2017

Factors Associated with Provider Utilization of the Heath Information Exchange in the State of Hawaii

Kris K. Wilson
Walden University

Walden University

College of Health Sciences

This is to certify that the doctoral dissertation by

Kris Wilson

has been found to be complete and satisfactory in all respects,
and that any and all revisions required by
the review committee have been made.

Review Committee
Dr. Michael Furukawa, Committee Chairperson, Health Services Faculty
Dr. Lee Bewley, Committee Member, Health Services Faculty
Dr. James Rohrer, University Reviewer, Health Services Faculty

Chief Academic Officer
Eric Riedel, Ph.D.

Walden University
2017

Abstract

Factors Associated with Physician Utilization of the Heath Information Exchange in the State of Hawaii

by

Kris K. Wilson

MA, Ashford University, 2011

BS, Ashford University, 2008

Dissertation Submitted in Partial Fulfillment

of the Requirements for the Degree of

Doctor of Philosophy

Health Services

Walden University

December 2017

Abstract

In a context where technology is increasingly being incorporated into health care practice, many U.S. health care providers and organizations are finding it challenging to connect disparate electronic documentation systems to retrieve patient information when coordinating care across providers and heath care entities. Local and regional health information exchange (HIE) systems were created to facilitate collecting information into one integrated patient record to address information transfer between heath care providers. Yet, adoption and use of HIEs have been low. The purpose of this study was to review the predictive factors accounting for physicians' use of a HIE in the U.S. state of Hawaii. Key factors from the technology acceptance model were evaluated to determine the behavioral intention resulting in actual use of the Hawaii health information exchange (HHIE). Physician characteristics (medical specialty, age, and gender) and location characteristics were also assessed. The total population of the study contained 1034 Hawaii physicians who have signed up to use the HHIE. Linear and logistic regression models were structured to evaluate the predictive nature of (a) use to determine if a physician has ever logged into the HIE and (b) usage to evaluate the extent to which a physician is logging into the HIE. Findings from the study reveal a predictive relationship between the characteristic of medical specialty and HHIE use when comparing primary care and emergency department physicians to physician specialists. Using study results, health care leaders can improve physician outreach and review barriers when using the HIE systems to coordinate care. Policy implications include the possible formulation of future requirements surrounding HIE physician participation.

Factors Associated with Provider Utilization of the Heath Information Exchange in the State of Hawaii

by

Kris K. Wilson

MA, Ashford University, 2011

BS, Ashford University, 2008

Dissertation Submitted in Partial Fulfillment

of the Requirements for the Degree of

Doctor of Philosophy

Health Services

Walden University

December 2017

Dedication

This dissertation is dedicated to my daughter, Sophia Elizabeth Wilson, for giving me the purpose, determination, and, most importantly, her patience as I spent countless hours focused on completing this process.

Sophia, may you forever chase your hopes and your dreams, and may you always believe in the impossible. You are my gift and the light of my life. No matter how hard things get, never, ever give up.

Acknowledgments

I would like to express the deepest appreciation to my committee chair, Professor Furukawa. His continued work in health information technology and health care policy gave me the interest and desire to pursue my research focus. Dr. Furukawa and my committee member, Dr. Bewley, have been instrumental in guiding me through this process. I am forever grateful for their support and mentorship.

I would also like to thank Francis Chan. His passion for information technology and enthusiasm to bridge gaps in care coordination for the state of Hawaii has assisted in the implementation of a statewide information exchange. Without his leadership and quest to improve information sharing, this research would not have been possible.

Lastly, I would like to thank my family for their love and encouragement during this very long, and very time-consuming, process. My parents, James and Adeline Correa gave me the perseverance and strength to keep going, no matter how hard things got. They have taught me to be a better parent, a better student, and a better person. I could not have made it through without my husband, Alika Querubin, and boys Logan and Callen, for being a welcomed source of laughter and happiness on the hardest days towards completion. A final thanks to my cohort of Walden classmates, who shared in the triumph and tribulations of shell, and to Heidi Waters for being my mentor, editor, and guide.

Table of Contents

List of Tables

List of Figures

Chapter 1: Introduction to the Study

From the turn of the 20th century, health care providers have increasingly incorporated technology into their medical practices. Paper charts are being phased out of existence and replaced with electronic health record (EHR) systems making data sharing easier (Randall, 2014). Access to a patient record that was once housed on a unit or on a shelf in a medical records department is now available on computers in the United States and other parts of the world (Randall, 2014). Creators of health information exchanges (HIEs) sought to generate one collective electronic record for a patient visiting multiple health care providers using disparate EHR systems (Vest & Jasperson, 2012). One record means that no matter where the patient receives care, all pertinent medical information, results, and progress notes are available in a combined chart accessible to all providers (Vest, 2010).

The power of having this information readily available may assist health care providers reduce redundant testing, increase communication between caregivers, and ultimately improve care coordination. For these reasons, lawmakers required HIE participation as one of the meaningful use measures within the American Recovery and Reinvestment Act (ARRA) 2009. However, even though HIEs are collecting information and making it readily available for providers, there seems to be a gap as to how many physicians are using HIEs to access data outside their practice or hospital EHR systems.

The Hawaii Health Information Exchange (HHIE) is the only participating HIE within the state of Hawaii designated by the Office of the National Coordinator (ONC; HealthIT.gov, 2014). Understanding the factors associated with physician usage of the

HHIE may help local healthcare leaders in U.S. counties and states target onboarding strategies and evaluate current barriers to the usefulness and ease of using the combined record. As a state, Hawaii is composed of separate eight islands and remains geographically challenged in coordinating care, and these challenges are projected to worsen because of Hawaii's increasing physician shortage (Withy, 2015). Every opportunity needs to be evaluated to help Hawaii health care providers bridge gaps in health care. A potential solution could be to incorporate technology into data sharing practices, but it will only be successful if everyone understands its full benefit and use.

In this chapter, I explain the background of the study, including the scope of the problem I addressed, gaps in the current literature, and the need for this study. The study design, research questions, hypotheses, and variables are then introduced. I then briefly discuss and highlight the relevance of the model which provided the theoretical foundation for the study. Important terms are also defined and the study assumptions, delimitations, and limitations outlined. Lastly, the significance of the study is explained. The chapter concludes with a summary of key points.

Background

When coordinating care, many providers struggle to obtain information and communicate between hospitals, primary care providers, and specialists (Daniel & Mensah, 2015). Primary care providers rely on hospital discharge summaries, diagnostic findings, consultations, and procedures to understand a patient's condition and to properly assemble a plan of care (Kripalani et al., 2007). Inadequate communication can lead to a decrease in care quality and efficiency, and a rise in preventable readmissions (Jones, Friedberg, & Schneider, 2011).

Physician shortages coupled with the geographic composition of the State of Hawaii make care coordination challenging when transferring information between islands (Hawaii Island Beacon Community, 2013). According to the University of Hawaii's annual report for the state legislature, by 2020 Hawaii will face a physician shortage estimated to be between 800 to 1500 providers (Withy, 2015). There is an ongoing 20% physician shortage of full-time equivalents between all Hawaii counties (Withy, 2015). As a state, Hawaii must seek innovative measures to remedy gaps in communicating critical patient information (Hawaii Island Beacon Community, 2013).

There are both opportunities and challenges in coordinating patient centric care throughout the multiple facets of the health care continuum amid the trending adoption of health information technology (HIT; ONC, 2014). As part of the ARRA, federal lawmakers appropriated over $34 billion dollars as part of the Health Information Technology for Economic and Clinical Health Act (HITECH) to fund financial incentives to promote the use of EHRs (Randall, 2014). The incentive program is based upon the objective of attaining meaningful use certification by adopting technology and demonstrating a set of core measures (Charles, Gabriel, & Searcy, 2015). HIE systems were developed to assist with the flow of information from multiple vendor EHRs and to share patient-level information throughout the continuum of care (Vest, Kern, Silver, & Kaushal, 2015).

In 2009, ONC designated and funded the HHIE as part of ARRA to assist health care providers in sharing patient information quickly and accurately (HealthIT.gov, 2014). As of 2016, the HHIE Health eNet contained over 20 million community patient records, which represented 84% of the state's population (Hawaii Health Information Exchange [HHIE], 2016). Fulfilling the vision and goals of the HHIE holds promise for increasing care coordination and reducing the impact of physician shortages in Hawaii. While much of Hawaii's population is contained within the HHIE, there is a gap in the literature in understanding the factors associated with provider utilization of HIE in the state of Hawaii.

Problem Statement

In this study, I researched the lack of information concerning the factors predicting physician HHIE usage. Specifically, I evaluated whether physician medical specialty, age, gender, or location predicts HHIE usefulness or ease of use. Previous researchers studying the use of HIEs have assessed some of these factors in disparate forms and within clustered locations throughout the United States (Vest et al., 2015; Yeager, Walker, Cole, Mora, & Diana, 2014). For Hawaii, the HHIE represents the total embodiment of the state HIE activity to reveal a complete collection of behavior. The study is important because care coordination has become an area of targeted improvement as noted by federal government programs (Rudin & Bates, 2014). I chose to study Hawaii due to its unique geographic challenges of coordinating care between islands, and the fact that specialty care is often sought on the island of Oahu, which houses the majority of the state's population (Alicata et al., 2016). In addition, Hawaii's health care provider shortage forecasted in the coming years will make care coordination increasingly difficult and important, according to Withy, Mapelli, Perez, Finberg, and Green (2017). Hawaii must realize the opportunity of an electronic coordinated exchange of information and try to make the best use of advancing technologies in care coordination. If specific predictive factors of participation or nonparticipation in HIEs can be better understood, targeted strategies to onboard providers could be designed by HIEs which may result in improved care management.

