identified as important in the provision of a good or service and asked to rank the services, rate them or make pairwise choices (Ryan, 1999). Respondents are presented with a number of choices and, for each question, asked to choose their preferred one" (Ryan & Farrar, 2000). In this study respondents are asked to rate a number of attributes relevant to the decision to download a mHealth app. The rating method requires the respondents to assign a score, 1 to 7 for each of the attributes. The power of conjoint analysis lies in its ability to find out from consumers what trade-offs they are accepting every time they make decisions (Steblea, Steblea & Pokela, 2009). A number of elicitation methods exist which include the direct method and the indirect method. Furthermore, a number of statistical methodologies exist to assess characteristics of goods or services. As noted in chapter five, an open-ended elicitation format is used to obtain respondents WTP. With respect to CA, the open-ended approach allows respondents to indicate directly their maximum WTP to receive a commodity through the valuation (rating) of the commodity's attributes (Ratcliffe, 2000). In this instance a onetime fee to purchase a mobile health application. This method can, therefore, inform the service design process (Cunningham et al., 2010) to further understand barriers to adoption of mobile technologies in healthcare or areas for policy improvement. This includes changes to the existing certification criteria to receive incentive payments associated with the Meaningful Use program.

3.4 Desired Sample Size

The Bureau of Labor and Statistics (BLS) provides information on the number of professionals in various categories. The BLS website was consulted for the most up to date figures for the professions of physicians, nurses, and health IT professionals. The estimated overall population size for the sample is 3,607,900 individuals. For a 95% confidence interval and 5% margin of error, a randomly selected sample size of

384 providers and hospital IT staff from varied geographical areas is preferred[6] (See Table 3.1). The sample population includes physicians, nurses and other care providers. The scope of the population is expanded to include health IT professionals to account for the potential of IT department or professional to exert influence over purchasing behavior of employees or organizations.

In summary, the determination of sample size for DCEs ultimately involves tradeoffs between cognitive efforts including the number of choice sets presented to respondents. After creation of the survey tool and determination of the population sample size, the survey instrument was further refined by conducting a pilot study discussed further in section 3.4.

Table 3.1 Desired Survey Sample Size

Demographic	Estimated Population	Relative Proportion	Desired Sample 95% Confidence Interval
Physicians	691,000	.20	77
Nurses	2,737,400	.75	288
Healthcare IT Professionals	179,500	.05	33
Total	3,607,900	1.0	384

---

[6] The sample size was created using the sample size calculator provided by Qualtrics. The estimate is based on the estimated total population of potential survey respondents in the United States reported by the Bureau of Labor Statistics for the various demographics. http://www.qualtrics.com/sample-size-whats-the-deal?utm_source=newsletter&utm_medium=email&utm_campaign=april2011newsletter

3.5 Survey Pilot Results and Survey Tool Modifications

The use of DCEs and WTP surveys requires pilot testing prior to formal data collection. A number of authors provide outlines on testing DCEs for validity (Ryan, 1999; Boardman, 2010; McIntosh, 2010). As noted by McIntosh, there is a need for survey instruments that “work” (McIntosh, 2010). Survey tools need to be understood by all respondents so that the questions will be meaningful to them, and will stimulate the choices an analyst wishes to observe (McIntosh, 2010). Evaluating tradeoffs in each task of the survey requires a high level of cognitive effort, depending on the number of attributes and the number of alternatives to be evaluated (McIntosh, 2010). The most basic protection against unknown or unexpected preference heterogeneity comes in the design phase of the survey (Ryan, 1999). Background research, discussion with experts, and, most importantly, careful pre-testing provide crucial information about subject preferences (Johnson & Mansfield, 2008). The cognitive interviewing approach assists to evaluate sources of response error in survey questionnaires. This technique was developed during the 1980's through an interdisciplinary effort by survey methodologists and psychologists (Willis, 2005).

Prior to distribution the survey tool was presented before the University of Delaware’s institutional review board for human subject’s research.[7] The protocol was exempted from additional human subjects review. An internet based pilot survey using a modified survey tool was conducted using a modified cognitive interviewing approach. A small sample size (n=10) of willing participants provided a qualitative assessment of the survey tool to determine cognitive effort and the validity of questions presented in the tool.

---

[7] The University of Delaware IRB protocol reference number is 410908-2.

For the purpose of the pilot, the survey tool was modified to include multiple free text entry areas for the collection of information regarding the respondents understanding of the questions presented in the survey tool. Respondents were then presented the online tool with multiple free text entry opportunities to obtain feedback as the respondent progressed through the survey tool.

The survey tool was amended as follows after conducting the pilot study. The word "multiple" in question 3 was placed in bold (See Appendix B for list of questions). The option for "other" was added to the type of healthcare setting a provider may work in and multiple selections were permitted. Clarification text was added to the question soliciting maximum willingness to pay. Due to a high volume of text responses for the direct elicitation of WTP during the pilot phase, the survey platform was adjusted to only allow for numerical entries with a range up to the maximum one time download fee for a healthcare application. The starting price point for contingent valuation questions was reduced to $25 dollars and the logical presentation of the questions to ascend or descend based on stated preference. The contingent valuation questions increased at an interval of $5 dollar increments (See Figure 5.2 and 5.3 and discussion in Chapter 5). Additional attributes of "App grounded in evidence based medicine" and "App improves productivity" were added.

All respondents successfully completed the survey tool in a relatively short time frame. No respondents reported an inability to complete the online instrument as a result of barriers created or enforced by an information technology department protocols preventing access to the webpage. Potential barriers included the inability to access the survey tool from a workstation at a place of work. The tool was deemed valid with minimal cognitive effort placed on the respondent. The tool was then placed into data collection on April, 1st 2013.

This survey was distributed using an email list of hospital and practice based care providers collected by HIMSS Analytics and MedTech Media. The database contains the work addresses, emails, and contacts for over 20,000 Physicians, Nurses, Health IT staff, and Chief Information Officers (CIOs) in the United States. In addition, the survey link was placed on a number of healthcare news outlets, professional websites, and newsletters with a focus on mHealth or health care.

The respondents were asked a number of qualifying questions including age, role in healthcare, hospital location size and type, and type of device they use most frequently in the care setting. In addition, respondents were asked a number of questions regarding the use of applications, important attributes, and WTP for smartphone applications. It is important to note that the survey tool only solicits feedback on apps which are available for purchase as a one-time fee per download. A number of other business models exist within the industry including the use of licenses associated with the use of additional software and a large number of free mobile apps. Respondents were instructed to only consider the single fee per download scenario when presented with WTP questions. See Appendix B for the full list of survey questions and Chapter 4 for description of the surveyed population and Chapters 5 and 6 for analysis. The full survey tool can be found in Appendix B.

3.6 Potential Sources of Bias

Rogers DOI theory is often critiqued for several flaws. One of the major challenges in conducting research on the movement of innovations includes the wide range of applications of DOI theory (Rogers, 2003). Rogers's framework establishes universal characteristics that present challenges to researchers in specific fields who must translate Rogers's characteristics into terms that will be understood by the target survey population but still capture the characteristic. Another challenge associated with the application of DOI theory include a pro innovation bias (Rogers, 2003). Pro innovation bias represents the ideal that an innovation should be adopted without consideration for potential changes in an innovation (Rogers, 2003). This study aims to provide further evidence of areas where focus should be driven by policy relative to the attributes important to the uptake of mobile applications.

The current state of mHealth research by both the academy and industry contain elements of pro innovation bias. Many solutions are presented which lack the proper characteristics necessary for quick adoption. mHealth represents a logical progression for use in healthcare due to the high adoption rate for the underlying technology, the smartphone. However, an assessment of the target population's willingness to adopt is challenging. Rogers cites funding of studies by "change agents" and a lack of research on unsuccessful innovations as key barriers to the state of DOI research (Rogers, 2003). To overcome some of these challenges, the survey instrument contains free text entries for respondents to address individual reasons for not adopting an innovation. While empirical assessment of qualitative information collected in these response fields is beyond the scope of this study, some discussion is provided in the summary of findings. In addition, this research provides an opportunity to revisit issues associated with the failure to adopt mHealth technologies in light of action or inaction by policymakers at a later point in time.

With respect to Utility Theory, research suggests that, when asked to place a monetary value on something people currently do not have to pay for, they tend to overestimate the amount they would be willing to pay (Griffin, 2011). The potential to overestimate the true willingness to pay represents the opportunity to interject bias into a traditional WTP study. WTP studies are routinely criticized as biased as respondents may overestimate WTP (Goldar & Misra, 2001). This study includes both iterative bid approaches to WTP and open ended elicitation of WTP to provide or account for overall validity of stated WTP values. This method of soliciting WTP values in multiple formats provides validity to the observed responses.

In addition, individuals have different preferences among attribute levels and across attributes, and the amount of disagreement across individuals will vary by attribute (Johnson & Mansfield, 2008). CA also poses some problems in determining appropriate attributes to assess. A possible reason for respondents' reluctance to choose is that some of the trade-offs do not have a logical pathway between their components (Wainwright, 2003). To the extent possible attributes or characteristics of apps were identified that were mutually exclusive and representative of a number of current industry trends. Utility is a latent unobserved quantity indirectly observed by indicators of utility presented in DCEs (Lancsar, 2008) and many outputs include latent variables. As such, the survey tool was designed to increase observable relative attributes and observable variables only in the context of the hypothesis.

Within this study additional sources of bias include unfamiliarity with the intricacies of the Meaningful Use program and potential disagreement on identified attributes of mHealth apps as outlined by Johnson and Mansfield (2008).

Chapter 4

PROFILE OF SURVEY RESPONDENTS

4.1 Description of Survey Tool

An internet survey was conducted as outlined in Chapter 3 with questions probing respondents WTP for mobile applications in light of potential changes to existing policy structures. Specifically questions focused on changes associated with the Meaningful Use program described in Chapter 1. The survey questions are detailed in Appendix B. Hypothetical alternatives to scenarios where policy changes were implied were presented to respondents as discrete choice experiments to respondents. Choices made in DCEs are analyzed using random utility theory discussed in Chapter 2. To restate, the overall utility (U) for individual expressed component or characteristic in question (V) and random events is:

$$U_{ij} = V_{ij} + \epsilon_{ij}$$

Utility, discussed in depth in Chapter 2, is a latent unobserved quantity observed by indicators of utility presented in DCEs (Lancsar, 2008). As such, the survey tool was designed to increase observable relative attributes and observable variables in the context of the hypothesis.

All analyses carried out using SPSS Version 21 and Excel 2010. For a full list of variables see Appendix C. As described in Chapter 3 a stratified population sample was surveyed which included individuals from Health IT professionals, nurses, and physicians. This survey was completed using an online instrument. The survey instrument was assessed for cognitive effort and approved by the Institutional Review Board. The following section details the characteristics of the respondents to the online survey tool and the variables created for data analysis. After data collection, responses were evaluated for completeness and accuracy. Responses to the WTP questions for contingent valuation and conjoint analyses are provided in chapters five and six.

4.2 Characteristics of Respondents

A total of 416 responses out of 451 were deemed appropriate for inclusion in the analysis. Individuals were excluded for failure to meet the desired survey population as outlined in Chapter 3. The following provides a summary of respondent demographics with reference tables. The average age of respondents was 48 years old ±10 years (see table 4.1). The breakdown of respondent employment demographics is as follows. 109 respondents were physicians, 134 were classified as hospital IT staff, and 236 were nursing professionals (See table 4.2). A full 317 respondents reported working in a hospital setting (See table 4.2). Of the non-hospital based respondents, 23% reported working in an office setting of various sizes (See table 4.3). Of the 317 individuals who reported working in a hospital environment, 59% reported working in an urban hospital setting with 16% working in a rural setting (See table 4.4). 46% of the respondents working in a hospital environment also reported working in a teaching hospital setting (See table 4.5). The bed size of hospitals reporting bed size is as follows (n=317). Under 100 beds 9.6%, 100-199 beds 8.4%, 200-299 beds 13%, 300-399 beds 8.9%, 400-499 beds 8.9%, and 500+ beds 27.4% (See table 4.6). With regards to income, the vast majority of respondents reported incomes over $100,000 per year (See table 4.7).

Table 4.1 Characteristics of Respondents Age

Age		
N	Valid	408
	Missing	4
Mean		48.47
Median		50.00
Mode		55
Std. Deviation		10.139
Variance		102.800

Table 4.2 Characteristics of Respondents Job Type

Job Description					
		Physician	Hospital IT	Nurse	Other
N		106	132	236	36

Table 4.3 Characteristics of Respondents Work Setting

Office Size				
		Frequency	Percent	Valid Percent
Valid	Office 1-3 providers	29	7.0	7.1
	Office 4-14 providers	27	6.6	6.6
	Office 15+ providers	36	8.7	8.8
	Hospital Based	317	76.9	77.5
	Total	409	99.3	100.0
Missing		3	.7	
Total		412	100.0	

Table 4.4 Rural or Urban Hospital Setting

Rural or Urban				
		Frequency	Percent	Valid Percent
Valid	Urban	246	59.7	77.8
	Rural	70	17.0	22.2
	Total	316	76.7	100.0

Table 4.5 Teaching or Non-Teaching Hospital

Teaching or Non-Teaching Hospital				
		Frequency	Percent	Valid Percent
Valid	Teaching Hospital	195	47.3	61.7
	Non-teaching Hospital	116	28.2	36.7
	NA/Federal Health Center/ Community Clinic	5	1.2	1.6
	Total	316	76.7	100.0

Table 4.6 Hospital Bed Size

Number of Hospital Beds				
		Frequency	Percent	Valid Percent
Valid	Under 100	40	9.7	12.6
	100 to 199	35	8.5	11.0
	200 to 299	54	13.1	17.0
	300 to 399	37	9.0	11.7
	400 to 499	37	9.0	11.7
	500+	114	27.7	36.0
	Total	317	76.9	100.0

Table 4.7 Income

Income				
		Frequency	Percent	Valid Percent
Valid	under $20,000	2	.5	.5
	20,000-49,999	7	1.7	1.7
	50,000-79,999	52	12.6	12.6
	80,000-99,999	44	10.7	10.7
	100,000+	202	49.0	49.0
	Prefer not to Disclose	105	25.5	25.5
	Total	412	100.0	100.0

Chapter 5

CONTINGENT VALUATION

The previous chapters detailed the major theoretical frameworks considered and the methodology for the observation of provider preference for certain attributes and hypothetical changes to existing policies. The purpose of this chapter is to present data analysis surrounding questions outlined in Chapter 1. This includes respondent attitudes towards potential changes associated with the Meaningful Use program. The hypothetical situation presented to respondents includes the use of mobile applications as a component of the attestation process to receive an incentive payment.

