

2017

# Internet Speed and the Effect on Health Information Technology Adoption

Matthew W. Yuen  
*University of South Carolina*

Follow this and additional works at: <https://scholarcommons.sc.edu/etd>

 Part of the [Health Services Administration Commons](#)

---

## Recommended Citation

Yuen, M. W.(2017). *Internet Speed and the Effect on Health Information Technology Adoption*. (Doctoral dissertation). Retrieved from <https://scholarcommons.sc.edu/etd/4366>

This Open Access Dissertation is brought to you by Scholar Commons. It has been accepted for inclusion in Theses and Dissertations by an authorized administrator of Scholar Commons. For more information, please contact [dillarda@mailbox.sc.edu](mailto:dillarda@mailbox.sc.edu).

INTERNET SPEED AND THE EFFECT ON HEALTH INFORMATION TECHNOLOGY  
ADOPTION

by

Matthew W. Yuen

Bachelor of Science  
University of California, Davis, 2010

Master of Public Health  
Texas A&M University, 2014

---

Submitted in Partial Fulfillment of the Requirements

For the Degree of Doctor of Philosophy in

Health Services Policy and Management

The Norman J. Arnold School of Public Health

University of South Carolina

2017

Accepted by:

Janice C. Probst, Major Professor

Kevin J. Bennett, Committee Member

Brian K. Chen, Committee Member

Elizabeth L. Crouch, Committee Member

Cheryl L. Addy, Vice Provost and Dean of the Graduate School

© Copyright by Matthew Yuen, 2017  
All Rights Reserved.

## DEDICATION

To my beloved parents, Ting and Wendy Yuen, I am eternally grateful for your wisdom, guidance, and support. There has been many times throughout my life that I have lost all hope in my work and no one else believed that I could succeed. Despite all the failures, you both were always there believing in me and pushing me on to where I am today. For that, I will never find the words and actions to thank you both enough. I would not be a fraction of the person I am today without your ever loving words of encouragement.

To my wife, Ashley Yuen, you have been the most understanding, loving, and patient spouse that any person could ever ask for during this dissertation process. The culmination of this work required many sacrifices on your part, yet you rarely complained. Rather you were always there with words of encouragement. I am incredibly thankful for you and look forward to our new future together. By the way, your advice finally worked ☺.

## ACKNOWLEDGEMENTS

Before all, I would like to thank God and the many blessings he has bestowed.

I want to acknowledge my committee chair, Dr. Janice Probst, for her guidance and mentorship during my entire program. I would not have been able to finish the program if it weren't for her guidance. I am grateful for kindness and dedication to her students to make them the best they could be.

I would also like to thank my committee members, Dr. Kevin Bennett, Dr. Brian Chen, and Dr. Elizabeth Crouch. Dr. Bennett's mentorship through my many challenges in the program has been more than helpful. I am grateful for his guidance through the program. On top of his work with this dissertation, Dr. Chen was also pivotal during my program to help me discover a passion for teaching. Dr. Crouch was also incredibly helpful during the course of the dissertation. It is through her guidance that helped my dissertation even better.

Finally, I would like to acknowledge Dr. Barbara Quiram of Texas A&M University. Dr. Quiram took a risk on me when I was at the Texas A&M which helped me begin on this path. Also, I would like to thank my friends, Jared Walker, Karen Jones, Claudia Cartledge, and Dr. Eliza Fishbein who gave me encouragement throughout this process. I am also incredibly grateful for becoming friends with Janie Godbold who has helped me multiple times throughout this program.

## ABSTRACT

*Background.* The Internet has become pervasive in everyday life; the Pew Research Center reported over 84% of Americans use the Internet either on their phone or a computer. However, due to the methods by which the Internet was created, an Internet digital divide was created. The Internet digital divide is the disparity in access and speed of Internet of certain populations. This study looked into the disparity between urban and rural populations and their Internet access in two forms: e-prescriptions adoptions and Internet health information seeking behavior (HISB) through their mobile devices.

*Methods.* This study used 4 datasets, the Health Information Trends Survey, Area Health Resource Files, Surescripts, and National Broadband Map to determine if there was a disparity related to Internet use between urban and rural populations. A logistic regression was used to determine if there was a disparity between urban and rural populations in mobile Internet based health information seeking behavior (IHISB). A multivariable regression analysis was conducted to determine if Internet speed was related to positive change in e-prescription adoption.

*Results.* There were mixed results in the relationship of rurality to mobile IHISB use. Once community factors were accounted for, rurality was statistically insignificant. At the person level, the characteristics of income and age played a role in whether mobile IHISB occurred. Multivariable regression analysis showed that Internet speed played no role in e-prescription uptake. However, counties with higher percentage of insured

patients and doctors aged under 55 are linked to positive changes in e-prescription adoption.

*Conclusion.* Income and age seem to play a statistically significant role in IHISB use. This suggests that there is an access and experience issue at play. In addition, Internet speed plays an insignificant role in e-prescription adoption change. However, it seems individual level factors play a larger role in e-prescription adoptions. More research is needed to determine what impacts e-prescription adoption change.

## TABLE OF CONTENTS

<b>DEDICATION</b> .....	iii
<b>ACKNOWLEDGEMENTS</b> .....	iv
<b>ABSTRACT</b> .....	v
<b>LIST OF TABLES</b> .....	xi
<b>LIST OF ABBREVIATIONS</b> .....	xiii
<b>CHAPTER 1: INTRODUCTION</b> .....	1
<b>Background</b> .....	1
<b>Purpose</b> .....	3
<b>Data Sources</b> .....	3
<b>CHAPTER 2:A BRIEF HISTORY OF THE INTERNET AND HEALTH</b> .....	5
<b>The History and Development of the Internet</b> .....	5
<b>The Digital Divide and Its Effect on Health Literacy</b> .....	9
<b>Theoretical Model for Uptake of New Technology - Unified Theory of Acceptance and Use of Technology Model 2</b> .....	11
<b>Moderating Factors of UTAT2 In Relation to Rural and Urban Divide</b> .....	21
<b>The Type of Device Used for Internet Health Information Seeking Behavior</b> .....	24



<b>Epidemiology of Internet Devices and Health Information Seeking Behavior .....</b>	<b>25</b>
<b>E-Prescriptions and the Digital Divide Speed.....</b>	<b>29</b>
<b>E-prescription Adoption in the United States .....</b>	<b>30</b>
<b>U.S. Policy’s Effect on Health Information Seeking Behavior and E-prescription .....</b>	<b>33</b>
<b>Adoption.....</b>	<b>33</b>
<b>Gaps in the Literature.....</b>	<b>40</b>
<b>CHAPTER 3: METHODOLOGY.....</b>	<b>43</b>
<b>Purpose.....</b>	<b>43</b>
<b>Data Sources .....</b>	<b>44</b>
<b>Data Source Descriptions – Aim 1 .....</b>	<b>44</b>
<b>Dataset Creation and Study Sample – Aim 1 .....</b>	<b>45</b>
<b>Study Variables – Aim 1 .....</b>	<b>45</b>
<b>Analysis Method – Aim 1.....</b>	<b>47</b>
<b>Data Source Descriptions – Aim 2 .....</b>	<b>48</b>
<b>Dataset Creation and Study Sample – Aim 2 .....</b>	<b>49</b>
<b>Study Variables – Aim 2 .....</b>	<b>50</b>
<b>Analysis Method – Aim 2.....</b>	<b>52</b>

**CHAPTER 4: DIFFERENCES AMONG RURAL AND URBAN RESIDENTS IN MOBILE DEVICE USAGE FOR HEALTH INFORMATION SEEKING BEHAVIOR..... 60**

<b>Abstract .....</b>	<b>61</b>
<b>Introduction .....</b>	<b>61</b>
<b>Methods .....</b>	<b>64</b>
<b>Results .....</b>	<b>69</b>
<b>Discussion .....</b>	<b>72</b>
<b>Limitations .....</b>	<b>76</b>
<b>Conclusion .....</b>	<b>78</b>

**CHAPTER 5: THE DIGITAL DIVIDE AND ITS EFFECT ON THE E-PRESCRIPTION ADOPTION IN RURAL AND URBAN COUNTIES FROM 2010-2014..... 91**

<b>Abstract .....</b>	<b>92</b>
<b>Introduction .....</b>	<b>92</b>
<b>Methods .....</b>	<b>96</b>
<b>Results .....</b>	<b>102</b>
<b>Discussion .....</b>	<b>105</b>
<b>Limitations .....</b>	<b>108</b>
<b>Conclusion .....</b>	<b>110</b>

**CHAPTER 6: CONCLUSION..... 123**

**REFERENCES..... 125**

## LIST OF TABLES

Table 2.1 UTAT2 and Aim 1 .....	41
Table 2.2 UTAT2 Model and Aim 2 .....	42
Table 3.1 Variables used for Aim 1 in HINTS dataset .....	54
Table 3.2 UTAT2 and Aim 1 .....	55
Table 3.3 Aim 2 variables used by dataset .....	56
Table 3.4 Variables listed by type.....	58
Table 3.5 UTAT2 model and Aim 2.....	59
Table 4.1 Construct and study variables .....	79
Table 4.2 Total population, by exclusion criteria, 2013-2014 HINTS .....	80
Table 4.3 Characteristics of respondents, by rurality, 2013-2014 HINTS .....	82
Table 4.4 Characteristics associated with use of IHISB, among respondents who reported HISB, 2013-2014 HINTS .....	84
Table 4.5 Characteristics associated with use of IHISB, among respondents who reported HISB, 2013-2014 HINTS .....	86
Table 4.6 Differences in mobile device use among people who use IHISB, 2013-2014 HINTS.....	88
Table 4.7 Characteristics associated with mobile device IHISB, 2013-2014 HINTS .....	90
Table 5.1 UTAT2 and variables used in study .....	111
Table 5.2 Differences between excluded and included counties from 2010-2014.....	112
Table 5.3 Characteristics of counties for rurality, Internet speed, and e-prescription adoption, 2010 and 2014.....	115

Table 5.4 Differences in key characteristics of counties, in quartiles based on 2010 value, by year.....	116
Table 5.5 2010 and 2014 upload and download speeds by e-prescription adoption rates for 2010 and 2014 .....	118
Table 5.6 Combined 2010-2014 upload and download speed variable, by rurality .....	119
Table 5.7 Factors associated with e-prescription adoption change.....	120

## LIST OF ABBREVIATIONS

ARPANET.....	Advanced Research Projects Agency Network
AHRF.....	Area Health Resource Files
CDC.....	Centers for Disease and Control
DARPA.....	Defense Advanced Research Projects Agency
ECPA.....	Electronic Communications Privacy Act of 1986
EHR.....	Electronic Health Records
EMR.....	Electronic Medical Records
E-prescriptions.....	Electronic Prescriptions
FCC.....	Federal Communications Commission
FDASIA...	Food and Drug Administration Safety and Innovation Act of 2012 Section 618
FTC.....	Federal Trade Commission
HIPAA.....	Health Insurance Portability and Accountability Act of 1996
HINTS.....	Health Information National Trends Survey
HISB.....	Health Information Seeking Behavior
HIT.....	Health Information Technology
HITECH...	Health Information Technology for Economic and Clinical Health Act of 2009
IHISB.....	Internet Health Information Seeking Behavior
IP.....	Internet Protocol Suite
IPv4.....	Internet Protocol Suite version 4
IMPs.....	Interface Message Processors

MIPPA.....	Medicare Improvements for Patients and Providers Act of 2008
NBM.....	National Broadband Map
ONC.....	Office of National Coordinator for Health Information Technology
RUCC.....	Rural - Urban Continuum Code
TCP.....	Transmission Control Protocol
UIC.....	Urban Identification Code
UTAT2.....	Unified Theory of Acceptance and Use of Technology Model 2

# CHAPTER 1

## INTRODUCTION

### Background

Since the beginning of its development, the Internet has been a disruptive innovation. The Internet is credited with creating entire new markets, job opportunities, new methods of communication, and other entities. The Internet has become pervasive; the Pew Research Center reported over 84% of Americans use the Internet either on their phone or a computer (Pew Research, 2015). The Internet has become so commonplace that Forbes wrote “Every Company Is a Tech Company” because nearly every business utilizes the Internet to function in everyday operations (Bruner, 2014). The Great Recession of 2008 showed how much of an impact the Internet had. Businesses and people who did not have access to the Internet had worse economic outcomes than people with access to high speed internet (McKinsey Quarterly, 2009). The lack of access to high speed Internet is due to a phenomenon called the digital divide.

The digital divide is a result of how the Internet was established. The cost of building infrastructure for the Internet was expensive, thus the Internet was geared toward higher population centers where large population bases could offset building costs (Smith, 2010). On the other hand, areas where Internet providers could not make a profit did not have Internet infrastructure built as quickly. By the mid 1990’s it was clear that there was an increasingly large digital divide; industrialized countries and urban areas reported rapid growth in Internet use while rural areas and third world countries lagged



behind (Leiner et al., n.d.; Hilbert and Lopez, 2011; Strover, 1999). The effect of the digital divide was clear; rural areas had slower Internet connectivity, which is linked to lower economic output compared to those who have access to high-speed Internet access (Douthit, 2015; Graham, 2008; Madon, 2000; Warren, 2007; Whitacre et al., 2016). The lack of high-speed Internet access poses a critical threat to rural areas health outcomes because of how the Internet is now linked to economic output (Harper and Lynch, 2007).

Prior to the Great Recession, rural areas had worse health outcomes and lower income rates than their urban counterparts (Bennett, 2016). One of the hallmarks of the Great Recession was how it negatively affected blue collar workers, who are over-represented in rural populations (Boston, 2009; Bureau of Labor and Statistics, n.d.). Reports show that blue collar workers had a prolonged recovery from the Great Recession due in large part for the need in the job market for computer and Internet related skills (Brookings Institute, 2013). The lack of high speed Internet in rural areas has continued to slow the recovery for rural areas, as seen by their unemployment rates, which still have yet to recover from the Great Recession (Bennett et al., 2016). Having lower income rates, or no income, only negatively affects the rural population's health and contributes to the growing rural-urban divide.

Another aspect of the digital divide contributing to the rural-urban health divide is how rural adults access the Internet for their health. Literature has researched how adults use the Internet to understand their health problems (Graetz, 2016). However, there is sparse research into the difference between the method that rural and urban adults access the Internet for health information seeking behavior. This is important for creators of Internet health information because rural adults are less likely to use the internet.

According to the Unified Theory of Acceptance and Use of Technology Model 2, it hypothesizes that rural residents are less likely to utilize mobile devices because they have less experience with them (Venakatesh, 2012). This dissertation will attempt to answer two questions related to the use of Internet and health.

## **Purpose**

To understand how Internet affects health outcomes and how it is used, I examined the following questions:

Aim 1: To examine differences among rural and urban residents in how they use their mobile devices for Internet health information seeking behavior (HISB).

Aim 2: To examine differences in physician e-prescription adoption change from 2010-2014, given that rural and urban areas have been adjusted for similar broadband speeds.

## **Data Sources**

To answer the questions posed, four relevant data sources were utilized: 1. Area Health Resource File (AHRF) 2. Health Information National Trends Survey (HINTS) 3. Office of National Coordinator for Health Information Technology (ONCHIT) 4. National Broadband Map (NBM).

### *Explaining the Data Sources*

#### 1. The Health Information National Trends (HINTS)

The HINTS database was created by the National Cancer Institute Division of Cancer Control and Population Sciences. The HINTS collects national representative data about Americans' use of cancer-related information and treatment. The HINTS database

was solely used to answer Aim 1, which is related to health information seeking behaviors between rural and urban populations.

## 2. The Area Health Resource File (AHRF)

The AHRF is a county-level database that is annually created by the Health Resources and Services Administration (HRSA). The data are collected annually to reflect every American county and every U.S. territory. The AHRF data gives a snapshot of conditions in three different categories: health care professions, hospitals and healthcare facilities, and census, population and environmental data. The AHRF was used for Aim 2 and contains independent variables which include rurality, county level demographic information, and health systems information.

## 3. Office of National Coordinator for Health Information Technology (ONCHIT) - Surescripts

The Surescripts dataset was created by ONCHIT. The database determines electronic prescribing adoption and use by county, state and national level. The Surescripts dataset was used solely in Aim 2, to determine the difference in e-prescription adoption between rural and urban physicians.

## 4. National Broadband Map (NBM)

The NBM is a database established by the Federal Communications Commission. The NBM shows data on a county, state, and national level of broadband availability and speed. The NBM was used in Aim 2 to determine broadband speeds of different counties.

## CHAPTER 2

### A BRIEF HISTORY OF THE INTERNET AND HEALTH

This chapter will have 5 major sections: 1)The History and Development of the Internet 2) Theory Discussion Related to Technology Adoption 3) Factors Associated with Differing Device Use for HISB 4) Factors Associated With Physician E-prescription Use 5) Policy Related to E-prescriptions, Device Use, and HISB.

#### **The History and Development of the Internet**

Over the past 40 years, the Internet has transformed from a data packet transferring system to a disruptive innovation that is still continually changing markets. In 2015, Pew Research found over 84% of Americans used the Internet either on their phone or on a computer (Pew Research, 2015). Despite the economic opportunities that the Internet has given, the Internet has also contributed to economic disparities. The digital divide, discussed below, created a disparity in Internet access between rural and urban areas. This literature review will discuss how the digital divide has contributed to different uptakes in both e-prescription adoption and health information seeking behavior (HISB).

In the early 1960's, the Defense Advanced Research Projects Agency (DARPA), located within the United States Department of Defense, first developed the Internet as a packet transferring network used to send documents between military research personnel (Cerf & Kahn, 1974; Leiner et al., n.d.). Sending physical pieces of intelligence and mail

required time, so the military instead wanted to design a system that could send information in mere seconds (Leiner et al., n.d.). In late 1969, the first Internet network system called Advanced Research Projects Agency Network (ARPANET) was able to successfully transfer information within its network (Savio, 2011). ARPANET consisted of existing phone lines and a set of dedicated computers called Interface Message Processors (IMPs) within 4 universities. By 1975, there were many more IMPs connected to ARPANET, and the project was considered an operational success. At the same time ARPANET was in development, other networks were being developed internationally, each with its own complexities.

In the mid 1970's, there was a move to unify the various international networks into one large international network, which would lead to the modern Internet. In order to merge the networks, linkages between them needed to be established, but each network in the world had a different method of sending information, which caused difficulty in establishing linkage (Segal, 1995). Under the guidance of the same leadership that developed ARPANET and NASA, a conceptual model and communication protocols were created to help link the different networks and allow communication to occur.

The conceptual model was called the Transmission Control Protocol (TCP) and the communication protocol was called the Internet Protocol Suite (IP); both are commonly referenced together as TCP/IP. During the 1980's, through the use of the TCP/IP standards, networks around the world began to connect to one central network despite having different complexities and set ups. Each of these new connections was assigned a new IP address under the naming methodology called Internet Protocol Suite version 4 (IPv4). Because of TCP/IP, the Internet was beginning to take shape as the

World Wide Web. Despite connecting the world, due to the guidelines by DARPA, the Internet was only open to a select few people.

It was clear that the Internet it was an innovative disruptor: That is, for people fortunate enough to use it. Via funding from the National Science Foundation Network in the 1980's, the Internet began to proliferate into civilian life for research use only (Leiner et al., n.d.; Savio, 2011; Segal, 1995). Researchers were able to quickly transfer information back and forth on the early Internet. Noticing the use by researchers, industries began realizing the potential use of the Internet, and began lobbying for the unrestricted use of the Internet by the public. In 1992, the Scientific and Advanced Technology Act of 1992 was passed which allowed for the commercial use of the Internet (GovTrack, 1991). As the Internet began transitioning out of restricted government and research use, commercial businesses quickly understood the unharnessed potential of the Internet, and began spending money to develop the modern Internet, which helped contribute to the digital divide (Leiner et al., 2009).

Digital divide refers to the disparity in telecommunication access among different demographic groups (Kruger & Gilroy, 2016) . Because the creation of Internet infrastructure was expensive, telecommunication companies focused building infrastructure for the internet in urban areas, where the high population base could offset building costs (West, 2015; Smith, 2010). Places with lower population bases could not offset the cost of building the Internet and were seen as less attractive options to build infrastructure (West, 2015; Whitacre, Wheeler, & Landgraf, 2016). To explain this phenomenon, the term digital divide was coined; industrialized countries and urban areas

reported the rapid growth in Internet use while rural areas and third world countries lagged behind (Leiner et al., 2009; Hilbert & Lopez, 2011).

*Present: The Internet Permeating Every Aspect of Society*

The Internet prior to the early 2000's was called Web 1.0, an Internet with very crude and minimal interaction (Cormode & Krishnamurthy, 2008). The Internet was seen as a method to communicate with other people either via email or in a newsletter format. Outside of email, users could not participate in creating content unless they were professional coders (Cormode & Krishnamurthy, 2008). Web 2.0, which was developed in the mid 2000's, and is much different; sites emphasizing user interaction, content creation, and apps are all hallmarks of Web 2.0 (Cormode & Krishnamurthy, 2008; O'Reilly, 2005). It was during this transition that the Internet sector spawned the coining of the catchall term, "tech sector" (Bruner, 2014).

Integrating Web 2.0 with everyday business functions made businesses more efficient and expanded business opportunities. Businesses reported decreasing overhead and benefits costs by contracting with web-based contractors for accounting and technical assistance instead of paying full-time employees (Mckinsey, 2009). This is because businesses could interact with multiple employees across video and file sharing platforms. This also meant that businesses could start up with very little start-up costs and have their services or products bought worldwide.

Not only were businesses working differently, but they also had changed how they reached their consumer bases. Social media websites like Facebook and Twitter have gone from sites for millennials to communicate to sites that must be considered as

part of a business marketing plan (Romaniuk, Ptak, & Switała, 2016; Westberg, Stavros, Smith, Munro, & Argus, 2016; Zadeh & Tremblay, 2016). Long-standing brick and mortar businesses began to integrate Internet commerce as part of their business plans in Web 2.0 (Mckinsey, 2009). As pointed out by Forbes, the Internet is a requirement to function as a business that they now consider “Every Company Is a Tech Company” (Bruner, 2014).

### *Emergence of the Digital Divide*

As of 2016, the digital divide still exists, but in a slightly different modality. Instead of a digital divide based on whether someone does or doesn't have Internet, the digital divide breaks down on disparities of speed (Whitacre, Wheeler, & Landgraf, 2016). Similar to the digital divide in access, areas that are more rural are less likely to have high speed Internet (Anderson, 2015; Rohman & Bohlin, 2012; Whitacre et al., 2016).

### **The Digital Divide and Its Effect on Health Literacy**

As much as fast speed is related to economic output and health, having faster Internet is not the only problem – there is also an issue of Internet literacy. Internet literacy a measure of how well a person is able to use the Internet (Chesser et al., 2016; Tennant et al., 2015; Yin et al., 2015). Internet literacy is linked to both education levels and the amount of experience one has with the Internet (Tennant et al., 2015). The higher a user's Internet literacy level is, the more likely they are able to use the Internet's functions (Chesser et al., 2016; Tennant et al., 2015; Yin et al., 2015). It isn't enough for people to just have access Internet, people need to be educated on how to use the Internet.



The best example of this is when surveying older populations, older populations stated they do not use the Internet because they believe it has no added utility to their lives (Watson et al., 2008). During the early beginnings of the digital divide, populations that had access to the Internet were able to use the Internet and learn how to use the Internet. For this reason, people who did have the Internet went into the modern age without having developed a reliance on the Internet (Yamin et al. 2016).

The impact of the digital divide of Internet literacy is best seen in the difference in types of work that urban and rural citizens do. Urban citizens typically do work that requires the Internet while rural area citizens do work that does not (Gibbs, Kusmin, & Cromartie, 2005). In a globalizing economy, middle to low skill jobs, predominately located in rural areas are likely to be outsourced, which in turns causes higher rates of unemployment (Gibbs, Kusmin, & Cromartie, n.d.; J. R. Young, 2013). This contributes to the higher rates of poverty and unemployment in rural areas (Bennett et al., 2016).

In the realm of healthcare, Internet literacy is becoming more important as the healthcare industry is becoming more integrated into the Internet (Tennant et al., 2015). For example, the healthcare industry has gradually adopted wearable technologies, which patients use to gain more accurate health tracking (Allen & Christie, 2016; Bentley et al., 2016). In both cases of electronic medical records (EMR) and wearable technology, both user and healthcare worker require the Internet for full functionality. For healthcare providers, Internet literacy is becoming a required asset among workers to treat patients.

## **Theoretical Model for Uptake of New Technology - Unified Theory of Acceptance and Use of Technology Model 2**

The Unified Theory of Acceptance and Use of Technology Model 2 (UTAT2) helps explain the digital divide in the adoption of e-prescription as well as the ways in which people use certain devices to access the Internet for HISB (IHISB).

This model was adapted from the Technology Acceptance Model (Venkatesh et al., 2012). The Technology Acceptance Model showed that External Variables, Perceived Ease of Use, and Perceived Usefulness all work in conjunction to affect the construct of Attitude Toward Technology, which determines whether a patient adopts certain technology. The UTAT2 theoretical model described by Venkatesh et al. adapted portions of the Technology Acceptance Model to better describe how a person is more likely to use technology based on multiple factors that are broken down on individual, social, and environmental factors (Venkatesh et al., 2012).

The UTAT2, which will be used to help guide this research, holds that there are seven key constructs in determining whether a user will have the intention to use a technology system and subsequently use the system (Venkatesh et al., 2012). These constructs are: 1) Performance, Expectancy, 2) Effort Expectancy, 3) Social Influence, 4) Facilitating Conditions, 5) Hedonic, Motivation, 6) Price Value, 7) Habit (Venkatesh et al., 2012). Each of these constructs is affected by the facilitating conditions of age, gender and experience (Venkatesh et al., 2012).