Purpose of the Study

The purpose of this study was to analyze the factors associated with provider perceived usefulness and ease of use of the HIE in the state of Hawaii. In conducting the study, I focused on the aspects of HIE use related to (a) provider characteristics and (b) area characteristics. Specific to provider characteristics, I assessed age, gender, and medical specialty. To evaluate area characteristics, I reviewed the use of the HHIE between locations in Hawaii. These variables further align with the technology acceptance model from the field of information systems which is based upon the constructs of perceived usefulness and perceived ease of use (Holden & Karsh, 2010). An evaluation of these factors may help local leaders define provider specific challenges to using HIEs between metropolitan, rural, and safety-net areas as well as evaluate different user intentions between providers. The state of Hawaii is comprised of eight islands divided by the Pacific Ocean. It provided a prime study site for examining the use of an HIE because health care is often sought on different islands because of the shortage of primary care and specialty care providers (Withy et al., 2017).

Research Questions and Hypotheses

RQ1: What is the predictive relationship, if any, between any HHIE use (as measured by login vs. no login) and (a) physician medical specialty (primary care, emergency medicine, or specialist), (b) physician age, (c) physician gender, and (d) location when controlling for the other variables?

$H_0 1$*:* There is no predictive relationship between any HHIE use (as measured by login vs. no login) and (a) physician medical specialty (primary care, emergency medicine, or specialist), (b) physician age, (c) physician gender, and (d) location when controlling for the other variables.

$H_A 1$*:* There is a predictive relationship between any HHIE use (as measured by login vs. no login) and (a) physician medical specialty (primary care, emergency medicine, or specialist), (b) physician age, (c) physician gender, and (d) location when controlling for the other variables.

RQ2: What is the predictive relationship, if any, between the extent of HHIE use (as measured by number of times logged in) and (a) physician medical specialty (primary care, emergency medicine, or specialist) (b) physician age, (c) physician gender, and (d) location when controlling for the other variables?

$H_0 2$*:* There is no predictive relationship between the extent of HHIE use (as measured by number of times logged in) and (a) physician medical specialty (primary care, emergency medicine, or specialist) (b) physician age, (c) physician gender, and (d) location when controlling for the other variables.

H_A2: There is a predictive relationship between the extent of HHIE use (as measured by number of times logged in) and (a) physician medical specialty (primary care, emergency medicine, or specialist) (b) physician age, (c) physician gender, and (d) location when controlling for the other variables.

Theoretical Foundation

The technology acceptance model (TAM) was first introduced in 1985 by Fred Davis to evaluate the association between perceived usefulness (PU) and perceived ease of use (PEOU) of information systems in relation to the behavioral intention (BI) to use information systems (Legris, Ingham, & Collerette, 2003). PU is defined as the degree to which the system would improve job functions, and PEOU as the degree to which a system is free of effort (Davis, Bagozzi, & Warshaw, 1989). A primary focus of those who use the TAM is evaluating both external factors and internal beliefs as to why an information system may be deemed acceptable or unacceptable to perform a function (Davis et al., 1989).

The TAM has been widely used as a theoretical foundation for evaluating a user's interaction with technology systems within the health care field. Holden and Karsh (2010) asserted that end user experience and environment weigh heavily on whether a user will work with an information system or merely work around it. Health care leaders have emphasized HIT adoption. However, adoption is often defined as the purchase and implementation of a system and does not clearly indicate how a system is being used in day-to-day workflows (Holden & Karsh, 2010). Previous studies have used the TAM framework to evaluate the divide between adoption and practice. Furthermore, the TAM is suggested to be the standard to which health information systems should be evaluated for predicted intention of use (Bagozzi, 2007), and studies have shown the TAM model to have positively identified up to 40% of the behavioral intention to use an information systems (Holden & Karsh, 2010).

Continuing the use of TAM for the evaluation of information systems, I examined factors related to PU and PEOU that may influence predictive behaviors in health care providers' use of the HHIE. I evaluated PU by assessing factors related to HHIE use between the variables of physician medical specialty and location. In evaluating PU, I sought to correlate whether providers are using the HHIE to review information on their patients and possibly improve the care coordination process.

HIEs are seen as a potential solution for electronic information sharing and physician collaboration (Rudin & Bates, 2014). Information sharing was also thought to lead to improved population health factors (Jones et al., 2011). For example, if a county (location) has low readmission rates with correlating high HHIE usage, it could suggest that using the HHIE has a potential impact on patient readmissions. I also calculated the predictive values between HHIE use and medical specialty to determine if a particular medical specialty has higher usage rates and, therefore, may have a higher behavioral intention to use the systems in comparison to other groups. In prior research using the TAM, authors found a statistically significant relationship between HHIE use and physician specialty when comparing general practitioners and specialists (Gagnon et al., 2013).

To evaluate PEOU, I determined whether the independent variables of age and gender are predictive factors of HHIE use. Previous researchers have used the TAM to predict whether age and computer self-efficacy (Chung, Park, Wang, Fulk, & McLaughlin, 2010) are factors of behavioral intention. The TAM has also been used to evaluate gender differences in terms of implications for social influence. Researchers in one longitudinal study found that women place a higher importance on PEOU in comparison to PU as a contributing factor for their use of technology (Venkatesh & Davis, 2000). The authors further reported that men did not associate PEOU within any period of time (initial training, or long-term use) as behavioral intention (Venkatesh & Davis, 2000). Conversely, in studies specific to HIE use between male and female users, researchers found no apparent differences between genders (Furukawa et al., 2014). In conducting my investigation, I was interested in whether gender is predictive characteristic of HIE use among Hawaii providers.

Researchers have used the TAM in numerous studies over the past 3 decades to evaluate information technology and system use. Although the TAM has only two constructs, it has also been revered as an effective predictor of behavioral intention and actual system use (Legris et al., 2003). For these reasons, I believed the TAM to be an applicable theoretical framework to evaluate provider use of HIE systems for this study.

Nature of the Study

The study was descriptive and quantitative in approach in that I statistically explored predictor variables of HHIE use among physicians. Descriptive studies help to explain what exists without changing the environment, according to Trochim and

Donnelly (2012). This can be often be accomplished by reviewing data collected on a group or cohort (Trochim & Donnelly, 2012). In descriptive research, participants are not randomly assigned to treatments; also, cause and effect interventions are not assessed (Thompson, Diamond, McWilliam, Snyder, & Snyder, 2005). A descriptive approach was the most appropriate one to use for the variables of interest in this study because I sought to review an archival data set on system use for Hawaii physicians. Further, the data was not collected in an experimental or intervention setting. To date, there are still very few studies, according to my review of the literature, on physician patterns of HIE use. Ongoing exploration may be helpful in guiding future researchers.

To statistically calculate predictive use, I used (a) logistic regression analysis and (b) multiple linear regression analysis. Logistic regression is used to predict the likelihood that an observation falls between two categories (Laerd Statistics, 2015a). For my study, I first used logistic regression to evaluate HHIE use in terms of whether the physician has logged into to the HHIE system. The HHIE has been onboarding new physicians to the community health record since 2014 (HHIE, 2016). However, signing up does not mean that physicians have logged in. For the logistic regression, the dependent variable was grouped, as follows:

(1) login count equals zero.

(2) login count equals 1 or more.

Next, I used multiple linear regression to evaluate usage in terms of how many times or the extent to which a provider has logged into the HHIE among physicians with one or more logins. This is an important factor in the analysis because it further aligns with the TAM theory to explore the extent of system use. If physicians find the system useful, they will likely use it more therefore have a higher login count which may affect local health care factors monitored by population health. The dependent variable was continuous which makes it appropriate for a linear regression calculation. Multiple linear regression aims to review relationships between two or more variables to determine statistical significance (Field, 2013). Multiple linear regression also explains the variation the independent variable may pose on the dependent variable and predictive values of the dependent variables as imposed by the independent variable (Laerd, 2015b)

The independent variables were defined as medical specialty, physician age, gender, and location. I further used medical specialty, age, gender, and location as control variables when computing the dependent variable of HHIE use and extent of usage as described above. The utilization of control variables lends further power into the study by reducing the external influences for the independent variable through spurious relation (Frankfort-Nachmias & Nachmias, 2008).

Medical specialty. The independent variable of physician medical specialty was grouped by primary care, emergency medicine, and specialists. In previous research by Furukawa et al. (2014) primary care physicians and specialists were compared for HIE use between groups. Yaraghi (2015) also pointed out that emergency departments are distinct users of HIEs and describes the benefits of HIE use in emergency department settings. Using these research designs helped to shape the groups included in my proposal. The American Academy of Family Physicians (2017) defines primary care as family medicine, internal medicine, and pediatricians. I followed this definition to group primary care physicians.