5.1 Estimates of WTP Values

To minimize bias, respondents were asked multiple questions to elicit WTP values. This included direct solicitation to state WTP at three different points in the survey tool. This variable associated with the first probing is labeled "WTP" prior to presenting various policy scenarios. Respondents were then presented information potential policy changes. Respondents were solicited a second time based on the use and inclusion of mobile applications as a component of the Meaningful Use attestation process. This term is labeled WTP_MU. Finally, at the end of the survey respondents asked to restate WTP as a result of inclusion in the Meaningful Use program. This term is labeled WTP_Final.

In general respondents reported a higher WTP for mobile applications as a result of inclusion in the Meaningful Use program. Mean WTP baseline values were approximately \$30.43 ± \$2.87 for a one time download fee (See Table 5.1)[8]. Stated WTP in light of changes to the Meaningful Use program –WTP_MU– increased values to \$34.75 ±\$3.22. A final probing of WTP –WTP_Final– yielded a result of \$38.23 ± \$3.06 (See Table 5.1). As outlined in Figure 5.1, the probability of a higher WTP value deceases as price decreases. This is to say that the higher the price, the lower the number of respondents indicated a willingness to pay. After data collection descriptive statistics were calculated for the populations various WTP values presented below in Table 5.1.

The first step in an estimate of the demand curve was generated using stated WTP values. The probability of stated WTP values was found to follow a normal demand distribution (Figure 5.1). After review in excel the logarithmic values of WTP values was created using the SPSS transform function. This distribution of probabilities is displayed in Figure 5.1 and Figure 5.2. A full list of variables and labels can be found in Appendix C.

---

[8] ± is the Standard Error of the Mean $s = \mathrm{sqrt}\left[\Sigma\left(xi - x\right)2 / \left(n - 1\right)\right]$

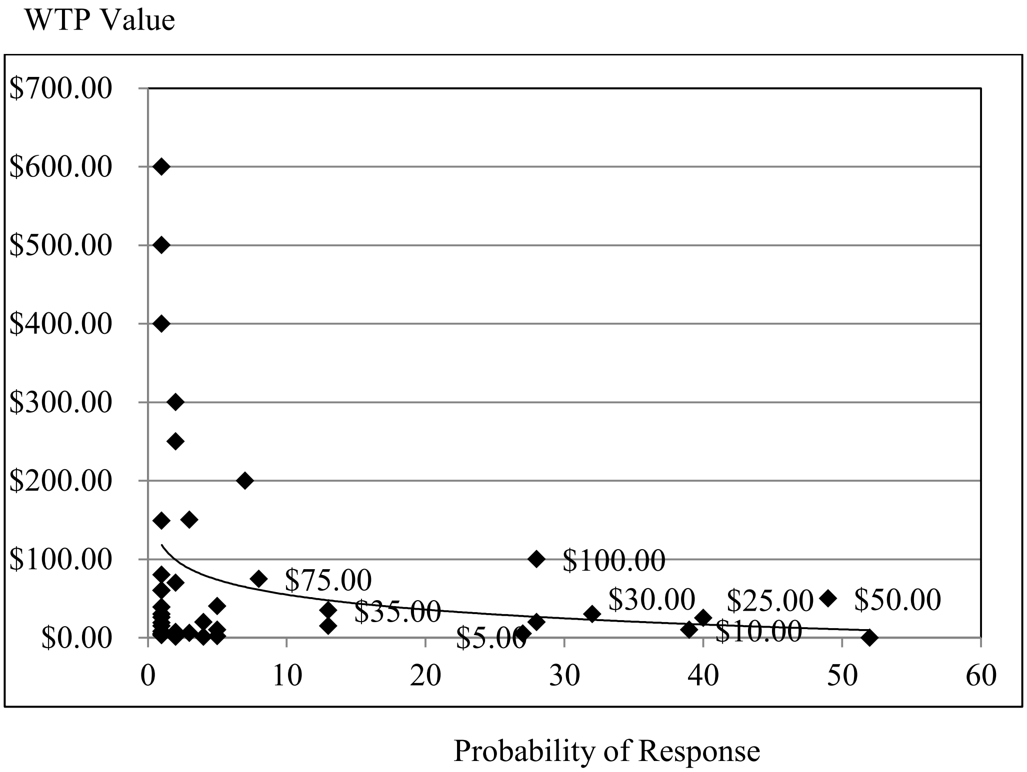

Figure 5.1 Demand Curve Estimate

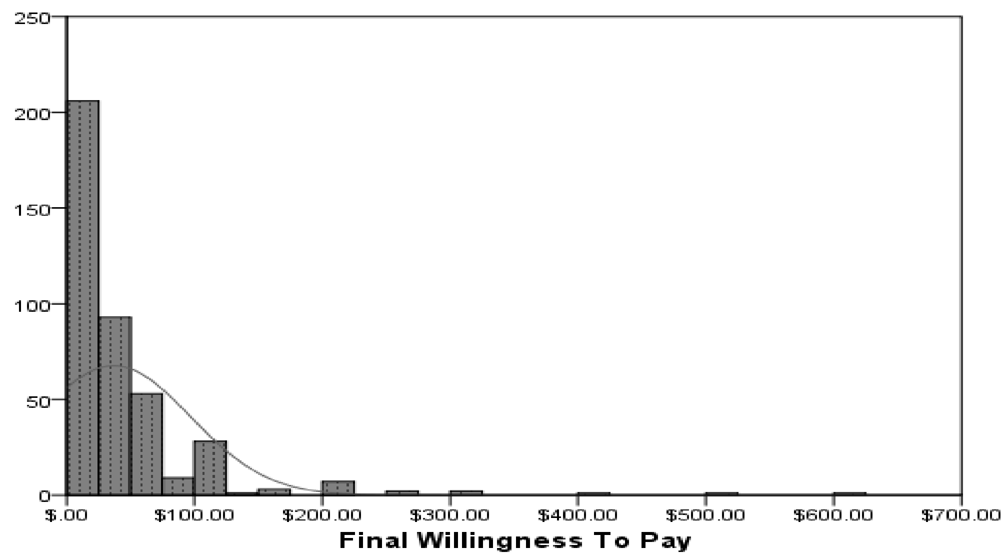

Figure 5.2 Distribution of Final Willingness to Pay

Table 5.1 WTP Descriptive Statistics

Statistics				
		WTP	WTPMU	FWTP
N	Valid	407	407	393
	Missing	0	0	14
Mean		$30.43	$34.02	$38.20
Std. Error of Mean		$2.87	$3.22	$3.06
Median		$10.00	$10.00	$25.00
Mode		$10.00	$0.00	$0.00
Std. Deviation		$58.06	$65.01	$60.70
Variance		3371.332	4226.572	3684.969
Range		$600.00	$600.00	$600.00
a. Multiple modes exist. The smallest value is shown				

Visual review of Figure 5.1 confirms a normal distribution of WTP values. As stated WTP values decrease, there is an increase in the probability of observing higher willingness to pay at lower dollar values for a user to purchase a mobile application. This is referred to as marginal utility (Fuguitt, 1999). One of the challenges of extending utility to the purchase of mobile applications is that quantities of apps are challenging to define. There is no additional utility gained from multiple purchases of the same app. This is to say that each app is unique with respect to its characteristics and that a consumer is likely to not purchase additional quantities of the same good. Thus Figure 5.1 represents an aggregation of individual demand schedules. It is important to note the previous discussion regarding the relationship between Utility Theory and Rogers Diffusion of Innovation Theory. Respondents are most likely to adopt or purchase at lower price points for a mobile application.

5.2 Validity and Consistency of WTP Estimates

The three different willingness to pay variables—outlined in Section 5.1.1—were assessed for consistency in their estimates across the different times of their measurement within the survey. Consistency between the three open ended elicitations of individuals' willingness to pay was evaluated with three bi-variate regression analyses. The general hypothesis tested was:

H1: The order of open ended solicitations of willingness to pay values presented to respondents was not consistent across the three estimates measured at different time points in the survey. Subsequent WTP elicitations are expected to be higher than previous especially with the introduction of meaningful use.

Assessment of this hypothesis was accomplished by analyzing the following three regressions (See Table 5.2, 5.3, and 5.4 for analysis):

$$WTPMU = \beta_0 + \beta_1 FWTP$$

$$WTPMU = \beta_0 + \beta_1 WTP$$

$$WTP = \beta_0 + \beta_1 FWTP$$

Table 5.2 WTPMU vs. FWTP Variables

Model Summary				
Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.689[a]	.474	.473	$47.19217
a. Predictors: (Constant), FWTP				

ANOVA[a]						
Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	814012.550	1	814012.550	365.503	.000[b]
	Residual	901975.698	405	2227.100		
	Total	1715988.247	406			
a. Dependent Variable: WTPMU						
b. Predictors: (Constant), FWTP						

Coefficients[a]						
Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	6.515	2.746		2.372	.018
	FWTP	.746	.039	.689	19.118	.000
a. Dependent Variable: WTPMU						

Table 5.3 WTPMU vs. WTP Variables

Model Summary				
Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.444[a]	.197	.195	$58.32418
a. Predictors: (Constant), WTP				

ANOVA[a]						
Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	338295.931	1	338295.931	99.449	.000[b]
	Residual	1377692.316	405	3401.709		
	Total	1715988.247	406			
a. Dependent Variable: WTPMU						
b. Predictors: (Constant), WTP						

Coefficients[a]						
Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	18.893	3.265		5.787	.000
	WTP	.497	.050	.444	9.972	.000
a. Dependent Variable: WTPMU						

Table 5.4 WTP vs. FWTP Variables

Model Summary				
Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.593[a]	.352	.350	$46.79825
a. Predictors: (Constant), FWTP				

ANOVA[a]						
Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	481779.915	1	481779.915	219.983	.000[b]
	Residual	886980.992	405	2190.077		
	Total	1368760.908	406			
a. Dependent Variable: WTP						
b. Predictors: (Constant), FWTP						

Coefficients[a]						
Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	9.271	2.723		3.404	.001
	FWTP	.574	.039	.593	14.832	.000
a. Dependent Variable: WTP						

All three regression equations had high statistically significant F values, and for all three equations, the coefficient of their single independent variables were also highly statistically significant at $p<0.00$ level. The coefficient estimates support the above-stated general hypothesis.

1.) WTPMU = f(FWTP): On average, for every dollar that was bid for the final WTP (FWTP) estimate , the corresponding value for WTPMU was 75 cents ($0.75). That is, individuals' bids for FWTP were higher than the bids given for willing to pay after Meaningful Use was introduced.
2.) WTPMU = f(WTP): On average, for every dollar that was bid for the initial willingness to pay, the corresponding value for the wiliness to pay after the introduction of Meaningful Use (WTPMU) was 50 cents ($0.497). Put differently, individuals' bids for inclusion of apps within the Meaningful Use program (variable: WTPMU) were higher than the bids given for the initial willing to pay (WTP) estimate.
3.) WTP = f(FWTP): On average, for every dollar that was bid for the final WTP (FWTP) estimate , the corresponding value for the initial willingness to pay by individuals' was 57 cents ($0.57). In other words, individuals' bids for FWTP were higher than the bids given for initial their willing to pay.

5.3 Assessment of Willingness to Pay Across Social and Economic Status

Respondents provided demographic information as outlined and presented in Chapter 4. This section assesses the impact of social and economic status on willingness to pay for smartphone applications and the impact support or awareness of the Meaningful Use program imparts on respondents (See Table 5.5 and Table 5.6). General hypothesis testing includes:

H1: Social or economic status impacts willingness to pay for healthcare related smartphone applications.

Table 5.5 Variables Associated with Social and Economic Demographics

Social and Economic Status	
Age	Continuous; Numerical
Income	Categorical; Recoded into dummy variables; Reference category is $90,000 and below; $90,000 and above, and no answer or unwilling to provide or did not provide; Labeled as INCOMDNP
Professional Demographic	Categorical; Recoded into dummy variables; Reference category is Hospital IT professionals

Table 5.6 OLS Regression of WTP and Social and Economic Status Variables

Model Summary				
Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.398[a]	.159	.144	1.447335051627459
a. Predictors: (Constant), Nurse, Age, IncomeDNP, YNWTPMOREDUMMY, SupportDummy, IncomeNinety, Physician				

ANOVA[a]						
Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	154.479	7	22.068	10.535	.000[b]
	Residual	819.058	391	2.095		
	Total	973.537	398			
a. Dependent Variable: lnFWTP						
b. Predictors: (Constant), Nurse, Age, IncomeDNP, YNWTPMOREDUMMY, SupportDummy, IncomeNinety, Physician						

Coefficients[a]						
Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	1.587	.436		3.644	.000
	Age	.006	.007	.042	.886	.376
	YNWTPMOREDUMMY	1.127	.161	.344	6.995	.000
	SupportDummy	.342	.165	.102	2.074	.039
	IncomeDNP	-.167	.180	-.047	-.929	.353
	IncomeNinety	-.244	.186	-.069	-1.313	.190
	Physician	-.068	.230	-.019	-.297	.767
	Nurse	-.096	.199	-.030	-.482	.630
a. Dependent Variable: lnFWTP						

Excluded Variables[a]						
Model		Beta In	t	Sig.	Partial Correlation	Collinearity Statistics
						Tolerance
1	IncomeOne	.[b]	.	.	.	.000
a. Dependent Variable: lnFWTP						
b. Predictors in the Model: (Constant), Nurse, Age, IncomeDNP, YNWTPMOREDUMMY, SupportDummy, IncomeNinety, Physician						

Analysis of the regression shows that of the variables included in the model, only support for the inclusion and a willingness to pay more- labeled as YNWTPMOREDUMMY - are statistically significant at $p<0.05$. Income, age, and job type are not significant predictors of changes in attitude towards a willingness to pay for mobile applications.