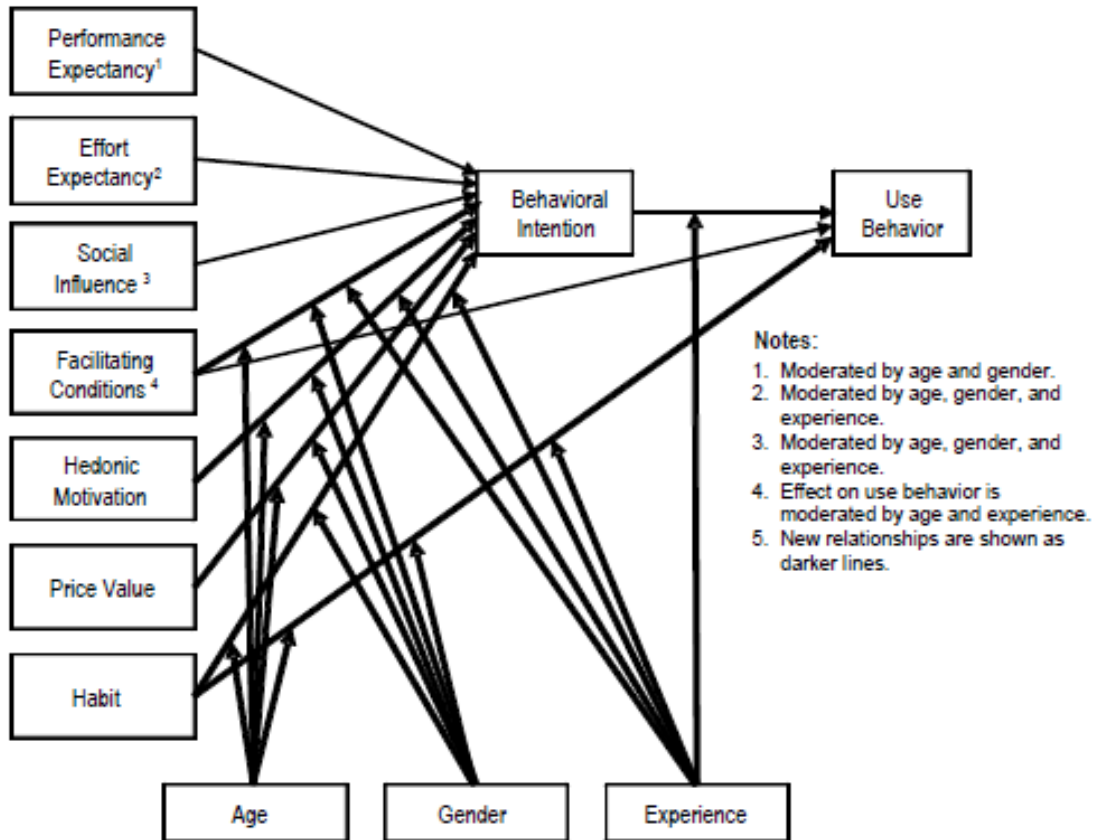


Figure 2.1: Unified Theory of Acceptance and Use of Technology Model 2

### *Performance Expectancy*

Performance expectancy is how the technology provides benefits to the user in performing certain activities; performance expectancy is adapted from the construct of Perceived Usefulness in the Technology Acceptance Model (Venkatesh et al., 2012). For many users, e-prescription presents a more convenient and safer option than written prescriptions (Frail, Kline, & Snyder, 2003; Odukoya & Chui, n.d.). E-prescription can cut out waiting time for patients, and can also help decrease the time physicians spend reviewing patient charts (Porterfield, Engelbert, & Coustasse, n.d.). Similar to e-prescription, HISB has a high performance expectancy because it cuts the time patients

spend visiting their physicians, and also provides a much more economical means of treating their own health issues (Higgins et al., 2011; Pang et al., n.d.).

### *Effort Expectancy*

Effort expectancy is defined as the degree of ease associated with consumer's use of technology (Venkatesh et al., 2012). For patients, e-prescription presents a low effort expectancy. This is because e-prescription requires very little work on patients' part. Studies have found that patients enjoy the fact that there is little work required on their part to receive an e-prescription compared to a paper prescription (Frail et al., 2015; Schleiden, Odukoya, & Chui, 2015). When viewing e-prescription from a physician's point of view, there is sparse research focusing on the act of e-prescribing by physicians. However, the research available shows that physicians like e-prescriptions because they allow physicians to become more efficient at their work instead of writing their prescriptions (Devine et al., 2010). In both the physician's and patient's cases, e-prescription presents low effort expectancy. Another aspect that has been cited as an impediment for e-prescription adoption is the issue of acquiring high speed Internet, which is a requirement for e-prescriptions (Gabriel et al., 2013; Pevnick et al., 2010).

The literature related to effort expectancy for patients utilizing IHISB shows that the effort varies depending on which population that is studied (Miller & Bell, 2012; Higgins et al., 2011; Tennant et al., 2015). For patients that use IHISB to treat their own health problems, there are two main concerns: the difficulty of IHISB and race/culture (Miller & Bell, 2012; Higgins et al., 2011; Tan & Goonawardene, 2017). When researching the difficulty of IHISB, Miller & Bell found that older populations had a

harder time looking for information than younger populations (Miller & Bell, 2012). It is suggested that the reason why elderly populations have a harder time looking for IHISB is that they have lower Internet literacy and less experience with Internet (Miller & Bell, 2012; Tennant et al., 2015). Another problem associated with the effort of the Internet was the ability for minority populations to relate to the material which was predominately geared toward White populations (Warren et al., 2010).

When determining the type of device that a person uses to access IHISB, effort expectancy is also a determinant. Mobile devices' smaller screens require users to tap their fingers on the screen more times to access the same information than one would on a traditional desktop computer (Budiu, 2015). However, the same study pointed out that despite being technically slower than desktops, the mobile device's largest strength is the fact that one can use it anywhere (Budiu, 2015). For people who do not readily access a computer as part of their work or daily lives, a mobile device presents a quicker option than turning on a traditional device.

### *Social Influence*

Social Influence is the amount of influence held by others within the potential user's social sphere, their views toward using the technology, and their thoughts on the user's use of the technology (Venkatesh et al., 2003; Venkatesh, Thong, & Xu, 2012). Because of the importance of social sphere in determining the use of technology, it is assumed that people who are clustered geographically near the user would have a higher influence on the user than those far away (Harton & Bullock, 2007).

This process can be best described by the Diffusion of Innovation. The Diffusion of Innovation states that there are five portions to any adoption of a new innovation or task: 1) Knowledge, 2) Persuasion, 3) Decision, 4) Implementation, and 5) Confirmation (Valente & Rogers, 1995). For diffusion to occur, each construct prior to the current construct must be satisfied (e.g. before persuasion the consumer must have knowledge of the innovation) (Valente & Rogers, 1995). Based on the fact that telecommunications companies did not focus on their efforts on building in rural areas, rural areas are more likely to have little to no access to the Internet (Carlson & Goss, 2016; Leiner et al., 2009). Due to the lack of access to the Internet, knowledge as a construct is less likely to be fulfilled. For instance, an urban area with access to high speed Internet is more likely to have people who use IHISB. This is because people within their social sphere, has Internet access and the needed Internet speed to learn from informative videos and written medical advice from websites such as YouTube, Mayo Clinic, Cleveland Clinic, and others. On the other hand, a person who lives in a rural area with slower Internet speeds would be less likely to have friends or family use IHISB.

Another factor in social influence of patients using IHISB is the effect of a physician's attitude, or perceived attitude toward HISB. Because the physician holds a strong influence over the patient's medical care, it is likely the patient will listen to the physician if the physician speaks out for or against HISB. Based on qualitative studies, patients reported physicians having a poor attitude when the patient brought information they found on the Internet into the visit, which decreases the likelihood of HISB (Stevenson et al., 2017). Another factor in social influence of patients related to physicians is the perceived reaction by the physician to the patient utilizing the Internet

for health information. If the patient believes that the physician's reaction to HISB will be negative, it decreases the likelihood they will use the Internet for HISB purposes (Tan & Goonawardene, 2017b).

Social influence in the form of e-prescriptions comes could be caused by geographic variation rather than lack of exposure. The reason why social influence is likely rather than lack of exposure is because physicians are required to have continuing education credits in most every state (Continuing Medical Education Web, 2016). Instead the lack of adoption could be seen more as an effect of geographic variation. Geographic variation is when physicians in different geographies treat the same problem in a different way; it is believed the geographic variation is caused by the training of the physician, but also the adoption of practices of their peers in their geographic area (Chen et al., 2014). Aside from cost, another reason for not adopting e-prescriptions is the added workload and security liability placed on the physician (Porterfield, Engelbert, & Coustasse, 2014). It is quite possible that a physician with more social influence, or even seen as a mentor, has practiced without e-prescriptions. Given the fact that rural physicians tend to be older and non-adopting e-prescription physicians are older as well, this is a very likely possibility (Fordyce et al., 2008).

### *Facilitating Conditions*

Facilitating conditions refers to consumer's perceptions of the resources and support available to them to perform that particular behavior. Facilitating conditions are drawn from Donabedian's quality concepts, where structure must be put in place before any quality improvement must occur (Moore et al., 2015). The structure needed for

someone to use the Internet is web-enabled device, electricity, a modem, and a router before any Internet use can occur.

The facilitating conditions that determine whether someone uses IHISB is on the basis of whether that person has the equipment necessary to look up information on the Internet. In the case of HISB, the person would need a computer, electricity, and the Internet. While the computer and the Internet has become commonplace in most homes, not every household has a computer with access to the Internet. According to Pew Research, as of 2014, only 84% of households have a computer, and of the group that has a computer, 73% of households have a computer that is connected to the Internet (Rainie & Cohn, 2014). Based on a report from U.S. Department of Commerce, aside from money, people reported that they did not own an adequate computer, lacked a connection to broadband Internet service, or lacked any type of Internet service (National Telecommunications and Information Administration, 2013). Aside from the initial cost, the results from the U.S. Department of Commerce and Pew Research suggests that for Americans to begin using the Internet, whether the issue is having a computer in the home or having Internet access in general, access is a factor (National Telecommunications and Information Administration, 2013; Rainie & Cohn, 2014). Facilitating conditions explain why lower income households are less likely to have traditional computer hardware and more likely to use their mobile devices ( Mccloud et al., 2016). In addition, because there are federal programs available for low-income populations to receive reduced or free smart phones, low income populations are much more likely to have just a mobile phone than a traditional computer(Federal Communications Comission, n.d.).



The facilitating factors for e-prescription adoption in physicians' offices are dependent on the equipment available and access to the Internet. Unlike HISB, e-prescription adoption requires software and technical support staff to support the adoption. During the literature review, there was no available literature on the amount of healthcare facilities with computer and Internet access. However, it is assumed that most healthcare facilities are built in populated areas that would have a connection to the Internet. This leaves the facilitating factors of software and technical support staff that a healthcare facility must overcome to adopt e-prescriptions. Based on reviews of literature, software and technical support staff are two major hurdles for e-prescription adoption (C. P. Thomas et al., 2012). The technical know-how related to installing and upkeep of the e-prescriptions are not only expensive, but also in some areas, impossible to find because of the lack of available workers (Center for Healthcare Research and Transformation, 2011; Thomas et al., 2012).

### *Hedonic Motivation*

Hedonic motivation is the amount of fun or pleasure derived from using a technology. Hedonic motivation's effect on behavioral intention is positively influenced by decreasing age, less experience, and male gender. In the case of e-prescribing, it is believed that HIT (which e-prescriptions are part of) are considered utilitarian in function and provide little hedonic motivation (Gu et al., 2010). However, current HIT has chat functions and community functions, which previous studies have considered giving hedonic motivation (Ha et al., 2007; Hsu & Lu, 2004).

### *Price Value*

Price value is the monetary value of the technology, which decreases likelihood of use as the price increases. For most people the price value is related to the equipment needed to get on the Internet. Compared to international rates, the U.S. rates are comparatively more expensive, which requires a person or organization to spend more for their subscription to the Internet provider (Yi, 2015). In addition, another factor is having the technology available to access the Internet. Both the Internet subscription and the device to access the Internet are costs that a person must be willing to pay before using the Internet for HISB. Based on studies, one of the most complained barriers was the cost associated with acquiring the technology needed for IHISB (Higgins et al., 2011; Viswanath et al., 2006; Warren et al., 2010). Other studies have shown that people with the lowest Internet and computer access are characterized as older and low income populations (Kruse et al., 2012; Miller & Bell, 2012).

Many of the studies related to HISB were performed under the assumption that the user was accessing the Internet via a computer. However, this presents a problem, as research has shown that low income residents are more likely to access the Internet on a mobile device compared to a traditional computer (Budiu, 2015; Li & Theng, 2016; McCloud, Okechukwu, Sorensen, & Viswanath, 2016; Salesforce, 2014). A possible reason why low income population are more likely to use mobile devices to access the Internet is because they lack the additional income and need for an additional computer. Rather, the mobile device gives the most value for a user low on money that doubles as both a communication and an Internet accessible device.

Organizations that have not adopted e-prescriptions have reported similar issues to individuals attempting to use the Internet for HISB; the most common barriers physicians cite when adopting e-prescription is related to the financial cost of the attaining or the upkeep of the system (Porterfield et al., 2014; Thomas et al., 2012; Zadeh et al., 2016). For many rural healthcare organizations, finances are a common problem due to the makeup of the payer mix in rural areas. For this reason, many rural organizations are have slowly adopted e-prescriptions.

### *Habit*

Of all the constructs, habit is the one construct that directly influences use behavior. The construct of habit is adapted from habit/automaticity perspective (HAP) and refers how automatic behavior is activated after multiple performances by a cue or stimulus (Venkatesh et al. 2003). Based on the facilitating factors of age, gender, and experience; older age, males, and more experience facilitates a positive effect on behavioral intention and use behavior.

When determining the habits of technology use, the literature reveals that there are differences in how someone utilizes the Internet by income. The differences can be attributed to technology access which has cemented preferences for certain devices to access the Internet over others. When broken down based on the amount of hours that one uses on a mobile device, low income populations (<\$25K) on average spent 2.9 hours more on a mobile device than high income populations (+\$100K) (Salesforce, 2014). Higher income and higher educated populations more likely used a traditional computer or laptop to access the Internet than lower income and educated populations (Li & Theng,

2016; Mccloud et al., 2016). In addition, high income populations are more likely to own traditional computers or laptops than low income population (Anderson, 2015). This difference in ownership is likely due to the fact that mobile phone are a requirement in society that also helps fulfill multiple uses (e.g. Internet access, phone, text message), while traditional computers provide sparse additional utility. Since low income populations are less likely to own traditional computers, a preference is built by lower income populations to use mobile devices while high income populations prefer using traditional computers.

This literature review will not focus on the construct of habit for e-prescriptions. Aim 2 focuses on the question of the adoption rates of e-prescriptions, but not the habit of using e-prescriptions. In addition, e-prescription adoptions in the U.S. seemed to be caused more by policy encouraging the adoption rather than general uptake by physicians; this is best seen by policies passed from 2008-2010 increasing e-prescription adoption from 8% in 2007 to 70+% in 2013 (Gabriel & Swain, 2014; Joseph et al., 2013).

### **Moderating Factors of UTAT2 In Relation to Rural and Urban Divide**

In this section, the literature review will focus on the moderating factors of UTAT2, with particular emphasis on the rural and urban divide.

#### *Experience and Use Behavior*

Experience also affects the link between behavioral intention and use behavior. Experience positively enhances use behavior by affecting the construct of habit. Experience also moderates the effects of behavioral intention. More experience positively affects behavioral intention, which in turn is linked to a higher likelihood of use behavior.

In the case of adopting e-prescriptions and IHISB, experience plays a pivotal role in the behavior.

Elderly patients are less likely to utilize IHISB because they see it as not needed, or they have yet to learn how to use IHISB (Chesser et al., 2016; Tennant et al., 2015). When determining the type of device that one uses to access IHISB, experience plays a large role as well. Someone who is not used to using a traditional computer due to financial reasons is more likely to favor a mobile device instead. Rural populations are less likely to own mobile devices than traditional computers (Anderson, 2015).

In the domain of e-prescription adoption, a different pattern emerged as some physicians had trouble exclusively using e-prescriptions while others used solely e-prescriptions (Pevnick et al., 2010). It was suggested that there is a role in habit building and the amount of experience a physician had with an e-prescription system played a role into whether a physician could adopt using an e-prescription system.

#### *Rural Moderating Factors - Experience*

The digital divide access occurred because Internet providers focused their efforts on urban areas. Based on the UTAT2, experience is a limiting factor to use behavior and use intention. Because there is less familiarity with the Internet, rural populations are less likely to use IHISB (Venkatesh et al., 2012).

Similarly, e-prescription experience for rural populations is limited because rural populations have not had as much experience with the Internet. One of the many impacts of lower Internet access is that rural areas have a lower e-prescription adoption rate than urban areas (65% vs. 75%) (Gabriel et al., 2013). Another study which looked into health

information technology (HIT) adoption by rural physicians found that in 2008 only 7% physicians' offices had adopted any form of HIT, in 2014, 76% had adopted any form of HIT (Gabriel & Swain, 2014). The statistic shows that HIT, which is tied to e-prescriptions, while it had large growth, is still a fairly recent phenomenon.

#### *Moderating Factors – Age*

The moderating factor of age decreases the likelihood of someone using the Internet as age increases. The older a person is, the more likely they did not use the Internet at all on any devices (Venkatesh et al., 2012). This is important because older populations make up a disproportionate amount of American healthcare expenses. In addition, rural areas are typically older than urban areas, and continue to age at a faster rate (Bennett et al., 2016).

#### *Moderating Factors – Sex*

Sex plays a role in whether or not someone uses the Internet and thereby, the type of device used in IHISB and e-prescription adoptions. In a poll that determined the demographics of people that do not use the Internet, women were less likely than men to use a mobile device, a traditional computer, or the Internet (Anderson & Perrin, 2016). However, recent research has shown that females are more likely to use IHISB than males (Feinberg et al., 2016; Pang et al., n.d.; Prestin, Vieux, & Chou, 2015; Tennant et al., 2015). This difference could be related to the fact that males have lower health literacy scores than females (Kutner et al., 2006; Mackert et al., 2016). On the other hand, studies have found that male physicians are more likely to prefer e-prescribing than female physicians (Jariwala et al., 2013).

## **The Type of Device Used for Internet Health Information Seeking Behavior**

As healthcare is becoming more integrated into the Internet, patients should also begin to use the Internet to help them search for health information. IHISB is the act of using the Internet to help find information related to the user's disease (McCloud et al., 2016; Zhao, 2009). HISB can occur in different forms, including going to the library, seeing a physician, and other forms. However, for this literature review, HISB will only be used in the context of using the Internet to look for information. Unlike previous generations, where the act of finding information required a medical profession or a library, the Internet has made health information readily available for anyone to find.

Research into how different populations utilize IHISB is important because of the potential benefits. People who utilize IHISB are more likely to have positive health outcomes than those who do not use the Internet (Li & Theng, 2016; Tennant et al., 2015). IHISB is also a viable option as healthcare premiums and deductibles have seen large percentage increases that continually outpace worker's salaries (Claxton et al. 2016; National Conference of State Legislatures 2016). However, people who use IHISB need to have a certain level of Internet literacy (Li & Theng, 2016). Some studies have taken into account the difference in accessing IHISB based on their Internet literacy level. Those studies, have found that people with higher Internet literacy were more likely to use IHISB than people with lower Internet literacy (Jeppesen et al., 2012; Tennant et al., 2015).

The problem is that people with low Internet literacy are typically from the same demographics as people in the digital divide—low income and/or low educational attainment (Collins et al., 2014; Jeppesen et al., 2012; Li & Theng, 2016; Sarkar et al.,

2011; Tennant et al., 2015; Young & Chaudhry, 2015). Research has shown that people from different demographic backgrounds tend to favor accessing the Internet on different types of devices. As noted above, people who are low income are more likely to access the Internet on mobile devices than people who are high income (Anderson, 2015; Serrano et al., 2017). At the same time, accessing the information on a mobile device takes a longer time than accessing the same information on a computer (Budi, 2015). If a health website is not optimized for use on a mobile device, it decreases the likelihood that someone with low income would use it.

### **Epidemiology of Internet Devices and Health Information Seeking Behavior**

This section will look into the epidemiology of Internet devices used for IHISB. Each characteristic discussed will be broken up into two portions: 1) IHISB in relation to that factor, and 2) The type of Internet device use in relation to that factor.

#### *Sex*

Studies have shown that females overwhelmingly take part in IHISB compared to males (Li & Theng, 2016; Mccloud et al., 2016; Miller & Bell, 2012). In addition, studies have found that while women are less likely to own mobile devices and computer devices, they are more likely to use a mobile device to access the Internet than males (Anderson, 2015; Serrano et al., 2017). Women were also most likely to use health apps than males (Bhuyan et al., 2016).

#### *Age*

People who seek information for themselves are typically working age adults. The reason that working age adults have high IHISB rates is that they are more likely to have



a higher Internet literacy rate than most groups studied (Li & Theng, 2016; Monteith, Glenn, & Bauer, 2013). For older populations and younger populations, they were less likely to use the Internet for health information (Mccloud et al., 2016; Miller & Bell, 2012). It is implied that younger participants have little use for health information since young populations rarely suffer from illness (Miller & Bell, 2012). However, one study found an exception: younger participants living in minority homes were more likely to use the Internet to search for health information for a non-Internet fluent adult in the household (Zhao, 2009). On the other hand, older populations are less likely to use the Internet, to have the equipment necessary to access the Internet, and have lower Internet literacy levels (Miller & Bell, 2012; Tennant et al., 2015).

Different groups of people prefer different devices to access the Internet. Younger populations were more likely to use Internet accessible mobile devices compared to older populations. Middle aged groups (30-49) were most likely of any group to use a traditional computer while age groups, below age fifty were more likely to use mobile devices and spend more time on their mobile devices surfing the Internet (Anderson, 2015; Salesforce, 2014; Serrano et al., 2017). Younger populations were also most likely to utilize health apps compared to other ages (Bhuyan et al., 2016).

### *Race*

Similar to the statistics on the digital divide, IHISB breaks down along racial lines as well. Whites are the racial group that is most likely to use IHISB (Li & Theng, 2016; Miller & Bell, 2012). In addition, Whites were more likely to use the Internet to help find their health problems and communicate with their providers about their

findings(Stevenson et al., 2007; Walsh, Rehman, & Goldhirsh, 2014). Based on recent trends, it found that minorities are beginning to use IHISB (Prestin et al., 2015).

When considering race as a factor, there were differences across ownership and use. Whites were most likely to own a traditional computer, laptop, or tablet (Anderson, 2015). However, African Americans were more likely to own a smartphone than any other race (Anderson, 2015). Looking further into research, minorities are also more likely to use the Internet on their mobile devices (Serrano et al., 2017). In addition, in a study that sent health information to smartphones, it found that minorities were most likely than any other race to use the links provided in the study (Brusk & Bensley, 2016). The results suggest that minorities are more comfortable with accessing the Internet on their mobile devices rather than traditional computer methods. However, White populations were most likely to utilize health apps on their phones compared to other populations (Bhuyan et al., 2016).

### *Education*

Breaking down IHISB by educational level, studies have found low educational attainment populations are less likely to use IHISB (Li & Theng, 2016; Miller & Bell, 2012). People with lower educational attainment are linked to lower Internet literacy and lower health literacy as well which are predictors for IHISB (Li & Theng, 2016; Tennant et al., 2015).

When looking into education, lower educational attainment was linked to a decreased likelihood of any technology ownership (Anderson, 2015; Anderson & Perrin, 2016). However, of all the available types of devices that could connect to the Internet,

low educational attainment groups were more likely to have a smartphone than a traditional computer or laptop (Anderson, 2015). This suggests that there is likely a price value relationship involved in which the smartphone is cheaper and has more utility to the average consumer than a traditional computer or laptop. Those with a high school diploma or less education were the most likely to use the Internet on their mobile device for the longest amount of time of all the age groups (Salesforce, 2014; Serrano et al., 2017). Higher education was linked to higher use of health apps than other levels of educational attainment (Bhuyan et al., 2016).

### *Income*

When breaking down IHISB by income levels, low income populations are less likely to use IHISB. Similar to low educational attainment, low income populations are less likely to use the Internet because they have lower Internet literacy levels (Collins et al., 2014; Li & Theng, 2016; Tennant et al., 2015). The low Internet literacy level is partially due to the fact that low income families are less likely to afford the necessary equipment and utilities to go on the Internet, which impacts the likeliness of using IHISB (Li & Theng, 2016; Sarkar et al., 2011).

Similar to educational attainment, lower income was linked to less likelihood of having an Internet-connectable device. The difference was that the effects were more pronounced than the effect of lower educational attainment (Anderson, 2015; Anderson & Perrin, 2016). Lower income populations were also most likely to log the most amount of time on their mobile devices on the Internet and most likely to use their mobile devices to access the Internet (Bensley, 2016; Salesforce, 2014; Serrano et al., 2017).

## *Rurality*

Taking rurality into account, rural residents are less likely to use IHISB than urban areas (Li & Theng, 2016; Liu et al., 2008). This disparity is likely due to the digital divide, with fewer rural residents using the Internet (Carlson & Goss, 2016; Wang, Bennett, & Probst, 2011). In addition, rural residents tend to be older, lower income, and lower educational attainments, all of which are major factors in determining Internet use (Carlson & Goss, 2016; Chesser et al., 2016; Peterson & Litaker, 2010).

Inhabitants of rural areas are less likely to own a mobile device than their urban counterparts (Anderson, 2015; Dotson et al., 2017). A mobile IHISB-based intervention in Montana found that rural populations with Internet-accessible cell phones did not preferred not to receive health information on their devices (Dotson et al., 2017; Wilson et al., 2016). A national study found that rural residents were less likely to use health apps on their smartphones (Bhuyan et al., 2016). This suggests that there is a preference factor involved in how likely one seeks their health information. Very little is known about how often rural populations use Internet accessible devices.

## **E-Prescriptions and the Digital Divide Speed**

This section will discuss two types of digital divides: digital speed divide and digital access divide. As discussed above, speed divide speaks to the difference in top speeds for different locations due to the fact the Internet infrastructure favored urban areas more than rural areas. Digital access divide refers to differences in different populations' levels of experience with the Internet, which impacts access.