Age and gender. The independent variable of provider age followed previous research by Egea and Gonzalez (2011) on physician use of EHR systems under the constructs of the TAM. Age will be grouped as follows: under 35 years of age, 35-44 years of age, 45-54 years of age, 55-64 years of age, 65 years of age and over. These groups are important in maintaining the consistent nature of reporting in terms of the TAM theory. The independent variable of gender was entered from HHIE enrollment forms and coded as “0” for male and “1” for female.

Location. For the last research question I reviewed differences of physician use based upon location. The state of Hawaii is made of four counties grouped between islands. The practicing location may help correlate future population health indicators such as readmission rates to perceived usefulness HHIE. Gaining a basic understanding of the locations using the HHIE and the possible differences between the Hawaii counties (Oahu, Hawaii, Maui, and Kauai) can add to the current role the HHIE is providing in care coordination as well as future implications of use.

Physician age, medical specialty, gender, and location are captured in the HHIE based upon the onboarding information provided by the physician. If the data was not available from the HHIE, I used publically available online records from the Centers for Medicare and Medicaid Services (CMS) or other public websites. To interpret results as significant, a p-value of <0.05 was used as a statistical measure with a confidence interval of 95% where appropriate. Regression analyses are be reported in terms of statistical significance, predictive value(s), and odds ratio(s), linear regression will be reported in terms of f-values and reported variance R^2. Assumptions for each test are also included in the reported findings.

Definitions

Electronic health record: An electronic health record is a digital version of a paper chart containing a patient's medical history (HealthIT.gov, 2016).

Hawaii counties: The University of Hawaii annual report identifies the state of Hawaii within four counties when defining physician shortages. The counties are (a) Big Island (Hawaii), (b) Kauai, (c) Maui, and (d) Oahu (Withy, 2017).

Hawaii Health Information Exchange (HHIE): The Hawaii Health Information Exchange is the state designated entity from the Office of National Coordinator, which was designed to provide a secure statewide exchange of health information. The HHIE connects a large number of Hawaii health care providers to gain critical patient information across different EHR systems (HHIE, 2016)

Health information exchange: A health information exchange (HIE) enables the electronic sharing of information between providers, hospitals, and health care entities. HIEs place emphasis on care coordination and the obtainment of critical patient information through the continuum of care (HealthIT.gov, 2014).

Medical specialty: A specialty in medicine is a particular field of medical practice dedicated to limited scope of care. Medical specialty may be further limited to problem origin, organ system, or diagnosis. (Association of American Medical Colleges, 2015).

Primary care: A primary care physician is a medical specialist in family medicine, internal medicine, or pediatrics who provides continuing comprehensive care or the patient. A primary care physician oversees the ongoing health care and wellness for the patient and manages care between medical specialists if needed. (American Academy of Family Physicians, 2017).

Hospital readmission: A situation when a discharged patient returns to a hospital and is admitted within a specified amount of time. For Medicare programs, the time period is defined as 30 days and is not dependent upon the reason for readmission (Kaiser Family Foundation, 2017).

Assumptions

I assumed the information provided to me by the HHIE is a true number (count) of logins per active provider. Within this assumption, I also assumed the participating providers listed by the HHIE reflect an accurate representation of those who have signed up to access the community health record. Lastly, I assumed this encompassed the total population of physician users of the HIE within the state of Hawaii.

Scope and Delimitations

The scope of the study includes the total population that meets research specifications (Frankfort-Nachimas & Nachimas, 2008). For the purposes of my study, I will be including login counts for users enrolled with the HHIE designated as a Doctor of Medicine (MD) or a Doctor of Osteopathic Medicine (DO). The HHIE allows access to a host of health care professionals, support staff, and licensed clinicians. These users have been excluded for the study, although it is understood in previous research that physician office staff also retrieve information from the HIE to help support the physician and medical practice (Vest & Jasperson, 2012; Vest, Zaho, Jasperson, Gamm, & Ohsfeldt, 2011).

Limiting the scope of the study to licensed MD and DO users offers a true comparison of physician activity. Ayanso, Herath, & O'Brien (2015) cited the physician carries much of the deciding vote when making EHR decisions therefore they are established as the key stakeholder in terms of power and influence. Further, physicians complete similar educational programs to become licensed, much of their formal medical training is focused on medicine and not computers (Rudin, Volk, Simon, & Bates, 2011). Limiting the scope of the study to one group of stakeholders further improves internal and external validity as results from the study can be generalized to similar physician populations in comparable settings. However, findings from this study will not be generalizable to other non-physician HIE users.

In terms of theory, I used the TAM model to evaluate information technology system use. Since its inception in 1989 the TAM model has been continuously studied and expanded upon. Venkatesh and Davis (2000) proposed a TAM2 model which incorporates social influence and cognitive instrumental processes to evaluate user acceptance. Building upon the TAM2 model, the Unified Theory of Acceptance and Use of Technology (UTAUT) was also derived by evaluating the constructs of performance expectancy, effort expectancy, social influence, and facilitating conditions toward information system usage (Venkatesh, Morris, Davis, & Davis, 2003). These theories were not chosen as a method of evaluation because the expanded constructs were not available variables of evaluation within the archival data set utilized for the study. Further studies on HHIE users may incorporate these aspects if additional information on user characteristics can be obtained.

Limitations

As noted in the previous section, one limitation of the study was the inclusion of only physician users. This study cannot be generalized to other non-physician HHIE users in terms of age, gender, medical specialty, or location. The study is also not a representation of the complete use of an HIE in the state of Hawaii as many support staff, office staff, and various members of the health care system may also have access to the system to assist physician practices and care coordination. However, this study could be generalized to physician use in similar settings. I have no affiliation to the HHIE or to the participating physicians within the HHIE that would result in bias to the study.

Significance of the Study

The 1999 Institute of Medicine (IOM) report 'To Err is Human: Building a Safer Healthcare System' cited at least 44,000 patients die each year because of preventable medical errors largely due to faulty processes (Kohn, Corrigan, & Donaldson, 2000). The report asserted patient safety would be improved if there were automated systems to alert caregivers of potential conflicts and was the catalyst in the creation and adoption of electronic recording systems in health care environments. Almost a decade later, the federal government has mandated both implementing an electronic record and reaching meaningful use measures, today EHR adoption levels reach its highest percentages in history (Randall, 2014). How we continue to use automated systems like EHRs should remain a constant focus in building a safer health care system.

In terms of significance to policy, results of this study revealed whether meaningful use mandates are being upheld to fulfill gaps in electronic documentation sharing across multiple systems. Within the findings from this study, there is potential for further insight to be drawn on how HIEs are utilized in business practice. Current mandates could be revised to increase mandatory HIE participation or add requirements to prove providers are logging in to HIEs to retrieve data.

Advancing theories on HIE and information system utilization have also resulted from this study. Researchers used the TAM as the theoretical foundation and in numerous perspectives surrounding information technology systems. To the best of my knowledge, no studies have been conducted using the TAM to evaluate physician HIE use in the state of Hawaii. A limited number of studies were previously conducted using the TAM to evaluate physician HIE utilization, but I did not located any studies inclusively using the predictor variables of medical specialty, age, gender, and location. These findings will add to the body of knowledge on the TAM theory.

In regard to social significance and positive social change, results of this study also evaluated the use of an HIE in coordinating patient care across the continuum of medical providers and facilities in Hawaii. Insights from the study can build upon the potential contribution HIEs are making toward communicating patient specific information among caregivers in community hospitals as well as opportunities to increase provider participation. An analysis of medical specialty, age, gender, and location may help target providers in need of greater assistance to ensure the ongoing success of the HIEs and other federally funded initiatives promoting care coordination. The overall use of the HHIE in the state of Hawaii may assist in filling communication gaps often found when patients travel between islands and health care facilities for care.

Summary and Transition

The HIE could assist as a major component of care coordination and the sharing of critical information across information systems. A common community health record should be the goal for many rural or geographically challenged areas such as Hawaii, yet it seems as though its full potential remains unfulfilled. In this chapter I have introduced the research study on factors of physician use of HIE systems. I have also presented the research problem on physician use of HIE systems which leaves for much exploration of the unknown. In evaluation of the predictor variables of age, gender, medical specialty, and location, this study has the potential to create positive social changes, and policy changes for future iterations of federal mandates.

In Chapter 2, I present an in-depth literature review of the concepts surrounding HIE utilization and the variables contained within the study. I also provide an overview of the TAM model used in practice to evaluate provider characteristics. Further, I provide a background on HIEs to lend foundation to how HIEs were created and implemented in the United States as a part of federally funded programs.

Chapter 2: Literature Review

Introduction

Access to the right data at the right time can help health care providers in achieving a positive patient outcome, especially when a patient is transitioning between health care providers and systems (Morton et al., 2015). Care coordination remains vital to ensure consistent treatment and timely follow-up care and avoid unnecessary testing (Daniel & Mensah, 2015). Researchers have shown that clinicians continue to rely on paper processes rather than electronic methods to manage care coordination (Hsiao, King, Hing, & Simon, 2015; Morton et al., 2015).