5.4 Analysis of Potential Changes to the Meaningful Use Program

Respondents were asked questions regarding the Meaningful Use program (See Appendix B). Questions ranged from awareness of the Meaningful Use program (Table 5.7) to the support for the direct inclusion of the use of mobile phones in the Meaningful Use program (Table 5.8). As previously discussed, respondents were asked if they were willing to pay more for a mobile app as a result of inclusion in the Meaningful Use program (Table 5.9). Overall, respondents were aware of the Meaningful Use program—92% of respondents were aware of the program—and support the inclusion of mobile apps 67% would support the inclusion of apps into the program. Additionally, providers are willing to pay an additional sum for an app should the Meaningful Use program be modified to include the use of mobile apps in the program's in future stages. To assess the relationship between two categorical variables, a Pearson chi-square test was used. Awareness for the Meaningful Use program, support for the inclusion of mobile applications and willingness to pay more for an application if included in the program at $p < 0.05$ (Table 5.10 and 5.11). Furthermore, the age group 30-39 represents a statistically significant demographic $p<0.016$ when assessing age groups against willingness to pay at the onset of the study (Table 5.12). Overall the willingness to pay variables collected in the survey tool are related, however, the Pearson chi-square test is a poor predictor of power or strength of relationship (Table 5.10). This relationship is further assessed in section 5.5.

Table 5.7 Awareness of the Meaningful Use Program

Aware of the Meaningful Use Program			
		Frequency	Percent
Valid	Yes	383	92.1
	No	31	7.5
	Total	414	99.5

Table 5.8 Support Inclusion of Apps Within the Meaningful Use Program

Support Inclusion of Apps			
		Frequency	Percent
Valid	Yes	282	67.8
	No	59	14.2
	No opinion	32	7.7
	No knowledge of the impact	41	9.9
	Total	414	99.5

Table 5.9 Willing to Pay More For a Mobile App if Included in the Meaningful Use Program

Willing To Pay More if Included in Program				
		Frequency	Percent	Valid Percent
Valid	Yes	263	63.8	64.9
	No	142	34.5	35.1
	Total	405	98.3	100.0

Table 5.10 Chi-Square Test Cross Tabulation Aware Meaningful Use and Support Inclusion

Chi-Square Tests			
	Value	df	Asymp. Sig. (2-sided)
Pearson Chi-Square	40.319[a]	3	.000
Likelihood Ratio	30.126	3	.000
Linear-by-Linear Association	32.157	1	.000
N of Valid Cases	409		
a. 3 cells (37.5%) have expected count less than 5. The minimum expected count is 2.43.			

Symmetric Measures					
		Value	Asymp. Std. Error[a]	Approx. T[b]	Approx. Sig.
Interval by Interval	Pearson's R	.281	.066	5.901	.000[c]
Ordinal by Ordinal	Spearman Correlation	.227	.060	4.706	.000[c]
N of Valid Cases		409			
a. Not assuming the null hypothesis.					
b. Using the asymptotic standard error assuming the null hypothesis.					
c. Based on normal approximation.					

Table 5.11 Chi-Square Test Cross Tabulation Support Inclusion and Willing to Pay More

Chi-Square Tests

	Value	df	Asymp. Sig. (2-sided)
Pearson Chi-Square	32.807[a]	3	.000
Likelihood Ratio	32.142	3	.000
Linear-by-Linear Association	22.611	1	.000
N of Valid Cases	403		

a. 0 cells (0.0%) have expected count less than 5. The minimum expected count is 10.92.

Symmetric Measures

		Value	Asymp. Std. Error[a]	Approx. T[b]	Approx. Sig.
Interval by Interval	Pearson's R	.237	.050	4.889	.000[c]
Ordinal by Ordinal	Spearman Correlation	.274	.050	5.703	.000[c]
N of Valid Cases		403			

a. Not assuming the null hypothesis.

b. Using the asymptotic standard error assuming the null hypothesis.

c. Based on normal approximation.

Table 5.12 Linear Regression of Age, Income, Job Type, and Willingness to Pay More

Variables Entered/Removed[a]

Model	Variables Entered	Variables Removed
1	Income, Age6069, HospitalIT, Age70, YNWTPMOREDUMMY, Age3039, Age2029, Physician, Age4049, Nurse[b]	.

a. Dependent Variable: lnWTP

b. Tolerance = .000 limits reached.

Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.287[a]	.082	.059	1.428022274807323

a. Predictors: (Constant), Income, Age6069, HospitalIT, Age70, YNWTPMOREDUMMY, Age3039, Age2029, Physician, Age4049, Nurse

ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	71.174	10	7.117	3.490	.000[b]
	Residual	793.267	389	2.039		
	Total	864.441	399			

a. Dependent Variable: lnWTP

b. Predictors: (Constant), Income, Age6069, HospitalIT, Age70, YNWTPMOREDUMMY, Age3039, Age2029, Physician, Age4049, Nurse

Coefficients[a]						
Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	2.235	.442		5.057	.000
	Age2029	.198	.376	.027	.525	.600
	Age3039	-.507	.210	-.129	-2.419	.016
	Age4049	-.180	.183	-.052	-.986	.325
	Age6069	-.196	.240	-.042	-.814	.416
	Age70	.057	1.027	.003	.056	.956
	YNWTPMOREDUMMY	.662	.152	.215	4.362	.000
	Physician	.478	.264	.140	1.814	.070
	HospitalIT	-.168	.186	-.054	-.907	.365
	Nurse	.256	.235	.086	1.092	.275
	Income	-.065	.072	-.046	-.904	.367

a. Dependent Variable: lnWTP

Excluded Variables[a]						
Model		Beta In	t	Sig.	Partial Correlation	Collinearity Statistics
						Tolerance
1	Age5059	.[b]	.	.	.	.000

a. Dependent Variable: lnWTP

b. Predictors in the Model: (Constant), Income, Age6069, HospitalIT, Age70, YNWTPMOREDUMMY, Age3039, Age2029, Physician, Age4049, Nurse

Ordinary least square regression analysis was used to estimate quantitative functional relationships between (a) support for the inclusion of apps in the meaningful use program as the dependent variable and (b) attitudes toward behavior. These included variables like history of previous payment and a willingness to pay more should apps become a component of the Meaningful Use program. For statistical testing, the level of significance was set at p=0.05 for the general sample population answering all relevant questions in this analysis n=402.

Regression analysis reveals that the models ANOVA is statistically significant with an R^2 of .136. For certain variables in the survey, statistical significance was achieved (Table 5.13). Awareness of the Meaningful Use Program exerted an influence on support for the inclusion on apps in the program p=0.00. Previous history of payment for mobile applications also contributed to support for inclusion of mobile applications in the program p= 0.04. A willingness to pay more should the program include mobile applications was also significant p=0.00. The total number of applications downloaded was not a significant predictor of support for the inclusion of applications in the meaningful use program p=0.321.

Table 5.13 Ordinary Least Squares- Relationship of Policy and Impact on Purchase Behaviors

Model Summary				
Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.369[a]	.136	.128	.931
a. Predictors: (Constant), AwareMU, AppsDL, YNWTPMore, PaidYN				

ANOVA[a]						
Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	54.380	4	13.595	15.698	.000[b]
	Residual	344.692	398	.866		
	Total	399.072	402			
a. Dependent Variable: SupportInclusion						
b. Predictors: (Constant), AwareMU, AppsDL, YNWTPMore, PaidYN						

Coefficients[a]						
Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	-.305	.282		-1.080	.281
	YNWTPMore	.433	.098	.208	4.430	.000
	PaidYN	.207	.102	.102	2.031	.043
	AppsDL	-.008	.008	-.050	-.993	.321
	AwareMU	.952	.177	.251	5.377	.000
a. Dependent Variable: SupportInclusion						

Table 5.14 One Sample Statistics

One-Sample Statistics				
	N	Mean	Std. Deviation	Std. Error Mean
AwareMU	409	1.08	.265	.013
SupportInclusion	409	1.60	1.000	.049
YNWTPMore	404	1.35	.478	.024
PaidYN	410	1.59	.493	.024

One-Sample Test						
	Test Value = 0					
	t	df	Sig. (2-tailed)	Mean Difference	95% Confidence Interval of the Difference	
					Lower	Upper
AwareMU	82.102	408	.000	1.076	1.05	1.10
SupportInclusion	32.386	408	.000	1.601	1.50	1.70
YNWTPMore	56.826	403	.000	1.351	1.30	1.40
PaidYN	65.237	409	.000	1.588	1.54	1.64

5.5 Iterative Bid Scenarios versus Open-ended Solicitation

There is a limited literature base specific to the use of online surveys to conduct WTP studies, both for conjoint and contingent valuation studies. The vast majority of CV studies are conducted by paper, mail, or interviews to obtain observations. In fact, this study may be the first such study to explore the use of online survey tools and deployment of iterative bid methods and open ended direct methods for elicitation of WTP values. Within the survey tool, respondents were asked multiple formats of WTP questions. The iterative bid structure is outlined in

Figure 5.2 and Figure 5.3. Respondents also stated WTP values given the hypothetical scenario that mobile apps are included in the Meaningful Use program. These values are clustered and additional research is needed to assess the impact of improvements in ascertaining WTP measurements associated the inclusion of these types of observations.

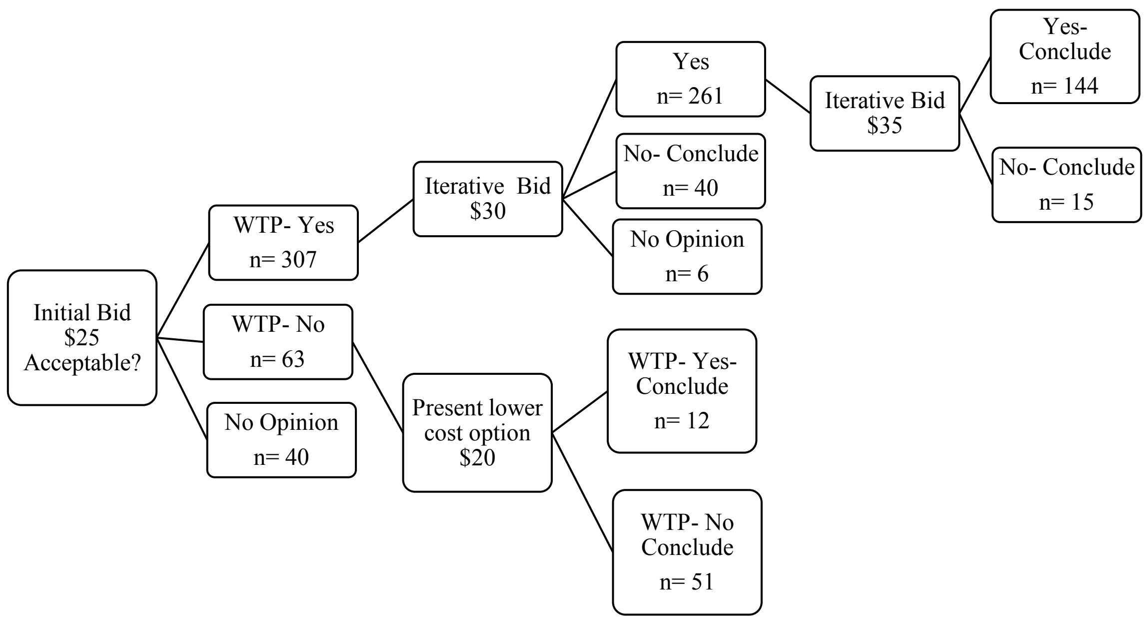

Figure 5.3 Iterative Bid Question: Apps Included In MU Program

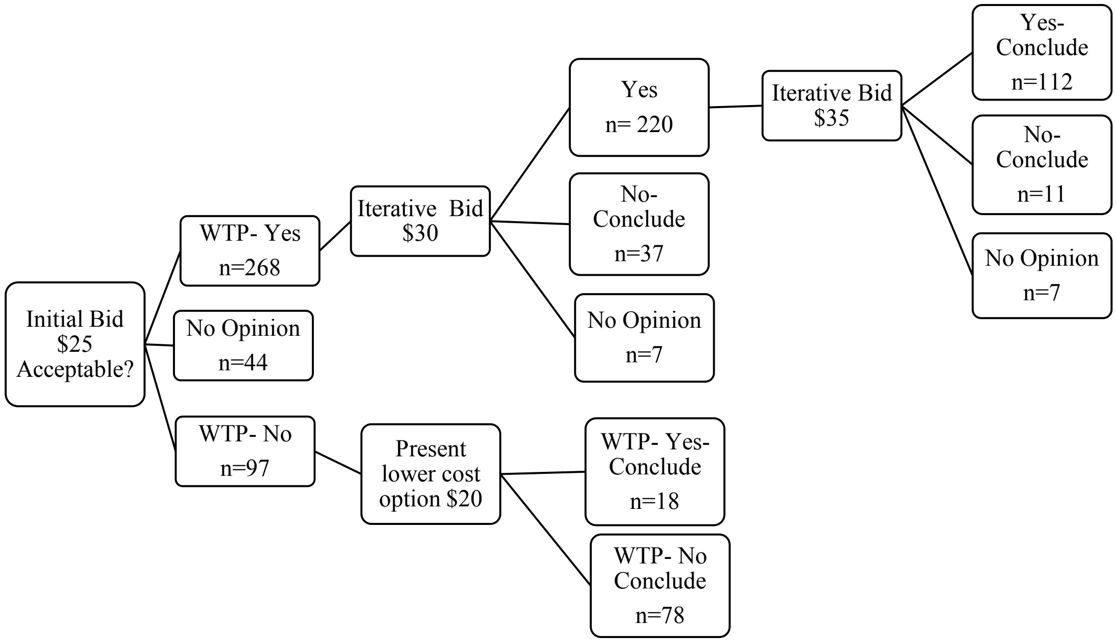

Figure 5.4 Iterative Bid Question: Apps ***Not*** Included in MU Program

5.6 Types of Apps Used On a Regular Basis in Healthcare Settings

Respondents were asked to report the types of apps used on a regular basis in the survey tool. The type of apps used on a regular basis is important for the formulation of any future policy surrounding mHealth technologies. A large number of industry reports provide varying details on physician and provider usage of apps in healthcare settings but estimates exceed 65% of providers owning a smartphone (Nguyen, 2012). Very few standards or techniques exist for data collection and categorization or classification of mHealth apps. In order to generalize findings, broad and well known categories of existing healthcare apps were presented to respondents. These attributes were similar to other industry reports to increase the generalization of findings. Two leading types of applications used by providers on a daily basis include medical reference calculators and EHR interface apps. Overall, 36% of respondents report using a mobile application to interact with an EHR on a daily basis. Other types of applications used by respondents include 28% of respondents reported the use of a medical reference calculator on a daily basis.