### *Bandwidth and Internet Speed*

Bandwidth is defined as the capacity to allow one to send information that is expressed in bit rate, while Internet speed is defined as the rate at which information sending can occur. Both speed and bandwidth have become interchangeable in use and will also be used interchangeably in this literature review. Based on the available research, most rural residents had slower broadband speeds than their urban counterparts (Whitacre et al., 2016). However, a study based in Oklahoma found that, despite slower broadband speeds, rural physicians had higher EMR adoption rates than their urban counterparts (Whitacre & Williams, 2015).

One of the other features of the digital speed divide is how it has impacted businesses. Areas with slower Internet access lag behind economically when compared to areas with faster Internet access (Warren, 2007). This is because faster Internet access allows more work to be done in a shorter time span, but also loads more complex pages. In healthcare, this effect is best seen by the adoption of HIT in urban versus rural areas in the first decade of the 2000s. Early on, rural areas were slow to adopt HIT because of financial and Internet barriers (National Council Survey, 2012). Based on a study determining HIT adoption, aside from upfront costs and maintenance costs, the top issues cited for lack of adoption of HIT were the lack of personnel, skillset to adopt the technology, or Internet speed (National Council Survey, 2012).

### **E-prescription Adoption in the United States**

E-prescriptions are a quality improvement in healthcare. E-prescription refers to physicians' issuing prescriptions to patients using the Internet and sending directly the

prescription directly to the pharmacy (Cooke et al., 2011; Powers et al., 2015; Zadeh et al., 2016). Instead of writing handwritten notes which can be lost or misread, e-prescriptions can be sent directly from the physician to the pharmacy (Cooke et al., 2011). The act of sending the prescription via computer reduces the chance of human error while decreasing the wait time for the patients to obtain the prescribed medication. For this reason, e-prescriptions are linked to a higher health outcome rate and lower mortality rates ( Salmon & Jiang, 2012; Zadeh & Tremblay, 2016). In addition, because e-prescriptions are used to monitor patients, e-prescriptions have been linked to decreased adverse reactions to drugs and a positive impact on curbing the opioid epidemic (Cicero et al., 2007; Salmon & Jiang, 2012; Weiss et al., 2015; Zadeh & Tremblay, 2016). This is because e-prescriptions can help monitor if a patient has been overprescribed certain drugs due to dosage errors, check for drug interactions, and other similar issues (Salmon & Jiang, 2012). Despite the positive features offered with e-prescriptions, as of 2014, it was reported that the United States has not fully adopted the e-prescriptions (Gabriel & Swain, 2014).

There are multiple reasons why some areas have not adopted e-prescriptions as quickly as others. Studies have cited different reasons why healthcare facilities are slow to adopt e-prescription. As cited in a study by the Office of National Coordinator for Health Information (ONC), reasons for not adopting e-prescriptions include cost, patients not understanding e-prescriptions, Internet speed, or attitudinal barriers toward using e-prescriptions (Gabriel & Swain, 2014). For organizations that cited Internet speed as an issue, it illustrated the economic problem that is associated with the digital divide. An organization may want to adopt better and faster technology that could help the

organization in the outcomes of quality and efficiency. Policies can attempt to stimulate adoption through incentives to encourage the organization to adopt the new technology in the form of grants and penalties. However, if there the pre-existing Internet infrastructure is unable to support the technology, the organization is unable to adopt the technology. Thus, causing the organization to continue to lag behind organizations with better infrastructure available to them.

The literature on e-prescription is still fairly new due to the low adoption rate prior to 2008. It was reported that less than 7% of practices utilized e-prescriptions in 2008, but through the HITECH act encouraging use among physicians e-prescriptions have increased to around approximately 76% adoption in 2014 (Gabriel & Swain, 2014).

#### *Sex of Physician*

Studies have looked into the physicians using e-prescriptions. It found that physicians who prefer to use e-prescriptions on a regular basis were more likely males than females (Thomas et al., 2012).

#### *Age of Physician*

A recent survey by mHealth found that older physicians aged over 40 were less likely to adopt EHRs than younger physicians under 40 (mHealth, 2015). This information is similar to a 2011 brief by the CDC, which found that among physicians under age 50, 64% were EHR adopters, while only 49% of physicians over 50 were EHR adopters (Jamoom & Hing, 2015). While there is no available evidence linking age to e-prescription adoption, physician age is linked to EHR which is a requirement for e-prescription.

### *Location of Healthcare Facility*

There are studies showing that urban areas were more likely than rural areas to adopt e-prescriptions (Powers et al., 2015). Based on national data, this study found that physicians in urban areas were more likely to give e-prescriptions than those in rural areas; it is believed that one of the limiting factors to e-prescription adoption in rural areas is high-speed Internet (Gabriel et al., 2013; Gabriel & Swain, 2014). Other research has shown that organizations located in close proximity to lower income populations were more likely to use e-prescriptions than organizations located near high income populations (King et al., 2012; Powers et al., 2015). Based on specialty type, family medicine physicians were most likely to use e-prescriptions in their practice compared to different type of specialists (Thomas et al., 2012).

### **U.S. Policy's Effect on Health Information Seeking Behavior and E-prescription Adoption**

Due to the newness of the Internet, compared to other forms of communication methods, there are relatively fewer laws governing Internet use. However, some policies have been geared toward regulating the Internet as well as the use of IHISB and e-prescription. This section will focus on policies that affect the realm of health information with regard to the digital divide, IHISB, and e-prescriptions.

### *Scientific and Technology Act of 1992*

The Scientific and Technology Act of 1992 worked to increase the amount of skilled technical labor in the advanced technology fields. Prior to the act, the Internet was restricted to academic and military use. When the act was passed, the act had a provision



that decreased the restrictions for use of the Internet to allow the commercial use of the Internet (GovTrack.us, n.d.). By doing so, the Internet would become open for members of the public to use, as long as they had Internet availability. The problem with the act was that the role of Internet infrastructure-building became a corporate responsibility, rather than a governmental responsibility. This caused the digital divide because telecommunications companies would only build in areas with high populations to offset the high costs of building the Internet (West, 2015; Smith, 2010).

#### *Electronic Communications Privacy Act of 1986 (ECPA)*

The Electronics Communications Privacy Act of 1986 prohibited wiretaps for privacy reasons for phone calls. While the law was written before the Internet was used commercially, the law has been adapted to the use of the Internet. During a landmark ruling in *United States v. Councilman*, ECPA was cited as a reason that a third party could not get information transferred between two parties on the Internet (Berkeley Technology Law Journal, 2005). It was through this ruling that ECPA guaranteed privacy for the transfer of private information between two parties via the Internet. This act would play a role in privacy for health information technology when the Health Insurance Portability and Accountability Act of 1996 (HIPAA) included wording that required patient privacy.

#### *Health Insurance Portability and Accountability Act of 1996 (HIPAA)*

The Health Insurance Portability and Accountability Act of 1996 (HIPAA) covers multiple aspects of healthcare regulations and healthcare delivery. Title 1 of HIPAA set down requirements for health insurance coverage for Americans, while Title

II set down standards for patient privacy and early EHR requirements for healthcare institutions (Atchinson & Fox, 1997). This literature review will focus on Title II only because of its relevance to the digital divide and e-prescriptions.

Title II established requirements for healthcare institutions to properly protect patient health information. Title II required that the information of the patient must be kept private which included, but not limited to: health status, health insurance type, health treatments, etc. (Atchinson & Fox, 1997). If Title II is breached, the health care facility involved is expected to pay a set amount not including personal lawsuits levied by the patient (United States Health and Human Services, n.d.). At the time of writing the bill, the Internet was just beginning to be used commercially. However, the bill was written in broad way that it is applicable to EHR use (United States Health and Human Services, n.d.). Since the passage of HIPAA in 1996, an amendment was made in January 2013 which updated the language regarding privacy, breaches, and how long records could be kept (Centers for Medicare & Medicaid Services, 2014).

Title II of HIPAA had two direct effects on the adoption of e-prescriptions: 1) All health information had to be kept private on the Internet; e-prescriptions fall under the umbrella of health information, and 2) The healthcare industry is one of the few industries in which the hacking of a company that holds patients' protected health information by a third party automatically results in the company's being fined for a breach of HIPAA, as well as a potential lawsuit from the Federal Trade Commission (United States Health and Human Services, n.d.). This is different compared to other industries in which the Federal Trade Commission must prove negligence on the part of the company that was hacked (Bergsieker, Cunningham, & Young, 2015). For this

reason, HIT systems are more expensive because security systems are built into the system to protect against hacking and the associated penalties. In addition, recent HIPAA amendments have specified levels of encryption (U.S. Department of Health and Human Services, n.d.).

### *Telecommunications Act of 1996 and the Lifeline Program*

The Telecommunications Act of 1996 was signed into law by President Bill Clinton to allow more competition between telecommunications companies. The act aimed to deregulate the telecommunications markets by allowing telecommunications companies to compete in any market they chose to (Federal Communications Commission, n.d.). Analysts believed this act actually led to the decrease in competition for the telecommunications market, since major companies were allowed to buy out smaller regional companies (McCabe, 2016). This in turn led to fewer choices for rural customers who were affected by a model that looked to offset costs by building Internet infrastructure in urban areas.

One of the other major effects of the Telecommunications Act of 1996 was to move funding toward the Lifeline program. The Lifeline program was created in 1985 by the Federal Communications Commission to connect low income populations with subsidized cell phones (Federal Communications Commission, n.d.). The Telecommunications Act of 1996 helped stabilize the funding for the Lifeline program through the Universal Service Fund (Federal Communications Commission, n.d.). The Universal Service Fund has not only helped connect lower income populations with smartphones, but it also helps build infrastructure for rural healthcare by providing

subsidies for telehealth and telemedicine services (Federal Communications Commission, n.d.).

#### *American Recovery and Reinvestment Act of 2009*

The American Recovery and Reinvestment Act of 2009 was passed in 2009 in response to the economic downturn of 2008. One of the provisions within the American Recovery and Reinvestment Act of 2009 was to direct federal money toward broadband and mobile broadband infrastructure; in particular to rural areas (Kruger & Gilroy, 2016). Through the stewardship efforts of both the U.S. Department of Agriculture and the Federal Communications Commission, grants were given out to areas that were underserved with poor broadband Internet access (Kruger & Gilroy, 2016). The American Recovery and Reinvestment Act of 2009 impacted e-prescription adoption in two ways: 1. It helped develop the American broadband infrastructure nationwide. 2. It gave incentives to physicians and organizations that adopted HIT (Burke, 2010).

#### *Food and Drug Administration Safety and Innovation Act of 2012 Section 618 (FDASIA)*

The Food and Drug Administration Safety and Innovation Act (FDASIA) of 2012 Section 618 was passed in 2012 to give more power to the Food and Drug Administration (FDA) in the development of drugs and medical innovations. The FDASIA had two effects on e-prescriptions. Taxes could be collected on technology that was being developed for e-prescriptions; the taxes collected would be used on other programs that could help continue developing e-prescriptions (United States Congress, n.d.). The second effect on e-prescriptions was the FDASIA developed a regulatory framework to increase the benefits of e-prescriptions: 1) Promoting the Use of Quality Management

Principles, 2) Identifying, Developing and Adopting Standards and Best Practices 3) Leverage Conformity Assessment Tools 4) Creating an Environment of Learning and Continual Improvement (Commissioner, n.d.; Office of the National Coordinator for Health Information Technology, 2014).

*Health Information Technology for Economic and Clinical Health Act of 2009 (HITECH)*

The Health Information Technology for Economic and Clinical Health Act of 2009 was designed to help stimulate the adoption of HIT systems in the United States health system (Henricks, 2011). The act was part of a larger act, the American Recovery and Reinvestment Act of 2009, which was passed to stimulate the American economy at the time. The HITECH Act of 2009 attempted to increase HIT adoption which in turn would increase healthcare quality by giving meaningful use guidelines and financial incentives for HIT adoption (Gold & McLaughlin, 2016; Henricks, 2011; United States Department of Health and Human Services, n.d.). By stimulating HIT adoption, it also helped encourage e-prescription adoption in healthcare facilities (Henricks, 2011; King, Furukawa, & Buntin, 2013). The HITECH Act stipulated penalties for providers failing to meet the meaningful use guidelines set by the HITECH Act (United States Department of Health and Human Services, n.d.).

The HITECH Act would pave the way for more HIT use within the healthcare system but there was a limitation to adoption. During the first years of the implementation, a digital divide developed between the type of healthcare facilities that could meet meaningful use versus those that could not (Gold & McLaughlin, 2016). Healthcare facilities that could meet meaningful use tended to be wealthier, while

healthcare facilities that were less well-off were unable to adopt HIT as quickly (Gold & McLaughlin, 2016; King et al., 2013). For many of the healthcare facilities, the limiting factor of money to pay the workforce associated with HIT adoption prevented the speed at which HIT was adopted (Gold & McLaughlin, 2016; King et al., 2013). Based on evaluation results, aside from the issue of money, training and Internet speeds were commonly cited reasons for slow HIT adoption (Jamoom & Hing, 2015; Kruse et al., 2016).

*Section 132 of the Medicare Improvements for Patients and Providers Act of 2008 (MIPPA) - Electronic Prescribing Incentive*

Passed in 2008, the Medicare Improvement for Patients and Providers Act of 2008 (MIPPA) was passed to make amendments to the Social Security Act (Social Security Administration, 2008). Within MIPPA, there was a section that helped create the Electronic Prescribing Incentive (Centers for Medicare & Medicaid Services, 2013). The E-prescribing Incentive is an incentive program that encourages healthcare organizations and physicians to adopt e-prescriptions (Centers for Medicare & Medicaid Services, 2013). From 2009 – 2013, both incentive payments and payment adjustments were given to physicians that used e-prescriptions as a method of encouraging adoption (Centers for Medicare & Medicaid Services, 2013). Research has shown that the federal incentive program was associated with a 9-11% increase in e-prescriptions among providers (Sow et al., 2013).

## **Gaps in the Literature**

During the course of this literature review, a gap in literature was identified for IHISB. Many of the studies that studied IHISB focused on the individual barriers that prevented someone from using the Internet, while other studies focused on which devices people use to partake in IHISB via the Internet. A gap exists in that very few studies that broke down their findings on the basis of rurality in the United States. As mentioned before, this is significant because rural populations have reduced access to the Internet compared to urban populations. To make IHISB more accessible to the larger population, research must be done to understand how different populations utilize their devices to look up IHISB. The first part of this dissertation will focus on the type of devices urban and rural residents are more likely to use to access IHISB.

For e-prescription adoption, a similar gap in literature was found. Many studies that looked into e-prescriptions focused on study populations from interventions or surveys, but rarely looked into nationwide data. As indicated by the adoption of HIT from the HITECH act, some organizations and physicians have cited Internet speed as a reason for not adopting HIT. During the course of the literature review, a gap in the literature was found regarding Internet speed and its effect on e-prescription. For this reason, this dissertation will focus on whether broadband speeds affect e-prescription adoption rates.

<i>Table 2.1 UTAT2 and Aim 1</i>	
<b>UTAT2 Construct</b>	<b>Variables Used</b>
Performance Expectancy	Internetype
Effort Expectancy	Healthdevicetype
Social Influence	Race Married Children
Facilitating Conditions	Rurality Health insurance
Hedonic Motivation	None Available
Price Value	Income
Habit	None Available
Age	Age
Gender	Gender
Experience	None Available



<i>Table 2. 2 UTAT2 Model and Aim 2</i>	
<b>UTAT2 Construct</b>	<b>Variables Used</b>
Performance Expectancy	Upload speed Download speed
Effort Expectancy	% of Bachelor's degree
Social Influence	Number of hospitals % minority
Facilitating Conditions	Percent of people 18-64 without health insurance Percent of people on Medicare Part D Percent of people under 65 Rurality
Hedonic Motivation	None available
Price Value	People in poverty
Habit	None Available
Age	Percent of M.D.'s aged younger than 55
Gender	Percent of males M.D.
Experience	None Available

## **CHAPTER 3**

### **METHODOLOGY**

#### **Purpose**

There are two purposes to this study. The first purpose of the study is to investigate the differences between rural and urban residents in the use of mobile devices for IHISB. The second purpose is to determine the relationship between Internet speed and e-prescription adoption. Analyses will be done using the AHRF, HINTS, Surescripts, and National Broadband Map datasets over a two to five year period.

The specific Aims of the study are:

Aim 1: To examine differences among rural and urban residents in the use of mobile devices for IHISB.

Hypothesis: Based on the literature review, rural and urban residents will have differences in what they use to access IHISB. Urban residents are more likely to access IHISB due to higher income and younger population the compared to their rural counterparts.

Aim 2: To examine differences in rural versus physician e-prescription adoption change from 2010-2014, statistically controlled for similar broadband speeds.

Hypothesis: Rural physicians are less likely to adopt e-prescribing than urban physicians. This is because rural physicians are less likely to adopt e-prescriptions because slower broadband availability.

## **Data Sources**

Four data sources will be utilized to address the specific Aims of the study. The first source is the Health Information National Trends Survey (HINTS), which will be used to determine the type of device which rural and urban residents use for IHISB. The second source is the Area Health Resource File (AHRF); the data was used to obtain county level information for demographic, income, education, amount of healthcare organizations, and population data. The third source is the National Broadband Map (NBM), which was used for county level data for different Internet speeds within counties. The final data source is the Surescripts database, which is a county level database for e-prescription adoption. For Aim 1, only the 2013-2014 HINTS database was used. For Aim 2, the 2010-2016 AHRF, 2010-2014 NBM, and Surescripts was combined.

### **Data Source Descriptions – Aim 1**

#### *Health Information National Trends (HINTS)*

The HINTS data was created by the National Cancer Institute Division of Cancer Control and Population Sciences. The HINTS is an annually updated, nationally representative cross-sectional dataset about American's use of cancer related information and treatment. For this analysis, the 2013-2014 HINTS database was used to determine if there were any differences in devices that rural and urban residents used to access the Internet.

## **Dataset Creation and Study Sample – Aim 1**

The years that were used for the HINTS database was 2013 and 2014. The two datasets were concatenated, which brought the sample size to 22 variables consisting of 9,555 observations.

## **Study Variables – Aim 1**

### *Dependent Variable*

For Aim 1, the dependent variable is the type of device that a patient uses to go online for HISB. The variable that was used to determine if respondents went online was the UseInternet variable (Do you ever go on-line to access the Internet or World Wide Web, or to send and receive e-mail? Responses available: Yes, No). If the respondent answered yes, then respondents were then asked what type of device was used (Please indicate if you have each of the following (Mark all that apply) A. Tablet computer B. Smartphone C. Basic cell phone only D. I do not have any of the above). If the respondent answered that they used any form of mobile device (tablet, cell phone, other mobile device) then they were recoded as using a mobile device. People who used the Internet, but did not use a mobile device were recoded as not using a mobile device.

The Whereseekhealthinfo variable was also used to determine who had used their mobile devices for online HISB (The most recent time you looked for information about health or medical topics, where did you go first? (Mark only one) A. Books B. Brochures, pamphlets, etc. C. Cancer organization D. Family E. Friend/Co-worker F. Doctor or

healthcare provider G. Internet H. Library I. Magazines J. Newspapers K. Telephone information number L. Complementary, alternative, or unconventional practitioner).

Along with the recoded mobile device variable, where seek health info was used to recode all the participants into a binary variable which determined if a participant had or had not used a mobile device for IHISB. The binary variable was created by determining if anyone who had chosen “Internet” as their first source of health information was coded a 1, while respondents who chose something else as their first source of health information was coded as a 0.

### *Independent Variable*

The independent variable that is used for this analysis is rurality. Rurality is determined by the Urban Influence Code (UIC), which has a total of 12 codes categorizing counties; Codes 1-2 are metropolitan areas, while codes 3-12 are rural, non-metropolitan areas (United States Department of Agriculture, n.d.).

### *Control Variables*

The control variables used to accomplish Aim 1 were sex, age, race, marriage status (married, non-married), number of children in household, Hispanic ethnicity, health insurance (Medicaid, Medicare, Private, No Insurance), and income level. Race was recoded to simplify all races into Whites, African Americans, AI/AN, Asian, or Other. When Hispanic was recoded as part of each race, observations for a majority of Hispanic categories fell below ten observations which affected statistical power. For this reason, ethnicity and race were recoded into a three level variable (Non-Hispanic White, Non-Hispanic Black, and Other). Income was reduced from nine ranges of incomes from

\$0 - \$200,000 to five ranges (<\$20,000, \$20,000-49,999, \$50,000-74,999, \$75,000-99,999, >\$100,000). All variables that were used from the HINTS database are listed in Table 3.1.

### **Analysis Method – Aim 1**

The unit of analysis for Aim 1 was the individual. To accomplish the first Aim, a univariate analysis provided estimates of the demographic characteristics of the study population. The UTAT2 model was used to guide the selection of variables, Table 3.2 shows the variables that will be used based on the UTAT2 model.

A bivariate analysis was conducted to determine if there was a difference in these characteristics between the rural and urban populations. Wald chi square test was used to determine if there were any differences between the two populations of rural and urban residents. The analysis was conducted at 95% confidence interval (alpha = .05).

A multivariate logistic regression analysis was then used to estimate the rural-urban differences in using certain devices when accessing IHISB, after controlling for difference in population characteristics. A total of two models will be performed. The first model only looked at rurality impact on mobile IHISB. The second model included all the factors from the study.

The models for this analysis were:

**Model 1:**  $OR_{\text{mobile vs non-mobile IHISB use}} = \beta_1(\text{Rurality}) + \text{error}$

**Model 2:**  $OR_{\text{mobile vs non-mobile IHISB use}} = \beta_1(\text{Rurality}) + \beta_2(\text{Sex}) + \beta_3(\text{Age}) + \beta_4(\text{Income}) + \beta_5(\text{Race}) + \beta_6(\text{Internet Type}) + \beta_7(\text{Hispanice}) + \beta_8(\text{Health Insruance}) + \beta_9(\text{Children}) + \beta_{10}(\text{Married}) + \text{error}$

## **Data Source Descriptions – Aim 2**

### *Area Health Resource File (AHRF)*

The AHRF database is a cross-sectional, national, county-level database that is annually created by the Health Resources and Services Administration (HRSA). The data includes every American county and every U.S. territory. The AHRF was used to determine variables for: 1. Health care professions, 2. Healthcare facilities, and 3. Population data. The AHRF is updated annually, but has an approximate two-year lag in data timeliness. In order to have all the relevant variable information for the five years (2010-2014) this Aim investigated, the datasets for 2011-2016 were used.

### *National Broadband Map (NBM)*

The National Broadband Map is a cross-sectional dataset that is updated annually by the Federal Communications and Commission (FCC), which includes county-level observations of a county's Internet upload and download speed of every telecommunications company in each county for each year. The years that were used were from 2010-2014. The NBM was used to identify broadband speeds by county. Because the number of telecommunications companies can change annually, observations ranged from 12,001,515 - 17,772,148.

### *Surescripts*

The Surescripts dataset was created by the Office of National Coordinator for Health Information Technology. The dataset is a cross-sectional dataset that includes data regarding electronic prescribing adoption by physicians at a county, state and national level. The Surescripts database is a cross-sectional data comprised of a total of 22,645 observations of every United States state and county from 2008-2014. For this Aim, the Surescripts data was delimited to the 50 states of the United States and only observations from 2010-2014. Within the Surescripts dataset every observation year was considered its own observation. For this reason, each county in the dataset had 6 observations, which led to the database having a total of 22,452 observations. This dataset was later broken up by year for analysis.

### **Dataset Creation and Study Sample – Aim 2**

For Aim 2, the three datasets (AHRF, NBM, and Surescripts) were merged by county to create one dataset. For all data, observations were delimited to the years 2010-2014, inclusive.

### *National Broadband Map*

The maximum download and upload speeds were chosen for each county. The average maximum download and upload speeds were calculated across all the companies within each county as well. This left the resulting data with 3,144 total county level observations and 21 variables.

### *AHRF*



For each year, the data was delimited to the 50 states within the United States and all relevant information pertaining to demographic and healthcare systems information was kept. This left the AHRF with a total of 3,147 observations and 43 variables. Variables from the AHRF used for this Aim are displayed in Table 3.3.

### *Surescripts*

Since the Surescripts dataset contained years 2008-2014, every needed observation year was separated into four different files (2010-2014). Every observation year was then merged together by their FIPS code, leaving the final dataset from Surescripts for Aim 2 with 3,144 total observations and seven variables. The variables utilized are summarized in Table 3.3.

### *Merged File*

The final merged database for Aim 2 consisted of the AHRF (2010-2016), NBM (2010-2014), and Surescripts (2010-2014) files. All the files were merged by county which consisted of a total 3,144 observations and 76 variables.

## **Study Variables – Aim 2**

### *Dependent Variable*

To accomplish Aim 2, the dependent variable was the percent of electronic prescription adoption within a county. This was calculated using the percent of physicians in the area that reported adopting electronic prescription adoption compared to those who did not which is found in the Surescripts dataset.

### *Independent Variables*

The independent variables that were used to accomplish Aim 2 were rurality, upload speeds, and download speeds. Rurality is determined by the Urban Influence Code (UIC), which has a total of 12 codes categorizing counties; Codes 1-2 are metropolitan areas, while codes 3-12 are rural, non-metropolitan areas (United States Department of Agriculture, n.d.).

The reason why this study utilized both upload and download speeds instead of choosing just solely upload or download speed is because of Internet bandwidth. Internet bandwidth, which is the ability to transfer information on a cable, is the barrier to faster speed because the amount bandwidth is the major factor in determining upload and download speeds (Comer, 2008). Download speeds can be decreased to increase upload speeds and vice versa, but bandwidth must increase to increase both maximum download speeds and maximum upload speeds concurrently (Comer, 2008). For this reason, download and upload speeds are not covariates and treated as individual variables.

### *Control Variable*

The control variables were percent of poverty in the county, the percent of bachelor's degree of the total population by county, the number of hospitals in the county, percent of Medicare part D enrollees of eligible residents in the county, percent of people ages 18-64 without health insurance in the county, percent of male doctors, and the rurality by county. All variables used are listed in the Table 3.4.