Using a HIE to electronically share patient data is a relatively new concept in health care. Recent mandates in U.S. federal programs such as those specified in ARRA and the attainment of meaningful use have resulted in greater use of HIEs in the United States. HIEs have the ability to collectively document medical treatments, progress notes, results, referrals, and continuum of care documentation (Dullabh, Moiduddin, Nye, & Virost, 2011). Researchers have identified that participation in meaningful use programs is the most prominent factor for use (Yeager et al., 2011). Yet, hospitals have fallen short with provider adoption of HIEs as a method for sharing information and coordinating care (Vest et al., 2015; Rudin et al., 2011). Although federal programs can incentivize hospitals to implement and participate in HIEs, if providers fail to see the value and usefulness of the technology, the full benefits of participating may not be realized (Rudin et al., 2011).

Research on hospital adoption factors for HIEs has been limited to a few geographical areas in the United States. Hospitals have been the main source of information surrounding HIE use because of the identified need for information during an emergency room visit or new admission (Vest, 2010). The authors of these studies found similar themes associating increased HIE use for hospitals with nonprofit status, willingness to share data, and noncompetitive market factors (Adler-Milsten & Jha, 2014; Vest, 2010). In the few studies regarding HIE and clinical user patterns, HIE use has been found to be positively correlated with ease of learning the system, grouping of information, and overall system functionality (Gadd et al., 2011; Politi, Codish, Sagy, & Fink, 2015). Higher rates of HIE use was also noted for patients with complex visits and frequent primary care visits (Vest et al., 2011) and providers practicing within a hospital setting (Vest & Jasperson, 2012).

Most HIE users accessed the application on the day they saw the patient in comparison to any other situation (Rudin et al., 2011; Vest & Jasperson, 2012). Barriers to using HIEs include questionable value, sustainability, and cost of implementation (Yeager et al., 2014). Authors of studies that were conducted on implemented exchanges found that HIE use in emergency departments was associated with a reduction in laboratory and radiology testing (Rudin, Motala, Goldzweig, & Shekelle, 2014; Yaraghi, 2015) and a reduction in readmissions (Vest et al., 2014).

The problem I addressed in this study is the use of an HIE to improve health care coordination in the state of Hawaii. To study this problem, I evaluated common physician factors associated with HIE usage levels. The state of Hawaii is made up of eight islands separated by the Pacific Ocean. The island of Oahu houses approximately 72% of the state's total population, and many residents fly to the island to seek specialty or critical care (Alicata et al., 2016). Communicating relevant medical information is difficult when providers and hospitals must share information between islands and on different documentation systems (Alicata et al., 2016). In addition, the state estimates physician shortages up to 1,500 full-time equivalents by 2020 (Withy et al., 2017). Hawaii, like many other states, must continue to look for ways to use technology to share and access patient information across multiple sites of care (Alicata et al., 2016). HIEs appear to fulfill this need if providers use the system.

Overall, the literature encompassing what is known about HIE adoption, implementation, usage, and the potential contributions of HIE to enhance patient care contains many gaps on how HIE are being incorporated into use. The purpose of this study was to assess predictive factors of (a) perceived usefulness by assessing the predictive relationship between HHIE use and medical specialty and location, and (b) perceived ease of use by assessing the predictive relationship between HHIE use and provider age and gender. I focused on HIE adoption in Hawaii; however, findings may be applicable to other U.S. communities. This chapter includes the following topics: (a) a review of the literature search strategies; (b) an overview of the TAM, the theoretical foundation of this study; (c) literature about adoption of HIEs; (d) literature related to study variables including provider characteristics and outcomes related to HIE use; and (d) gaps in prior research, pointing to a need for the current study and literature related to the variables used in the current study.

Literature Search Strategy

In searching for studies and publications for the literature review, I used several databases: CINAHL, MEDLINE (Ovid), PubMed, ProQuest, EBSCOhost, Sage, Science Direct, and Google Scholar. I also searched additional websites related to health policy and federal mandates including HealthIT.gov, Centers of Medicare and Medicaid Services, Centers of Disease Control and Prevention, and the Agency for Healthcare Research and Quality. Key terms used when searching these resources were *Health information exchange*, *technology acceptance model, meaningful use*, and *Hawaii Health Information Exchange*.

Many of the publications selected for the literature review were published within the past 6 years; however, some earlier articles were included due to the relevance of the research and the limited number of studies published on the subject surrounding factors of HIE usage in the United States. Research conducted outside the United States was reviewed for relevance to health care policies and environmental factors. Ultimately, only two studies conducted in Israel on HIE usage were included in the literature review. I was unable to locate any studies specific to provider age and medical specialty relating to HIE use, yet authors of several studies reported on age, gender, location, and specialty as a portion of their findings or as covariates in their analysis. In addition, I did not locate any studies that included information for the state of Hawaii.

Theoretical Foundation

The theoretical foundation for this study was the TAM (Davis, 1989). The TAM is originally derived from the theory of reasoned action (TRA), which postulates that a person's actions are often influenced by his or her behavioral intention (BI) to produce a specific outcome (Fishbein & Ajzen, 1975). BI is determined by both a person's attitude (A) and subjective norms (SN; Fishbein & Ajzen, 1975). Attitude is further defined as a person's negative or positive opinion and subjective norms as individual's external social pressures to perform the behavior (Fishbein & Ajzen, 1975).

Building upon the definition of BI suggested by TRA, Davis (1989) developed the TAM to evaluate user intentions surrounding the (a) use, and (b) adoption of computer based systems. The TAM contains two variables to evaluate whether a person's intentions will result in computer system use: (a) PU of a system to assist in performing a job or function and (b) PEOU, which is based upon the effort needed to use the system (Davis, 1989). Davis (1989) conducted two initial studies on his model by testing four computer application programs. Results of one study indicated an inference between self-reported current technology usage and self-reported future usage with the model's variables of PU and PEOU. In review of the two variables, a stronger correlation was found for computer application usefulness compared to computer application ease of use. Through this study, Davis also introduced new measurement scales for subjective self-reporting of PU and PEOU. The six-item scale statistically confirmed reliability of .98 for PU and .94 for PEOU. The study established a systematic approach to evaluate computer systems from an end-user perspective by reviewing two major factors involved in information technology (IT) adoption and implementation (Davis 1989).

TAM has been used as the foundation for prior studies also assessing age as a factor for participation in computer online communities (Chung, Park, Wang, Fulk, &

McLaughlin, 2010). The authors hypothesized that age would be negatively associated with internet self-efficacy and that young adults would likely have a higher self-efficacy in comparison to older counterparts. Self-efficacy was defined as the belief and confidence that a person could perform a task. The study's authors also hypothesized age would be a factor of online internet use with direct associations toward PU, PEOU, and BI. Despite previous literature supporting these hypotheses, the authors found no age-related correlations for PU, PEOU, and BI (Chung et al., 2010). However a negative relationship between self-efficacy and age ($p < .05$) of online internet users was found (Chung et al., 2010).

In a study by Gagnon et al. (2013), the authors found the TAM to explained 44% of the variance in physician's intention to use an electronic health record (EHR). Using the TAM, the study confirmed provider age ($p = .0032$), medical specialty (specialist or general practitioner; $p < .001$), and prior EHR experience ($p = .008$) as significant predictors of EHR use. The study also evaluated whether gender was a predictor of EHR use, yet found no significant relationship. Additional EHR features such as applicability to medical discipline and substantial impact on a business were found to facilitate BI (Gagnon et al., 2013). Authors of a separate study also found that physician specialty (surgeons vs. pathologists) was a moderating factor in use of clinical information systems. Authors found surgeons placed an increased importance on PEOU in order for the system to be considered useful (PU). In comparison, pathologists associated PU with the features of the computer technology application (Melas, Zampetakis, Dimopoulou, & Moustakis, 2011).

Authors of an additional study conducted on physician adoption of EHRs applied the TAM model to identify the main determinants of behavioral intention (Chen & Hsiao, 2012). Structured physician surveys based upon the TAM constructs to measure factors associated with PU, PEOU, and BI were distributed to assess certain activities associated to physician's use of an EHR or clinical information system. Activities that were statistically associated with use of EHRs included staff competencies ($p < .001$) and management support ($p < .001$; Chen & Hsiao, 2012). Authors also found physicians' perception of system usefulness ($p < .05$) and ease of use ($p < .001$) had a significant impact on the acceptance of an EHR by health care professionals.

A review of historical studies identified the TAM as a proven model by which to evaluate IT projects (Legirs, Inham, & Collerette, 2011). Authors of a judicial meta-analysis of the literature from 1980 to 2001 specific to using TAM to evaluate IT implementation projects concluded that studies have consistently used the TAM as an indication of successful implementation of information systems (Legris et al., 2001). A second review of TAM and health care by Holden and Karsh (2010) indicated the TAM was a consistent model for most health related studies, especially with regard to the construct of PU. However researchers proposed that the model could be altered to include additional variables for analysis and better alignment with PEOU. This finding was consistent with previous studies citing that professional training received by physicians differs from users of technology in other fields (Yarbrough & Smith, 2007). Researchers have suggested the TAM include external variables and barriers to technology acceptance due to the uniqueness of the health care work environment and motivating factors influencing the physician population (Yarbrough & Smith, 2007).