In addition to probing the overall type of applications used on a daily basis, respondents were queried as to whether or not there is a high demand to utilize certain types of applications in absence of a current offering by the organization. 25% of respondents reported that access to an EHR interface app is desirable. Furthermore, 17% of respondents reported a desire to use an app that enabled clinical communication or collaboration among colleagues. As highlighted earlier in the discussion, a number of policies prevent this from occurring due to the impacts of HIPAA and statements by the JCAHO. It is also important to note that a number of technology solutions exist which, if properly incentivized, could provide this type of engagement between healthcare providers.

Table 5.15 Use of Medical Calculators

Medical Calculator			
		Frequency	Percent
Valid	Multiple use per day	61	14.8
	Daily	57	13.9
	Once a week	46	11.2
	Multiple use per week	39	9.5
	Once a Month	35	8.5
	Multiple times a Month	15	3.6
	Less than once a month	54	13.1
	Never	70	17.0
	Currently unavailable to me in a suitable form but high desire to use	25	6.1
	Total	402	97.8
Missing	System	9	2.2
Total		411	100.0

Table 5.16 Use of EHR Interfaces on Mobile Devices

EHR Interface			
		Frequency	Percent
Valid	Multiple use per day	103	25.1
	Daily	52	12.7
	Once a week	9	2.2
	Multiple use per week	16	3.9
	Once a Month	11	2.7
	Multiple times a Month	8	1.9
	Less than once a month	14	3.4
	Never	83	20.2
	Currently unavailable to me in a suitable form but high desire to use	107	26.0
	Total	403	98.1
Missing	System	8	1.9
Total		411	100.0

Table 5.17 Use of Prenatal of Infant Specific Apps

Prenatal or Infant Specific Apps			
		Frequency	Percent
Valid	Multiple use per day	15	3.6
	Daily	17	4.1
	Once a week	11	2.7
	Multiple use per week	13	3.2
	Once a Month	17	4.1
	Multiple times a Month	8	1.9
	Less than once a month	37	9.0
	Never	238	57.9
	Currently unavailable to me in a suitable form but high desire to use	47	11.4
	Total	403	98.1
Missing	System	8	1.9
Total		411	100.0

Table 5.18 Use of Chronic Disease Management Apps

Chronic Disease Management Apps			
		Frequency	Percent
Valid	Multiple use per day	39	9.5
	Daily	48	11.7
	Once a week	34	8.3
	Multiple use per week	37	9.0
	Once a Month	21	5.1
	Multiple times a Month	18	4.4
	Less than once a month	37	9.0
	Never	117	28.5
	Currently unavailable to me in a suitable form but high desire to use	50	12.2
	Total	401	97.6
Missing	System	10	2.4
Total		411	100.0

Table 5.19 Use of Emergency Information Access Apps

Emergency Information Access			
		Frequency	Percent
Valid	Multiple use per day	41	10.0
	Daily	37	9.0
	Once a week	36	8.8
	Multiple use per week	28	6.8
	Once a Month	43	10.5
	Multiple times a Month	19	4.6
	Less than once a month	49	11.9
	Never	108	26.3
	Currently unavailable to me in a suitable form but high desire to use	40	9.7
	Total	401	97.6
Missing	System	10	2.4
Total		411	100.0

Table 5.20 Use of Collaboration and Consultation Apps

Collaboration and Consultation			
		Frequency	Percent
Valid	Multiple use per day	33	8.0
	Daily	43	10.5
	Once a week	28	6.8
	Multiple use per week	26	6.3
	Once a Month	26	6.3
	Multiple times a Month	16	3.9
	Less than once a month	24	5.8
	Never	136	33.1
	Currently unavailable to me in a suitable form but high desire to use	70	17.0
	Total	402	97.8
Missing	System	9	2.2
Total		411	100.0

Table 5.21 Use of Other Apps

Other App Use			
		Frequency	Percent
Valid	Multiple use per day	67	16.3
	Daily	63	15.3
	Once a week	30	7.3
	Multiple use per week	32	7.8
	Once a Month	24	5.8
	Multiple times a Month	21	5.1
	Less than once a month	23	5.6
	Never	87	21.2
	Currently unavailable to me in a suitable form but high desire to use	44	10.7
	Total	391	95.1
Missing	System	20	4.9
Total		411	100.0

Table 5.22 Use of Medical Reference Apps

Medical Reference			
		Frequency	Percent
Valid	Multiple use per day	104	25.3
	Daily	72	17.5
	Once a week	49	11.9
	Multiple use per week	44	10.7
	Once a Month	19	4.6
	Multiple times a Month	25	6.1
	Less than once a month	28	6.8
	Never	42	10.2
	Currently unavailable to me in a suitable form but high desire to use	21	5.1
	Total	404	98.3
Missing	System	7	1.7
Total		411	100.0

Overall respondents indicate using medical reference apps and EHR interface apps on a regular basis (Table 5.14 and Table 5.16. Further examination of Table 5.16 indicates and interesting dichotomy. A full 26% of respondents indicate that this type of application is unavailable but that there is a high desire to use this type of app in a clinical setting. This finding further bolsters the argument that potential changes to the Meaningful Use program should be considered as the ONC enters deliberations on option criteria for 2015 certification period.

5.7 Significance of Findings

Overall findings suggest that healthcare providers support the inclusion of mobile apps as a component of Meaningful Use. As noted earlier, federal agencies have solicited comments regarding scaled approaches to criteria for successful attestation to the Meaningful Use program. The use of the mobile device in healthcare represents one potential avenue for ONC to purse as the Meaningful Use program enters later stages around the year 2016/17[9]. Overall, providers and hospital IT staff support the inclusion of mobile apps as a component of the meaningful use program. Providers and staff are willing to pay more for a mobile app should it be included in the framework of the program. Respondents indicated a substantial dollar value for payment associated with the purchase of a mobile application, regardless of the current approach to inclusion in the Meaningful Use program. Previous payment for mobile applications in healthcare and awareness of the meaningful use program are significant

---

[9] At the current time of writing --c.2013-- the points in time when certain stages of the Meaningful Use Program occur are moving at the discretion of the ONC. Stage 2 would occur in 2016 with Stage 3 commencing in 2017.

predictors of support for support of the inclusion of mobile apps in the Meaningful Use program. Furthermore, a high number of providers indicated a previous history of payment which influences support for the program. As adoption of EHRs increases, criticisms of the Meaningful Use program turn to inclusion of additional forms of technology (Sarkar & Bates, 2014). Consideration regarding the modification of the ERH certification program overseen by CCHIT or influenced by the ONC's federal advisory committee's should be considered in light of these findings.

Chapter 6

CONJOINT ANALYSIS

The previous chapter provided data analysis using the contingent valuation method. The focus of the previous chapter is on providing background regarding the demographics of study respondents and the perceptions of the population on hypothetical changes to existing policy. The previous chapter provides information relevant to changes in consumer demand as a result of hypothetical changes in policy structure. Respondents were presented the option for the inclusion of mobile technologies as a component of attestation for the Meaningful Use program. In this chapter I focus on the attributes of mHealth apps which exert an influence to stimulate willingness to pay using the method conjoint analysis.

One of the greatest challenges facing health services researchers concerned with technology assessment is the identification and valuation of benefits from healthcare interventions (Ryan, 1999). Cost benefit assessment in health economics has been dominated by an assumption that only health outcomes are important (Ryan, 1999). This chapter provides information which policymakers can use to optimize project design to advance the adoption of mHealth technologies in the U.S. healthcare system and improve the Meaningful Use program.

6.1 Attributes Presented to Respondents

A SPDCE survey was conducted among N=451 providers and health IT professionals to assess attributes important to the provider and hospital IT community to download a smartphone application. A total of 416 responses were deemed appropriate for inclusion in the analysis. Respondents were excluded for failure to meet criteria outlined in Chapter 3. A list of mutually exclusive attributes was created based on widely accepted industry terminology. Table 6.1 presents ten attributes identified and used to create a statistical model reflecting the impact of attributes on overall willingness to pay.

Attributes of healthcare related apps were presented to survey respondents as a Likert scale rating system. The Likert scale ranged from one to seven where one was very likely to influence purchase and seven not influential to purchase. Attributes presented to respondents included the following generalized characteristics of current healthcare apps present within the marketplace (See Table 6.1).

Table 6.1 Likert Scale Containing Attributes of Apps Presented to Respondents

App supports care: App fails to support care 1-7
App is interoperable with other systems: App is not interoperable with other systems 1-7
Policy supports use: Policy fails to support use 1-7
App is private and secure: App is not private and secure
Friend or Colleague Approves or recommends: Friend or Colleague Disapproves or fails to recommend 1-7
App is certified or approved by a governing body: App is not certified or approved by a governing body 1-7
App decreases steps to communicate: App increases steps to communicate 1-7
App increases productivity: App decreases productivity 1-7
App is simple and easy to operate: App is not simple and easy to operate 1-7
App is grounded in clinical best practice: App is not grounded in best practice 1-7

6.1.1 Types of Phones Providers Use

Respondents were asked to provide the type of device used on a daily basis within a healthcare setting (Table 6.2). 64.9% of providers utilized an Apple iPhone using iOS on a daily basis. The second most popular platform was the Android operating system. These findings are in line with other widely reported industry figures (Franko, 2012; Karl, Frederick, Braekkan & Payne, 2012).

Table 6.2 Types of Mobile Devices Used in Healthcare Settings

Phone Type			
		Frequency	Percent
Devices	Apple iPhone	270	64.9
	Android Phone	103	24.8
	Microsoft Phone	4	1.0
	Blackberry	16	3.8
	Other	4	1.0
	No Smartphone	19	4.6
	Total	416	100.0

6.1.2 Number of Applications Downloaded

Respondents were asked to provide the total number of healthcare applications downloaded directly related to the provision of healthcare. On average, respondents had downloaded 5 applications of the provision of care (See Table 6.3).

Table 6.3 Number of Apps Downloaded by Respondents

Statistics		
Number of Apps Downloaded		
N	Valid	416
	Missing	0
Mean		5.39
Median		3.00
Mode		0

6.1.3 Previous History of Payment for a Mobile App

Respondents were asked whether or not payment was made for an app. On average forty percent of respondents reported paying for an application. 58% of respondents reported never paying for an app for the delivery of healthcare (See Table 6.4).

Table 6.4 Previous History of Payment

Previously Paid for Healthcare App Y/N			
		Frequency	Percent
Valid	Yes	173	41.6
	No	242	58.2
	Total	415	99.8
Missing	System	1	.2
Total		416	100.0

6.2 Data Analysis

Chi-square and t tests were used to examine the differences between proportions and means. A multiple ordinary least squares (OLS) regression was created to assess factors associated with WTP for smartphone applications targeted at healthcare providers. Respondent variables included socioeconomic demographics and attributes important to consumers when downloading a healthcare related app as outlined in Table 6.5. A linear regression was estimated using the following equation:

$$
\begin{aligned}
lnWTP = \beta_{\circ} + \beta_1 AppSupp + \ \beta_1 AppInterop + \ \beta_1 Policy + \beta_1 AppPrivate \\
+ \beta_1 FriendColl + \ \beta_1 Decrease + \ \beta_1 IncreasePro + \beta_1 Simple \\
+ \ \beta_1 ClinicalBest
\end{aligned}
$$

Regression analysis included a test of interaction effects between variables (See Appendix D). Regression analysis revealed that of the attributes presented to respondents, clinical best practices and simplicity are preferential to users and results in an impact on purchasing. An additional regression adding age and income as covariates reveals that age of a respondent also impacts willingness to pay.