## Analysis Method – Aim 2

The unit of analysis for Aim 2 was the county. To accomplish the second Aim, a univariate analysis was first done to summarize the characteristics of the study population. Because the study population is comprised of county level observations, the analysis was split into community demographic and community healthcare level information to see if the county level demographics played a role in e-prescription adoption. The UTAT2 model was used to guide the selection of variables regarding the adoption behavior of physicians, below is a table showing which variables that will be used based on the UTAT2 model.

The community demographic level information that will be used is average age, median household income, percent of minority population, percent of people in poverty, percent of people ages 18-64 without health insurance, and rurality. The community healthcare level information is any information that is related to how healthcare is delivered within the community. A bivariate analysis was done on the population to determine if there were any differences based on rurality. A Wald chi square test was used to determine if there were any differences between the rural and urban populations. The analysis will be conducted at a 95% confidence interval ( $\alpha = .05$ ).

A multivariate regression analysis was conducted to determine how likely e-prescription adoption would occur based on different factors. Three models were used. The first model consisted of Internet speeds and its relation to e-prescription adoption in 2014. The second model consisted of Internet speeds and rurality, and their relation to e-prescription adoptions in 2014. The third model added county level information to

determine their relation to e-prescriptions adoption in 2014. Below is the model for that was used for this Aim:

**Model 1:**  $OR_{e\text{-prescription adoption in 2014}} = \beta_1(\text{Internet speed change from 2010} - 2014)$   
+ error

**Model 2:**  $OR_{e\text{-prescription adoption in 2014}} = \beta_1(\text{Internet speed change from 2010} - 2014)$   
+  $\beta_2(e\text{-prescription adoption in 2010}) + \beta_3(\text{rurality})$  + error

**Model 3:**  $OR_{e\text{-prescription adoption in 2014}} = \beta_1(\text{Internet speed change from 2010} - 2014) + \beta_2(e\text{-prescription adoption in 2010}) + \beta_3(\text{rurality}) + \beta_4(\% \text{ minority}) + \beta_5(\text{number of hospitals in county}) + \beta_8(\text{ratio of physicians to population}) + \beta_9(\text{Ratio of male physicians}) + \beta_{10}(\% \text{ Medicare Part D Enrolees}) + \beta_{11}(\% \text{ 18} - 64 \text{ without health insurance})$   
+ error

*Table 3. 1 Variables used for Aim 1 in HINTS dataset*

Internet_Dialup	Internet_Cell	Internet_Broadband	Where_sought_health_info_OS	Use_Internet	Internet_Wifi
white	black	Chinese	Filipino	incomeranges	selfgender
Vietnamese	othasian	Hawaiian	Guamian	Japanese	Korean
selfage	RUC2003	Hispanic	Samoan	Othpascis1	

<i>Table 3. 2 UTAT2 and Aim 1</i>	
<b>UTAT2 Construct</b>	<b>Variables Used</b>
Performance Expectancy	Internetype
Effort Expectancy	Healthdevicetype
Social Influence	Race Married Children
Facilitating Conditions	Rurality Health insurance
Hedonic Motivation	None Available
Price Value	Income
Habit	None Available
Age	Age
Gender	Gender
Experience	None Available

Table 3. 3 Aim 2 variables used by dataset					
<b>Surescripts</b>					
FIPS Code	Percent e-prescription 2010	Percent e-prescription 2011	Percent e-prescription 2012	Percent e-prescription 2013	Percent e-prescription 2014
<b>NBM</b>					
FIPS Code	Average upload speed 2010	Average upload speed 2011	Average upload speed 2012	Average upload speed 2013	Average upload speed 2014
	Average download speed 2010	Average download speed 2011	Average download speed 2012	Average download speed 2013	Average download speed 2014
	Fastest upload speed 2010	Fastest upload speed 2011	Fastest upload speed 2012	Fastest upload speed 2013	Fastest upload speed 2014
	Fastest download speed 2010	Fastest download speed 2011	Fastest download speed 2012	Fastest download speed 2013	Fastest download speed 2014
<b>AHRF</b>					
FIPS	Population 2010	Population estimate 2011	Population estimate 2012	Population estimate 2013	Population estimate 2014
Rurality (based on UIC)	White population 2010	Black Population 2010	AI/AN Population 2010	Some other race population 2010	Hispanic/Latino Population 2010
	Total M.D.'s 2010	Total M.D.'s 2011	Total M.D.'s 2012	Total M.D.'s 2013	Total M.D.'s 2014
	Total Male MD's 2010	Total Male MD's 2011	Total Male MD's 2012	Total Male MD's 2013	Total Male MD's 2014

	# of hospitals 2010	# of hospitals 2011	# of hospitals 2012	# of hospitals 2013	# of hospitals 2014
	Percent in poverty 2010	Percent in poverty 2011	Percent in poverty 2012	Percent in poverty 2013	Percent in poverty 2014
	% 18-64 with no health insurance 2010	% 18-64 with no health insurance 2011	% 18-64 with no health insurance 2012	% 18-64 with no health insurance 2013	% 18-64 with no health insurance 2014
	# of Medicare Prescription Drug Plans 2010	# of Medicare Prescription Drug Plans 2011	# of Medicare Prescription Drug Plans 2012	# of Medicare Prescription Drug Plans 2013	# of Medicare Prescription Drug Plans 2014
	# Eligible for Medicare 2010	# Eligible for Medicare 2011	# Eligible for Medicare 2012	# Eligible for Medicare 2013	# Eligible for Medicare 2014



*Table 3. 4 Variables listed by type*

<b>Dependent Variables</b>	<b>Variable Type</b>
Percent of e-prescription adoption	Continuous
<b>Independent Variable</b>	
Rurality	Categorical
<b>Control Variables</b>	
<i>Internet provider based variables</i>	
Typical Upload Speed	Continuous
Typical Download Speed	Continuous
<i>County level demographics based information</i>	Continuous
Percent of people in poverty	Continuous
Percent of population with bachelor's degree	Continuous
Percent of minority population	Continuous
Population	Continuous
<i>County level healthcare based information</i>	
Amount of hospitals to population	Continuous
% male physicians	Continuous
Amount of physicians to population	Continuous
Percent of Medicare part D enrollees of eligible residents in the county	Continuous
Percent of people 18-64 Without health insurance	Continuous

*Table 3.5 UTAT2 model and Aim 2*

<b>UTAT2 Construct</b>	<b>Variables Used</b>
Performance Expectancy	Upload speed Download speed
Effort Expectancy	% of Bachelor's degree
Social Influence	Number of hospitals % minority
Facilitating Conditions	Percent of people 18-64 without health insurance Percent of people on Medicare Part D Percent of people under 65 Rurality
Hedonic Motivation	None available
Price Value	People in poverty
Habit	None Available
Age	Percent of M.D.'s aged younger than 55
Gender	Percent of males M.D.
Experience	None Available

## CHAPTER 4

### MANUSCRIPT 1

#### **Differences among rural and urban residents in mobile device usage for health information seeking behavior<sup>1</sup>**

---

<sup>1</sup> Yuen M.W., Probst J.C., Bennett K.J., Crouch E.L, Chen B.K., To be submitted to *Journal of Rural Health*

## **Abstract**

Mobile devices such as cell phones have made the Internet more accessible. Internet health information seeking behavior (IHISB) is linked to better health outcomes and decreases in health services used. Traditionally, IHISB use has been lower among low income and rural populations due in large part to the lack of Internet access. However, with mobile devices becoming more popular, the Internet has become more accessible for these populations, which could possibly impact the number of people engaging in IHISB.

The purpose of this study is to examine disparities among populations for mobile device IHISB use. This study utilized Health Information National Trends Survey (HINTS) data from 2013-2014 to determine if there were any differences in mobile device IHISB use between urban and rural residents. Rural populations were less likely to own a mobile device than their urban counterparts (78.1% vs. 86.4%), which likely played a role in a lower number of rural residents engaging in IHISB (47.2% vs. 56.3%). Low income populations were also less likely to engage in IHISB than their higher income counterparts. More programs are needed to help make the Internet accessible for vulnerable populations to look up IHISB. In addition, web designers of IHISB should also cater to the needs of low income populations.

## **Introduction**

One of the uses of the Internet is for acquiring knowledge about a health problem, which is also known as health information seeking behavior (HISB) (Bhuyan et al., 2016; Li & Theng, 2016; Pang et al., n.d.; Tan & Goonawardene, 2017; Tennant et al., 2015). Engaging in Internet based health information seeking behavior (IHISB) is advantageous

for users because they are able to save time and money before visiting a physician for their health problems (Manierre, 2015; McCloud et al., 2016). The benefits of engaging in IHISB isn't confined just to time or money; those who used IHISB are linked to better health outcomes than those who did not (Tennant et al., 2015). Engaging in IHISB has many benefits for users compared to those who do not; however, there are clear disparities between income levels, race, and education (Bhuyan et al., 2016; Manierre, 2015; J. R. Warren et al., 2010).

There are several barriers associated with engaging in IHISB. The first is attitudinal in nature, where populations believe that there is very little use for IHISB or have a generally negative feeling toward using IHISB (Manierre, 2015; McCloud et al., 2016; Miller & Bell, 2012). The second type is educational; those who do not engage in IHISB tend to have lower health literacy and Internet literacy scores (Chesser, Burke, Reyes, & Rohrberg, 2016; Gazmararian, Williams, Peel, & Baker, 2003; Tennant et al., 2015). The final type of barrier is lack of access to Internet, which could be due to the cost associated with an Internet subscription, living in an area without access to the Internet, or lacking the necessary equipment needed to go onto the Internet (Dotson et al., 2017; Ronquillo & Currie, 2012). This is also often known as the Internet digital divide.

Since the beginning of the Internet, there has been an Internet access digital divide across populations. The Internet digital divide is the observation that certain populations are less likely to access the Internet because of particular barriers (Kruger & Gilroy, 2016). It is believed one of the main factors of the digital divide stemmed from how the Internet infrastructure was created when it became commercialized. Telecommunications companies built internet infrastructure in densely populated, high income areas to offset

the costs (West, 2015; Smith, 2010). Due to government policy in recent years, the Internet has become more accessible for populations of different income levels to access, which has decreased the gap in Internet access (Pew Research Center, 2017; West, 2015).

In addition, there are now disparities in Internet speed across different populations, particularly among rural and low income populations (Anderson & Perrin, 2016; Hong & Cho, 2016; Pew Research Center, 2017; Wang et al., n.d.; West, 2015; Yamin et al., 2016). The demographics of people who do not have access to high speed Internet are similar to the demographics of people who do not participate in IHISB (Leiner et al. 2009; Hilbert and Lopez, 2011). Barriers to high speed internet include cost of the Internet, lack of access, and lack of understanding (Hong & Cho, 2016; Wang et al., n.d.; West, 2015). Recent technological changes have made high speed Internet more accessible, however gaps still remain.

Smartphones and mobile devices are capable of doubling as both a communication device and an Internet accessible device, are playing a critical role in making the Internet more accessible (Anderson, 2015; Bardus et al. , 2016; Budiu, 2015; Ronquillo & Currie, 2010). Mobile devices that utilize only a wireless connection are also more cost-effective options than a traditional laptop or desktop computer. For populations where cost is a barrier to Internet access, federal provisions for mobile devices has become an effective method for populations to access the Internet (Bardus et al., 2016; Bhuyan et al., 2016; Federal Communications Commission, n.d.; Ronquillo & Currie, 2012; Serrano et al., 2017). This is especially important for populations that traditionally cannot access the Internet which includes rural and low income populations.

This study will investigate whether there are differences in rural and urban populations in how they access IHISB. With this information, website content creators at public health and advocacy organizations could understand how to tailor their content for their target audiences to better meet the needs of their audiences. This would allow increased use of IHISB by the general population.

## **Methods**

### *Theoretical Model*

The theoretical model used to guide the analysis for this study was the Unified Theory of Acceptance and Use Technology Model 2 (UTAT2). The UTAT2 is a model that was adapted from Davis's Technology Acceptance Model, which describes the behavioral process of how one adopts new technology (Venkatesh et al., 2012). The reason why the UTAT2 model was used is because it is able to model individual technological adoption behavior; in this case the adoption of the behavior of using their mobile devices for IHISB. The UTAT2 model consists of ten total constructs. For information of how the variables used will fit into the construct, refer to Table 4.1.

Based on the theoretical model, the hypothesis for this study is that rural populations would be less likely to use a mobile device for IHISB than urban populations. Older age is considered a negative impact on technology adoption and rural residents are older in age (Bennett et al., 2016). Also, it is shown that rural residents are less likely to have an Internet connection which would also negatively impact technology adoption (Anderson, 2015).

### *Data Sources*

The Health Information National Trends Survey (HINTS) 2013-2014 datasets were utilized for this analysis. The HINTS is a nationally representative mail based survey of U.S. adults that tracks how Americans access health information, health, attitudes, and other behaviors. The HINTS datasets are updated on a yearly basis from the National Cancer Institute (National Cancer Institute, 2014).

### *Population Studied*

The HINTS datasets from 2013 and 2014 were concatenated, yielding a total of 6,862 unweighted observations. The study population was delimited by excluding observations containing one or more missing or invalid responses on questions of interest (respondent incorrectly answered questions (i.e. putting more than one answer when only one was required), unreadable, or missed by the respondent). Excluded observations totaled 2,498, for a final study sample of 4,364. A Wald chi-square was conducted to determine if there was a difference in characteristics between excluded and included samples.

Compared to included respondents, excluded respondents were similar in rurality (urban 85%, rural 15%; p-value 0.078). In addition, the exclusion sample did not differ from the inclusion sample in the areas of gender (p-value 0.114) and children (p-value: 0.448). Demographically, the excluded population was more diverse and younger than the included population, and also had a higher proportion of people in lower income brackets (<\$20,000: 22% vs. 43%). The two major factors that created the variable of interest for this study, mobile device usage and where a patient first seeks health



information, had statistically significant differences when the inclusion group was compared to the exclusion group. Where patients first seek health information had a smaller proportion of respondents using IHISB in the excluded group compared to the inclusion group (21% vs. 60%; p-value: .0099). In addition, for mobile device usage, the exclusion population was less likely to have a mobile device capable of accessing the Internet (76% vs. 63%; p-value: <.0001). These results are summarized in Table 4.2.

Due to major differences between the included and the excluded group, there is very little generalizability for this study to the general American population. For this reason, this study can only make conclusions regarding persons, generally white and higher-income, who are likely to complete surveys.

#### *Any Type of HISB*

This study first sought to determine if there were any major differences within the study population in overall HISB use. The population was restricted to individuals who answered the question *Wheresekhealthinfo*. *Wheresekhealthinfo* is a categorical variable with 13 options in response to the question “The most recent time you looked for information about health or medical topics, where did you go first? Mark only one.” Responses included: Inapplicable, books, brochures, cancer organization, family friend/co-worker, doctor, Internet, library, magazines, newspapers, telephone information number, or complementary practitioner. The variable for where participants seek health information was then recoded into a two option variable called *InternetbasedHISB* (Internet based HISB, no Internet based HISB). Respondents that did not look for IHISB

were coded as not using IHISB, while respondents that did, were coded as people who did look for IHISB.

### *IHISB*

Next, the analysis was restricted to respondents who reported IHISB as their first means of health information (n= 2,551 unweighted observations). This was done to determine the device preferences among respondents who engaged in IHISB as their first option. The variable utilized to determine device preference was based on two variables: UseInternet and devicetype. The UseInternet variable which asks the survey taker, “Do you ever go on-line to access the Internet or World Wide Web, or send or receive and e-mail” (yes, no). Devicetype which asks the respondent to “please indicate if you have each of the following” (tablet, smartphone, basic cell phone, or none of the above). If a respondent used any mobile device type of mobile device type, they were coded as using a mobile device. If a respondent answered that they did not use the Internet, but had the devices necessary to access the Internet, they were considered a mobile device user. This was because it was assumed that if the person has the mobile devices to access the Internet and marked IHISB, they have the capacity of using their mobile device to access IHISB. However, if a respondent did not use a mobile device or had a non-Internet accessible cell phone, but did use a form of Internet, they were considered a non-mobile device owner only.

### *Variables Used*

The dependent variable for this analysis was device type used to access IHISB, dichotomized as mobile versus non-mobile device.

The independent variable of interest for this analysis was rurality (rural, urban). The HINTS dataset used the 2013 Rural - Urban Continuum Code (RUCC) to determine the rurality each respondent's residence. RUCC is a county level measurement that uses a 1-9 continuum classification scheme that signifies the rurality of a county; 1 being the most urban population with over 1 million people and 10 being the most remote populations with less than 2,500 people (United States Department of Agriculture, n.d.). For the purposes of this study, RUCC was separated into a binary rural/urban classification. Counties coded in the HINTS dataset as RUCC 1 to 3 were classified urban while 4-9 were classified rural.

The control variables used for this analysis were ethnicity (Non-Hispanic White, Non-Hispanic Black, and Other), income (<\$20,000, \$20,000-49,999, \$50,000-74,999, \$75,000-99,999, \$100,000+), age (>24, 25-34, 35-44, 45-54, 55-64, 65+), education (some high school, high school, some college, college, postgraduate), health insurance (yes, no), marital status (married, not married), children (children, no children), and gender (male, female). The variable of ethnicity did not account for Hispanic Other, Hispanic Whites, and Hispanic Blacks because of the lack of observations in the dataset. For this reason, both categories were collapsed into the Other category.

### *Data Analysis*

All data were weighted utilizing the Jackknife replicate weights for more accurate variance measurements for the nationally representative estimates.

A descriptive analysis was first performed to determine total population estimates. Wald chi-square tests were done to determine if there were any differences between

populations that engage in IHISB and by rurality as well. Once a subset was created based on people who engaged in IHISB was created, a descriptive analysis was done. To determine if there were differences in mobile device ownership in rural and urban populations, Wald chi-square tests were conducted. Two logistic regression models were utilized to determine how likely respondents were to use their mobile devices for health information seeking based on rural and urban residence. The first model determined the sole effect of rural/urban residence on mobile device health information seeking behavior. A second logistic regression model was reran accounting for community level factors. All data analyses were conducted on SAS v9.4.

## **Results**

### *Rural – urban differences among respondents*

The proportion of respondents who lived in urban areas was 81.8%, with 18.2% in rural areas. Rural and urban respondents did not differ significantly by gender (p-value: 0.869) or age distribution (p-value: 0.071) (See Table 4.3). The rural population had more non-Hispanic White respondents (87.0% vs 68.7%; p-value: 0.0001) and proportionately fewer non-Hispanic Blacks (7.0% vs 12.4%; p-value: 0.0001). Rural residents also had more respondents in both the <\$20,000 (27.5% vs. 20.5%) and \$20,000-49,999 brackets (33.2% vs. 24.2%; p-value: <0.0001). A smaller proportion of rural respondents reported owning a mobile device than their urban counterparts (78.1% vs. 67.3%; p-value: <0.0001). In addition, a smaller proportion of rural residents reported using IHISB as their first option (47.2% vs. 56.3%; p-value: 0.0001).

### *IHISB among respondents*

A smaller proportion of rural residents used IHISB as their first source of information compared to their urban counterparts (53.2% vs. 61.8%; See Table 4.4). White respondents had a higher proportion use IHISB than Black respondents (63.6% vs. 50.6%; p-value: .0001). More respondents with an educational level post college (77.4%) used IHISB than respondents with a high school degree or less (38.8%). Higher income respondents reported using IHISB in higher proportions than lower income respondents. The highest proportion among age groups reporting IHISB were 25-34 (69.2%), 35-44 (64.0%), and 45-54 (65.4%) (p-value: .0001). There were significant drop offs in 65+ bracket (39.7%) and <24 (53.5%) age groups for IHISB.

### *Results by respondents who reported IHISB, by rurality*

Despite urban residents being more likely to own (86.4%) mobile devices than rural residents (78.1%) differences in mobile use for IHISB were statistically insignificant (p: 0.098) (See Table 4.5). In terms of demographics, there was no statistical difference in gender or age among those who reported IHISB for among gender (p-value: 0.337) and age (p-value: 0.424). The \$100,000+ income bracket (25.8%) was the highest proportion of income bracket that use IHISB, followed by the \$20,000-49,999 bracket (23.0%). The rural population had more White respondents who reported using IHISB as their first source of health information (90.5% vs. 73.4%; p-value: <0.001) than the urban population. Based on age, 25-34 year olds was the highest proportion to use IHISB (24.3%), while 65+ year olds (9.7%) were the smallest proportion to use report using IHISB.

### *Differences in mobile device use among people who conduct IHISB*

Among people who engage in IHISB, a higher proportion of urban respondents (86.4%) than rural respondents (78.1%) owned a mobile device (See Table 4.6). When it came to race, a larger proportion of minority respondents owned a mobile device than non-Hispanic White respondents (non-Hispanic Black – 89.0%, other – 87.8%, non-Hispanic White – 84.1%; p-value: 0.0385). The age group of 25-34 year olds had the highest proportion owning a mobile device (93.1%), while 65+ (60.5%) had the smallest proportion. As household income increased, mobile device ownership increased as well.

In the first, unadjusted logistic regression model, residents of rural areas were less likely than residents of urban areas to use a personal mobile device for IHISB (OR: 0.56; 95% CI 0.36-0.88) (See Table 4.7). However, once individual and community factors were accounted for, there was no longer a difference by rurality alone (OR: 0.76; 95% CI 0.45-1.30). In this second model, age and income levels were both strong predictors of the likelihood of the use of mobile devices for IHISB. When compared to household incomes of \$20,000-49,999, households with incomes of \$50,000-74,999 (OR: 1.68; 95% CI 1.01-2.82), \$75,000-99,999 (OR: 2.91; 95% CI 1.60-5.30), and \$100,000+ (OR: 4.03; 95% CI 1.50-10.82) were all more likely to use a mobile device for IHISB than any other income group. When compared to the 45-54 age bracket, age brackets that are 35-44 (OR 2.02; 95% CI 1.01-4.08) and 25-34 (OR 3.07; 95% CI 1.60-5.91) were more likely to use mobile devices for IHISB.

## Discussion

Previous research found that the 40-70% of the population participates in IHISB at any point of their health problem (Fox & Purcell, 2010; Weaver et al., 2010). This study found that 54.7% of the population uses IHISB first before any other methods (Table 4.1). To understand where best to target interventions to increase rates of IHISB, the populations that are less likely to use IHISB must be identified. This study found that elderly populations, rural populations, and low income populations were the least likely to engage in IHISB on any device, which is similar to other studies that have examined IHISB (Table 4.4) (Feinberg et al., 2016; Furtado et al., 2016; Li & Theng, 2016).

When adjusted for various factors, rurality did not impact mobile device based IHISB usage. Among the population studied, a larger proportion of rural residents reported not using the Internet than urban residents (Table 4.3). However, when community factors were accounted for in the multivariable model, rurality was no longer associated with the use of a mobile device for IHISB. These results are similar to another study by Bhuyan et al., which found that rurality had no statistical significance with IHISB (Bhuyan et al., 2016). Previous studies have suggested that there was an access issue to for IHISB use by rural residents (Anderson & Perrin, 2016; Ronquillo & Currie, 2010). Because traditional Internet infrastructure is too costly to build in remote areas, rural residents would likely to need to resort to an Internet accessible device to access the Internet (West, 2015; Smith, 2010). However, rural respondents are less likely to have a mobile device than a non-mobile device as seen by this study and pre-existing literature (Table 4.3) (Anderson, 2015).

The literature suggests that one of the top issues for rural residents using mobile devices to access the Internet was having a consistent signal for Internet access (Anderson, 2015; Dotson et al., 2017; Wilson et al., 2016). A two part approach should be followed to encourage more mobile device IHISB use by rural residents. The first is to have the infrastructure created for steady Internet access on phones. To accomplish this goal, telecommunications companies will need to focus on building better networks in rural areas. The second part of the approach is for web content creators of IHISB to create information geared toward rural users should have less pictures per web page to decrease the amount of information downloaded to make up for inconsistent connections.

Education is required because a lower proportion of rural populations utilizing their smartphones for IHISB use cannot just be attributed to the lack of access to cell phones. The results from this study is consistent with literature; rural and low income populations were less likely to use IHISB while urban, younger, and higher income populations were more likely to use IHISB (Table 4.4) (Li & Theng, 2016; Pang et al., n.d.). As studies have shown, health literacy and Internet literacy plays a large role in whether someone engages in IHISB regardless of the type of device (Mackert et al., 2016; Tennant et al., 2015). This means that there either is a usability or a health literacy factor at play. Literature has suggested that school curriculum can be augmented to increase health literacy (Jacque, Koch-Weser, Faux, & Meiri, 2016). Due to the digital divide's impact on rural populations, it is likely that the rural population has not had as much experience as urban populations to use the Internet, which in turn has a negative impact on Internet literacy in rural populations. As postulated by Venkash et al. in the UTAT2 model, more experience with a technology increases the likeliness of adoption



behavior occurring (Venkatesh et al., 2012). School curricula should be adjusted accordingly to not only teach students to increase health literacy, but also to encourage IHISB use.

Of the different factors, age and income were two of the strongest predictors in the multivariable analysis for determining how likely one is to use their mobile device for IHISB (Table 4.6). Income levels below \$20,000 were the least likely to own phones compared to other populations (Table 4.6). Mobile device access is important for low income populations because low income populations are less likely to access the Internet and have access to traditional computers due than other income levels (Anderson, 2015). Therefore, mobile devices often present the only means of access to the Internet for low income population. This is important in light of the fact that FCC programs, Universal Service and Lifeline, are available for populations below the federal poverty level to receive free Internet accessible smartphones with a reduced subscription fees totaling less than \$20 per month (Federal Communications Commission, n.d.). There are two possible explanations for these results. The first is the lack of awareness by low income populations for phones. More studies should be conducted to determine if there is a lack of awareness for smartphones by low income populations. The second explanation is that phones meant for low income population are being fraudulently used by people ineligible for the programs. Previous FCC filings suggest that every year upwards of 1.1 million subscriptions are fraudulently receiving cell phones designed for low income populations (Federal Communications Commission, 2013; Federal Communications Commission, 2016). The millions of cell phones that are being fraudulently used could be repurposed for people below the federal poverty level who do not have access to cell phones. In

addition, more fraud protection is needed to allow low income populations the opportunity to receive smartphones and redirect funding to decrease subscription fees.