Similar to the studies cited above, I will use the TAM as the theoretical basis for the current study, as the literature supports the TAM as a viable approach to evaluate physician use of the HIE and to assess factors relating to BI, PU, and PEOU. Several studies have also assessed the TAM across age groups, gender, and physician variables, as this study will address. Adopting the TAM to statistically evaluate HIE usage among providers in the state of Hawaii expands upon the current literature, as no studies have taken place in Hawaii.

Literature Review Related to Key Concepts

Use of HIEs has evolved in the U.S. over the past few decades, and studies related to HIEs have ranged from review of usage to a deeper understanding of physician habits and system design. A variety of health care laws and regulations have impacted use of HIEs, while adoption and implementation vary across settings. This next section will explore literature related to the history and use of HIEs in the U.S. and Hawaii specifically.

Evolution of Health Information Exchange

Initially formed by the Hartford Foundation, the concept of HIE dates back to 1990 when seven communities aligned to create a centralized data sharing center. Similar efforts followed in the mid-1990s when community health information networks (CHINs) were created to share critical patient data across communities (Dullabh et al., 2011). Both initiatives faced significant challenges including high cost, lack of interoperability, and lack of political backing (Dullabh, et al., 2011).

The 1999 Institute of Medicine report "To Err is Human" garnered support and interest towards using information technology (Kohn, Corrigan, & Donaldson, 2000). In 2004 the U.S. department of Health and Human Services established the Office of National Coordinator (ONC) funding $166 million towards technology to improve health care quality and safety (HealthIT.gov, 2014). The ONC was the custodian of establishing state designated entities for community exchanges. In 2014 the ONC released its publication “Connecting Health and Care for the Nation: A 10-Year Vision to Achieve an Interoperable Health IT Infrastructure” (HealthIT.gov, 2014). The vision included an “IT ecosystem” to make data available “to the right people at the right time” with a goal date of year 2024 for health IT to achieve secure data sharing across all forums without limitations upon vendors, organization, or practice (HealthIT.gov, 2014). To date, the ONC remains the principal body for the HIE governance across U.S. locations and health care systems.

HIE and HITECH

The American Recovery and Reinvestment Act (ARRA), passed on February 17, 2009, and subsequent Health Information Technology for Economic and Clinical Health (HITECH) were enacted to change the way healthcare was delivered, funded, and maintained across America. More importantly, the HITECH act supported the adoption of Health Information Technology (HIT), and secured IT permanence within health care practice (U.S. Department of Health & Human Services, n.d.). HITECH also provided an unprecedented amount of funding for HIT. Under direction and distribution of the ONC, $548 million was allocated for the development of state HIE programs (Dullabh et al., 2011). In January 2011, an additional $16 million was available through the ONC's program to encourage ongoing HIE state advancements (healthIT.gov, 2014). To govern the award process, the ONC formed the State Health Information Exchange Cooperative Agreement whereby State Designated Entities (SDE) received HIE award funding. This funding was a one-time investment intended to address gaps in current funding to enable the technology needed for large-scale data sharing. Within a year, 50 SDEs and six territories received initial awards for establishing an HIE framework (Dullabh et al., 2011).

Meaningful Use Stages One and Two

The CMS incentive program for widespread EHR adoption is divided into stages (a) meaningful use one (b) meaningful use two and (c) meaningful use three (CMS, 2015). The program is centered on the concept of "meaningful use" that encompasses five pillars of health outcome priorities outlined by the Centers for Disease Control and Prevention (Centers for Disease Control and Prevention, 2016). The CDC cited the five pillars as the following:

1. Improving quality, safety, efficiency, and reducing health disparities
2. Engage patients and families in their health
3. Improve care coordination
4. Improve population and public health
5. Ensure adequate privacy and security protection for personal health

Meaningful use stage one criteria became effective on September 26, 2010. For eligible hospitals, the final rule established a mandatory 14 core set of objectives; hospitals were also required to select five other objectives from a list of ten possible options (Centers of Medicare and Medicaid Services [CMS], 2014). Stage one objectives focused upon an organization's ability to capture and share data with the patient, while stage two meaningful use objectives built upon stage one constructs and focused upon advancing clinical processes (healthIT.gov, 2015). Meaningful use stage two final ruling was published on August 23, 2012 and required implementation of 16 core objectives and three of six additional objectives (Centers of Disease Control, 2016). In stage two, many of the stage one objectives were combined and a few additional measures became mandatory. Specific to HIE, a new core objective required hospitals to electronically transmit a summary of care records for more than 10% for all patients discharged to another care setting of care using Certified EHR Technology (CHERT) of a nationwide health information network (NwHIN) exchange participant consistent with ONC standards (CMS, 2015). Additionally, the measure required hospitals to exchange information using a different CEHRT vendor for at least one of the exchanges within the reporting period (CMS, 2015). There were no exclusions to the measure, leaving many hospitals to either become certified to electronically send and receive summary information or become reliant upon an HIE to fulfill the requirements. Because of the complicated matrix of becoming certified, most hospitals relied on HIEs to fulfill data exchange requirements (Esmaeizadeh & Sambasvian, 2016).

The final ruling for meaningful use stage three was published on October 6, 2015. Participation in stage three is optional in 2017 and will become mandatory for all eligible hospitals and providers participating in Medicare or Medicaid programs in 2018. Stage three will further the HIE measures introduced in stage two within three aspects to include (a) more that 50% of continuity of care documents and referrals be done in an HIE, (b) 40% of new visit encounters have their information retrieved from the HIE, and (c) using the HIE to reconcile medications for more than 80% of new patient encounters (CMS, 2016).

Characteristics of HIE Adopters

An essential component of whether or not HIE is adopted and used appropriately has to do with end user characteristics. A framework proposed by Tornatzky and Fleischer (1990) identified three major situations in which organizations implement and adopt functionality as: 1) technological, 2) organizational, and 3) environmental (TOE). This framework has been used as the basis for other studies on HIEs. Vest (2010) studied the adoption and implementation of HIE across U.S. hospitals using the Health Information and Management Systems Society 2008-2009 database and the 2007 American Hospital Association (AHA) Annual Survey. The study represented 4,830 hospitals and has been helpful in understanding the use of HIE related to various HITECH adoption measures. Authors assessed differences between HIE adopters and non-adopters and evaluated hospital level characteristics related to HIE adoption. The authors found that only 18% of hospitals had implemented and HIE. Hospitals more likely to adopt HIE included non-profit hospitals or public hospitals, hospitals with high emergency department volumes, as well as those with implemented physician portals (Vest, 2010). Further, hospitals with lower market competition coupled with a willingness to share data had an increased odds of implementation of 85%. Additional factors related to adoption of HIE included hospitals within a referral network and those having a certified EHR (Vest, 2010).

Adler-Milstein and Jha (2014) conducted a macro review of hospital participation HIE across U.S. hospitals using data from the 2012 AHA IT Supplement. The authors found similar factors to those noted by Vest (2010), including adoption and implementation of HIE being associated with non-profit status, maintaining a larger market share, and lower market completion. The study also illustrated the variation and inconsistency in HIE adoption across states (Adler-Milstein & Jha, 2014). Grouping these findings together with the TOE framework proposed by Tornatzky and Fleischer, technological context would include EHR adoption, technological readiness, and the adoption of physician portals (Vest, 2010). Organizational context includes non-profit status and an association to a referral network, whereas environmental factors point towards decreased data sharing if the hospital is in a competitive market area and restricting participation in data sharing systems (Vest, 2010).

HIE Usage in Different Settings

Vest et al., (2011) researched HIE usage in emergency departments among a safety-net Integrated Care Collaboration (ICC) in Austin Texas (I-Care), comprised of a 26-member network whose goal was to support the medically indigent (Vest et al., 2011). The study was conducted using data from January 1, 2006 to June 30, 2009 including a patient population from ages 18 to 64, the resulting data set contained 271,304 encounters from 10 facilities. Four hypotheses were tested in the study: 1) HIE usage would be higher for patients who were new or infrequent to the facility; 2) usage would be higher for patients with chronic conditions; 3) patients who were seen or hospitalized in the past year would have higher usage rates; 4) usage would be lower for patients who had time constraints or were seen for injuries or accidents (Vest et al., 2011). User logs revealed how many screens were accessed in the record during the visit and were defined as usage categories of no usage, basic usage, and novel usage. Patient complexity was based on the Charleston Comorbidity Index (CCI). The authors hypothesized that higher CCI scores (e.g. greater comorbidity) would be related to positive associations; however this hypothesis was not upheld. Instead higher usage patterns were associated with frequent primary care visits (odds ratio [OR]: 1.76; 95% confidence interval [CI]: 1.60 to 1.94) and charity care encounters (OR: 1.51; 95% CI: 1.33 to 1.72), while lower usage patterns were associated with busy days (OR: 0.84; 95% CI: 0.78 to 0.90) and unfamiliar patients (OR: 0.32; 95% CI: 0.29 to 0.35; Vest et al., 2011).

A second study by Vest and Jasperson (2012) also utilized the I-Care data from January 1, 2006 to June 30, 2009 to assess usage patterns of the I-Care HIE system. They evaluated the system viewer activity for 105,705 unique user sessions containing over 1,661 different user patters. In this study, usage patterns were classified according to the length, breadth, and information category. Findings indicated that 61.8% of all sessions had minimal use of I-Care, in which the patient name was searched and a history of visits were displayed. In 11.2% of user activity, the patient search and visit history was reviewed multiple times during the session, and 11.6% of the sessions only clinical information was reviewed. Clinical and demographic information were reviewed in 11.3% of sessions whereas demographic information only was reviewed in 4.2% of sessions (Vest and Jasperson, 2012).