Table 6.5 One Sample Statistics

One-Sample Statistics				
	N	Mean	Std. Deviation	Std. Error Mean
AppSupp	401	1.72	1.195	.060
AppInterop	401	2.92	1.942	.097
Policy	401	2.65	1.762	.088
AppPrivate	402	1.98	1.521	.076
FriendColl	402	2.96	1.566	.078
AppCert	401	2.80	1.799	.090
Decrease	402	2.25	1.572	.078
IncreasePro	402	1.61	1.160	.058
Simple	402	1.53	1.128	.056
ClinicalBest	402	1.48	1.085	.054

One-Sample Test						
	Test Value = 0					
	T	df	Sig. (2-tailed)	Mean Difference	95% Confidence Interval of the Difference	
					Lower	Upper
AppSupp	28.794	400	.000	1.718	1.60	1.84
AppInterop	30.055	400	.000	2.915	2.72	3.11
Policy	30.104	400	.000	2.648	2.48	2.82
AppPrivate	26.100	401	.000	1.980	1.83	2.13
FriendColl	37.901	401	.000	2.960	2.81	3.11
AppCert	31.179	400	.000	2.800	2.62	2.98
Decrease	28.679	401	.000	2.249	2.09	2.40
IncreasePro	27.865	401	.000	1.612	1.50	1.73
Simple	27.241	401	.000	1.532	1.42	1.64
ClinicalBest	27.254	401	.000	1.475	1.37	1.58

Table 6.6 OLS Regression Impact of Attributes on Payment

Tests of Between-Subjects Effects					
Dependent Variable: lnWTP					
Source	Type III Sum of Squares	df	Mean Square	F	Sig.
Corrected Model	109.669[a]	58	1.891	1.245	.124
Intercept	42.437	1	42.437	27.948	.000
AppSupp	8.374	5	1.675	1.103	.359
AppInterop	8.190	6	1.365	.899	.496
Policy	3.624	6	.604	.398	.880
AppPrivate	6.223	6	1.037	.683	.663
FriendColl	16.811	6	2.802	1.845	.090
AppCert	4.965	6	.828	.545	.774
Decrease	12.365	6	2.061	1.357	.232
IncreasePro	13.508	6	2.251	1.483	.184
Simple	18.164	6	3.633	2.392	.038
ClinicalBest	25.270	6	5.054	3.328	.006
Error	461.609	304	1.518		
Total	3276.621	363			
Corrected Total	571.278	362			
a. R Squared = .192 (Adjusted R Squared = .038)					

Table 6.7 GLM Model with Age and Income Effects

Tests of Between-Subjects Effects					
Dependent Variable: lnWTP					
Source	Type III Sum of Squares	df	Mean Square	F	Sig.
Corrected Model	115.455[a]	60	1.924	1.299	.083
Intercept	9.111	1	9.111	6.152	.014
Age	11.424	1	11.424	7.714	.006
Income	2.567	1	2.567	1.733	.189
AppSupp	8.017	5	1.603	1.083	.370
AppInterop	7.410	6	1.235	.834	.544
Policy	2.201	6	.367	.248	.960
AppPrivate	6.662	6	1.110	.750	.610
FriendColl	12.135	6	2.023	1.366	.228
AppCert	3.540	6	.590	.398	.880
Decrease	14.416	6	2.403	1.622	.141
IncreasePro	12.351	6	2.058	1.390	.218
Simple	19.606	5	3.921	2.648	.023
ClinicalBest	17.806	5	3.561	2.405	.037
Error	441.317	298	1.481		
Total	3251.088	359			
Corrected Total	556.772	358			
a. R Squared = .207 (Adjusted R Squared = .048)					

6.3 Significance of Findings

As stated earlier, the valuation of improvements in non-health outcomes associated with the use of technology adoption is challenging. However, many of the factors identified as non-health outcomes and process attributes associated with the use of technology are capable of being directly influenced by policymakers (Ryan, 1999). Conjoint Analysis is one technique that can assist policymakers with optimal program design and potential incentives for the use of technology in healthcare. As highlighted by Rogers, incentives play an important role in diffusion of technology. In theory the use of WTP assessments allows individuals to value certain aspects of care that are described to them; i.e., health outcomes, non-health outcomes, and process attributes (Ryan, 1999).

With respect to diffusion of technology among healthcare providers, the adoption of smartphones among providers is quite high. A relatively small number of respondents reported not owning a smartphone. Furthermore, via conjoint analysis, attributes important to policymakers can be identified without consideration or association with changes in direct health outcomes. Overall, providers continue to request evidence that supports the direct use of mobile technology to initiate or trial mobile applications without regard to inclusion of these types of technology in the Meaningful Use program. With respect to current discussion on assessing mHealth, a critical mass is needed to increase adoption. A rising critical mass of users will make policy decisions much more palatable to decision makers. As noted earlier by Ryan, additional assessment of the role of technology is needed to understand the impacts of adoption of technology into the U.S. system of health care. In addition to the assessment of technology, researchers and practitioners continue to evaluate the role of evidence based medicine in the adoption of new forms of medical practices

(Ioannidis, 2013). Ioannidis further notes with regards to the impact of specific journals on the adoption of new practices "*Some of the messaging may require inclusion in guidelines, given the widespread attention that these documents gain, particularly when issued by authoritative individuals or groups, and their capacity to affect clinical practice*" (Ioannidis, 2013). While beyond the scope of this body of work, policymakers should remain mindful of the role that critical assessment plays with regards to the adoption of both digital technology and innovative forms of medical care. The Meaningful Use program, while not a medical journal, represents a major authoritative source for the adoption of technology.

Respondents also indicate that simplicity is a major attribute for consideration when making a one-time purchase of a mobile application. While the analysis was constrained to one-time download fees, the finding that simplicity is a contributing attribute to influence purchase should resonate with policymakers. The usability of desktop EHR systems is commonly cited as a barrier to successful adoption of EHR technology by providers (Holden, 2011). Furthermore, key criteria which identifies metrics related to "adoption" of EHRs continues to evolve (Blavin, 2010). A major industry metric related to adoption includes the Healthcare Information Management Systems Society EMR Adoption Model or EMRAM℠ score. Consideration for the expansion of these models to include the use of mobile technologies is warranted given the high number of respondents indicating the use of a mobile EHR interface on a regular basis.

As noted in Chapter 5, section 5.6, the daily use of EHRs on mobile devices is split between those with access and those that desire access. Given that ONC is currently entering a planning stage for the later stages of the Meaningful Use program, consideration should be given on how to increase use of mobile devices and address usability issues.

Chapter 7

CONCLUSIONS

7.1 Overview

This study focused on issues surrounding policymaking in the mHealth space and attributes important to individuals to adopt mHealth technologies into the clinical setting. Chapter 2 provided discourse on the relationship between major methodological frameworks presented for consideration as an avenue to create understanding in the space. Chapter 2 created a linkage between Rogers Diffusion of Innovation Theory and Utility Theory. As discussed earlier, attributes associated with Rogers DOI theory include the use of incentives to increase adoption. In relationship to Utility Theory, these incentives can be probed within the framework of assessing willingness to pay with a further refinement and delineation of attributes outlined by Rogers. From a policy making perspective this relationship is useful for the formulation and assessment of potential policy changes.

As Chapters 5 and 6 highlight, consumer demand for solutions and incentives associated with existing policies remain high for mHealth technologies in the healthcare space. The ubiquity of the mobile device—currently 322 million wireless subscribers exist in the US representing 102% of the total population (CTIA.org, 2011)—will ultimately allow mHealth to gain traction and acceptance as the policy discussion on mHealth emerges and evolves. It is also important to note that many of the scenarios presented in this study are contingent on policy change. As discussed below, many of the policy scenarios presented here require additional investigation as their relationship is contingent on the adoption of other technologies and refinement of existing policy frameworks. This includes potential revisions to the Meaningful Use program and other areas of healthcare which impact the adoption of technology.

Policy change takes time, but the rapid rise of mHealth as a viable solution presents major challenges to policymakers. It is important to note that diffusion of EHRs occurred at a much slower pace when compared to other industry sectors originally identified by the Office of Technology Assessment (OTA) circa 1994. The need for the use of technology in healthcare was highlighted in 1994 by the now defunct OTA, but no substantial policy initiatives occurred until 2009. With respect to the mobile device and the current path of technology adoption in healthcare, one could expect movement on the issue sometime in 2028 given the current policy trajectory. Over time, providers and advocacy organizations will continue to advance positions that further incent the direct use of mobile technologies in healthcare. Below I discuss some of the additional small scale efforts to realign policies or update existing policy frameworks to incorporate mobile technologies further into the healthcare delivery system.

7.2 Diffusion of Innovation

It is important to note that individuals have different preferences associated with the decision to adopt mHealth technologies. The amount of disagreement across individuals will vary by attribute (Johnson & Mansfield, 2008) which can impact the design and deployment of the methodologies described in this study. The methods outlined in previous chapters explore the advantages and present the disadvantages of employing DOI theory to assess consumer or provider preference for mHealth apps and technologies. Understanding the attributes important to adopters of technology can improve policymaking and adoption of technology. As noted earlier, many of the elements of Rogers Diffusion of Innovation theory apply to mHealth.

With regards to individual attributes that providers find desirable, integration with an electronic health record is highest ranked use of mobile applications within a healthcare setting. This desire is amplified by an increased willingness to pay more for smartphone applications if included in the Meaningful Use program.

Other attributes which rank high in daily use include medical reference calculators. These reference apps are widely available but require contextual information regarding the patient not contained within the app.

Finally, respondents indicated a high desire to use clinical collaboration types of apps. While not directly probed in this study, future research could evaluate existing means of communication against mobile apps which provide additional information. It is important to note the challenges associated with HIPAA defined earlier and are discussed further in subsequent sections. This information was presented to highlight the incongruence between somewhat divergent interpretations and solutions for the market which directly impact the adoption of mobile technology in care settings. While privacy and security was not a statistically significant predictor of WTP in this study, it is a major concern among policymakers and providers. Overall, individual attributes of mobile applications most likely to impact purchase include information regarding the clinical best practice for use and ease of operation by end users.

With respect to Rogers's discussion on organizational decision making the Meaningful Use program represents a major authoritarian vehicle for the adoption of technology. Many of the attributes discussed in this study reflect a combination of individual and organizational approaches to the adoption of technology. While difficult to directly parse the weight each lends to a decision to adopt, the framework provides a context for critical assessment. Overall, individuals have adopted mHealth applications for the purpose of the provision of health care on a small scale as witnessed by the number of applications downloaded for the provision of healthcare. However, authoritarian organizations play a role in establishing criteria for certification of products which impacts consumer preference for these products. This includes building upon work by Green (2009) and Lopez (2008) which further assesses optimization of mobile technology for the dissemination of research findings which assist or accelerate adoption in the field of healthcare.

Given the uptick in pending legislation at federal and state level, many policymakers have recognized the importance of extending the benefits of mHealth into the general population. This provides additional avenues for further research and investigation with respect to how policymakers become aware of innovations in healthcare settings. Further areas of research include the comparison of the technology adoption model with Rogers DOI theory.

7.3 Policy Considerations

As noted earlier, a number of critiques have focused on potential future changes to the Meaningful Use program (Furukawa, 2011; Sarkar & Bates, 2014). A number of existing policy structures which could be further refined to accommodate advancements in mHealth technology. These include changes to existing standards and modification of the criteria used to attest to receive an incentive payment. The Meaningful Use program is entering a period of deliberation for Stage 3 of the program. There is a possibility that voluntary criteria could accompany the formal criteria for the certification of an EHR by CCHIT accompanied by a notice of request for information in 2014. This request is presently occurring. In light of the findings, consideration should be given to making access to an EHR via a mobile device a voluntary requirement. ONC will explore creating a more flexible certification process in 2015 which includes voluntary certification criteria which includes the integration of feedback from stakeholders in the healthcare system. As discussed below, conjoint and contingent studies could improve this policy making process. Furthermore, these types of studies could assist in understanding consumer behavior towards mHealth applications as the field grows in maturity and scope. As noted earlier, a major challenge present is isolating the benefits associated with the use of ancillary technology in the provision of preventive healthcare.

7.4 Additional Areas of Inquiry- Addressing Privacy and Security Issues

As outlined earlier in chapter one, a number of policy considerations provided conflicting information regarding advancement of technology in healthcare. A large number of providers surveyed respond that information is often communicated via text message (Terry, 2008). This often results in violations of HIPAA and if a device is lost patient information could be compromised. This is referred to as a data breech. HIPAA breeches as a result of mobile devices are increasing (Ponemon, 2009; Morgan, 2012). The fines associated with data breeches often reach into the millions of dollars (Thomas, 2007). With respect to JCAHO guidelines outlined earlier regarding computer order entry and the Meaningful Use program goals of increased technology adoption, changes could be instituted to require commercial secure messaging platforms as a component of the attestation program or a requirement for EHR platform certification. This would increase compliance resulting in an economic impact. Cost Benefit Analysis could be deployed to assess the impacts of this type of policy change. While not formally assessed in this work, future research could examine the prevalence of the use of secure methods of communication or lack thereof to guide policymaking.

7.5 Additional Areas of Inquiry- Organizational Response to mHealth

In addition to the formal analysis above, an informal analysis of free text response areas within the survey instrument yield interesting points for discussion. Heretofore, the discussion presented is largely focused on macro policy trends at the federal level. A number of respondents indicated challenges with immediate or direct organizational policy surrounding the use of mobile devices in the workplace setting. This presents two major areas for future analysis. The first are of investigation surrounds an organizational attitudes towards the use of mobile devices at the point of care. The second area of inquiry, if an organization permits the use of mobile devices, involves to process by which a mobile app is deemed appropriate for use or reimbursement. While not statistically analyzed or empirically assessed, a few key points are presented within the context of potential areas for future investigation.