This study showed that low income populations do not readily access IHISB despite the availability of programs that assist the indigent with access to Internet (Table 4.4). The results from this study echoes pre-existing literature which shows that low income populations do not participate in IHISB in high proportions (Feinberg et al., 2016; Weaver et al., 2010). Literature has shown that low income populations do access their mobile devices readily for social media sites such as Facebook and Instagram at higher rates than higher income populations (Greenwood, Perrin, & Duggan, n.d.). Therefore, it does not seem that Internet literacy fully explains the lack of IHISB among low income populations. Rather, it could possibly be a user experience design (UX) access issue. UX is the process of designing technology so that the target population can use the technology with relative ease (effort expectancy) and pleasure (hedonic motivation) (Kujala et al., 2011). Based on UAT2, as effort expectancy decreases and hedonic motivation increases, adoption behavior increases (Venkatesh et al., 2012). Accessing the Internet from mobile devices is a vastly different user experience than from the desktop computer or laptop which could play a role in why low income populations are not accessing IHISB (Brusk & Bensley, 2016). The mobile device experience is a slower process requiring more touches of by the user; it is even more time consuming when the sites accessed are not optimized for mobile devices (Budiu, 2015). It could be quite possible that mobile devices users are not accessing IHISB because the websites are not formatted for the use of low income populations. More research into

why low income populations do not access IHISB should be done to determine whether it is an UX issue or a health literacy issue.

## **Limitations**

This study had several limitations that impacts the generalizability of the study, primarily the high exclusion rate, the vagueness of the items, and biases related to self-response surveys. A total of 2,498 observations (36.4%) were excluded from the original 6,862 observations. The high exclusion rate caused the sample to have a higher proportion of white, older, and higher income populations; all three are factors associated with how likely one uses a mobile device and IHISB. The large population of missing translated its impact across all the analyses, in particular the multivariate analysis which showed very little statistical significance.

There are multiple reasons why the high exclusion rate occurred. One of the reasons could be due to the fact the survey was a mail-in survey, with only a phone number to call for clarification. This is particularly important when items sometimes required respondents to mark the multiple answers for a series of items, while other items required the respondent to mark one answer. This became problematic when questions with different answering formats occurred one after the other. In particular, one of the main variables (whereseekehealthinfo) was a mark only one answer that had occurred after several questions that asked the respondents to mark all that apply. Respondents could have accidentally marked multiple response by accident as evidenced by the 716 respondents that marked more than one answer. Due to the format of the different answering formats, this could have contributed to the high exclusion rate.

Another possible limitation was the fact that some items were written very generally which impacted the definition of IHISB. For instance, using the example of where seek health info again; if a respondent saw a picture about health on their social media account, it would not be the same in value as someone who actively seeks out information on a website for their health problems. Because the survey does not differentiate the motive for HISB, both cases of HISB would be considered equal in impact, and left to the respondent to interpret the item. The impact of this limitation could not be quantified. This is consequential to the analysis because the study design utilized only three items in the HINTS survey (use Internet, where seek health information, device type). Since the purpose of the HINTS survey is to give broad overview of health problems, this study was constrained to those variables. A much more reliable and valid scale should be used to determine how likely one engages in HISB to give a more accurate estimate.

The HINTS dataset is a cross-sectional dataset that is collected every year utilizing different participants. Because the HINTS dataset is a survey, the dataset is prone to self-reporting biases. There could be a possibility that people over or under reported certain behaviors due social desirability bias. Questions regarding technology would likely have younger populations skewing their answers toward partaking in Internet related activities or having certain technologies because of the social acceptability of technology. In addition, the survey responses could be affected by recall bias of the respondents who may not recall partaking in certain activities.

## Conclusion

This study provides information for the health communication field and policy makers. In terms of health communication, higher income and younger populations are more likely to respond to health information placed online because they are more likely to be exposed to it. However, for reasons that are not fully understood, older and low income populations are less likely to use IHISB. This could be due to the fact that such individuals lack internet access, do not understand how to use the Internet, or are unaware that health information is available online. More research is needed to determine an appropriate action from a health communication and health policy role.

*Table 4.1 Construct and study variables*

<b>UTAT2 Construct</b>	<b>Variables Used</b>
Performance Expectancy	Where the respondent first seeks health information (whereseekhealthinfo, later transformed into InternetHISB based on mobile device use by respondent)
Effort Expectancy	None Available
Social Influence	Ethnicity
Facilitating Conditions	Rurality Amount of children in household
Hedonic Motivation	None Available
Price Value	Household income
Habit	None Available
Age	Age of respondent
Gender	Gender of respondent
Experience	Educational attainment

<i>Table 4.2 Total population, by exclusion criteria, 2013-2014 HINTS</i>					
	<b>Exclusion N= 2,498</b>		<b>Included N= 4,364</b>		
	<b>Weighted %</b>	<b>Standard Error</b>	<b>Weighted %</b>	<b>Standard Error</b>	<b>p-value</b>
<b>Rural</b>					
Urban	85%	1.2	82%	1.2	0.07752
Rural	15%	1.2	18%	1.2	
<b>Sex</b>					
Male	40%	1.3	48%	0.8	0.1142
Female	38%	1.5	52%	0.8	
Missing	21%	1.4			
<b>Ethnicity</b>					
White, Non-Hispanic	60%	1.4	56%	1.2	<.0001
Black, Non – Hispanic	10%	1.0	20%	0.8	
Other	14%	1.3	24%	1.1	
Missing	16%	1.4			
<b>Race</b>					
White	54%	1.3	81%	0.5	0.0004
Black	13%	1.0	12%	0.5	
Other	6%	0.7	7%	0.5	
Missing	27%	1.4			
<b>Age</b>					
15-24	27%	1.8	10%	1.0	<.0001
25-34	14%	1.2	21%	1.0	
35-44	14%	1.2	20%	0.7	
45-54	14%	1.2	19%	0.6	
55-64	13%	0.8	16%	0.3	
65+	18%	0.8	15%	0.4	
<b>Income</b>					
<20,000	43%	1.4	22%	1.0	<.0001
20,000-49,999	24%	1.5	26%	1.3	
50,000-74,999	13%	1.4	17%	0.8	
75,000-99,999	8%	1.2	14%	0.8	
100,000+	12%	1.1	21%	0.9	
<b>Married</b>					
Yes	48%	1.3	59%	0.7	0.0045
No	42%	1.3	41%	0.7	
Missing	10%	1.1			
<b>Education</b>					
Less than high school	17%	1.1	7%	0.6	<.0001

High school	23%	1.3	20%	0.6	
Some college	23%	1.2	34%	0.9	
College	18%	1.2	24%	0.8	
Post College	10%	1.0	15%	0.7	
Missing	8%	0.7			
<b>Children</b>					
Yes	27%	1.3	63%	1.1	0.4481
No	43%	1.6	37%	1.1	
Missing	30%	1.4			
<b>Health Insurance</b>					
Yes	79%	1.2	86%	0.5	0.0116
No	17%	1.1	14%	0.5	
Missing	4%	0.5			
<b>Mobile device used at all to access the Internet</b>					
Non-mobile device access only	14%	1.4	14%	1.0	<.0001
Mobile device used	63%	1.6	76%	0.9	
Does not use the Internet in any form	23%	1.3	10%	0.5	
<b>Where do you go first for health information</b>					
Does not seek health information	19%	1.3	19%	1.0336	0.0099
Books	2%	0.4	2%	0.2603	
Brochures	3%	0.6	3%	0.3567	
Family	1%	0.4	3%	0.4757	
Friend/Co-worker	0%	0.1	1%	0.2851	
Physician or HCP	10%	0.9	10%	0.7274	
Internet	21%	1.2	60%	1.2704	
Printed Media	1%	0.2	81%	0.1736	
Other	1%	0.3	1%	0.2172	
Missing	41%	1.5			



<i>Table 4.3 Characteristics of respondents, by rurality, 2013-2014 HINTS</i>							
	<b>Total N = 4364</b>		<b>Urban, N= 3710</b>		<b>Rural, N = 654</b>		<b>P- Value +</b>
	<b>Weighte d %</b>	<b>SE</b>	<b>Weighte d %</b>	<b>SE</b>	<b>Weighte d %</b>	<b>SE</b>	
<b>Rurality</b>							
Urban	81.8	1.21					
Rural	18.2	1.21					
Total							
<b>Gender</b>							
Male	48.1	0.76	48.2	0.96	47.6	3.28	0.869 2
Female	51.9	0.76	51.8	0.96	52.4	3.28	
<b>Ethnicity</b>							
White, Non-Hispanic	72.1	0.56	68.7	0.80	87.0	1.99	<.000 1
Black, Non – Hispanic	11.4	0.47	12.4	0.60	7.0	1.55	
Other	16.5	0.58	18.9	0.75	6.0	1.31	
<b>Age</b>							
<24	14.9	0.90	10.4	1.14	8.0	3.15	0.096 2
25-34	19.3	0.87	22.6	1.15	14.4	2.88	
35-44	17.7	0.52	19.2	0.67	22.0	2.62	
45-54	17.4	0.39	18.9	0.68	19.5	2.24	
55-64	15.0	0.20	15.0	0.46	17.7	1.74	
65+	15.7	0.33	13.8	0.51	18.4	1.97	
<b>Income</b>							
<20,000	27.4	0.89	20.5	1.08	27.5	3.26	<.000 1
20,000-49,999	25.5	1.11	24.2	1.30	33.2	3.04	
50,000-74,999	15.5	0.77	16.2	0.85	18.4	2.22	
75,000-99,999	12.9	0.63	15.1	0.86	11.6	1.94	
100,000+	18.6	0.77	24.1	1.03	9.3	1.67	
<b>Marital Status</b>							
Married	58.3	0.57	57.9	1.04	65.4	3.00	0.041 7
Not Married	41.7	0.57	42.1	1.04	34.6	3.00	
<b>Education</b>							
High school or less	20.7	0.72	24.4	0.85	38.6	3.52	<.000 1

Some college	32.2	0.77	32.7	1.07	38.8	3.17	
College	23.1	0.59	26.1	0.97	15.2	2.04	
Post College	13.8	0.52	16.8	0.82	7.3	1.11	
<b>Children</b>							
Yes	63.6	0.99	64.1	1.26	60.2	3.13	0.2919
No	36.4	0.99	35.9	1.26	39.8	3.13	
<b>Device Type</b>							
Non-mobile device	14.2	0.74	13.2	0.81	19.1	2.43	0.0006
Mobile Device	72.1	0.83	78.1	0.95	67.3	2.76	
No Internet	13.6	0.52	8.7	0.54	13.6	1.54	
<b>Health Insurance</b>							
Yes	84.4	0.2339	71.4	1.0562	15.1	0.9336	0.1512
No	14.6	0.2328	10.4	0.6494	3.1	0.5674	
<b>Where do you go first for health information</b>							
Does not seek health information	21.7	0.94	20.3	1.00	28.2	0.65	0.0993
Books	2.4	0.24	2.3	0.23	3.1	0.13	
Brochures	3.1	0.33	2.9	0.29	4.4	0.18	
Family	2.6	0.37	2.8	0.39	1.8	0.09	
Friend/Co-worker	1.3	0.22	1.4	0.22	0.8	0.06	
Physician or HCP	11.6	0.62	11.5	0.61	12.2	0.22	
Internet	54.7	0.96	56.3	1.11	47.2	0.68	
Printed Media	1.0	0.15	1.0	0.12	1.2	0.11	
Other	1.5	0.19	1.6	0.18	1.1	0.06	
+Rural statistically different from urban if alpha =0.05							

Table 4.4 Characteristics of study respondents, subset by the use IHISB

N = 4364	IHISB N= 2541		Did not use IHISB N = 1824		P-Value <sup>+</sup>
	Weighted %	SE	Weighted %	SE	
<b>Rurality</b>					
Urban	61.8	1.5	38.2	1.5	0.0298
Rural	53.2	3.3	46.8	3.3	
<b>Gender</b>					
Male	56.8	1.7	43.2	1.7	0.0088
Female	63.4	1.6	36.6	1.6	
<b>Race</b>					
White, Non-Hispanic	63.6	0.9	36.4	1.6	0.0003
Black, Non-Hispanic	50.6	0.7	49.3	1.6	
Other	52.1	0.7	47.9	1.6	
<b>Age</b>					
<24	53.5	6.8	46.5	6.8	<.0001
25-34	69.2	3.4	30.8	3.4	
35-44	64.0	3.2	36.0	3.2	
45-54	65.4	2.3	34.6	2.3	
55-64	60.7	1.9	39.3	1.9	
65+	39.7	2.2	60.3	2.2	
<b>Income</b>					
<20,000	43.8	2.9	56.2	2.9	<.0001
20,000-49,999	53.6	2.1	46.4	2.1	
50,000-74,999	65.4	3.3	34.6	3.3	
75,000-99,999	72.7	3.9	27.3	3.9	
100,000+	72.6	2.4	27.4	2.4	
<b>Marital Status</b>					
Married	64.4	1.5	35.6	1.5	0.0002
Not Married	54.2	2.1	45.8	2.1	
<b>Education</b>					
High school or less	38.8	2.1	61.2	2.1	<.0001
Some college	64.5	2.7	35.5	2.7	
College	67.6	2.5	32.4	2.5	
Post College	77.4	2.2	22.6	2.2	
<b>Children</b>					
Yes	59.4	1.5	40.6	1.5	0.2715
No	61.7	1.8	38.3	1.8	
<b>Device Type</b>					
Non-mobile device	60.5	2.8	39.5	2.8	<.0001
Mobile Device	67.3	1.7	32.7	1.7	

No Internet	3.6	1.3	96.4	1.3	
<b>Health Insurance</b>					
Yes	61.1	1.4	38.9	1.4	0.0995
No	54.6	3.6	45.4	3.6	
+ Rural statistically different from urban if alpha =0.05					

Table 4.5 Characteristics associated with use of IHISB, among respondents who reported HISB, by rurality, 2013-2014 HINTS

	Total N = 2541		Urban N= 2200		Rural N = 341		
	Weight ed %	Standar d Error	Weight ed %	Standar d Error	Weight ed %	Stand ard Error	P- Value
<b>Rurality</b>							
Urban	83.9	1.4					
Rural	16.1	1.4					
Total							
<b>Gender</b>							
Male	45.3	1.4	46.1	1.4	41.1	5.1	0.3369
Female	54.7	1.4	53.9	1.4	58.9	5.1	
Total							
<b>Race</b>							
White, Non-Hispanic	76.1	0.9	73.4	1.1	90.5	2.4	0.0001
Black, Non-Hispanic	9.6	0.7	10.3	0.8	5.7	2.0	
Other	14.3	0.8	16.3	0.9	3.9	1.2	
<b>Age</b>							
<24	8.9	1.2	9.3	1.4	6.4	2.3	0.4239
25-34	24.3	1.4	25.2	1.6	19.6	4.4	
35-44	21.0	1.1	20.4	0.9	23.7	4.3	
45-54	20.6	1.0	20.8	1.0	19.4	3.1	
55-64	15.6	0.6	14.7	0.7	20.1	2.6	
65+	9.7	0.5	9.5	0.5	10.7	2.1	
<b>Income</b>							
<20,000	15.8	1.2	15.5	1.5	17.7	3.4	0.0006
20,000- 49,999	23.0	1.5	20.7	1.5	34.9	3.9	
50,000- 74,999	18.0	1.3	17.6	1.2	20.1	3.5	
75,000- 99,999	17.4	1.2	17.8	1.2	15.3	3.1	
100,000+	25.8	1.3	28.4	1.5	12.0	2.7	
<b>Marital Status</b>							
Married	63.4	1.2	61.8	1.4	71.9	4.1	0.0358
Not Married	36.6	1.2	38.2	1.4	28.1	4.1	
<b>Health Insurance</b>							
Yes	87.7	0.8	75.3	1.3	12.4	0.9	0.016

No	12.3	0.8	8.5	0.7	3.7	0.9	
<b>Children</b>							
Yes	62.5	1.5	63.4	1.6	57.6	4.3	0.2316
No	37.5	1.5	36.6	1.6	42.4	4.3	
<b>Device Type</b>							
Mobile Device	85.1	1.1	86.4	1.1	78.1	3.4	0.0978
Non-mobile device	14.9	1.1	13.6	1.1	21.9	3.4	
<b>Education</b>							
High school or less	17.4	1.1	29.6	4.1	15.1	0.9	0.0006
Some college	36.2	1.3	41.5	3.8	35.2	1.5	
College	27.1	1.2	18.8	3.2	28.7	1.4	
Post College	19.3	1.0	10.1	2.0	21.1	1.2	

Table 4.6 Differences in mobile device use among people who use IHISB, 2013-2014  
HINTS

N = 2541	Mobile Device Owned N = 2083		No Mobile Device Owned N = 468		P- Value
	Weighted %	Standard Error	Weighted %	Standard Error	
<b>Rurality</b>					
Urban	86.4	1.1	13.6	1.1	0.0304
Rural	78.1	3.4	21.9	3.4	
<b>Gender</b>					
Male	86.5	1.3	13.5	1.3	0.0995
Female	83.9	1.3	16.1	1.3	
<b>Race</b>					
White, Non-Hispanic	84.1	1.3	15.9	1.3	0.0385
Black, Non-Hispanic	89.0	2.3	11.0	2.3	
Other	87.8	2.2	12.2	2.2	
<b>Age</b>					
<24	86.8	6.0	13.2	6.0	<.0001
25-34	93.1	1.7	6.9	1.7	
35-44	91.2	2.3	8.8	2.3	
45-54	85.5	2.2	14.5	2.2	
55-64	78.0	2.5	22.0	2.5	
65+	60.5	2.6	39.5	2.6	
<b>Education</b>					
High school	15.5	1.1	28.6	3.7	0.0003
Some college	35.6	1.5	39.7	3.5	
College	28.6	1.3	18.5	2.5	
Post College	20.4	1.1	13.2	2.0	
<b>Income</b>					
<20,000	75.2	3.3	24.8	3.3	<.0001
20,000-49,999	77.3	2.6	22.7	2.6	
50,000-74,999	85.3	2.6	14.7	2.6	
75,000-99,999	91.2	1.9	8.8	1.9	
100,000+	93.8	1.8	6.2	1.8	
<b>Marital Status</b>					
Married	86.0	1.2	14.0	1.2	0.3152
Not Married	83.5	2.0	16.5	2.0	
<b>Health Insurance</b>					
Yes	88.0	0.9	86.4	2.5	0.5719

No	12.0	0.9	13.6	2.5	
<b>Children</b>					
Yes	60.3	1.7	74.9	3.1	<.0001
No	39.7	1.7	25.1	3.1	



<i>Table 4.7 Characteristics associated with mobile device IHISB, 2013-2014 HINTS</i>		
<b>Variable n = 2541</b>	<b>OR (95%CI)</b>	<b>OR (95%CI)</b>
<b>Rurality (ref = Urban)</b>		
Rural	0.56 (0.36-0.88)	0.76 (0.44-1.30)
<b>Gender (ref = Males)</b>		
Female		0.96 (0.70-1.30)
<b>Race (ref = White, Non-Hispanic)</b>		
Black, Non-Hispanic		1.44 (0.79-2.61)
Other		.993 (0.61-1.63)
<b>Age ( ref = 45-54)</b>		
<24		2.26 (0.51-9.88)
<b>25-34</b>		<b>3.07 (1.60-5.91)</b>
<b>35-44</b>		<b>2.02 (1.01-4.08)</b>
55-64		0.76 (0.45-1.27)
65+		0.34 (0.22-0.54)
<b>income (ref = \$20,000-49,999)</b>		
<\$20,000		0.78 (0.42-1.45)
<b>50,000-74,999</b>		<b>1.68 (1.01-2.82)</b>
<b>75,000-99,999</b>		<b>2.91(1.60-5.30)</b>
<b>100,000+</b>		<b>4.03(1.50-10.82)</b>
<b>Education (ref = HS or less)</b>		
Some college		1.31(0.82-2.12)
<b>College</b>		<b>1.74(1.06-2.85)</b>
Post College		1.50(0.87-2.52)
<b>Health Insurance Coverage (ref = Yes)</b>		
No		1.01 (0.55-1.85)
<b>Marital Status (ref = Married)</b>		
Not Married		0.84 (0.53-1.34)
<b>Children (ref = 1)</b>		
No Children		0.85 (0.52-1.35)

## CHAPTER 5

### MANUSCRIPT 2

**The digital divide and its effect on the e-prescription adoption in rural and urban counties from 2010-2014<sup>2</sup>**

---

<sup>2</sup> Yuen M.W., Probst J.C., Bennett K.J., Crouch E.L., Chen B.K., To be submitted to *Journal of Rural Health*

## **Abstract**

In 2008 and 2009, dual legislation encouraging electronic prescription adoption was passed. Subsequently, e-prescription adoption has increased significantly across the United States. Qualitative studies have shown that Internet access is considered a barrier for adoption of e-prescription systems. The Internet in the United States has had a digital divide where low income and rural areas have poor Internet access compared to their urban counterparts. Researchers has believed the digital divide has caused disparities across industries that utilize the Internet between rural and urban areas. For this reason, this study sought to determine if Internet speed affects e-prescription adoption. The study utilized data from the 2010-2014 from the Area Health Resources File, Surescripts, and the National Broadband Map to answer the study question. A multivariate regression analysis was conducted to determine if Internet speeds impacted e-prescription adoption by county in 2014. Based on the findings of this study, Internet speed plays a role in e-prescription adoptions. However, once community factors were accounted for, Internet speeds impact on e-prescription adoptions was diminished. Rather, the county characteristics such as rurality and amount of physicians under the age 55 in a county impacted e-prescription adoptions more. As counties became more rural and the smaller the proportion of physicians under the age 55 became, the less likely e-prescription adoptions became.

## **Introduction**

Effective use of health information technology (HIT) is commonly linked to better delivery of quality care and better health outcomes in patients (Buntin et al., 2011;

Chaudhry et al., 2006; Salmon & Jiang, 2012). One component of HIT systems is the capability to electronically transmit prescriptions from a provider to the pharmacy (e-prescriptions). Because e-prescriptions are electronically created and sent, they decrease the opportunity for human error which in turn reduces adverse events and harm (Joseph et al., 2013; Odukoya et al., 2016; Salmon & Jiang, 2012). E-prescribing also helps track the prescriptions a patient is given (Kecojevic et al., 2015; Zadeh et al., 2016).

Despite the benefits, e-prescription system adoption by providers has been slow (Joseph et al., 2013). In 2008, e-prescriptions were uncommon, with only 7 percent of physicians reported having any systems capable of transmitting e-prescriptions to pharmacies (Health IT, 2013). Then, a part of the Medicare Improvements for Patients and Providers Act (2008) and Health Information Technology for Economic and Clinical Act (2009) (HITECH), incentives were given out to physicians to adopt e-prescription systems (Joseph et al., 2013). E-prescription system adoption picked up very quickly because of the two acts; in 2010, it was reported over 40% of all U.S. physicians had adopted an e-prescription system – a 33 point increase in two years (Joseph et al., 2013). Despite the initial impact of both policies, there have been signs of a slowdown in the rate of e-prescription system adoption. The most recent report from the Office of National Coordinator for Health Information Technology (ONC) showed that 66% of doctors had an e-prescription system in 2013- only a 26 point increase in three years (Health IT, 2013). While both the HITECH and Medicare Improvements for Patients and Providers Act attempted to address the cost of the system, they did very little to address the underlying structural Internet access problem.

The reasons for not adopting e-prescription systems include: the cost of an e-prescription system, the learning curve associated with the system, the lack of available staff, and not having the proper Internet access available to adopt e-prescriptions (Ross, Stevenson, Lau, & Murray, 2016). Even among organizations that adopt e-prescription systems, unreliable Internet speeds are a hindrance (e.g. Internet outage, inconsistent speeds) in some areas which requires organizations to revert to traditional e-prescription writing (Nanji et al., 2014).

The structural access issue is commonly referred to as the digital divide, the phenomenon where certain populations are less likely to access the Internet because of a wide array of barriers (Kruger & Gilroy, 2016). One of the causes of the cause of the digital divide stems from how the Internet infrastructure was created when it became commercialized. Telecommunications companies focused their building efforts in densely populated, high income areas to maximize the return on the cost of building Internet infrastructure (West, 2015; Smith, 2010). Due to policies aimed at decreasing the Internet digital divide, Internet access is now more accessible (West, 2015). However, there is still an Internet digital divide based on speed, not access. As research has shown, rural areas lag behind in Internet speed compared to their urban counterparts (Chesser et al., 2016; Whitacre et al., 2016).

Based on national data which estimates commercially available Internet, only 55% of rural areas have download speeds faster than Federal Communications Commission standards compared to 94% in urban areas (Whitacre et al., 2016). Organizations with higher operating margins, such as hospitals, have the ability to

acquire expensive dedicated business lines, with most organizations left to commercially available Internet (Hayford, Nelson, & Diorio, 2016).

Internet speed impacts e-prescription adoptions in rural areas due to the speed requirements for e-prescription systems. Based on guidelines set by the federal government, target speeds which can range anywhere from 4 mbps to 100+ mbps of speed dependent upon the number of physicians using the system, the location of the organization, the type of hardware used, and a various set of factors (Health IT, 2013). For instance, a single practice physician is suggested to have 4+ mbps of speed which also is the minimum Internet speed set by the FCC to be considered high speed Internet (Health IT, 2013; Federal Communications Commission, n.d.). As organizations becomes larger, it is expected that they have higher Internet speeds, so rural organizations are suggested to have minimum speeds of 10 mbps, while large clinics are suggested to have 25 mbps of speed. In 2014, the AMA reported only 17.1% of physicians worked in single physician practices which would only require 4 mbps of speed (American Medical Association, 2015). The same study found that a majority of physicians work in practices with 10 or fewer people (57.8%), which means the need for faster Internet speeds is integral to a health system (American Medical Association, 2015).