Vest and Jasperson (2012) also reviewed roles interacting with the I-Care HIE and found users in the administrative job category accessed the system the most. The median number of HIE logins per user was calculated at two with the highest location of access in hospital settings at 37.6%, ambulatory care settings next at 20.7%, children's emergency departments at 21.2%, and emergency departments at 20.0%. There was nominal usage from public or mental health organizations (0.6%; Vest & Jasperson, 2012). Relative to the patient visit date and HIE usage, 50% of user sessions matched the day of patient visit, while 11% of the sessions did not correspond to any patient encounter (Vest & Jasperson, 2012). This study helped to understand the degree to which users were interacting with an HIE system. Associated discussion points from Vest and Jasperson (2012) surface the importance of HIE design to guide the ease of finding a patient and the prioritization of patient data. The authors suggested a user interface design similar to the search engine Yahoo! may create a simpler interactive process to promote HIE usage. They also suggested that information views based upon user role to may be useful in reducing the number of screens needed to find information. Also emphasized in the study was the importance of creating a correct master patient index as many users performed multiple searches to locate a particular patient (Vest & Jasperson, 2012).

Establishing HIE in Hawaii

Currently all 50 states have some form of HIE services available (healthIT.gov, 2014). The Agency for Healthcare Research and Quality (AHRQ; 2014) estimated that there are approximately 280 active HIEs and over half of U.S. hospitals are participating in a regional, State, or private HIE. Private HIEs have seen significant growth. From 2010 to 2011, the number of private HIEs rose from 52 to 161 and live public HIEs rose from 37 to 67 (Agency for Healthcare Research and Quality [AHRQ], 2014).

In September 2009 as part of ARRA legislation, the HHIE was designated as the SDE for the state of Hawaii (Chin & Sakuda, 2011). The HHIE was established in 2006 as a 501(c)(3) non-profit organization with a mission to positively transform health care in the state of Hawaii by enabling the exchange of critical information between providers, patients, and associated entities (HHIE, n.d.). Hawaii received $5.6 million in award monies for the initial HIE start-up (Healthit.gov, 2014). Over the past few years the HHIE has since grown to contain over 20 million clinical records and 1.2 million unique patients totaling over 84% of the state's population (HHIE, 2016). HHIE also has over 600 trained providers and spans to all eight islands comprising the state of Hawaii. To maintain ongoing fiscal operations the HHIE has transitioned to a subscription model for ongoing access (HHIE, 2016). Although the HHIE reports a large number of participants in the exchange, I could not locate any studies published on the usage of the HHIE. Therefore, the current study will add to the body of knowledge about this specific U.S. HIE.

Literature Review Related to Study Variables

As noted above, I will assess whether medical specialty or location are predictive factors of PU and whether provider age, specialty, and gender are predictive factors of PEOU. The next section of this chapter explores earlier studies related to HIE use and readmission rates, then reviews the literature related to HIE use for the provider characteristics assessed in this study. Gaps in prior research are identified and the need for the current study is explained.

HIE Use and Location

Reviewing location impacts of HIE use may help to illuminate the output effects an HIE has on local health care, hospital operations, and population health factors. I started with a systematic review of HIE literature to evaluate the use and effect of HIEs on clinical care including health outcomes, efficiency, utilization, costs, satisfaction, HIE usage, sustainability, and attitudes or barriers. Despite over 100 implemented HIE systems across the U.S., findings from the study indicated a low number of evaluations performed yielding a lack of understanding about the potential contributions to health care resulting from HIE usage. Only seven to ten studies were found to evaluate quality, costs, usage, efficiency and sustainability. Authors found some evidence that HIE usage was associated with reduced emergency department costs (Rudin et al., 2014). Authors of another study indicated a 52% reduction in laboratory tests and a 36% reduction in radiology exams associated with HIE use among emergency department visits (Yaraghi, 2015). For those who have implemented HIEs, the ongoing challenge will be to create a business case with a continuous focus on derived value (Rudin et al., 2014). Additional studies will help to support inferences on how HIEs affect outcomes of care (Rudin et al., 2014).

One way to assess the value of an HIE between hospital locations is to assess the impact on inpatient admissions and readmissions. According to CMS (2017), health care expenditures reached $3.2 trillion in 2015, or $9,990 per person. Hospital care and physician care collectively attributed to over 50% of the market spending displaying increases to years prior. The decision to admit a patient to an inpatient facility has been under increased analysis as hospital admissions continue to rise (Gorski et al., 2016). Hospital admissions increased from 34.7 million in 2003 to 36.1 million in 2009 (Morganti et al., 2013) with associated increased cost and lengths of stay (Gorski et al., 2016). Use of HIE technology to make decisions among some providers may help drive the behavioral intentions of others. Patterns of HIE use for admission to the hospital and intensive care unit (ICU) in a large Israeli hospital from 2010 to 2012 were reviewed to assess HIE patterns of use and the association with clinical decision making in Soroka University Medical Center (Politi et al., 2015). SUMC treats over 50% of Israel’s population; the HIE system was implemented in 2005 and contains data from secondary contributory sources such as ambulance records. Results indicated that HIE use was correlated with a 31% increase in the odds of admitting a patient to the ICU. Patterns of HIE usage were also predictive of the clinical decision to admit a patient to the hospital (Politi et al., 2015).

CMS defines hospital readmission as an unplanned return to a hospital within 30 days of initial discharge for any condition (CMS, 2016). Readmissions are a costly detriment for patients and hospitals. Currently 17.5% of all admissions result in a readmission (American Hospital Association, 2015), and readmissions account for over $7 billion in costs (Fingar & Washington, 2015). Using HIE technology to span the continuum of care may provide positive assistance to reduce readmissions. A study by Jones et al. (2011) reviewed the relationship between participation in HIE and the use of HIT with hospital readmission rates. Use of HIT was defined as performing medication ordering, laboratory ordering, and clinical documentation in an EHR, as reported on the 2007 AHA database. Hospital readmission data for acute myocardial infarction, heart failure, and pneumonia were extracted from the 2009 CMS Hospital Compare website. The authors found no substantial relationship between HIE participation and readmission rates. However associations between the use of electronic documentation and reduced readmission for heart failure (p = .02) and pneumonia (p = .003) calculated notable impacts (Jones et al., 2011). This study did not indicate the extent to which HIE was used within an organization (Jones et al., 2011), which may be an area for future research.

Further studies have assessed the relationship between HIE use and a reduction in hospital admissions and related cost savings. Vest, Kern, Champion, Silver, and Kaushal, (2014) reviewed HIE use in the emergency department within New York state for years 2009-2010. The study found a 30% lower probability of inpatient admission if an HIE was accessed during the emergency department visit (Vest et al., 2014). Using the same dataset Vest et al. (2015) assessed HIE use on 30-day readmissions. Findings indicate a 57% reduction in probable 30-day same-cause readmission associated with HIE use

(Vest et al., 2015). Similarly, HIE emergency department access for seven hospitals in Israel was evaluated, results showed a reduction in single day and seven-day admissions (Ben-Assuli, Shabtai, & Leshno, 2013). Frisse et al. (2012) studied the financial impact of HIEs in Memphis Tennessee, calculating up to 212 fewer readmissions and over $800K reduction in medical expenses if the benefits of fewer admissions and a reduction of imaging tests were fully realized (Frisse et al., 2012).

Common limitations of all studies cited regarding HIE and readmission rates include the low percentage of HIE use in comparison to patient visits. Studies reviewing impacts to health care must continue to examine the impact of HIEs on post-discharge care and readmission rates. A qualitative study of health care stakeholders participating in an HIE within the state of Louisiana was conducted to assess barriers to HIE adoption (Yeager et al., 2014). Themes emerging from semi-structured interviews identified several barriers to participation in an HIE, these included questionable value, low implementation efforts, usability, market conditions, and cost. The authors concluded that the most prominent reason for participating in HIE efforts was to meet ARRA meaningful use requirements, yet this measure was not enough to drive users towards high levels of HIE use. Secondary themes from the study consistent to other studies maintain HIE barriers of sustainability, workflow hindrances, and financial costs. This study was the first to question market value as a barrier to implementation (Yeager et al., 2014).

Yeager et al. (2014) discussed many important points of the study and differences compared to previous empirical studies on reductions in cost, readmission rates, and stakeholder perceptions. There could have been inconsistent information on user patters gleaned from user logs in comparison to the actual user perception resulting from system use. Further research from several vantage points may corroborate HIE user patters for improved stakeholder onboarding. The authors of a similar qualitative study suggested that policy implications and monetary incentives may not be enough to encourage HIE use, and that HIE developers should consider helping users establish clinical workflows and develop metrics to monitor both HIE use and its contribution to care coordination (Rudin et al., 2011). Motivators and moderators of use are relatable concepts to the TAM model of PU and PEOU and may parallel reasons for use of HIE in Hawaii. Furthermore, data regarding the value of HIE use on readmission rates may help make the case for the value of these systems, thus increasing use among stakeholders.