One of the major areas for further investigation outlined in the free text response area is the seeming divergent view of organizational attitudes regarding the use of mobile devices at the point of care. Some respondents indicated that organizations are beginning to provide monetary reimbursement for providers who download smartphone applications for the delivery of healthcare. This trend presents a number of interesting questions for future research. First, the price point at which organizations should reimburse mobile applications is of note. This work provides insight into potential monetary limits which organizations could use to establish reimbursement programs. Second, the development of organizational frameworks for the oversight and administration of such scenarios is also of note. For example, the review or oversight necessary within an organizations formal policy or review process to deem an app necessary or appropriate prior to offering apps to a healthcare provider(s). As noted earlier attempts to provide a commercially available certification program exist. The challenge is reaching a critical mass of applications which are certified and users with interest in adoption.   Finally, as ONC advances the Meaningful Use program and looks for feedback from stakeholders, conjoint and contingent valuation methodologies can serve as useful methods for understating attributes important to the overall adoption of technology. This includes examining areas of technology which extend beyond the scope of the EHR and into other areas of "ancillary technology" which improves the delivery of care.

7.6 Limitations of this Study

A number of limitations are present in this study. First there is limited ability to extrapolate findings broadly beyond the scope of inclusion of mobile applications within the meaningful use program. This includes the notion that access is available to providers in a number of different form factors and business models outside the one time down load fee assessed in this work. Furthermore the adoption of mHealth technologies is not specifically dependent on inclusion in the Meaningful Use program. However, the findings do present an interesting question surrounding the potential to further adoption by including certain types of mobile applications within the Meaningful Use program. Second, important variables or terms exist outside the models presented to respondents. As a number of respondents indicated in free text areas that the use of personal mobile devices is not permitted on hospital wards. This finding brings to light the possibility to explore the use of unified communications solutions -commonly observed in the form of Voice of Internet Protocol devices- as potential candidates for inclusion in the program. To state more simply, future research could further investigate alternative technologies which could impact the Meaningful Use program. Many of these issues are highlighted in the previous sections on organizational response and issues surrounding privacy and security.

7.7 Concluding Remarks

This work further strengthens the relationship between Rogers Diffusion of Innovation Theory and Utility Theory. Incentives play an important role in adoption of new technologies and exert an influence on the individual's willingness to pay. As policymakers continue to examine the use of incentives to advance technological innovation in healthcare, an understanding of the underlying attributes of a good or service provides an important foundation to facilitate adoption. Cost Benefit Analysis and Rogers Diffusion of Innovation provide methods and theoretical frameworks for this type of assessment. Incentives play an important role in the adoption of new technologies and exert an influence on the individual's willingness to pay. Authoritarian organizations play an important role to increase adoption in the absence of evidence for providers to individually adopt. Consideration and flexibility of the Meaningful Use program to include other forms outside an EHR should be considered by policymakers. Furthermore, consideration should be given to the expansion of the Meaningful Use program to include mobile applications which may not establish access to an EHR but rather expand the program to facilitate the increased collaboration between providers and other avenues to manage chronic diseases. Much of the information presented in this study is for consideration during the upcoming rule making process progresses overseen by ONC and enforced by current and future entities responsible for the certification of EHR technology.

REFERENCES

Adler-Milstein, J., Kvedar, J., & Bates, D. W. (2014). Telehealth among US hospitals: Several factors, including state reimbursement and licensure policies, influence adoption. *Health Affairs (project Hope), 33*(2), 207-215.

Atienza, A. A., & Patrick, K. (2011). Mobile health: The killer app for cyberinfrastructure and consumer health. *American Journal of Preventive Medicine, 40*(5), 151-153.

Barnett, J., Vasileiou, K., Djemil, F., Brooks, L., & Young, T. (2011). Understanding innovators' experiences of barriers and facilitators in implementation and diffusion of healthcare service innovations: a qualitative study. *Bmc Health Services Research, 11*, 342-354.

Bech, M., Kjaer, T., & Lauridsen, J. (2011). Does the number of choice sets matter? Results from a web survey applying a discrete choice experiment. *Health Economics, 20*(3), 273-286.

Benjamini, Y., & Gafni, A. (1986). The diffusion of medical technology: A "prisoner's dilemma" trap?. *Socio-economic Planning Sciences, 20*(2), 69-74.

Blavin, F. E., Buntin, M. J., & Friedman, C. P. (2010). Alternative measures of electronic health record adoption among hospitals. *The American Journal of Managed Care, 16*(12), 293-301.

Boardman, A. E. (1996). *Cost-benefit analysis: Concepts and practice*. Upper Saddle River, NJ: Prentice Hall.

Bonnichsen, O. (2011). Elicitation of ostomy pouch preferences. *The Patient: Patient-Centered Outcomes Research, 4*(3), 163-175.

Broch, S. W., & Vedel, S. E. (2012). Using Choice Experiments to Investigate the Policy Relevance of Heterogeneity in Farmer Agri-Environmental Contract Preferences. *Environmental and Resource Economics, 51*(4), 561-581.

Carroll, F. E., Al-Janabi, H., Flynn, T., & Montgomery, A. A. (2013). Women and their partners' preferences for Down's syndrome screening tests: A discrete choice experiment. *Prenatal Diagnosis, 33*(5), 449-456.

Charles, D., King, J., Patel, V., & Furukawa, M. F. (2013). ONC Data Brief No. 9 Adoption of Electronic Health Record Systems among US Non-federal Acute Care Hospitals: 2008-2012.

Choi, Y. B., Krause, J. S., Seo, H., Capitan, K. E., & Chung, K. (2006). Wireless technology—Advances and challenges for telemedicine—Standardization through information management and technical applications. *IEEE Communications Magazine, 44*(4), 41-45.

Cocosila, M. (2008). *Judging the value of mobile healthcare solutions for improving outpatient adherence*. Healthcare Information Systems Press.

Cunningham, C., Deal, K., Rimas, H., Campbell, H., Russell, A., Henderson, J., Matheson, A., & Melnick, B. (2010). Using conjoint analysis to model the preferences of different patient segments for attributes of patient-centered care. *The Patient: Patient-Centered Outcomes Research, 1*(4), 317-330.

Desai, D., Wu, G., & Zaman, M. H. (2011). Tackling HIV through robust diagnostics in the developing world: current status and future opportunities. *Lab on a Chip, 11*(2), 194-211.

Diener, A., O'Brien, B., & Gafni, A. (1998). Health care contingent valuation studies: A review and classification of the literature. *Health Economics, 7*(4), 313-326.

Dobkin, B. H., & Dorsch, A. (2011). The promise of mHealth: Daily activity monitoring and outcome assessments by wearable sensors. *Neurorehabilitation and Neural Repair, 25*(9), 788-798.

Dolan, P. (2013). Many dissatisfied physicians to switch EHR vendors. *American Medical News*. Retrieved from http://www.amednews.com/article/20130312/business/130319987/8/

Drummond, M. (2010). *Methods for the economic evaluation of health care programmes*. Oxford: Oxford University Press.

Epocrates (2013). Mobile trends report. Retrieved from http://www.epocrates.com/oldsite/statistics/2013%20Epocrates%20Mobile%20Trends%20Report_FINAL.pdf

Farr, A. C., & Ames, N. (2008). Using diffusion of innovation theory to encourage the development of a children's health collaborative: A formative evaluation. *Journal of Health Communication, 13*(4), 375-388.

Food and Drug Administration (2013). *Keeping up with progress in mobile medical apps*. FDA Consumer Updates. Retrieved from http://www.fda.gov/ForConsumers/ConsumerUpdates/ucm368634.htm

Ford, F. N., Rainer, R. K., Cegielski, C. G., Weigel, F. K., & Hazen, B. T. (2012). Use of diffusion of innovations theory in medical informatics research. *International Journal of Healthcare Information Systems and Informatics, 7*(3), 44-56

Franko, O. I., & Tirrell, T. F. (2012). Smartphone app use among medical providers in ACGME training programs. *Journal of Medical Systems, 36*(5), 3135-3139.

Fuguitt, D., & Wilcox, S. J. (1999). *Cost-benefit analysis for public sector decision makers*. Westport, Connecticut: Quorum.

Furukawa, M. F., & Poon, E. (2011). Meaningful use of health information technology: Evidence suggests benefits and challenges lie ahead. *The American Journal of Managed Care, 17*, 76-77.

Geibert, R. C. (2006). Using diffusion of innovation concepts to enhance implementation of an electronic health record to support evidence-based practice. *Nursing Administration Quarterly, 30*(3), 203-210.

Goldar, B., & Misra, S. (2001). Valuation of environmental goods: Correcting for bias in contingent valuation studies based on willingness-to-accept. *American Journal of Agricultural Economics, 83*(1), 150-156.

Green, L. W., Ottoson, J. M., García, C., & Hiatt, R. A. (2009). Diffusion theory and knowledge dissemination, utilization, and integration in public health. *Annual Review of Public Health, 30*, 151-174.

Griffin, R. (2011). Willingness to pay. *Training Journal Ely-,* 2010 (5), 27-30.

Günther, O. H., & König, H.-H. (2006). Decision makers' and scientists' opinion about contingent valuation and choice experiments for measuring willingness to pay in health care: Results from a survey in Germany. *International Journal of Technology Assessment in Health Care, 22*(3), 351-361.

Hahm, M. I., Park, E. C., Choi, K. S., Lee, H. Y., Park, J. H., & Park, S. (2011). Inequalities in adoption of cancer screening from a diffusion of innovation perspective: Identification of late adopters. *Cancer Epidemiology, 35*(1), 90-96.

Handel, M. J. (2011). mHealth (Mobile Health)—Using apps for health and wellness. *Explore: the Journal of Science and Healing, 7*(4), 256-261.

Hensher, D. A., Stopher, P. R., & Louviere, J. J. (2001). An exploratory analysis of the effect of numbers of choice sets in designed choice experiments: an airline choice application. *Journal of Air Transport Management, 7*(6), 373-379.

Herigon, J. (2011). Why industry surveys on physician adoption of smart phones could be overestimating reality. Retrieved from http://www.imedicalapps.com/2011/01/survey-physician-adoption-smart-phone-reality/

Hillestad, R., Bigelow, J., Bower, A., Girosi, F., Meili, R., Scoville, R., & Taylor, R. (2005). Can electronic medical record systems transform health care? Potential health benefits, savings, and costs. *Health Affairs, 24*(5), 1103-1117.

Hilz, L. M. (2000). The informatics nurse specialist as change agent. Application of innovation-diffusion theory. *Computers in Nursing, 18*(6), 279-281.

HIMSS Analytics (2011). HIMSS Mobile Technology Survey. Retrieved from http://www.himss.org/ResourceLibrary/ContentTabsDetail.aspx?ItemNumber=28585

Holden, R. J. (2011). What stands in the way of technology-mediated patient safety improvements? A study of facilitators and barriers to physicians' use of electronic health records. *Journal of Patient Safety, 7*(4), 193-203.

Howe, C. W., Lee, B.-J., & Bennett, L. L. (1994). Design and analysis of contingent valuation surveys using the nested tobit model. *The Review of Economics and Statistics, 76*(2), 385-389.

Ioannidis, J. P. A. (2013). How many contemporary medical practices are worse than doing nothing or doing less?. *Mayo Clinic Proceedings, 88*(8), 779-781.

Jacson, S. (2011). Joint Commission: Doc texting unacceptable for clinical care. Retrieved from http://www.fiercemobilehealthcare.com/story/joint-commission-doc-texting-unacceptable-clinical-care/2011-11-18

Jamoom, E., & Bercovitz A,. (2011). Physician adoption of electronic health record systems. *National Center for Health Statistics Data Brief* 98.

Johnson, F., & Mansfield, C. (2010). Survey-design and analytical strategies for better healthcare stated-choice studies. *The Patient: Patient-Centered Outcomes Research, 1*(4), 299-307.

Karasz, H. N., Eiden, A., & Bogan, S. (2013). Text messaging to communicate with public health audiences: How the HIPAA security rule affects practice. *American Journal of Public Health*, *103*(4), 617-622.

Karl, F. B. P., Heather, W., & Kim, W. (2012). Smartphone and medical related app use among medical students and junior doctors in the United Kingdom (UK): A regional survey. *Bmc Medical Informatics and Decision Making, 12*(1), 121-132.

Kotz, D., Avancha, S., & Baxi, A., 1st ACM Workshop on Security and Privacy in Medical and Home-Care Systems, SPIMACS '09, Co-located with the 16th ACM Computer and Communications Security Conference, CCS'09. (December 01, 2009). A privacy framework for mobile health and home-care systems. *Proceedings of the Acm Conference on Computer and Communications Security,* 1-12.

Lancsar, E., & Louviere, J. (2008). Conducting discrete choice experiments to inform healthcare decision making: A user's guide. *Pharmacoeconomics, 26*(8), 661-677.

Larkin, H. (2011). mHealth: Hospitals & health networks. *Journal of the American Hospital Association 85*(4), 22-26.

López-Nicolás, C., Molina-Castillo, F. J., & Bouwman, H. (2008). An assessment of advanced mobile services acceptance: Contributions from TAM and diffusion theory models. *Information & Management*, *45*(6), 359-364.

Lund, S., Hemed, M., Nielsen, B. B., Said, A., Said, K., Makungu, M. H., & Rasch, V. (2012). Mobile phones as a health communication tool to improve skilled attendance at delivery in Zanzibar: A cluster-randomised controlled trial. *Bjog: an International Journal of Obstetrics & Gynaecology, 119*(10), 1256-1264.

Martin, T. (2012). Assessing mHealth: Opportunities and barriers to patient engagement. *Journal of Health Care for the Poor and Underserved 23*(3), 935-941.

McIntosh, E. (2010). *Applied methods of cost-benefit analysis in health care*. Oxford: Oxford University Press.

Mele, N. L. (2008). Conjoint analysis: using a market-based research model for healthcare decision making. *Nursing Research, 57*(3), 220-224.

Mickan, S., Tilson, J. K., Atherton, H., Roberts, N. W., & Heneghan, C. (2013). Evidence of effectiveness of health care professionals using handheld computers: A scoping review of systematic reviews. *Journal of Medical Internet research*, *15*(10), e212.