It is important to understand how Internet speed effects e-prescription system adoption. While research has examined the rate of e-prescription system adoption in counties, very little research has taken into account Internet speed. This study will attempt to determine if there is a link between Internet speed and the adoption of e-prescription systems at the county level.

## Methods

### *Model*

The model used to guide the analysis of this study was the Unified Theory of Acceptance and Use Technology Model 2 (UTAT2). The UTAT2 was adapted from Davis' Technology Acceptance Model which models the behavior process of how one adopts new technology (Venkatesh et al., 2012). The reason why the UTAT2 model was used is because it models technology adoption behavior. Although the UTAT2 models individual adoption behavior, it is appropriate to use for this county level study because the variable of interest is related to adoption behavior of multiple individuals.

The UTAT2 model consists of eight total constructs (performance expectancy, effort expectancy, social influence, facilitating conditions, hedonic motivation, price value, habit, age, gender, and experience) that impact technology adoption. Behavioral intention which is affected by the constructs of age, gender, and experience which have modulating factors on all the rest of the constructs (Venkatesh et al., 2012). How the county level variables correspond with the model is shown in Table 5.1.

Based on the model, it is hypothesized that as upload and download speeds increase, e-prescription adoptions should increase as well. This is because increased Internet speed increases performance expectancy since more Internet speed increases the speed at which e-prescriptions can be sent and downloaded. Despite having similar Internet speeds, rural areas will see a slight decrease in e-prescription adoption rates compared to their urban counterparts. This is because literature has shown that physicians in rural areas are older and lower operating margins by rural healthcare organizations

(Bennett, 2016; Hayford et al., 2016). Based on the UTAT2 model, it postulates that older age and lower facilitating conditions (low operating margins) negatively impact technology adoption.

### *Data Sources*

Data for this study were drawn from the following sources: the Area Health Resource File (AHRF), the National Broadband Map (NBM), and Surescripts datasets. The AHRF is a national database that contains cross sectional county level data which is updated on an annual basis. The 2011 – 2016 AHRF datasets were used for the community and healthcare system variables in the study. The 2011-2016 AHRF datasets were used because the AHRF data has a 1-2 year lag in updating data for the 2010-2014 data of interest. The NBM is a national database that contains longitudinal county level Internet speed information that is updated on an annual basis. The NBM collects Internet speed data from telecommunications providers. Data from the NBM was taken from 2010-2014 and used in this study to identify different broadband speeds across counties. Surescripts is a national, county level cross sectional dataset collected by the Office of the National Coordinator for Health Information Technology (ONC), which shows the percentage of physicians who have adopted e-prescription adoption in a county by year. The Surescripts is a single dataset that contains data from 2008 to 2014. The time period that this study focused on was from 2010-2014.

### *Sample Creation*

The unit of analysis for this study was county. All three datasets (AHRF, NBM, and Surescripts) were combined at the county level. The dataset was then reduced to only



counties in the United States, excluding counties that are part of territories or colonies. The resulting sample had a total of 3,141 counties.

### *Exclusion Criteria*

All counties missing data on one or more variables were excluded from the study sample. Excluded counties totaled 208, which left the total number of counties studied as 2,933.

A Wald chi-square test was done to determine the difference between excluded and included counties. Overall, the exclusion group was different across every characteristic compared to the inclusion group. The exclusion group had more counties from rural areas (88.0%) than urban areas (12.0%). When we divided the data into the four levels of rurality, we found that a large percentage of the exclusion group was made of remote counties (57.7%).

Due to the high proportion of remote (n=120) counties excluded, this study is not generalizable to remote counties. In addition, the majority of the excluded counties did not have any form of e-prescription adoption (98.1%). However, the sample is representative with regard to urban, micropolitan, and small adjacent counties. For information pertaining to the included and excluded counties, refer to Table 5.2.

### *Variables Used*

The dependent variable for this study was percent e-prescription adoption rate. E-prescription adoption rate was categorized into quartiles based on 2010 values (0, 1-15%, 15-32%, >32%).

This study used three independent variables: rurality and Internet upload and download speed. The reason why this study utilized both upload and download speed instead of choosing just solely upload or download speed is because of Internet bandwidth. Internet bandwidth, which is the ability to transfer information on a cable, is the major factor in determining upload and download speeds (Comer, 2008). Download speeds can be decreased to increase upload speeds and vice versa, but bandwidth must increase to increase both maximum download speeds and maximum upload speeds concurrently (Comer, 2008). To mitigate the issue of decreased bandwidth, telecommunications practice the use “throttling” or decreasing Internet speeds for high intensity users which help keep overall Internet speeds high enough for everyone else to use (Bode, 2009; Marcon et al., 2011). The differences in the bandwidth of rural and urban areas which translate into Internet speeds is an example of the digital divide. In addition, because a person is more likely to download information than upload information, companies have typically grown and kept download speeds faster than upload speeds (Federal Communications Commission, 2016)

For the multivariate regression analysis, both upload and download speed were combined based on their changes in speed from 2010-2014 and placed into a ten level categorical variable. The reason why Internet speed was categorized into a ten level category is to determine the impact of Internet speed on e-prescription adoptions. There are two possible ways that Internet speed can impact e-prescription adoptions. The first method assumes that Internet speed acts as a threshold, where once the absolute minimum speed criteria is achieved (i.e. the federal minimum), e-prescription adoption is more likely to occur. On the other hand, the second method assumes that increasing

Internet speed acts as an increasing continuum to e-prescription adoption; the faster the Internet speed causes an increase in workflow (performance expectancy) which will lead to more e-prescription adoption. To test these two theories, low, medium, high speed categories were created based on upload and download speeds in 2010 and 2014. The low category represents Internet speeds that are below the government standards (< 4 mbps download speed, <1 mbps upload speed), the medium Internet speeds represents download and upload speeds that are acceptable for a physician offices and clinics (4-10 mbps download, 2-8 mbps upload), while the high category represents fast Internet speeds that are above the range of a clinic (11+ mbps download, 9+ mbps upload) (Federal Communications Commission, n.d.).

To see how maximum upload speed and download speed was categorized across time in the multivariate regression model refer to the figure below:

1. low download and upload, no change
2. medium download and upload, no change
3. high download and upload, no change
4. both change from low to medium
5. both change from low to high
6. both change from medium to high
7. both decreased
8. upload and download are different
9. download speed increased, but upload speed decreased
10. upload speed increased, but download speed decreased
<i>Figure 5.1 - Maximum Internet download and upload speed change categories for multivariate analysis, 2010-2014</i>

The third independent variable for this study was rurality. Rurality was measured at the county level using Urban Influence Codes (UIC) (United States Department of

Agriculture, n.d.). UIC codes measure rurality based on the size of the population and how far the county is from a metropolitan area. Based on the UIC codes, a two level categorical definition was utilized: urban (UIC: 1, 2) and rural (UIC: 3, 4, 5, 6, 7, 8, 9, 10, 11, 12). In order to give better insight into the rural population, rurality was also broken into urban (1, 2), micropolitan (3, 5, 8), small adjacent (4, 6, 7), and remote (9, 10, 11, 12) (United States Department of Agriculture, n.d.). Rurality was selected by the UTAT2 model as part of the construct, facilitating conditions, because rural counties are more likely to be economically deprived.

The control variables that were derived from the model were county level variables from both 2010 and 2014. For consistency in measurement, each county level variable, based on percentages or numbers, was categorized into quartiles based on the 2010 values: percent of male physicians (<66.6%, 66.7-73.6%, 73.5480.0%, >80.0%), percent physicians under 55 (<48.2%, 48.2-58.8%, 58.8-66.8%, >66.8%), percent of poverty (<5.7%, 5.7-14.1%, 14.11-32.9%, >32.9%), percent of non-white residents in the county (<5.2%, 5.2-11.1%, 11.1-19.2%, >19.2%), percent of residents without health insurance (<17.5%, 17.5-22.0%, 22.0-26.7%, >26.7%), percent of residents with Medicare Part D (39.8%, 39.8-48.0%, 48.0-57.6%, >57.6%), ratio of population to physicians (<515.5, 515.5-981.6, 981.6-1720.2, 1720.2%), and number of hospitals (0, 1, 2+).

### *Analysis Method*

Mean values of each county characteristic were calculated across all the counties for the different characteristics to show trends across the years. In addition, one way

ANOVA testing and paired t-tests were done to determine the differences across four level rurality and across the years 2010-2014. A Wald chi-square test was then conducted to determine if there were any significant differences across rurality. To determine if there were any impact of Internet speed on e-prescription adoption a multivariate regression analysis was conducted using three models. The first model consisted of determining the association of the impact of Internet speed on e-prescription adoption in 2014. The second model consisted of determining the association of Internet speed and rurality on e-prescription adoptions in 2014. The final model consisted of all the factors mentioned in Table 5.1 and determining their adjusted impact on e-prescription adoptions in 2014.

## **Results**

### *Key characteristics for e-prescription adoption and Internet speeds for 2010 and 2014*

The sample had a higher number of rural counties (65.3%) than urban counties (34.7%). Within rural, the counties were fairly evenly distributed into micropolitan counties (35.1%), small adjacent counties (33.3%), and remote counties (31.6%).

In 2010, 40.8% of counties had upload speeds of 2-5 mbps and 47.7% of counties had upload 5-8 mbps. The highest proportion of counties had download speeds of 7-10 mbps (74.8%) and 4-7 mbps (11.1%). From 2010 to 2014 there was a noticeable increase in Internet speed. In 2014, the highest proportion of counties that had upload speeds of 5-8 mbps (44.3%) and 8+mbps (34.0%). The majority of counties had download speeds of 11+ mbps (52.5%) and 7-10 mbps (38.5%). For the characteristics of counties by the independent variables used for this study, refer to Table 5.3.

### *Other key characteristics of counties*

From 2010 to 2014, changes in distribution of counties across key characteristics varied. There was a decline in the proportion of physicians who are male between 2010 and 2014. While the 26.2% of counties fell into the lowest quartile for percent male in 2010, this increased to 33.0% by 2014. The mean age of physicians in studied counties increased between 2010 and 2014. Thus, the proportion of counties in which two thirds (> 66.82%, highest quartile in 2010) of the physicians were under age 55 declined from 24.6% in 2010 to 16.5% in 2014. There was little change from 2010-2014 across counties for in proportion of residents in poverty (p-value: <.0001). The percentage of people without health insurance decreased as evidenced by the lowest two quartiles making significant gains while the highest two quartiles decreased significantly (p-value: <.0001). The characteristics of the county are listed in Table 5.4 below.

### *E-prescription adoption and Internet upload and download speeds from 2010-2014*

Generally, the faster the Internet was in 2010, the higher e-prescription adoption rate in 2010. The only exception for this rule was the lowest speed category (<4mbps) which had higher rates of e-prescription adoptions (Table 5.5). For instance, the 32%+ category for e-prescription adoptions in 2010 was higher for counties that had higher download speeds in 2010 (11+ mbps – 26.3%; 7-10 mbps – 26.1%; 4-7 mbps – 24.4%; <4mbps – 28.1%; p-value: <.0001). The relationship of faster Internet speed became more pronounced in the 2014 e-prescription adoptions for the 32%+ category (11+ mbps – 92.0%; 7-10 mbps – 87.7%; 4-7 mbps – 77.5%; <4mbps - 82.6%; p-value: <.0001).

Similar increases in e-prescription adoptions occurred for increasing upload speeds as well.

Comparatively, upload and download speeds in 2014 had a similar relationship with e-prescription adoptions in 2014 as 2010 upload and download speeds. As speed increased, e-prescription adoptions in the highest e-prescription adoption for 2010 category increased as well (11+ mbps – 27.1%; 7-10 mbps – 24.3%; 4-7 mbps – 25.5%; <4mbps – 28.4%; p-value: <.0001). When looking at the relationship of 2014 download speeds and 2014 e-prescription adoptions, it found a similar relationship (11+ mbps – 90.1%; 7-10 mbps – 82.7%; 4-7 mbps – 80.4%; <4mbps – 85.2%; p-value: <.0001). For e-prescription adoptions based on 2010 and 2014 upload speeds, refer to Table 5.5.

#### *Internet upload and download speed based on change categories*

Among all the categories every county had the largest proportion of their counties increase their download speed, but decrease their upload speed. For small adjacent (21.4%) counties and remote (18.4%) counties, the second highest proportion saw no change in medium speed. Urban (22.0%) and micropolitan (21.2%) counties second largest category saw speed changes that were under upload and download are different. For the combined 2010-2014 upload and download speed changes by rurality, refer to Table 5.6.

#### *Characteristics influencing e-prescription adoption from 2010-2014*

In the model that determined the impact of Internet speeds on e-prescription adoption quartile, it found the counties that began with high download and upload speeds in 2010 were more likely to increase e-prescriptions adoptions. In addition, counties that

experienced an increase of upload speeds from medium to high speeds saw similar increases in e-prescription adoptions. However, counties which started with low Internet speeds and increased to faster speeds had a negative impact on e-prescription adoptions (Table 5.7, Model A).

When community characteristics were accounted for, all the categories for Internet speed changes were rendered insignificant with the exception of “Upload speed increased, but download speed decreased”, which had a negative impact on e-prescription adoptions. (Table 5.7, Model B). Also, both rural and remote were less likely than urban counties to adopt e-prescription systems in 2014.

Based on the final adjusted model, the category of “Upload speed increased, but download speed decreased”, was still negatively associated with e-prescription adoptions compared to counties that had “Medium download and upload speeds, no change” (Table 5.8, Model C). Both remote and rural counties remained negative in impact to e-prescription adoptions in 2014 compared to urban counties. Counties with lower than 66.81% of their physicians under the age of 55 were statistically less likely to adopt e-prescriptions. The table for characteristics of change by quartile is in Table 5.7.

## **Discussion**

Changes in e-prescription adoption rates at the county level were associated with changes in Internet speed within the county (Table 5.7). However, once community characteristics were accounted for, all the Internet speed categories were rendered statistically insignificant with the exception of one category. For counties that had upload



speeds increased, but download speeds decreased during the study period, it found that they were statistically less likely to increase in e-prescription quartile. No previous literature explains why increasing upload speeds but decreasing download speeds would have a negative impact on e-prescription adoptions. More research is needed to understand this phenomenon.

Previous qualitative research has found the main barriers of e-prescription adoption to be financially based, ease of use related, and Internet speed (C. P. Thomas et al., 2012). After adjusting for various community level factors, we found that Internet speed did not play a statistically significant role in e-prescription adoptions from 2010-2014 (Table 5.7). This may mean that ease of use and financial barriers play a role in e-prescription system adoption.

Confirming previous research, we found rural areas were less likely to adopt e-prescribing than urban areas. For rural organizations, a large barrier to e-prescription adoption is cost. Rural hospitals, on average, have lower operating profit margins than their urban counterparts and are also less likely to adopt e-prescription systems (Adler-Milstein et al., 2015; Hayford et al., 2016). The difference in operating profit margins only adds to the growing disparity between areas that do not adopt e-prescription systems and do adopt e-prescription systems. Previous iterations of policy encouraging e-prescription adoption in the form of the Medicare Improvements for Patients and Providers Act (2008) and HITECH Act, has occurred to encourage e-prescription adoptions among all providers. However, based on our analysis, rural counties lag behind in e-prescription adoptions compared to their urban counterparts. More policies are needed to target low resource counties to adopt e-prescription systems.

The results from our study show that counties with higher proportions of physicians under the age of 55 were more likely to have higher an increase in e-prescription adoption change (Table 5.7). This finding agrees with the UTAT2 model where younger age is a positive modulating factor on adoption behavior. Medical schools and residency programs should consider encouraging the use of e-prescription systems over the traditional prescription writing. Studies have linked practice variation to habits built at the residency program of the physicians; using e-prescriptions is a habit that young physicians can build during their residency programs (Chen et al., 2014; Phillips et al., 2017; Sirovich et al., 2014). Literature has also shown that once a physician adopts an e-prescription system, the system is considered an improvement over paper based prescription writing which increases workflow and allows physicians to see more patients (Devine et al., 2010).

One of the community level factors that were statistically significant was counties with one hospital were less likely to adopt e-prescriptions than counties with more than 2 hospitals in the county. This suggests that there is also a competition aspect to e-prescription adoption. Studies have shown that areas with more competition are more likely to adopt HIT than places that do not have as many hospitals (Kazley & Ozcan, 2014; Vest et al., 2011). Counties with one hospital, often located in rural or financially underserved areas, were also less likely to have HIT. Therefore, cost of the e-prescription system is potentially a limiting factor to e-prescription adoption. Hospitals located in low competition area may have the most to gain from HIT adoption. Similar to HIT, hospitals in low competition areas have the most to gain from e-prescription adoption (Vest et al., 2011).

Based on the fully adjusted model it concluded that county level characteristics (rurality, e-prescription adoption in 2010, number of physicians under 55, and the number of hospitals in the county) made a statistically significant impact on e-prescription system adoption. This does fit in with the model that was used, the UTAT2, which suggests that age (physicians under 55) and facilitating conditions (amount of hospitals) are strong effectors of e-prescription adoption. Nevertheless, this study could not account for the constructs of habit, experience, hedonic motivation, social influence, and effort expectancy of e-prescription adoptions (Venkatesh et al., 2012). Since there were multiple missing constructs, it may have led to an omitted variable bias, since there is collinearity between all the constructs.

### **Limitations**

This study suffered from several limitations, which were mitigated as much as possible. The study was not able to account for dedicated Internet lines, changes in FCC Internet speed guidelines, how the NBM dataset was put together, and how the Surescripts dataset collected their data. In addition, this study utilized cross-sectional datasets which only gives a snapshot in time for the information.

The NBM did not account for the fact that businesses are able to get a dedicated business Internet line. While the initial cost of the dedicated business Internet line is expensive, it guarantees the business that their Internet would be comparatively faster than the average consumers of Internet in the same area. Because the study attempted to measure the entire health system in the county ability to adopt e-prescriptions, this study did not account for healthcare organizations with dedicated business Internet lines.

The NBM compiles Internet speed based on the reporting from the telecommunications companies of their Internet speed. Each company in each ZIP Code reported their own individual speeds. There were several speeds reported for Internet speeds, which included maximum speed and typical speed. This study chose maximum speed to give the most accurate picture of what a physician or consumer would choose. This is because typical speed is not usually advertised to the customer. However, maximum speed reported by the telecommunications company is not the best barometer of how fast or reliable Internet is. Speed is controlled by various factors which include the computer hardware used by the physicians and the number of people using the Internet at any given time. In addition, telecommunications companies practice “throttling” Internet speeds of customers, which does impact the speed of the Internet (Bode, 2009; Marcon et al., 2011).

How the e-prescription adoption rate variable was collected is also a limitation. The Surescripts dataset lists only the adoption percentage that occurred within a county. However, it does not take into account the changing number of physicians within the county. For instance, if a county had 25 of their 50 physicians using e-prescriptions in 2010, then 50% of their county would have been considered adopted e-prescriptions. However, if in 2014, the number of physicians increased to 100, but none of the new physicians in the county adopted e-prescriptions, Surescripts would show their adoption rate at 25%, which would signify that physicians had decided to stopped using e-prescriptions, when in fact no growth had occurred. In addition, if the opposite happened where the adoption percentage grew, but the number of physicians in the county decreased, Surescripts would show that growth had occurred. Based on the data from

AHRF, which show the number of physicians within a county, there were 1,437 instances where e-prescription adoption rates changed and physician numbers also changed. The data points were not excluded from the sample because it is possible that the increase in physicians in a county had occurred solely in an organization that already had e-prescriptions recruiting more physicians. Because there was no certain method to account for changes in physician numbers impacting e-prescription adoptions, it could be quite possible this had an adverse effect on the resulting data.

## **Conclusion**

The hypothesis that faster Internet speeds account for higher e-prescription adoption was not supported by this study. Rather, there seems to be other factors involved aside from Internet speed which have more to do with cost and personal preferences. More research is needed to determine what barriers are preventing the remaining physicians and facilities from adopting e-prescriptions.

*Table 5.1 UTAT2 and variables used in study*

<b>UTAT2 Construct</b>	<b>Variables Used</b>
Performance Expectancy	Upload speed Download speed
Effort Expectancy	None available
Social Influence	Ratio of physicians to population Amount of hospitals in county Percent of non-white population
Facilitating Conditions	Percent of people 18-64 without health insurance Percent of people on Medicare Part D Percent of people under 65 Rurality
Hedonic Motivation	None available
Price Value	Percent in poverty
Habit	None Available
Age	Percent of M.D.'s aged 55
Gender	Percent of males M.D.
Experience	None Available

<i>Table 5.2 Differences between excluded and included counties from 2010-2014</i>			
	<b>Included, n = 2933</b>	<b>Excluded, n = 208</b>	<b>p-value</b>
	<b>%</b>	<b>%</b>	
<b>Percent E-prescription adoption, 2010</b>			
0%	24.6	98.1	<.0001
0.01-15%	22.4	0.5	
15-32%	26.9	0.0	
32%+	26.0	1.4	
<b>Percent E-prescription adoption, 2014</b>			
0%	4.8	98.1	<.0001
0.01-15%	2.0	0.5	
15-32%	6.5	0.0	
32%+	86.6	1.4	
<b>Rurality</b>			
Urban	36.3	12.0	<.0001
Rural	63.7	88.0	
<b>Rurality</b>			
Urban	36.3	12.0	<.0001
Micropolitan	22.4	9.1	
Small Adjacent	21.2	21.2	
Remote	20.2	57.7	
<b>Upload Speed, 2010</b>			
<2mbps	4.4	12.0	<.0001
2 to 5 mbps	40.8	60.1	
5-8 mbps	47.7	22.1	
8+ mbps	7.2	5.8	
<b>Upload Speed, 2014</b>			
<2mbps	5.1	12.5	<.0001
2 to 5 mbps	16.7	32.2	
5-8 mbps	44.3	32.7	
8+ mbps	34.0	22.6	
<b>Download speed, 2010</b>			
<4mbps	6.1	20.7	<.0001
4-7mbps	11.1	38.5	
7-10mbps	74.8	38.9	
11+mbps	8.1	1.9	
<b>Download speed, 2014</b>			
<4mbps	5.5	14.9	<.0001
4-7mbps	3.5	10.1	
7-10mbps	38.5	49.5	
11+mbps	52.5	25.5	
<b>Percent of physicians who are male, 2010</b>			

<66.67%	26.2	60.6	<.0001
66.67- 73.53%	24.7	2.4	
73.54 - 80.00%	27.4	7.7	
80.00%+	21.8	29.3	
<b>Percent of physicians who are male, 2014</b>			
<66.67%	33.0	63.5	<.0001
66.67- 73.53%	26.7	1.0	
73.54 - 80.00%	23.6	8.2	
80.00%+	16.7	27.4	
<b>Percent of physicians who are under 55, 2010</b>			
< 48.15%	25.1	72.1	<.0001
48.15-58.82%	25.0	7.2	
58.83-66.82%	25.2	7.2	
66.82%+	24.6	13.5	
<b>Percent of physicians who are under 55, 2014</b>			
< 48.15%	34.1	69.7	<.0001
48.15-58.82%	28.9	9.1	
58.83-66.82%	20.5	7.7	
66.82%+	16.5	13.5	
<b>Percent of poverty, 2010</b>			
<5.7%	25.3	30.8	0.1119
5.7-14.1%	24.4	27.4	
14.2-32.9%	25.1	19.7	
33.00%+	25.2	22.1	
<b>Percent of poverty, 2014</b>			
<5.7%	26.0	39.4	<.0001
5.7-14.1%	24.0	24.0	
14.2-32.9%	24.4	15.4	
33.00%+	25.6	21.2	
<b>Percent of non-white population, 2010</b>			
<5.15%	24.1	38.9	0.0078
5.16 to 11.09%	25.5	17.3	
11.10 to 19.20%	25.4	18.8	
19.20%+	25.0	25.0	
<b>Percent of non-white population, 2014</b>			
<5.15%	18.7	30.3	0.0078
5.16 to 11.09%	27.6	24.0	
11.10 to 19.20%	27.1	18.3	
19.20%+	26.7	27.4	
<b>Percent without health insurance, 2010</b>			
<17.51%	25.9	12.5	<.0001
17.51-22.03%	25.3	21.6	
22.04-26.70%	25.0	24.5	



26.70%+	23.8	41.4	
<b>Percent without health insurance, 2014</b>			
<17.51%	55.4	44.2	<.0001
17.51-22.03%	23.4	17.8	
22.04-26.70%	15.3	17.8	
26.70%+	5.93	20.2	
<b>Percent of population over age 65 with Medicare Part D, 2010</b>			
<39.77%	25.8	14.9	<.0001
39.77-48.03%	25.6	16.4	
48.04-57.64%	25.0	24.5	
57.64%	23.6	44.2	
<b>Percent of population over age 65 with Medicare Part D, 2014</b>			
<39.77%	14.0	11.1	<.0001
39.77-48.03%	19.8	10.6	
48.04-57.64%	31.2	23.1	
57.64%	35.0	55.3	
<b>Ratio of population to physicians, 2010</b>			
<515.52	23.6	46.2	0.016
515.52 - 981.62	26.2	7.7	
981.63 - 1720.20	25.7	14.4	
1720.20+	24.5	31.7	
<b>Ratio of population to physicians, 2014</b>			
<515.52	24.6	45.7	0.0097
515.52 - 981.62	25.6	8.2	
981.63 - 1720.20	23.6	16.4	
1720.20+	26.2	29.8	
<b>Number of hospitals, 2010</b>			
0	16.2	68.3	<.0001
1	49.2	30.8	
2+	34.6	1.0	
<b>Number of hospitals, 2014</b>			
0	16.2	69.7	<.0001
1	49.3	29.3	
2+	34.5	1.0	

*Table 5.3 Characteristics of counties for rurality, Internet speed, and e-prescription adoption, 2010 and 2014*