HIE Usage and Provider Characteristics

Age and gender. There have been several studies citing age as a barrier to EHR adoption, although findings have not been consistent. Researchers have shown that older physicians had lower adoption rates of an EHR (13.6%) compared to younger counterparts (23.1%; Bae & Encinosa, 2016). Hamid and Cline (2013) also cite age as a factor for EHR adoption ($p < .05$). Physicians aged 45 or younger were twice as likely to adopt an EHR system than physicians 55 and older (Decker, Jamoom, & Sisk, 2012). However in contrast, other studies indicated no predictive relationship between EHR adoption and age (Hudson, Neff, Padilla, Zhang, & Mercer, 2012). Furukawa and colleagues (2014) examined responses to the 2009 National Ambulatory Medical Care Survey and the 2009-2013 Electronic Health Records Survey, they found that only 14%

of providers were participating in an exchange of information. However, age was not associated with EHR adoption or patient engagement. The results of the study did not directly report on age as a predictor of HIE use (Furukawa et al, 2014), which will be addressed in the current study. Similar to the findings regarding age, this study also found no association between gender and EHR use.

Researchers conducted a cross sectional survey of 345 health care professionals assessing user perspectives of a regional HIE based on TAM theory constructs of usability, trust, and socio-demographic factors (Gadd et al., 2011). This study specifically assessed ease of learning the system and trust in the information, which may be associated with provider age. Findings indicated an encouraging level of HIE usability with positive relationships to the ease of learning the system and overall functionality. However, the study found no associated relationship with trust in the data sources and usage. There was also no significant difference between the age and gender of users and non-users in comparison to other studies performed on demographic factors (Gadd et al., 2011).

Physician specialty. Data regarding the association of physician specialty and HIE adoption and use are also are limited. Rudin et al. (2011) conducted 20 interviews of staff and clinicians (including 11 physicians) from the Massachusetts eHealth Collaborative on the factors surrounding HIE usage. Clinicians interviewed felt that differences between particular medical specialties also determined the value of HIEs. The interviews found hospitalists treating acute hospital patients accessed the HIE routinely, whereas specialty providers like pediatricians and psychologists did not think the information in the HIE applied to their treatment of the patient (Rudin et al., 2011). A second study, however, found no association between physician specialty and EHR adoption or patient engagement (Furukawa et al., 2014).

Summary and Conclusions

Despite widespread HIE adoption largely incentivized by meaningful use programs (Yeager et al., 2014), literature focusing upon HIE implementation, adoption, benefits, and use has been limited (Adler-Milstein & Jha, 2014; Yeager et al., 2014). The research included in the review of literature has covered many aspects surrounding HIE engagement, diffusion, factors of known usage, usage patterns, motivators, and barriers to using HIE systems. A complete understanding of the literature on HIEs has assisted in identifying the gaps in our knowledge of HIE use and allow for new constructs to be studied. Specific to my study, the variables of age, medical specialty, gender, and location were evaluated for the state of Hawaii. As a state, Hawaii was cited as encompassing widespread adoption of HIE efforts (Chin & Sakuda, 2011). Hawaii's HIE contains over 80% of the state's population (HHIE, 2016), an evaluation of provider usage in a state with high patient participation will be productive in reviewing commonalities between users. In previous literature, age was not a statistically significant predictor of HIE usage (Gadd et al., 2011) and medical specialty was found to have both positive associations (Rudin et al., 2011) and no association (Furukawa et al., 2014) to HIE use. While researchers have assessed the impact of HIE on readmission rates, findings suggested both a positive (Vest et al., 2014) and no impact (Jones et al., 2011). Using the TAM model to assess the variables of age, gender, medical specialty and location as factors for physician use will advance our understanding of how HIEs are viewed in terms of ease of use and usefulness.

In Chapter 3 I describe the methodology used in this study to include a comprehensive explanation of the research questions and variables. I will then define the statistical methods used to evaluate predictive relationships and levels of significance. Included in Chapter 3 is also discussion on threats to the study validity and any ethical considerations incorporated into the research plan.

Chapter 3: Research Method

The purpose of this study was to conduct a quantitative non-experimental analysis on physician users of the HHIE. The study sought to understand if there is a predictive relationship between HHIE use and PU or PEOU of the HHIE as proxied by the variables of (a) medical specialty, (b) age, (c) gender, or (d) location of use between Hawaii counties. In evaluating the relationship between physician use between these variables, I sought to gain a better understanding of HHIE PU and PEOU. The research in my study may help promote future growth and adoption of HIEs a means of coordinating care. Findings may also provide helpful advice for policy makers on the use of HIEs in future revisions of information technology incentive programs. In this chapter, I will describe how the study was designed and how it was aligned with prior research conducted using the TAM theory. I will also discuss the population included in the research, the limitations of the data, and the data analysis plan.

Research Design and Rationale

I evaluated the factors associated with HHIE use drawing from TAM constructs and from archival data. Specifically I reviewed (a) whether a provider has used the HHIE and (b) the extent to which a provider has used the HHIE. Observing whether a physician has ever logged into the HHIE aligned with the dependent variable of HHIE use (as measured by use vs. no use) and the independent variables of medical specialty, age, gender, and location. Covariates included provider medical specialty, age, gender, and location. In the second analysis I reviewed the dependent variable of use in terms of the extent that a physician has used the HHIE (as measured by number of logins) and the independent variables of medical specialty, age, gender, and location while controlling for other variables in the analysis.

Quantitative research is a method of inquiry that can be applied across many disciplines including those in the social sciences (Lester, Inman, & Bishop, 2014). The fundamental purpose of quantitative research is to investigate societal phenomena by applying statistical techniques to evaluate connections between observations and relationships (Lester et al., 2014). A quantitative research design was chosen for this study because variables of interest could be statistically assigned and evaluated for predictive patterns. To evaluate HHIE physician activity, I used archival data collected from the HHIE which I narrowed to the population of physician users.

During the design of the research, alternate evaluation methods were considered but were not used due to the scope and data of interest. For example, experimental research involves administering an intervention or grouping subjects for comparison outcomes (Frankfort-Nachmias & Nachias, 2008). I analyzed physicians' activity in their natural environment and did not include an intervention or control group; therefore, the research did not qualify for experimental research. Further, I sought to generate a broad understanding of physician characteristics and area characteristics for HHIE use. The variables chosen could be applied to the total population of users. Additionally, direct provider participation was not required at the time of the data collection. By using archival data, this study did not alter a physician's normal activity or workflow. Due to the recent implementation of the HHIE, a time-series study was not chosen. Future researchers may wish to use a time-series design in order to evaluate ongoing participation.

The study design and rationale assembled used constructs from former research. Previous researchers have included hospital characteristics of HIE adoption to include commonalities such as profit or nonprofit status, emergency department volumes, and market share (Adler-Milstien & Jah, 2014; Vest, 2010). Use of these macro themes allow a large number of organizations to be compared, similar to the variables included in this study. Regarding the independent variable of medical specialty, prior qualitative researchers studying HIEs found differences in perceived HIE value between specialties (Rudin et al., 2011; Vest et al., 2011); therefore, I considered this variable an important factor of continued investigation. I defined medical specialty between groupings of primary care, specialists, and emergency medicine. I also chose to include emergency medicine as a medical grouping because previous researchers used exclusive data sets from emergency departments to study HIE activity (Vest, 2010; Vest & Jasperson, 2012). Several studies on the use of a HIEs in emergency department settings have resulted in a reduction of diagnostic testing and costs (Rudin et al., 2014; Yaraghi, 2015). Identification of the emergency department physician user group may provide additional understanding of emergency department physician activity.

Methodology

An overview of the methodology used to assemble the study will be explained in this section. Information in the section includes the total population, sampling and sampling procedures, and the archival data set used in the study.

Population

The AHRQ (2014) estimates that there are as many as 280 HIEs across the United States. One single HIE in Indiana has over 14,000 participating physicians (AHRQ, 2014), and the AHRQ (2014) expects 50% of the nation's physicians to join an HIE. For Hawaii, the HHIE website lists 600 providers as having been trained from July 2015 to August 2016 (HHIE, 2016). Because the HHIE is the only exchange in the state of Hawaii (HHIE, 2016), the data set used in this study included the total population of HHIE users. To maintain the study design, I limited the population to physicians with certifications of MD or DO. As indicated previously, I limited the population of providers who are credentialed physicians in order to improve the validity by ensuring similar education, training, and comparison characteristics.

Sampling and Sampling Procedures

The data set received encompassed the total population of physician users. This was due to the HHIE being the only information exchange identified by the ONC for the state of Hawaii. However, if additional HIEs are created in the state of Hawaii, future researchers should use a purposeful sample narrowed to a cohort of physician users. A purposeful sample is one in which the total population of a given interest is able to be represented (Palinkas et al., 2015). This sampling technique is common in implementation research where the researcher aims to review barriers and facilitators of an implementation process or outcome (Palinkas et al., 2015). By design, purposeful samples are intended to illuminate (a) similar and (b) different characteristics of the group. In using this sampling technique, researchers can measure the diffusion or comparison and dispersion or contrasts of the sample (Palinkas et al., 2015).