Morgan Sa, A. N. H. (2012). Mobile healthcare. *Frontiers of Health Services Management, 29*(2), 3-10.

Nguyen, T.-A. (2012). The FCC's road to mHealth adoption. Retrieved from http://hcpolicymatters.com/the-fcc-s-road-to-mhealth-adoption/

Nilsen, W., Kumar, S., Shar, A., Varoquiers, C., Wiley, T., Riley, W. T., Pavel, M., & Atienza, A. A. (2012). Advancing the science of mHealth. *Journal of Health Communication, 17*, 5-10.

Norris, A. C., Stockdale, R. S., & Sharma, S. (2009). A strategic approach to m-health. *Health Informatics Journal*, *15*(3), 244-253.

O'Neill, L., Talbert, J., & Klepack, W. (2009). Physician characteristics associated with early adoption of electronic medical records in smaller group practices. *International Journal of Healthcare Information Systems and Informatics, 4*(2), 69-80.

Pankratz, M., Hallfors, D., & Cho, H. (2002). Measuring perceptions of innovation adoption: the diffusion of a federal drug prevention policy. *Health Education Research, 17*(3), 315-326.

Ponemon says data breach costs rising. (2009). *Computer Fraud & Security, 2009, 2*, 20.

Promberger, M., Dolan, P., & Marteau, T. M. (2012). "Pay them if it works": Discrete choice experiments on the acceptability of financial incentives to change health related behaviour. *Social Science & Medicine*, *75*(12), 2509-2514.

Ratcliffe, J. (2000). The use of conjoint analysis to elicit willingness-to-pay values. *International Journal of Technology Assessment in Health Care*, *16*(1), 270-290.

Raths, D. (2012). The path ahead: Taking the next steps toward meaningful use. *Healthcare Informatics: The Business Magazine for Information and Communication Systems*, *29*(1), 8-10.

Rogers, E. M. (2003). *Diffusion of innovations*. New York, Free Press.

Ryan, M. (1999). A role for conjoint analysis in technology assessment in health care?. *International Journal of Technology Assessment in Health Care, 15*(3), 443-457.

Ryan, M. (1999). Using conjoint analysis to take account of patient preferences and go beyond health outcomes: an application to in vitro fertilisation. *Social Science & Medicine, 48*(4), 535-546.

Ryan, M., & Farrar, S. (2000). Using conjoint analysis to elicit preferences for health care. *Bmj (clinical Research Ed.), 320*(7248), 1530-1533.

Ryan, M., Bate, A., Eastmond, C. J., & Ludbrook, A. (2001). Use of discrete choice experiments to elicit preferences. *Quality in Health Care: Qhc, 10*, 55-60.

Ryan, M., & Gerard, K. (2003). Using discrete choice experiments to value health care programmes: current practice and future research reflections. *Applied Health Economics and Health Policy, 2*(1), 55-64.

Ryan, M. (2004). Discrete choice experiments in health care: NICE should consider using them for patient centred evaluations of technologies. *Bmj: British Medical Journal, 328*(7436), 360-361.

Miguel, F. S., Ryan, M., & McIntosh, E. (2000). Applying conjoint analysis in economic evaluations: an application to menorrhagia. *Applied Economics, 32*(7), 823-833.

Sarkar, U., & Bates, D. W. (2014). Care partners and online patient portals. *The Journal of the American Medical Association*. *311*(4), 357-358.

Siegal, G. (2012). Jump-starting telemedicine. *Ear, Nose and Throat Journal, 91*(7), 266-269.

Steblea, I., Steblea, J., & Pokela, J. (2009). Healthcare's best-kept secret: use of conjoint analysis in healthcare marketing research. *Marketing Health Services 29*(4), 1-10.

Stockwell, M. S., Kharbanda, E. O., Martinez, R. A., Vargas, C. Y., Vawdrey, D. K., & Camargo, S. (2012). Effect of a text messaging intervention on influenza vaccination in an urban, low-income pediatric and adolescent population: A randomized controlled trial. *The Journal of the American Medical Association, 307*(16), 1702-1708.

Szolovits, P. (2011). Possibilities for Healthcare Computing. *Journal of Computer Science and Technology*, *26*(4), 625-631.

Terry, M. (2008). Text messaging in healthcare: the elephant knocking at the door. *Telemedicine Journal and E-Health : The Official Journal of the American Telemedicine Association, 14*(6), 520-524.

Thomas, G. M. T. I. T., & Botha, R. A. P. D. (2007). Secure mobile device use in healthcare guidance from HIPAA and ISO17799. *Information Systems Management, 24*(4), 333-342.

United States Department of Health and Human Services. (2010). HealthCare.gov Retrieved from http://purl.fdlp.gov/GPO/gpo906.

United States Congress (1994). Office of Technology Assessment. Identifying health technologies that work: searching for evidence. *Washington DC (US Government Printing Office)*.

Viney, R., Lancsar, E., & Louviere, J. (2002). Discrete choice experiments to measure consumer preferences for health and healthcare. *Expert Review of Pharmacoeconomics & Outcomes Research, 2*(4), 319-326.

Wainwright, D. M. (2003). More 'con' than 'joint': Problems with the application of conjoint analysis to participatory healthcare decision making. *Critical Public Health, 13*(4), 373-380.

Ford, F. N., Rainer, R. K., Cegielski, C. G., Weigel, F. K., & Hazen, B. T. (2012). Use of diffusion of innovations theory in medical informatics research. *International Journal of Healthcare Information Systems and Informatics (ijhisi), 7*(3), 44-56.

Whitty, J. A., Rundle-Thiele, S. R., & Scuffham, P. A. (2012). Insights from triangulation of two purchase choice elicitation methods to predict social decision making in healthcare. *Applied Health Economics and Health Policy, 10*(2), 113-26.

Willis, G. B. (2005). *Cognitive interviewing: A tool for improving questionnaire design*. Thousand Oaks, California: Sage Publications.

Wiseman, V. (2004). Aggregating public preferences for healthcare: putting theory into practice. *Applied Health Economics and Health Policy, 3*(3), 171-179.

Appendix A

GLOSSARY OF TERMS

(ARRA) American Recovery and Reinvestment Act

(BLS) U.S. Bureau of Labor Statistics

(CA) Conjoint Analysis

(CBA) Cost Benefit Analysis

(CCHIT) Certification Commission for Health Information Technology

(CIO) Chief Information Officer

(CMS) Centers for Medicare & Medicaid Services

(CPOE) Computerized Physician Order Entry

(CV/M) Contingent Valuation/Method

(DCE) Discrete Choice Experiment

(DOI) Diffusion of Innovation

(EHR) electronic health records

(FCC) Federal Communications Commission

(FDA) Food and Drug Administration

(HHS) Health and Human Services

(HIPAA) Health Insurance Protection and Accountability Act

(HIT) Health Information Technology

(HITECH) Health Information Technology for Economic and Clinical Health

(JCAHO) Joint Commission for the Accreditation of Hospital Organizations

(ONC) Office of the National Coordinator for Health Information Technology

(OTA) Office of Technology Assessment

(PHI) Protected Health Information

(QUALY) Quality-Adjusted Life Year

(SMS) Simple Message Service

(WTA) Willingness to Accept

(WTP) Willingness to Pay

Appendix B

SURVEY INSTRUMENT

Q1 We are conducting a study of how nurses, physicians, and hospital IT staff feel about the price of smart phone applications. If you continue, you will be asked to complete a brief survey about your use of, and perceptions about, smart phone applications. In addition, you will also be asked some questions about yourself. The survey will take approximately 5 to 10 minutes to complete. Participation is completely voluntary. Participants can choose not to answer any question and terminate the survey. Your answers will be anonymous. The results may be published in a scholarly journal or industry research publication. If you have any questions about this study, feel free to contact Thomas Martin trm@udel.edu or (412) 992-1285. (Use the Arrow Below to Advance)

Q2 Please provide your age.

Q3 Please describe your role in healthcare. (Multiple answers are allowed if a respondent continues to see patients in addition to other IT related responsibilities.)

- ❑ Physician (1)
- ❑ Hospital IT (Executive, Staff, or Manager) (2)
- ❑ Nurse or Clinical Staff (3)
- ❑ Other (4)

Q4 What is the primary type of smart phone platform do you use on a daily basis?

- ❍ Apple iPhone (1)
- ❍ Android Phone (2)
- ❍ Microsoft Phone (3)
- ❍ Blackberry (4)
- ❍ Other (5)
- ❍ No Smartphone (6)

Q5 Please indicate the type of healthcare setting you operate in.

- ❍ Office 1-3 providers (1)
- ❍ Office 4-14 providers (2)
- ❍ Office 15+ providers (3)
- ❍ Hospital Based (4)
- ❍ Other (Clinic, Federal Health Center, etc.) (5)

Q6 If other please describe your type of healthcare setting?

Q7 If other please describe your role?

Q8 Is your hospital rural or urban?

- ❍ Urban (1)
- ❍ Rural (2)

Q9 Is your hospital a teaching or non-teaching hospital?

- ❍ Teaching Hospital (1)
- ❍ Non-teaching Hospital (2)
- ❍ NA/Federal Health Center/ Community Clinic (3)

Q10 Please provide the number of licensed hospital beds in your organization?

- Under 100 (1)
- 100 to 199 (2)
- 200 to 299 (3)
- 300 to 399 (5)
- 400 to 499 (6)
- 500+ (7)

Q11 How many healthcare applications or "apps" have you downloaded to your smart phone for the provision of patient care?

Q12 Have you paid for a mobile healthcare app, clinical or non-clinical? (This includes medical reference apps and pharmaceutical calculators. Do not consider apps that require an additional licensing fee to operate or are free to download).

- Yes (1)
- No (2)

Q13 If no, are there any reasons why have you not paid for an app?

Q14 When purchasing healthcare smart phone applications, rate the following major attributes that would influence downloading the app and using on a regular basis? (Where 1 is very influential and 7 is not influential. Do not consider apps that are free, or that require an additional licensing fee to enable operation.)

	1 (1)	2 (2)	3 (3)	4 (4)	5 (5)	6 (6)	7 (7)
1 App supports care:7 App fails to support care (1)	❍	❍	❍	❍	❍	❍	❍
1 App is interoperable with other systems:7 App is not interoperable with other systems (2)	❍	❍	❍	❍	❍	❍	❍
1 Policy supports use:7 Policy fails to support use (3)	❍	❍	❍	❍	❍	❍	❍
1 App is private and secure:7 App is not private and secure (4)	❍	❍	❍	❍	❍	❍	❍
1 Friend or Colleague Approves or recommends:7 Friend or	❍	❍	❍	❍	❍	❍	❍

Colleague Disapproves or fails to recommend (5)							
1 App is certified or approved by a governing body:7 App is not certified or approved by a governing body (6)	❍	❍	❍	❍	❍	❍	❍
1 App decreases steps to communicate:7 App increases steps to communicate (7)	❍	❍	❍	❍	❍	❍	❍
1 App increases productivity:7 App decreases productivity (8)	❍	❍	❍	❍	❍	❍	❍
1 App is simple and easy to operate:7 App is not simple and easy to	❍	❍	❍	❍	❍	❍	❍

operate (9)							
1 App is grounded in clinical best practice:7 App is not grounded in best practice (10)	❍	❍	❍	❍	❍	❍	❍

Q15 What is the maximum price you are willing to pay to purchase and download a healthcare related app? (Please answer in $USD amounts. What is the maximum price you are willing to pay for an app? Please answer in numerical format only 0.00.)

Q16 Meaningful Use is a form of incentive payments from CMS to adopt and demonstrate functionality of electronic health records (EHRs).

Q17 Are you aware of the Meaningful Use program?
- ❍ Yes (1)
- ❍ No (2)

Q18 Would you support the inclusion of mobile apps as a component of Meaningful Use as an integral approach to the provision of care?
- ❍ Yes (1)
- ❍ No (2)
- ❍ No opinion (3)
- ❍ No knowledge of the impact (4)

Q19 If providers were reimbursed for the use of apps in care delivery, as a component of Meaningful Use, would you pay more for an app?
- ❍ Yes (1)
- ❍ No (2)

Q20 How much more, based on your original payment statement, would you be willing to pay for an app, if it was a Meaningful Use objective? (In $USD. For example, if you responded $5 in your original statement and would now be willing to pay $7, answer $7. Please answer in numerical format only 0.00)

Q21 The following series of questions will change depending on your answer. Please note the change in price depending on your answer. In addition, the scenario's include the following two situations. The first scenario presents an increase in Meaningful Use payment's. The second scenario only presents the inclusion of apps in Meaningful Use requirements/objectives.