	2010		2014	
	Frequency	%	Frequency	%
<b>Rurality</b>				
Urban	1064	36.3		
Rural	1869	63.7		
<b>Rurality</b>				
Urban	1064	36.3		
Micropolitan	656	22.4		
Small Adjacent	622	21.2		
Remote	591	20.2		
<b>Upload speed</b>				
<2mbps	128	4.4	148	5.1
2 to 5 mbps	1196	40.8	489	16.7
5-8 mbps	1399	47.7	1299	44.3
8+ mbps	210	7.2	997	34.0
<b>Download speed</b>				
<4mbps	178	6.1	162	5.5
4-7mbps	324	11.1	102	3.5
7-10mbps	2,195	74.8	1,129	38.5
11+mbps	236	8.1	1,540	52.5
<b>Percent E-prescription adoption</b>				
0%	724	24.7	141	4.8
0.01-15%	657	22.4	60	2.1
15-32%	789	26.9	191	6.5
32%+	763	26.1	2,541	86.6

*Table 5.4 Differences in key characteristics of counties, in quartiles based on 2010 value, by year*

	2010		2014		
	Frequency	%	Frequency	%	p-value
<b>Percent of physicians who are male</b>					
<66.67%	767	26.2	969	33.0	<.0001
66.67- 73.53%	725	24.7	784	26.7	
73.54 - 80.00%	803	27.4	691	23.6	
80.00%+	638	21.8	489	16.7	
<b>Percent of physicians who are under 55</b>					
< 48.15%	735	25.1	999	34.1	<.0001
48.15-58.82%	734	25.0	847	28.9	
58.83-66.82%	740	25.2	602	20.5	
66.82%+	724	24.6	485	16.5	
<b>Percent of poverty</b>					
<5.7%	742	25.3	763	26.0	0.5929
5.7-14.1%	716	24.4	703	24.0	
14.2-32.9%	737	25.1	715	24.4	
33.00%+	738	25.2	752	25.6	
<b>Percent of non-white population</b>					
<5.15%	708	24.1	548	18.7	<.0001
5.16 to 11.09%	748	25.5	808	27.6	
11.09 to 19.20%	745	25.4	795	27.1	
19.21%+	732	25.0	782	26.7	
<b>Percent without health insurance</b>					
<17.51%	760	25.9	1624	55.4	<.0001
17.51-22.03%	742	25.3	686	23.4	
22.04-26.70%	733	25.0	449	15.3	
26.70%+	698	23.8	174	5.9	
<b>Percent of population over age 65 with Medicare Part D</b>					
<39.77%	758	25.8	411	14.0	<.0001
39.77-48.03%	751	25.6	580	19.8	
48.04-57.64%	732	25.0	916	31.2	
57.64%	692	23.6	1026	35.0	
<b>Ratio of population to physicians</b>					
<515.52	693	23.6	721	24.6	0.7022
515.52 - 981.62	767	26.2	751	25.6	
981.63 - 1720.20	755	25.7	692	23.6	
1720.20+	718	24.5	769	26.2	

Number of hospitals					
0	474	16.2	476	16.2	0.5352
1	1444	49.2	1445	49.3	
2+	1015	34.6	1012	34.5	

Table 5.5 2010 and 2014 upload and download speeds by e-prescription adoption rates for 2010 and 2014

	E-prescription adoption, 2010 (in quartiles based on 2010 values)					E-prescription adoption, 2014 (in quartiles based on 2010 values)				
	0	0.01-15%	15-32%	32%+	p-value	0	0.01-15%	15-32%	32%+	p-value
<b>Upload speeds, 2010</b>										
<2mbps	20.3	26.6	26.6	26.6	<.0001	5.5	1.6	6.3	86.7	<.0001
2 to 5 mbps	33.1	21.1	20.1	25.8		6.4	3.1	8.5	82.0	
5-8 mbps	19.0	22.8	31.7	26.5		3.8	1.3	4.9	90.0	
8+ mbps	17.1	24.8	33.8	24.3		2.4	1.4	5.7	90.5	
<b>Download speeds, 2010</b>										
<4mbps	24.7	24.7	22.5	28.1	<.0001	7.9	2.8	6.7	82.6	<.0001
4-7mbps	46.6	15.1	13.9	24.4		9.3	2.8	10.5	77.5	
7-10mbps	22.7	22.9	28.3	26.1		4.3	1.9	6.1	87.7	
11+mbps	13.1	25.9	34.8	26.3		1.3	2.1	4.7	92.0	
<b>Upload speeds, 2014</b>										
<2mbps	17.6	23.7	29.7	29.1	<.0001	3.4	2.7	8.1	85.8	0.0
2 to 5 mbps	39.9	18.6	17.0	24.5		6.5	2.9	9.4	81.2	
5-8 mbps	23.9	23.8	28.4	23.9		4.9	2.3	6.5	86.2	
8+ mbps	19.3	22.3	29.4	29.1		4.0	1.2	4.8	90.0	
<b>Download speeds, 2014</b>										
<4mbps	19.8	22.8	29.0	28.4	<.0001	4.3	2.5	8.0	85.2	<.0001
4-7mbps	47.1	16.7	10.8	25.5		5.9	2.9	10.8	80.4	
7-10mbps	32.2	20.7	22.8	24.3		7.2	2.7	7.4	82.7	
11+mbps	18.2	24.0	30.8	27.1		3.1	1.5	5.4	90.1	

*Table 5.6 Combined 2010-2014 upload and download speed variable, by rurality*

	<b>Urban, N = 1069</b>	<b>Micropolitan , N = 656</b>	<b>Small Adjacent, N = 622</b>	<b>Remote, n =591</b>	<b>p- value</b>
	<b>%</b>	<b>%</b>	<b>%</b>	<b>%</b>	
Low download and upload, no change	4.7	2.0	1.5	0.9	<.0001
Medium download and upload, no change	14.0	14.9	21.4	18.4	
High download and upload, no change	5.8	4.3	2.3	0.9	
Both change from low to medium	2.0	3.4	5.8	10.5	
Both change from low to high	0.1	1.4	2.6	2.5	
Both change from medium to high	21.4	16.6	9.2	10.8	
Both decrease	2.5	2.6	2.9	3.2	
Upload and download are different	22.0	21.2	19.6	16.2	
Download speed increased, but upload speed decreased	26.1	33.1	34.7	35.7	
Upload speed increased, but download speed decreased	1.3	0.6	0.2	0.9	

<i>Table 5.7 Factors associated with e-prescription adoption change</i>												
Variable (n= 2933)	Est.	SE	t-value	P-value	Est.	SE	t-value	P-value	Est.	SE	t-value	P-value
	Model A				Model B				Model C			
<b>Intercept</b>	3.70	0.03	114.44	<.0001	3.97	0.04	97.33	<.0001	3.98	0.08	52.72	<.0001
<b>Upload and Download Speed (ref = Medium download and upload, no change)</b>												
Low download and upload, no change	0.12	0.09	1.4	0.1605	-0.02	0.08	-0.29	0.7716	0.02	0.08	0.01	0.9887
High download and upload, no change	0.19	0.08	2.45	0.0143	0.02	0.07	0.33	0.7402	0.01	0.07	-0.02	0.9811
Both change from low to medium	-0.18	0.07	-2.6	0.0093	-0.08	0.06	-1.28	0.2002	-0.07	0.06	-1.12	0.262
Both change from low to high	-0.18	0.12	-1.58	0.0149	-0.12	0.11	-1.15	0.2511	-0.14	0.11	-1.26	0.2067
Both change from medium to high	0.17	0.05	3.74	0.0002	0.05	0.04	1.13	0.2584	0.02	0.04	0.41	0.6846
Both decrease	0.05	0.09	0.53	0.5958	0.02	0.08	0.26	0.7974	0.05	0.08	0.69	0.4905
Upload and download are different	0.11	0.04	2.48	0.0130	0.05	0.04	1.21	0.226	0.03	0.04	0.76	0.4451
Download speed increased, but upload speed decreased	0.02	0.04	0.62	0.5335	0.01	0.04	0.15	0.8816	0.01	0.04	-0.01	0.9893
Upload speed increased, but download speed decreased	-0.32	0.15	-2.15	0.032	-0.38	0.14	-2.74	0.0063	-0.40	0.14	-2.9	0.0038
<b>Rurality (ref = Urban)</b>												
Micropolitan					0.01	0.03	0.23	0.8157	0.01	0.04	0.19	0.8495
Rural					-0.11	0.04	-3.2	0.0014	-0.07	0.04	-1.74	0.0418
Remote					-0.17	0.04	-4.63	<.0001	-0.11	0.04	-2.52	0.0119
<b>E-prescription adoption, 2010 (ref = 32%+)</b>												
0.00					-0.60	0.04	-16.84	<.0001	-0.51	0.04	-13.87	<.0001

0.01-15%		-0.10	0.04	-2.91	0.0037	-0.13	0.04	-3.68	0.0002
15-32%		-0.02	0.03	-0.48	0.6306	-0.05	0.03	-1.41	0.1577
<b>Percent of physicians who are male, 2010 (ref = 80.00%+)</b>									
<66.67%		-0.01	0.04	-0.15					0.8798
66.67- 73.53%		0.06	0.04	1.45					0.1478
73.54 - 80.00%		0.05	0.04	1.27					0.2056
<b>Percent of non-white population, 2010 (ref = &lt; 5.15%)</b>									
5.16 to 11.09%		0.06	0.04	1.64					0.1009
11.09 to 19.20%		0.06	0.04	1.65					0.1
>19.21%		0.02	0.04	0.48					0.6279
<b>Percent of poverty, 2010 (ref = 32.9%+)</b>									
<5.7%		0.03	0.04	0.78					0.433
5.7-14.1%		0.05	0.04	1.19					0.2332
14.2-32.9%		0.03	0.04	0.6					0.5501
<b>Percent without health insurance, 2010 (ref = &lt;17.51%)</b>									
17.51-22.03%		-0.02	0.04	-0.64					0.524
22.04-26.70%		0.01	0.04	-0.09					0.9319
26.70%+		-0.05	0.05	-0.96					0.3365
<b>Percent of physicians who are under 55, 2010 (ref = 66.81%+)</b>									
<48.15%		-0.12	0.04	-3.2					0.0014
48.15-58.82%		0.01	0.04	-0.04					0.9703
58.83-66.82%		-0.04	0.03	-1.01					0.0314
<b>Percent of population over age 65 with Medicare Part D, 2010 (ref = &lt;39.77%)</b>									
39.77-48.03%		0.01	0.04	0.36					0.7186
48.04-57.64%		-0.03	0.04	-0.73					0.4634
57.64%		-0.10	0.04	-2.43					0.0151
<b>Ratio of population to physicians, 2010 (ref = 1720.20+)</b>									
<515.52		-0.03	0.04	-0.75					0.4535



515.52-981.62		0.06	0.04	1.52	0.1292
981.63 - 1720.20		0.04	0.04	1.19	0.2334
<b>Amount of hospitals, 2010 (ref = 2+)</b>					
1		-0.21	0.05	-4.7	<.0001
2		-0.03	0.03	-0.86	0.3915

## CHAPTER 6

### CONCLUSION

This study began as an effort to understand the impact of the Internet digital divide in healthcare. The Internet is so ubiquitous in everyday life, its impact is felt in everyday transactions from swiping a credit card during a transaction, which requires the Internet to transfer the information, to the cars we drive, which used the Internet to transfer plans to manufacturers. It is unquestioned that the Internet has aided significantly in the development of new technologies and implementation of new programs in healthcare as well. However, with every new technology, as pointed out by Valente and Rogers in the theory Diffusion of Innovations, there are always a group of people who are called “laggards” who will never adopt a new innovation. The reason for the lack of adoption stems from a bevy reasons, which include personal preferences or lack of structure in place to help foster adoption. This study attempted to quantify if the lack of adoption was due to personal preferences or structure (i.e. the Internet being structure).

Based on the results from both manuscripts, it seems that that structure may play a role in adoption of IHISB, but for e-prescription adoptions structure plays a less than significant role. Using the HINTS datasets from 2012-2013, manuscript 1 sought to answer among people who use mobile devices, if there were differences in IHISB among rural and urban residents. It was found that there were differences among the two populations – rural residents were less likely to use IHISB. However, rural residents had a larger proportion of their population that didn’t own a mobile device or have access to

any form of Internet than the urban population. This suggests that there is an access problem among rural residents. On the other hand, manuscript 2 looked to answer if Internet speed was a significant factor in e-prescription adoptions among rural and urban counties. Utilizing the NBM, AHRF, and Surescripts dataset, it found that despite differences in Internet speed, when community factors were accounted for, e-prescription adoptions did not differ much. In addition, the variables used provided very little sure answers aside from physician based factors. For this reason, based on the UTAT2 model, it is likely there are organizational and personal preferences factor involved in e-prescription adoption that cannot be quantified using national datasets.

## REFERENCES

- Adler-Milstein, J., DesRoches, C. M., Kralovec, P., Foster, G., Worzala, C., Charles, D., ... Jha, A. K. (2015). Electronic health record adoption in us hospitals: Progress continues, but challenges persist. *Health Affairs*, *34*(12), 2174–2180.  
<http://doi.org/10.1377/hlthaff.2015.0992>
- Allen, L. N., & Christie, G. P. (2016). The Emergence of Personalized Health Technology Corresponding Author :, *18*, 1–5. <http://doi.org/10.2196/jmir.5357>
- Anderson, M. (2015). Technology Device Ownership: 2015. *Pew Research Reports*, 1–26. <http://doi.org/10.3916/C43-2014-17>
- Anderson, M., & Perrin, A. (2016). 13% of Americans don't use the internet. Who are they? | Pew Research Center. Retrieved January 26, 2017, from <http://www.pewresearch.org/fact-tank/2016/09/07/some-americans-dont-use-the-internet-who-are-they/>
- Atchinson, B. K., & Fox, D. M. (1997). The Politics of the Health Insurance Portability and Accountability Act. *Health Affairs*, *16*(3), 146–150.  
<http://doi.org/10.1377/hlthaff.16.3.146>
- Bardus, M., Smith, J. R., Samaha, L., & Abraham, C. (2016). Mobile and Web 2.0 interventions for weight management: an overview of review evidence and its methodological quality. *European Journal of Public Health*, *26*(4), 602–610.  
<http://doi.org/10.1093/eurpub/ckw090>

- Bennett, K., Lin, Y., Yuen, M., Leonhirth, D., & Probst, J. (2016). RUCA Rural Health Research Center, (July), 1–21. Retrieved from <http://depts.washington.edu/uwruca/ruca-about.php>
- Bentley, C. L., Otesile, O., Bacigalupo, R., Elliott, J., Noble, H., Hawley, M. S., ... Cudd, P. (2016). Feasibility study of portable technology for weight loss and HbA1c control in type 2 diabetes. *BMC Medical Informatics and Decision Making*. <http://doi.org/10.1186/s12911-016-0331-2>
- Bergsieker, R. T., Cunningham, R. H., & Young, L. (2015). The Federal Trade Commission ' s Enforcement of Data Security Standards. *Antitrust and Consumer Protection Law*, 44(6), 39–43.
- Berkeley Technology Law Journal, \_ . (2005). United States v . Councilman. *Berkeley Technology Law Journal*, 20(1). <http://doi.org/10.15779/Z38Q10N>
- Bhuyan, S. S., Lu, N., Chandak, A., Kim, H., Wyant, D., Bhatt, J., ... Chang, C. F. (2016). Use of Mobile Health Applications for Health-Seeking Behavior Among US Adults. *Journal of Medical Systems*, 40(6). <http://doi.org/10.1007/s10916-016-0492-7>
- Brusk, J. J., & Bensley, R. J. (2016). A Comparison of Mobile and Fixed Device Access on User Engagement Associated With Women, Infants, and Children (WIC) Online Nutrition Education. *JMIR Research Protocols*, 5(4), e216. <http://doi.org/10.2196/resprot.6608>
- Budiu, R. (2015). Mobile User Experience: Limitations and Strengths. Retrieved March 26, 2017, from <https://www.nngroup.com/articles/mobile-ux/>
- Buntin, M. B., Burke, M. F., Hoaglin, M. C., & Blumenthal, D. (2011). The benefits of

health information technology: A review of the recent literature shows predominantly positive results. *Health Affairs*, 30(3), 464–471.

<http://doi.org/10.1377/hlthaff.2011.0178>

Burke, T. (2010). Law and the Public' s Health, *125*(February), 1–5.

Care, M. (2013). Emerging and Encouraging Trends in E-Prescribing Adoption Among Providers and Pharmacies, (September), 760–767.

Carlson, E., & Goss, J. (2016). The State of the Urban/Rural Digital Divide | NTIA. Retrieved January 24, 2017, from <https://www.ntia.doc.gov/blog/2016/state-urbanrural-digital-divide>

Center for Healthcare Research and Transformation. (2011). E-Prescribing: Barriers and Opportunities, (August).

Centers for Medicare & Medicaid Services (CMS), H. H. S. (2014). Part II Department of Health and Human Services, *77*(171), 1–196.

Centers for Medicare and Medicaid Services, \_\_\_\_\_. (2013). Electronic Prescribing Incentive Fact Sheet, (October 2008), 1–2.

Chaudhry, B., Wang, J., Wu, S., Maglione, M., Mojica, W., Roth, E., ... Shekelle, P. (2006). Annals of Internal Medicine Improving Patient Care Systematic Review : Impact of Health Information Technology on. *Annals of Internal Medicine*, *144*(10), 742–752.

Chen, C., Petterson, S., Phillips, R., Bazemore, A., & Mullan, F. (2014). Spending patterns in region of residency training and subsequent expenditures for care provided by practicing physicians for Medicare beneficiaries. *Jama*, *312*(22), 2385–93. <http://doi.org/10.1001/jama.2014.15973>

Chesser, A., Burke, A., Reyes, J., & Rohrberg, T. (2016). Navigating the digital divide: A systematic review of eHealth literacy in underserved populations in the United States. *Informatics for Health & Social Care*, 41(1), 1–19.

<http://doi.org/10.3109/17538157.2014.948171>

Chesser, A., Burke, A., Reyes, J., Rohrberg, T., Chesser, A., Burke, A., ... Rohrberg, T. (2016a). Navigating the digital divide : A systematic review of eHealth literacy in underserved populations in the United States Navigating the digital divide : A systematic review of eHealth literacy in underserved populatio. *Informatics for Health and Social Care*, 8157(October).

<http://doi.org/10.3109/17538157.2014.948171>

Chesser, A., Burke, A., Reyes, J., Rohrberg, T., Chesser, A., Burke, A., ... Rohrberg, T. (2016b). Navigating the digital divide : A systematic review of eHealth literacy in underserved populations in the United States Navigating the digital divide : A systematic review of eHealth literacy in underserved populatio. *Informatics for Health and Social Care*, 8157(October).

<http://doi.org/10.3109/17538157.2014.948171>

Cicero, T. J., Dart, R. C., Inciardi, J. a., Woody, G. E., Schnoll, S., & Muñoz, A. (2007).

The development of a comprehensive risk-management program for prescription opioid analgesics: Researched abuse, diversion and addiction-related surveillance

(RADARS ®). *Pain Medicine*, 8(2), 157–170. [http://doi.org/10.1111/j.1526-](http://doi.org/10.1111/j.1526-4637.2006.00259.x)

[4637.2006.00259.x](http://doi.org/10.1111/j.1526-4637.2006.00259.x)

Claxton, G., Rae, M., Long, M., Damico, A., Whitmore, H., & Foster, G. (2016). Health Benefits In 2016: Family Premiums Rose Modestly, And Offer Rates Remained

- Stable. *Health Affairs*, 35(10), 1908–1917. <http://doi.org/10.1377/hlthaff.2016.0951>
- Collins, S. a, Yoon, S., Rockoff, M. L., Nocenti, D., & Bakken, S. (2014). Digital divide and information needs for improving family support among the poor and underserved. *Health Informatics Journal*, *October*, 1–11. <http://doi.org/10.1177/1460458214536065>
- Continuing Medical Education Web. (2016). Continuing Medical Education. Retrieved January 24, 2017, from [http://www.cmeweb.com/gstate\\_requirements.php](http://www.cmeweb.com/gstate_requirements.php)
- Cooke, C. E., Xing, S., Lee, H. Y., & Daniel, A. (2011). You wrote the prescription, but will it get filled? *The Journal of Family Practice*, 60(6), 321–327.
- Devine, E. B., Williams, E. C., Martin, D. P., Sittig, D. F., Tarczy-Hornoch, P., Payne, T. H., & Sullivan, S. D. (2010). Prescriber and staff perceptions of an electronic prescribing system in primary care: a qualitative assessment. *BMC Medical Informatics and Decision Making*, 10(1), 72. <http://doi.org/10.1186/1472-6947-10-72>
- Dotson, J., Nelson, L., Young, S., Buchwald, D., Roll, J., Jaw, D., ... Si, Y. (2017). Use of cell phones and computers for health promotion and tobacco cessation by American Indian college students in Montana. *Rural and Remote Health*, 17, 4014–2017.
- Federal Communications Commission. (n.d.-a). Telecommunications Act of 1996 | Federal Communications Commission. Retrieved March 27, 2017, from <https://www.fcc.gov/general/telecommunications-act-1996>
- Federal Communications Commission, \_\_\_\_\_. (n.d.-b). Lifeline Support for Affordable Communications | Federal Communications Commission. Retrieved March 27,



2017, from <https://www.fcc.gov/consumers/guides/lifeline-support-affordable-communications>

Federal Communications Commission, \_\_\_\_\_. (2013). FCC proposes nearly \$33 million in penalties against Lifeline providers that sought duplicate payments for ineligible subscribers.

Federal Communications Commission, \_\_\_\_\_. (2016). *FCC Filing 16-44: Notice of Apparent Liability for Forfeiture and Order*.

Federal Communications Commission, \_\_\_\_\_. (n.d.). Universal Service | Federal Communications Commission. Retrieved March 27, 2017, from <https://www.fcc.gov/general/universal-service>

Feinberg, I., Frijters, J., Johnson-Lawrence, V., Greenberg, D., Nightingale, E., & Moodie, C. (2016). Examining Associations between health information seeking behavior and adult education status in the U.S.: An analysis of the 2012 PIAAC data. *PLoS ONE*, *11*(2), 1–20. <http://doi.org/10.1371/journal.pone.0148751>

Fordyce, M. A., Doescher, M. P., Skillman, S. M., & Larson, E. H. (2013). The Aging of the Rural Primary Care Physician Workforce: Will Some Locations Be More Affected than Others? *WWAMI Rural Health Research Center*. Retrieved from <http://depts.washington.edu/uwrhrc/>

Fox, S., & Purcell, K. (2010). Chronic Disease and the Internet. *Pew Internet and American Life Project*, 1–35. <http://doi.org/10.1071/PY04018>

Frail, C. K., Kline, M., & Snyder, M. E. (2003). HHS Public Access. *Journal American Pharamacy Association*, *54*(6), 630–633. <http://doi.org/10.1331/JAPhA.2014.13176.Patient>

- Frail, C. K., Systems, H., Lafayette, W., Kline, M., Pharmacy, W., Lafayette, W., & Snyder, M. E. (2015). HHS Public Access, *54*(2003), 630–633.  
<http://doi.org/10.1331/JAPhA.2014.13176.Patient>
- Furtado, K. S., Kaphingst, K. A., Perkins, H., & Politi, M. C. (2016). Health Insurance Information-Seeking Behaviors Among the Uninsured. *Journal of Health Communication, 21*(2), 148–158. <http://doi.org/10.1080/10810730.2015.1039678>
- Gabriel, M., Furukawa, M., & Vaidya, V. (2013). Emerging and Encouraging Trends in E-Prescribing Adoption Among Providers and Pharmacies. *American Journal of Managed Care*, (September), 760–767.
- Gabriel, M. H., & Swain, M. (2014). E-prescribing Trends in the United States. *ONC Data Brief*, (18), 1–10.
- Gazmararian, J. a., Williams, M. V., Peel, J., & Baker, D. W. (2003). Health literacy and knowledge of chronic disease. *Patient Education and Counseling, 51*(3), 267–275.  
[http://doi.org/10.1016/S0738-3991\(02\)00239-2](http://doi.org/10.1016/S0738-3991(02)00239-2)
- Gibbs, R., Kusmin, L., & Cromartie, J. (n.d.). Low-Skill Employment and the Changing Economy of Rural America.
- Gibbs, R., Kusmin, L., & Cromartie, J. (2005). Low-Skill Employment and the Changing Economy of Rural America. *United States Department of Agriculture*, (10).
- Gold, M., & McLaughlin, C. (2016). Assessing HITECH Implementation and Lessons: 5 Years Later. *Milbank Quarterly, 94*(3), 654–687. <http://doi.org/10.1111/1468-0009.12214>
- GovTrack.us, \_ . (n.d.). Scientific and Advanced-Technology Act of 1992 (1992; 102nd Congress S. 1146). Retrieved January 28, 2017, from

<https://www.govtrack.us/congress/bills/102/s1146>

Greenwood, S., Perrin, A., & Duggan, M. (n.d.). Demographics of Social Media Users in

2016 | Pew Research Center. Retrieved May 18, 2017, from

<http://www.pewinternet.org/2016/11/11/social-media-update-2016/>

Gu, J.-C., Fan, L., Suh, Y. H., & Sang-Chul, L. (2010). Comparing Utilitarian and Hedonic Usefulness to User Intention in Multipurpose Information Systems.

*CyberPsychology, Behavior & Social Networking*, 13(3), 287–297.

<http://doi.org/10.1089/cyber.2009.0167>

Harton, H. C., & Bullock, M. (2007). Dynamic Social Impact: A Theory of the Origins and Evolution of Culture. *Social and Personality Psychology Compass*, 1(1), 521–

540. <http://doi.org/10.1111/j.1751-9004.2007.00022.x>

Hayford, T., Nelson, L., & Diorio, A. (2016). Congressional Budget Office Projecting Hospitals ' Profit Margins Under Several Illustrative Scenarios Alexia Diorio September 2016 Working Paper 2016-04. *Congressional Budget Office*.

Health IT. (2013). Physician e-Rx through an EHR. Retrieved June 2, 2017, from

<https://dashboard.healthit.gov/quickstats/pages/FIG-Percent-Physicians-eRx-through-EHR.php>

Henricks, W. H. (2011). “Meaningful use” of electronic health records and its relevance to laboratories and pathologists. *Journal of Pathology Informatics*, 2, 7.