Q22 Incentive: Use of apps included in Meaningful Use objectives with an increase in Meaningful Use payments or other payment. OPTION I: If Meaningful Use requirements allowed providers and hospitals to include mobile apps within a later stage of Meaningful Use, and if you had already decided to download an application, how acceptable is this alternative? (The app would need to align with the goals of achieving Meaningful Use, for example exchange of patient information.) App Price: $25

- ❍ Definitely Not Acceptable (0)
- ❍ Somewhat Acceptable (1)
- ❍ Definitely Acceptable (2)
- ❍ No Opinion (3)

Q23 Incentive: Use of apps included in Meaningful Use objectives with an increase in Meaningful Use payments or other payment. OPTION I: If Meaningful Use requirements allowed providers and hospitals to include mobile apps within a later stage of Meaningful Use, and if you had already decided to download an application, how acceptable is this alternative? (The app would need to align with the goals of achieving Meaningful Use, for example exchange of patient information.) App Price: $20

- ❍ Definitely Not Acceptable (0)
- ❍ Somewhat Acceptable (1)
- ❍ Definitely Acceptable (2)
- ❍ No Opinion (3)

Q24 Incentive: Use of apps included in Meaningful Use objectives with an increase in Meaningful Use payments or other payment. OPTION I: If Meaningful Use requirements allowed providers and hospitals to include mobile apps within a later stage of Meaningful Use, and if you had already decided to download an application, how acceptable is this alternative? (The app would need to align with the goals of achieving Meaningful Use, for example exchange of patient information.) App Price: $30

- Definitely Not Acceptable (0)
- Somewhat Acceptable (1)
- Definitely Acceptable (2)
- No Opinion (3)

Q25 Incentive: Use of apps included in Meaningful Use objective with an increase in Meaningful Use payments or other payment. OPTION I: If Meaningful Use requirements allowed providers and hospitals to include mobile apps within a later stage of Meaningful Use, and if you had already decided to download an application, how acceptable is this alternative? (The app would need to align with the goals of achieving Meaningful Use, for example exchange of patient information.) App Price: $35

- Definitely Not Acceptable (0)
- Somewhat Acceptable (1)
- Definitely Acceptable (2)
- No Opinion (3)

Q26 Note the scenario has changed. Incentive: Use of apps included in Meaningful Use objectives without payment increase. OPTION II: If Meaningful Use requirements allowed providers and hospitals to include mobile apps within a later stage of Meaningful Use, and if you had already decided to download an application, how acceptable is this alternative? (The app would need to align with the goals of achieving Meaningful Use, for example exchange of patient information.) App Price: $25

- ❍ Definitely Not Acceptable (0)
- ❍ Somewhat Acceptable (1)
- ❍ Definitely Acceptable (2)
- ❍ No Opinion (3)

Q27 Incentive: Use of apps included in Meaningful Use objectives without payment increase. OPTION II: If Meaningful Use requirements allowed providers and hospitals to include mobile apps within a later stage of Meaningful Use, and if you had already decided to download an application, how acceptable is this alternative? (The app would need to align with the goals of achieving Meaningful Use, for example exchange of patient information.) App Price: $20

- ❍ Definitely Not Acceptable (0)
- ❍ Somewhat Acceptable (1)
- ❍ Definitely Acceptable (2)
- ❍ No Opinion (3)

Q28 Incentive: Use of apps included in Meaningful Use objectives without payment increase. OPTION II: If Meaningful Use requirements allowed providers and hospitals to include mobile apps within a later stage of Meaningful Use, and if you had already decided to download an application, how acceptable is this alternative? (The app would need to align with the goals of achieving Meaningful Use, for example exchange of patient information.) App Price: $30

- ❍ Definitely Not Acceptable (0)
- ❍ Somewhat Acceptable (1)
- ❍ Definitely Acceptable (2)
- ❍ No Opinion (3)

Q29 Incentive: Use of apps included in Meaningful Use objectives without payment increase. OPTION II: If Meaningful Use requirements allowed providers and hospitals to include mobile apps within a later stage of Meaningful Use, and if you had already decided to download an application, how acceptable is this alternative? (The app would need to align with the goals of achieving Meaningful Use, for example exchange of patient information.) App Price: $35

- ❍ Definitely Not Acceptable (0)
- ❍ Somewhat Acceptable (1)
- ❍ Definitely Acceptable (2)
- ❍ No Opinion (3)

Q30 As stated in an earlier question, if an app contained all the appropriate qualities, what would be your maximum willingness to pay for a one-time fee per download with Meaningful Use incentives for clinical use? (Answer in numerical format only 0.00)

Q31 What is the frequency of use of the following types of healthcare apps?

	Multiple use per day (1)	Daily (2)	Once a week (3)	Multiple use per week (4)	Once a Month (5)	Multiple times a Month (6)	Less than once a month (7)	Never (8)	Currently unavailable to me in a suitable form but high desire to use (9)
Medical Reference Guide (1)	❍	❍	❍	❍	❍	❍	❍	❍	❍
Medical Calculator (2)	❍	❍	❍	❍	❍	❍	❍	❍	❍
EHR Interface app (3)	❍	❍	❍	❍	❍	❍	❍	❍	❍
Prenatal/Infant Care (4)	❍	❍	❍	❍	❍	❍	❍	❍	❍
Chronic Disease Management App (5)	❍	❍	❍	❍	❍	❍	❍	❍	❍
Emergency Info (6)	❍	❍	❍	❍	❍	❍	❍	❍	❍

Collaboration or Consultation App (7)	❍	❍	❍	❍	❍	❍	❍	❍	❍
Other App Use (8)	❍	❍	❍	❍	❍	❍	❍	❍	❍

Appendix C

LIST OF VARIABLES

Variable Description	Type	Variable Name
Age	Numeric	Age
Physician	Numeric	Phys
Hospital IT	Numeric	HospitalIT
Nurse	Numeric	Nurse
Other	Numeric	Other
Phone	Numeric	Phone
Office Size	Numeric	OfficeSz
Other Setting	String	OtherSetting
Other Role	String	OtherRole
Rural Urban	Numeric	RurualUrban
Teaching Non	Numeric	TeachingNon
Number of Hospital Beds	Numeric	HospitalBed
Apps Downloaded	Numeric	AppsDL
Paid for Healthcare App? YN	Numeric	PaidYN
If No Reason	Free Text	NoReason
App Supports Care	Numeric	AppSupp
App is Interoperable	Numeric	AppInterop
Policy Supports Use	Numeric	Policy
App is Private and Secure	Numeric	AppPrivate
Friend or Colleague Recommends	Numeric	FriendColl
App is Certified	Numeric	AppCert
Decrease Steps to Communicate	Numeric	Decrease
Increase Productivity	Numeric	IncreasePro
Simple to Use	Numeric	Simple
Clinical Best Practice Supports Use	Numeric	ClinicalBest
Aware of Meaningful Use	Numeric	AwareMU
Support Inclusion of Mobile Apps in Program	Numeric	SupportInclusion

Yes or No WTP More	Numeric	YNWTPMore
Incremental Iterative Bid	Numeric	IB25MUP
Incremental Iterative Bid	Numeric	IB20MUP
Incremental Iterative Bid	Numeric	IB30MUP
Incremental Iterative Bid	Numeric	IB35MUP
Incremental Iterative Bid	Numeric	IB25
Incremental Iterative Bid	Numeric	IB20
Incremental Iterative Bid	Numeric	IB30
Incremental Iterative Bid	Numeric	IB35
Medical Reference	Numeric	MedRef
Medical Calculator	Numeric	MedCalc
EHR Interface	Numeric	EHRInter
Prenatal Infant Care	Numeric	PrenatalInfant
Clinical Disease Management App	Numeric	CDMApp
Emergency	Numeric	Emergency
Collaboration or Consult	Numeric	CollabConsul
Other App Use	Numeric	OtherAppUSe
Text Entry	Text Entry	TextEntry
Income	Numeric	Income
Initial WTP	Dollar	WTP
WTP Meaningful Use	Dollar	WTPMU
Expected Meaningful Use WTP	Dollar	WTPMUExpect
Final WTP	Dollar	FWTP
lnWTP	Numeric	lnWTP
lnWTPMU	Numeric	lnWTPMU
lnFWTP	Numeric	lnFWTP

Appendix D

INTERACTION EFFECTS OF VARIABLES

Parameter Estimates						
Dependent Variable: lnWTP						
Parameter	B	Std. Error	t	Sig.	95% Confidence Interval	
					Lower Bound	Upper Bound
Intercept	9.276	2.488	3.728	.000	4.380	14.171
[AppSupp=1]	-3.358	1.715	-1.958	.051	-6.733	.017
[AppSupp=2]	-3.458	1.721	-2.010	.045	-6.844	-.072
[AppSupp=3]	-3.365	1.718	-1.959	.051	-6.746	.015
[AppSupp=4]	-3.502	1.692	-2.070	.039	-6.832	-.173
[AppSupp=5]	-4.270	1.976	-2.161	.031	-8.158	-.381
[AppSupp=6]	0[a]	.	.	.	.	.
[AppInterop=1]	-.142	.320	-.443	.658	-.772	.488
[AppInterop=2]	.142	.359	.396	.692	-.565	.849
[AppInterop=3]	.220	.353	.622	.534	-.475	.915
[AppInterop=4]	.317	.350	.906	.366	-.371	1.005
[AppInterop=5]	.014	.398	.034	.973	-.769	.797
[AppInterop=6]	.439	.456	.964	.336	-.457	1.336
[AppInterop=7]	0[a]	.	.	.	.	.
[Policy=1]	-.208	.456	-.455	.649	-1.105	.690
[Policy=2]	-.108	.469	-.230	.818	-1.030	.814
[Policy=3]	-.120	.481	-.249	.804	-1.066	.827

[Policy=4]	-.319	.466	-.686	.493	-1.235	.597
[Policy=5]	.216	.567	.382	.703	-.899	1.331
[Policy=6]	-.009	.567	-.017	.987	-1.126	1.107
[Policy=7]	0[a]	.	.	.	.	.
[AppPrivate=1]	-.540	.673	-.803	.423	-1.864	.784
[AppPrivate=2]	-.312	.682	-.457	.648	-1.654	1.030
[AppPrivate=3]	-.725	.699	-1.036	.301	-2.101	.651
[AppPrivate=4]	-.513	.700	-.732	.465	-1.890	.865
[AppPrivate=5]	-1.172	.877	-1.337	.182	-2.897	.553
[AppPrivate=6]	-.683	.895	-.763	.446	-2.445	1.078
[AppPrivate=7]	0[a]	.	.	.	.	.
[FriendColl=1]	-1.177	.457	-2.574	.011	-2.077	-.277
[FriendColl=2]	-1.174	.463	-2.539	.012	-2.084	-.264
[FriendColl=3]	-1.272	.452	-2.814	.005	-2.162	-.383
[FriendColl=4]	-.968	.462	-2.096	.037	-1.877	-.059
[FriendColl=5]	-1.123	.518	-2.168	.031	-2.142	-.104
[FriendColl=6]	-.401	.638	-.628	.530	-1.657	.855
[FriendColl=7]	0[a]	.	.	.	.	.
[AppCert=1]	-.206	.346	-.595	.552	-.886	.475
[AppCert=2]	-.398	.363	-1.096	.274	-1.112	.317
[AppCert=3]	-.428	.370	-1.154	.249	-1.157	.301
[AppCert=4]	-.118	.369	-.319	.750	-.843	.608
[AppCert=5]	-.084	.449	-.188	.851	-.968	.800
[AppCert=6]	-.212	.519	-.408	.683	-1.234	.810
[AppCert=7]	0[a]	.	.	.	.	.
[Decrease=1]	-.263	.424	-.621	.535	-1.097	.571
[Decrease=2]	-.488	.462	-1.056	.292	-1.396	.421
[Decrease=3]	-.095	.467	-.204	.838	-1.014	.823

[Decrease=4]	-.632	.498	-1.269	.206	-1.613	.348
[Decrease=5]	.526	.661	.796	.427	-.774	1.826
[Decrease=6]	.338	.866	.390	.697	-1.366	2.041
[Decrease=7]	0[a]	.	.	.	.	.
[IncreasePro=1]	.819	1.348	.607	.544	-1.834	3.471
[IncreasePro=2]	.845	1.355	.623	.534	-1.822	3.511
[IncreasePro=3]	.940	1.395	.674	.501	-1.805	3.686
[IncreasePro=4]	1.154	1.430	.807	.420	-1.660	3.967
[IncreasePro=5]	-1.452	1.580	-.919	.359	-4.561	1.657
[IncreasePro=6]	-.155	2.063	-.075	.940	-4.215	3.904
[IncreasePro=7]	0[a]	.	.	.	.	.
[Simple=1]	-8.105	3.588	-2.259	.025	-15.164	-1.045
[Simple=2]	-8.287	3.586	-2.311	.022	-15.344	-1.230
[Simple=3]	-7.956	3.604	-2.208	.028	-15.048	-.865
[Simple=4]	-7.815	3.623	-2.157	.032	-14.944	-.687
[Simple=5]	-12.312	3.878	-3.175	.002	-19.943	-4.682
[Simple=6]	-6.321	3.330	-1.898	.059	-12.874	.231
[Simple=7]	0[a]	.	.	.	.	.
[ClinicalBest=1]	6.532	2.977	2.194	.029	.673	12.391
[ClinicalBest=2]	6.402	2.989	2.142	.033	.520	12.284
[ClinicalBest=3]	5.415	3.036	1.783	.076	-.560	11.389
[ClinicalBest=4]	5.439	2.986	1.822	.069	-.436	11.314
[ClinicalBest=5]	7.633	3.508	2.176	.030	.730	14.537

[ClinicalBest=6]	0[a]	.	.	.	.	.
[ClinicalBest=7]	0[a]	.	.	.	.	.

a. This parameter is set to zero because it is redundant.

Appendix E

IRB APPROVAL LETTER

RESEARCH OFFICE

210 Hullihen Hall
University of Delaware
Newark, Delaware 19716-1551
Ph: 302/831-2136
Fax: 302/831-2828

DATE:	February 8, 2013
TO:	Thomas Martin, MBA
FROM:	University of Delaware IRB
STUDY TITLE:	[410908-1] Applications of Contingent Valuation and Conjoint Analysis in mHealth: Understanding the Willingness to Pay for Healthcare Smartphone Applications
SUBMISSION TYPE:	New Project
ACTION:	DETERMINATION OF EXEMPT STATUS
DECISION DATE:	February 8, 2013
REVIEW CATEGORY:	Exemption category #2

Thank you for your submission of New Project materials for this research study. The University of Delaware IRB has determined this project is EXEMPT FROM IRB REVIEW according to federal regulations.

We will put a copy of this correspondence on file in our office. Please remember to notify us if you make any substantial changes to the project.

If you have any questions, please contact Clara Simpers at 302-831-2137 or csimpers@udel.edu. Please include your study title and reference number in all correspondence with this office.