<http://doi.org/10.4103/2153-3539.76733>

Hong, Y. A., & Cho, J. (2016). Has the Digital Health Divide Widened ? Trends of Health-Related Internet Use Among Older Adults From 2003 to 2011. *Journals of Gerontology Social Science*, 0(0), 1–8. <http://doi.org/10.1093/geronb/gbw100>

- Jacque, B., Koch-Weser, S., Faux, R., & Meiri, K. (2016). Addressing Health Literacy Challenges With a Cutting-Edge Infectious Disease Curriculum for the High School Biology Classroom. *Health Education & Behavior*, 43(1), 43–53.  
<http://doi.org/10.1177/1090198115596163>
- Jamoom, E., & Hing, E. (2015a). Progress with electronic health record adoption among emergency and outpatient departments: United States, 2006-2011. *National Center for Health Statistics*, (187), 1–8.
- Jamoom, E., & Hing, E. (2015b). Progress with electronic health record adoption among emergency and outpatient departments: United States, 2006-2011. *NCHS Data Brief*, (187), 1–8. Retrieved from <http://www.ncbi.nlm.nih.gov/pubmed/25714041>
- Jeppesen, K. M., Hull, B. P., Raines, M., & Miser, W. F. (2012). A Validation Study of the Spoken Knowledge in Low Literacy in Diabetes Scale (SKILLD). *Journal of General Internal Medicine*, 27(2), 207–212. <http://doi.org/10.1007/s11606-011-1900-9>
- Joseph, S. B., Sow, M. J., Furukawa, M. F., Posnack, S., & Daniel, J. G. (2013). E-prescribing adoption and use increased substantially following the start of a federal incentive program. *Health Affairs*, 32(7), 1221–1227.  
<http://doi.org/10.1377/hlthaff.2012.1197>
- Kazley, A. S., & Ozcan, Y. A. (2014). Organizational and Environmental Determinants of Hospital EMR Adoption : A National Study, (2007), 375–384.  
<http://doi.org/10.1007/s10916-007-9079-7>
- Keckojevic, A., Wong, C. F., Corliss, H. L., & Lankenau, S. E. (2015). Risk factors for high levels of prescription drug misuse and illicit drug use among substance-using

young men who have sex with men (YMSM). *Drug and Alcohol Dependence*.

<http://doi.org/10.1016/j.drugalcdep.2015.02.031>

King, J., Patel, V., & Furukawa, M. (2012). Physician Adoption of Electronic Health Records Technology to Meet Meaningful Use Objectives: 2009-2013. *The Office of the National Coordinator for Health Information Technology*, (7), 2009–2012.

King, J., Furukawa, M. F., & Buntin, M. B. (2013). Geographic variation in ambulatory electronic health record adoption: Implications for underserved communities. *Health Services Research*, 48(6 PART1), 2037–2059. <http://doi.org/10.1111/1475-6773.12078>

Kruger, L. G., & Gilroy, A. A. (2016). Broadband Internet Access and the Digital Divide : Federal Assistance Programs.

Kruse, C. S., Kristof, C., Jones, B., Mitchell, E., & Martinez, A. (2016). Barriers to Electronic Health Record Adoption: a Systematic Literature Review. *Journal of Medical Systems*, 40(12). <http://doi.org/10.1007/s10916-016-0628-9>

Kruse, R. L., Koopman, R. J., Wakefield, B. J., Wakefield, D. S., Keplinger, L. E., Canfield, S. M., & Mehr, D. R. (2012). Internet use by primary care patients: where is the digital divide? *Fam Med*, 44(5), 342–347. Retrieved from <http://www.ncbi.nlm.nih.gov/pubmed/23027117>

Kujala, S., Roto, V., Vaananen-Vainio-Mattila, K., Karapanos, E., & Sinnela, A. (2011). UX Curve: A method for evaluating long-term user experience. *Interacting with Computers*, 23(5), 473–483. <http://doi.org/10.1016/j.intcom.2011.06.005>

Kutner, M., Greenberg, E., Jin, Y., & Paulsen, C. (2006). The health literacy of America's adults: results from the 2003 National Assessment of Adult Literacy.

*Education*, 6, 1–59. <http://doi.org/10.1592/phco.22.5.282.33191>

Leiner, B. M., Clark, D. D., Kahn, R. E., Kleinrock, L., Lynch, D. C., Postel, J., ...

Wolff, S. (2009). A Brief History of the Internet Professor of Computer Science, *39*(5), 22–31.

Li, J., & Theng, Y. (2016a). Predictors of online health information seeking behavior : Changes between 2002 and 2012. <http://doi.org/10.1177/1460458215595851>

Li, J., & Theng, Y. (2016b). Predictors of online health information seeking behavior : Changes between 2002 and 2012. *Health Informatics Journal*, 22(4), 804–814. <http://doi.org/10.1177/1460458215595851>

Liu, J., Bellamy, G., Barnet, B., & Weng, S. (2008). Bypass of local primary care in rural counties: Effect of patient and community characteristics. *Annals of Family Medicine*, 6(2), 124–130. <http://doi.org/10.1370/afm.794>

Mackert, M., Mabry-flynn, A., Champlin, S., Donovan, E. E., Dean, W., & Keeton, A. (2016). Health Literacy and Health Information Technology Adoption : The Potential for a New Digital Divide Corresponding Author :, 18, 1–16. <http://doi.org/10.2196/jmir.6349>

Manierre, M. J. (2015). Gaps in knowledge: Tracking and explaining gender differences in health information seeking. *Social Science & Medicine*, 128C, 151–158. <http://doi.org/10.1016/j.socscimed.2015.01.028>

McCabe, D. (2016). Bill Clinton’s telecom law: Twenty years later | TheHill. Retrieved March 27, 2017, from <http://thehill.com/policy/technology/268459-bill-clintons-telecom-law-twenty-years-later>

Mccloud, R. F., Okechukwu, C. A., Sorensen, G., & Viswanath, K. (2016). Beyond

access : barriers to internet health information seeking among the urban poor, 1–7.  
<http://doi.org/10.1093/jamia/ocv204>

McCloud, R. F., Okechukwu, C. A., Sorensen, G., & Viswanath, K. (2016). Beyond access: barriers to internet health information seeking among the urban poor. *Journal of the American Medical Informatics Association : JAMIA*, 1–7.  
<http://doi.org/10.1093/jamia/ocv204>

mHealth, \_\_\_\_\_. (2015). Physician Telemedicine Adoption Opinions Vary by Age, Specialty. Retrieved March 22, 2017, from  
<http://mhealthintelligence.com/news/physician-telemedicine-adoption-opinions-vary-by-age-specialty>

Miller, L. M. S., & Bell, R. a. (2012). Online Health Information Seeking: The Influence of Age, Information Trustworthiness, and Search Challenges. *Journal of Aging and Health*, 24(3), 525–541. <http://doi.org/10.1177/0898264311428167>

Monteith, S., Glenn, T., & Bauer, M. (2013). Searching the internet for health information about bipolar disorder : some cautionary issues. *International Journal of Bipolar Disorders*, 1–6.

Nanji, K. C., Rothschild, J. M., Boehne, J. J., Keohane, C. A., Ash, J. S., & Poon, E. G. (2014). Unrealized potential and residual consequences of electronic prescribing on pharmacy workflow in the outpatient pharmacy: Table 1. *Journal of the American Medical Informatics Association*, 21(3), 481–486. <http://doi.org/10.1136/amiajnl-2013-001839>

National Cancer Institute. (2014). Analytics Recommendations for HINTS 4 – Cycle 3 Data. Retrieved from <http://hints.cancer.gov/>

- National Conference of State Legislatures. (2016). Health Insurance: Premiums and Increases. Retrieved January 20, 2017, from <http://www.ncsl.org/research/health/health-insurance-premiums.aspx>
- National Council Survey, \_ . (2012). HIT Adoption and Readiness for Meaningful Use in Community Behavioral Health About the National Council, (June).
- National Telecommunications and Information Administration, \_ . (2013). Exploring the Digital Nation: America's Emerging Online Experience, 1–58.
- O Higgins, J Sixsmith, MM Barry, C. D. (2011). A literature review on health information-seeking behaviour on the web : a health consumer and health professional perspective.
- Odukoya, O. K., & Chui, M. A. (n.d.). Older Adults ' Perceptions of E-Prescribing : Impact on Patient Care.
- Odukoya, O. K., Pharm, B., Chui, M. A., Pharm, D., & Ph, D. (2013). E-prescribing : A focused review and new approach to addressing safety in pharmacies and primary care. *Research in Social and Administrative Pharmacy*, 9(6), 996–1003. <http://doi.org/10.1016/j.sapharm.2012.09.004>
- Pang, P. C., Chang, S., Pearce, J., & Verspoor, K. (n.d.). ONLINE HEALTH INFORMATION SEEKING BEHAVIOUR :
- Peterson, L. E., & Litaker, D. G. (2010). County-Level Poverty Is Equally Associated With Unmet Health Care Needs in Rural and Urban Settings. *Jornal of Rural Health*, 26, 373–382. <http://doi.org/10.1111/j.1748-0361.2010.00309.x>
- Pevnick, J. M., Asch, S., Adams, J., Mattke, S., Patel, M., Ettner, S., & Bell, D. (2010). Adoption and Usage of Stand-Alone Electronic Prescribing in a Health Plan-



Sponsored Initiative. *American Journal of Managed Care*, 16(3), 182–189.

<http://doi.org/10.1002/aur.1474>.Replication

Pew Research Center, \_ . (2017). Demographics of Internet and Home Broadband Usage in the United States | Pew Research Center. Retrieved February 1, 2017, from <http://www.pewinternet.org/fact-sheet/internet-broadband/>

Phillips, R. L., Petterson, S., Bazemore, A., Wingrove, P., & Puffer, J. C. (2017). The Effects of Training Institution Practice Costs, Quality, and Other Characteristics on Future Practice. *Annals of Medicine*, 15(2), 140–148.

Porterfield, A., Engelbert, K., & Coustasse, A. (n.d.). Electronic Prescribing : Improving the Efficiency and Accuracy of Prescribing in the Ambulatory Care Setting.

Porterfield, A., Engelbert, K., & Coustasse, A. (2014). Electronic prescribing: improving the efficiency and accuracy of prescribing in the ambulatory care setting.

*Perspectives in Health Information Management / AHIMA, American Health Information Management Association*, 11, 1g. Retrieved from

<http://www.pubmedcentral.nih.gov/articlerender.fcgi?artid=3995494&tool=pmcentrez&rendertype=abstract>

Powers, C., Gabriel, M. H., Encinosa, W., Mostashari, F., & Bynum, J. (2015).

Meaningful use stage 2 e-prescribing threshold and adverse drug events in the Medicare Part D population with diabetes. *Journal American Medical Information Association*, (22), 1094–1098. <http://doi.org/10.1093/jamia/ocv036>

Prestin, A., Vieux, S. N., & Chou, W. S. (2015a). Is Online Health Activity Alive and Well or Flatlining ? Findings From 10 Years of the Health Information National Trends Survey Is Online Health Activity Alive and Well or Flatlining ? Findings

From 10 Years of the Health Information National Trends Surv. *UHCM*, 20(7), 790–798. <http://doi.org/10.1080/10810730.2015.1018590>

Prestin, A., Vieux, S. N., & Chou, W. S. (2015b). Is Online Health Activity Alive and Well or Flatlining? Findings From 10 Years of the Health Information National Trends Survey. *Journal of Health Communication*, 0(0), 1–9. <http://doi.org/10.1080/10810730.2015.1018590>

Rainie, L., & Cohn, D. (2014). Computer ownership, internet connection varies widely across U.S. | Pew Research Center. Retrieved January 26, 2017, from <http://www.pewresearch.org/fact-tank/2014/09/19/census-computer-ownership-internet-connection-varies-widely-across-u-s/>

Rohman, I. K., & Bohlin, E. (2012). Does Broadband Speed Really Matter for Driving Economic Growth? Investigating OECD Countries. *SSRN Electronic Journal*, 1–16. <http://doi.org/10.2139/ssrn.2034284>

Romaniuk, P., Ptak, E., & Switała, M. S.-. (2016). Perspectives for the Use of Social Media in e-Pharmamarketing, 7(November), 1–5. <http://doi.org/10.3389/fphar.2016.00445>

Ronquillo, C., & Currie, L. (2010). The digital divide : Trends in global mobile and broadband Internet access from 2000-2010.

Ronquillo, C., & Currie, L. (2012). The digital divide: Trends in global mobile and broadband Internet access from 2000-2010. *Nursing Informatics*, 2012, 346. Retrieved from <http://www.ncbi.nlm.nih.gov/pubmed/24199118>

Ross, J., Stevenson, F., Lau, R., & Murray, E. (2016). Factors that influence the implementation of e-health: a systematic review of systematic reviews (an update).

- Implementation Science*, 11(1), 146. <http://doi.org/10.1186/s13012-016-0510-7>
- Salesforce, \_\_\_\_\_. (2014). 2014 Mobile Behavior Reporting. *Salesforce*. Retrieved from <https://www.marketingcloud.com/sites/exacttarget/files/deliverables/etmc-2014mobilebehaviorreport.pdf>
- Salmon, J. W., & Jiang, R. (2012). E-prescribing: history, issues, and potentials. *Online Journal of Public Health Informatics*, 4(3). <http://doi.org/10.5210/ojphi.v4i3.4304>
- Sarkar, U., Karter, A. J., Liu, J. Y., Adler, N. E., Nguyen, R., López, A., & Schillinger, D. (2011). Social disparities in internet patient portal use in diabetes: evidence that the digital divide extends beyond access. *Journal of the American Medical Informatics Association : JAMIA*, 18(3), 318–21. <http://doi.org/10.1136/jamia.2010.006015>
- Sarkar, U., Karter, A. J., Liu, J. Y., Adler, N. E., Schillinger, D., Nguyen, R., & Lo, A. (2011). Social disparities in internet patient portal use in diabetes : evidence that the digital divide extends beyond access. *Journal of American Informatics Association*, 318–321. <http://doi.org/10.1136/jamia.2010.006015>
- Schleiden, L., Odukoya, O. K., & Chui, M. A. (2015). Older Adults ' Perceptions of E-Prescribing : Impact on Patient Care. *Perspectives in Health Information Management*.
- Serrano, K. J., Thai, C. L., Greenberg, A. J., Blake, K. D., Moser, R. P., & Hesse, B. W. (2017). Progress on Broadband Access to the Internet and Use of Mobile Devices in the United States. *Public Health Rep*, 132(1), 27–31. <http://doi.org/10.1177/0033354916679365>
- Sirovich, B., Lipner, R., Johnston, M., & Holmboe, E. (2014). The association between

residency training and Internists' ability to practice conservatively. *JAMA Internal Medicine*, 16(7), 700–710. <http://doi.org/10.1037/emo0000122>.Do

Social Security Administration, \_\_\_\_\_. (2008). House and Senate Override President's Veto of H.R. 6331, the "Medicare Improvements for Patients and Providers Act of 2008" (P.L. 110–275). Retrieved March 21, 2017, from [https://www.ssa.gov/legislation/legis\\_bulletin\\_071708.html](https://www.ssa.gov/legislation/legis_bulletin_071708.html)

Stevenson, F. A., Kerr, C., Murray, E., & Nazareth, I. (2007). Information from the Internet and the doctor-patient relationship : the patient perspective – a qualitative study. *BMC Family Practice*, 8(47), 1–8. <http://doi.org/10.1186/1471-2296-8-47>

Stevenson, F., Kerr, C., Murray, E., & Nazareth, I. (2007). Information from the Internet and the doctor-patient relationship: the patient perspective - a qualitative study. *BMC Family Practice*, 8(1), 47. <http://doi.org/10.1186/1471-2296-8-47>

Tan, S. S., & Goonawardene, N. (2017a). Internet Health Information Seeking and the Patient-Physician Relationship : A Systematic Review Corresponding Author :, 19. <http://doi.org/10.2196/jmir.5729>

Tan, S. S., & Goonawardene, N. (2017b). Internet Health Information Seeking and the Patient-Physician Relationship : A Systematic Review Corresponding Author : *Journal of Medical Internet Research*, 19(1). <http://doi.org/10.2196/jmir.5729>

Tennant, B., Stellefson, M., Dodd, V., Chaney, B., Chaney, D., Paige, S., & Alber, J. (2015). eHealth literacy and Web 2.0 health information seeking behaviors among baby boomers and older adults. *Journal of Medical Internet Research*, 17(3), 1–16. <http://doi.org/10.2196/jmir.3992>

Thomas, C. P., Kim, M., McDonald, A., Kreiner, P., Jr, S. J. K., Blackman, M. B., ...

Carrow, G. M. (2012). Prescribers' expectations and barriers to electronic prescribing of controlled substances. *Journal of American Informatics*, 19, 375–381.

<http://doi.org/10.1136/amiajnl-2011-000209>

Thomas, C. P., Kim, M., McDonald, a., Kreiner, P., Kelleher, S. J., Blackman, M. B., ...

Carrow, G. M. (2012). Prescribers' expectations and barriers to electronic prescribing of controlled substances. *Journal of the American Medical Informatics Association*, 19(3), 375–381. <http://doi.org/10.1136/amiajnl-2011-000209>

<http://doi.org/10.1136/amiajnl-2011-000209>

U.S. Department of Health and Human Services, \_\_. (n.d.). Security Rule Guidance

Material | HHS.gov. Retrieved March 22, 2017, from

[https://www.hhs.gov/hipaa/for-](https://www.hhs.gov/hipaa/for-professionals/security/guidance/index.html?language=es)

[professionals/security/guidance/index.html?language=es](https://www.hhs.gov/hipaa/for-professionals/security/guidance/index.html?language=es)

United States Congress, \_\_\_\_\_. (n.d.). Food and Drug Administration Safety and

Innovation Act (FDASIA).

United States Department of Agriculture. (n.d.-a). USDA ERS - Geography of Poverty.

Retrieved January 19, 2017, from <https://www.ers.usda.gov/topics/rural-economy-population/rural-poverty-well-being/geography-of-poverty.aspx>

United States Department of Agriculture. (n.d.-b). USDA ERS - Urban Influence Codes.

Retrieved April 11, 2017, from <https://www.ers.usda.gov/data-products/urban-influence-codes.aspx>

United States Department of Health and Human Services, \_\_. (n.d.). HITECH Act

Enforcement Interim Final Rule | HHS.gov. Retrieved January 29, 2017, from

[https://www.hhs.gov/hipaa/for-professionals/special-topics/HITECH-act-](https://www.hhs.gov/hipaa/for-professionals/special-topics/HITECH-act-enforcement-interim-final-rule/index.html?language=es)

[enforcement-interim-final-rule/index.html?language=es](https://www.hhs.gov/hipaa/for-professionals/special-topics/HITECH-act-enforcement-interim-final-rule/index.html?language=es)

- United States Health and Human Services, \_\_\_\_\_. (n.d.). HIPAA for Professionals | HHS.gov. Retrieved January 28, 2017, from <https://www.hhs.gov/hipaa/for-professionals/index.html>
- Valente, T. W., & Rogers, E. M. (1995). The Origins and Development of the Diffusion of Innovations Paradigm as an Example of Scientific Growth. *Science and Communications*, (16), 242–273.
- Venkatesh, V., Morris, M. G., Davis, G. B., & Davis, F. D. (2003). User acceptance of information technology: Toward a unified view. *MIS Quarterly*, 27(3), 425–478. <http://doi.org/10.2307/30036540>
- Venkatesh, V., Thong, J. Y., & Xu, X. (2012). CONSUMER ACCEPTANCE AND USE OF INFORMATION TECHNOLOGY : EXTENDING THE UNIFIED THEORY. *MIS Quarterly*, 36(1), 157–178.
- Vest, J. R., Yoon, J., & Bossak, B. H. (2011). Changes to the electronic health records market in light of health information technology certification and meaningful use, 227–232. <http://doi.org/10.1136/amiajnl-2011-000769>
- Viswanath, K., Nagler, R. H., Bigman-galimore, C. A., & Mccauley, M. P. (2006). The Communications Revolution and Health Inequalities in the 21st Century : Implications for Cancer Control. *Cancer Epidemiology, Biomarkers and Prevention*, 10(21), 1701–1708. <http://doi.org/10.1158/1055-9965.EPI-12-0852>
- Walsh, K. P., Rehman, S., & Goldhirsh, J. (2014). Disparities in internet use among orthopedic outpatients. *Orthopedics*, 37(2), e133-40. <http://doi.org/10.3928/01477447-20140124-14>
- Wang, J., Bennett, K., Probst, J., & Bennett, K. (n.d.). Subdividing the Digital Divide :

- Differences in Internet Access and Use among Rural Residents with Medical Limitations Corresponding Author :, *13*, 1–10. <http://doi.org/10.2196/jmir.1534>
- Wang, J. Y., Bennett, K., & Probst, J. (2011). Subdividing the digital divide: Differences in internet access and use among rural residents with medical limitations. *Journal of Medical Internet Research*, *13*(1), 1–10. <http://doi.org/10.2196/jmir.1534>
- Warren, J. R., Kvasny, L., Hecht, M. L., Burgess, D., Ahluwalia, J. S., & Okuyemi, K. S. (2010a). Barriers, control and identity in health information seeking among African American women, *3*(3), 68–90.
- Warren, J. R., Kvasny, L., Hecht, M. L., Burgess, D., Ahluwalia, J. S., & Okuyemi, K. S. (2010b). Barriers, control and identity in health information seeking among African American women. *Journal of Health Disparities Research and Practice*, *3*(3), 86–90. Retrieved from <http://digitalscholarship.unlv.edu/jhdrp/vol3/iss3/5/>
- Warren, M. (2007). The digital vicious cycle: Links between social disadvantage and digital exclusion in rural areas. *Telecommunications Policy*, *31*(6–7), 374–388. <http://doi.org/10.1016/j.telpol.2007.04.001>
- Watson AJ, Bell AG, Kvedar JC, G. R. (2008). Reevaluating the Digital Divide : Current Lack of Internet Use Is Not a Barrier to Adoption of Novel Health Information Technology. *Diabetes Care*, *31*(3), 433–435. <http://doi.org/10.2337/dc07-1667>.Abbreviations
- Weaver, J. B., Mays, D., Weaver, S. S., Hopkins, G. L., Eroglu, D., & Bernhardt, J. M. (2010). Health information-seeking behaviors, health indicators, and health risks. *American Journal of Public Health*, *100*(8), 1520–1525. <http://doi.org/10.2105/AJPH.2009.180521>

- Weiss, R. D., Potter, J. S., Griffin, M. L., Provost, S. E., Fitzmaurice, G. D., McDermott, K. a., ... Carroll, K. M. (2015). Long-term Outcomes from the National Drug Abuse Treatment Clinical Trials Network Prescription Opioid Addiction Treatment Study. *Drug and Alcohol Dependence, 150*, 112–119.  
<http://doi.org/10.1016/j.drugalcdep.2015.02.030>
- West, D. M. (2015a). Digital divide: Improving Internet access in the developing world through affordable services and diverse content, (February).
- West, D. M. (2015b). Digital divide: Improving Internet access in the developing world through affordable services and diverse content. *Center for Technology Innovation at Brookings*, (February).
- Westberg, K., Stavros, C., Smith, A. C. T., Munro, G., & Argus, K. (2016). An examination of how alcohol brands use sport to engage consumers on social media. *Drug and Alcohol Review*, (August). <http://doi.org/10.1111/dar.12493>
- Whitacre, B. E., Wheeler, D., & Landgraf, C. (2016a). What Can the National Broadband Map Tell Us About the Health Care Connectivity Gap ? *Journal of Rural Health, 0*, 1–6. <http://doi.org/10.1111/jrh.12177>
- Whitacre, B. E., Wheeler, D., & Landgraf, C. (2016b). What Can the National Broadband Map Tell Us About the Health Care Connectivity Gap ?, *0*, 1–6.  
<http://doi.org/10.1111/jrh.12177>
- Whitacre, B. E., & Williams, R. S. (2015). Electronic Medical Record Adoption in Oklahoma Practices : Rural-Urban Differences and the Role of Broadband Availability. *Journal of Rural Health, 31*, 47–57. <http://doi.org/10.1111/jrh.12086>
- Wilson, S. M., Hair, L. P., Hertzberg, J. S., Kirby, A. C., Olsen, M. K., Lindquist, J. H.,



... Calhoun, P. S. (2016). Abstinence Reinforcement Therapy (ART) for rural veterans: Methodology for an mHealth smoking cessation intervention.

*Contemporary Clinical Trials*, 50, 157–165. <http://doi.org/10.1016/j.cct.2016.08.008>

Yamin CK, Emani S, Williams DH, Lipsitz SR, Karson AS, Wald JS, B. D. (2016). The Digital Divide in Adoption and Use of a Personal Health Record, *171*(6), 568–574.

Yin, H. S., Jay, M., Maness, L., Zabar, S., & Kalet, A. (2015). Health Literacy: An Educationally Sensitive Patient Outcome. *Journal of General Internal Medicine*, 1363–1368. <http://doi.org/10.1007/s11606-015-3329-z>

Young, A., Chaudhry, H., Pei, X., Halbesleben, K., Polk, D., & Dugan, M. (2015). A census of actively licensed physicians in the United States, 2014. *Journal of Medical Regulation*, 101(2), 11–24.

Young, J. R. (2013). Middle-Skill Jobs Remain More Common Among Rural Workers.

Zadeh, P. E., Ph, D., Tremblay, M. C., & Ph, D. (2016). A review of the literature and proposed classification on e-prescribing : Functions , assimilation stages , benefits , concerns , and risks. *Research in Social and Administrative Pharmacy*, 12(1), 1–19. <http://doi.org/10.1016/j.sapharm.2015.03.001>

Zadeh, P. E., & Tremblay, M. C. (2016). A review of the literature and proposed classification on e-prescribing : Functions , assimilation stages , benefits , concerns , and risks. *Research in Social and Administrative Pharmacy*, 12(1), 1–19. <http://doi.org/10.1016/j.sapharm.2015.03.001>

Zhao, S. (2009). Parental education and children ' s online health information seeking : Beyond the digital divide debate q. *Social Science & Medicine*, 69(10), 1501–1505. <http://doi.org/10.1016/j.socscimed.2009.08.039>