Due to the inclusion of the entire population of users, a power analysis to determine the sample was not a requirement. The HHIE website estimates over 600 physician users which I initially forecasted my population size upon. If the data available reflected differently once received, I would have used an alpha level (or p-value) of 0.05 as a parameter of statistical significance with a confidence interval of 95%. The alpha level indicates the probability (p) for chance of error, and the confidence interval specifies the estimated assurance that reanalyzing the data would have the same result (Field, 2013). Further, an effect size indicates the strength between the selected variables (Field, 2013). Based on this size, the power of a study indicates the percentage of effect achievement (Field, 2013). I used a small effect size of .10 and a power of .8 or 80%. With these parameters, I used the application G* Power to compute a sample size for multiple logistic regression with four predictors at 176 to reach a power of .95 and a sample size for multiple linear regression at 107 for the basis of my methods design.

Archival Data

Under arrangement, the HHIE agreed to provide an archival data set containing a listing of logins from all date ranges available since the inception of the community health record in 2014. The HHIE had also have agreed to provide data specific to the physician's age, gender medical specialty, and location as obtained from HHIE sign-up forms. To retrieve the data, I received a written consent letter from the HHIE executive director. The consent letter in was approved by the Institutional Review Board (IRB) to fulfill data exchange requirements (see Appendix A).

In the event medical specialty, age, gender, or location data was not available from the HHIE, I used using information from the CMS.gov or online websites. CMS began the Physician Compare initiative to meet requirements of the 2010 Affordable Care Act, the website delivers information on quality scores, metrics, program eligibility, and general provider information. Age, gender, or medical specialty information was also retrieved from publically available websites such as Healthgrades.com, Doximity.com, or doctor.webmd.com.

Operationalization of Variables

Dependent variables. To assess HHIE use, the logistic regression dependent variable was coded as a “1” if a provider has logged into the system with a count of 1 or greater and a “0” if a provider has no record of logins to the system. Next, the extent of HHIE use was studied using multiple linear regression, and the dependent variable was the sum of all logins for each physician for physicians with one or more logins. Physicians with no login counts on record were entered as a “0”, and all others were entered as a number starting from the number 1.

Independent variables. Medical specialty was determined by the physician stated enrollment information in the HHIE. For the purpose of this study, medical specialty was defined and coded as groupings of (1) primary care physicians, (2) emergency medicine physicians, and (3) specialists. Previous research on the variable of medical specialty use on HIEs was not clearly defined in the literature. Findings suggested both an influence towards HIE use by medical specialty (Patel, Abramson, Edwards, Malhotra, & Kaushal, 2011) while others did not find any statistical significance (Furukawa et al., 2014). I could not locate a study that evaluated information technology use in primary care, emergency physicians, and specialist groups in Hawaii. In the study, I suggested the inclusion of emergency medicine as a specialty based on previous research on the unique workflows of emergency physicians and the benefits of HIE use (Rudin et al., 2014; Yaraghi, 2015). However, in future analysis, if there are not enough participants to reach statistical power for emergency medicine, the providers could be grouped together with specialists. Broad groupings may also be necessary to maintain physician anonymity dependent upon the archival data available.

Location is another important consideration for HHIE use. Withy et al. (2017) reports on the unique challenges and physician shortages between the four Hawaii counties. To gain a better understanding on how the HHIE is used in different areas of the state, I included location as an independent variable. Under the constructs of the TAM theory, medical specialty and location also align with PU as it relates to user activity.

Gender and age were also evaluated under the TAM framework for PEOU lending toward predictor values for HHIE usage. Following previous research by Egea and Gonzales (2011) who used the TAM associate and provider age and EHR use, age were grouped by under (a) 35 years of age, (b) 35-44 years of age, (c) 45-54 years of age, (d) 55 to 64 years of age, and (e) 65 years of age and older. Reporting age in groups may also be necessary to maintain provider anonymity for a study. Gender was coded "0" for male and "1" for female.

Covariates. Covariates or predictor variables can be used in regression analysis to assist in the evaluation of the data and any additional influences on the outcome (Field, 2013). I used medical specialty, age, gender, and location as covariates when analyzing each of these independent variables.

Data Analysis Plan

To perform calculations, I used SPSS Statistics version 21 for Windows student edition which is installed on my personal device. SPSS performs a variety of calculations and is useful program to manipulate data and analyze information (Gerber & Finn, 2013). Data was manually uploaded in to SPSS and reviewed for any significant outliers or discrepancies in the source file.

The research questions and hypotheses were, as follows:

RQ1: What is the predictive relationship, if any, between any HHIE use (as measured by login vs. no login) and (a) physician medical specialty (primary care, emergency medicine, or specialist), (b) physician age, (c) physician gender, and (d) location when controlling for the other variables?

$H_0$1: There is no predictive relationship between any HHIE use (as measured by login vs. no login) and (a) physician medical specialty (primary care, emergency medicine, or specialist), (b) physician age, (c) physician gender, and (d) location when controlling for the other variables.

H_A1: There is a predictive relationship between any HHIE use (as measured by login vs. no login) and (a) physician medical specialty (primary care, emergency medicine, or specialist), (b) physician age, (c) physician gender, and (d) location when controlling for the other variables.

RQ2: What is the predictive relationship, if any, between the extent of HHIE use (as measured by number of times logged in) and (a) physician medical specialty (primary care, emergency medicine, or specialist) (b) physician age, (c) physician gender, and (d) location when controlling for the other variables?

H_02: There is no predictive relationship between the extent of HHIE use (as measured by number of times logged in) and (a) physician medical specialty (primary care, emergency medicine, or specialist) (b) physician age, (c) physician gender, and (d) location when controlling for the other variables.

H_A2: There is a predictive relationship between the extent of HHIE use (as measured by number of times logged in) and (a) physician medical specialty (primary care, emergency medicine, or specialist) (b) physician age, (c) physician gender, and (d) location when controlling for the other variables.

RQ1 logistic regression. The first analysis I ran was a logistic regression. Researchers use logistic regression because it allows for a categorical outcome variable and continuous or categorical predictor variables (Field, 2013). This is appropriate to determine HHIE use since usefulness is coded as a binary variable. Logistic regression models were previously used to evaluate hospital characteristics between HIE adopters and non-adopters (Vest, 2010; Vest et al., 2015) and decision to admit a patient based on

HIE use (Politi et al., 2015). Further logistic regression studies reviewed impacts to clinical care and the reduction of imaging studies (Frisse et al., 2012)

I constructed a model to evaluate each predictor variable of interest while controlling for the other variables. The model assessed the predictive relationship between any HHIE use and each independent variable (physician specialty, age, gender, and location) while controlling for the other variables in the regression. Further, I tested for the presence of multicollinearity and significant outliers (Field, 2013). All covariates were entered using forced entry as additional predictor variables. Results were reported in odds ratios and interpreted by indicating a significance or p-value < .05 with a confidence interval of 95%.

RQ2 multiple linear regression. Linear regression models were used in previous research under the TAM theory to evaluate physician adoption of EHR clinical practice guidelines (Hsiao & Chen, 2016). I used multiple linear regression to evaluate the extent of HHIE use by evaluating login counts, starting with the number one. Multiple linear regression allows for a continuous predictor variable and several outcome variables in the calculation (Field, 2013). The main objective of this analysis was to see if there is a predictive relationship in the amount of use (sum of login counts) between independent variables.

For the RQ2 multiple linear regression linear model I assessed was the predictive relationship between the extent of HHIE use and physician specialty, age, gender, and location while controlling for the other variables. I also used forced entry for the covariates variables. Assumptions for multiple linear regression were tested including reviewing the Durbin-Watson statistic to ensure the independence of observations and the assurance of linear relationships between outcome and predictor variables and homoscedasticity of residuals (Field, 2013). Additional assumptions were tested to ensure no multicollinearity and significant outliers are present (Field, 2013). Results from the multiple linear regression model were reported for statistical significance to include a p-value $< .05$ and a confidence interval of 95%. Tests also included an F ratio to report the fit of the model and R^2 indicating the degree of variance. Table 1 illustrates how variables were coded for the two research questions.

Table 1

Coding of Variables for RQ 1 and RQ 2

Variable	Type of variable	Coding
Independent variable		
HHIE use	Binary	0 = no use; 1 = any use
HHIE extent of use	Continuous	Sum of all login counts in data set by provider
Dependent variables		
Medical specialty	Nominal	1= primary care; 2= specialist; 3= emergency medicine
Age	Nominal	1= <35 years of age; 2= 35-44 years of age; 3= 45-54 years of age; 4= 55 to 64 years of age; 5= >65 years of age
Gender	Nominal	0= male; 1= female
Location	Nominal	1=Oahu; 2= Hawaii; 3= Maui; 4= Kauai

Treats to Validity

External Validity

External validity confirms that research findings can be further applied or generalized to similar populations outside of the research sample (Frankfort-Nachmias &

Nachmias, 2008). The first threat to external validity is representativeness of the population under evaluation (Frankfort-Nachmias & Nachmias, 2015). Representativeness in my study included all physicians designated as an MD or DO who have signed up to participate in the HHIE community record, this encompassed the entire population of physician HHIE users in the state of Hawaii. As mentioned previously, physicians were selected as the population due the similar backgrounds of schooling in medical school. The consistencies credentials will further add to external validity of the study.

The next threat to external validity is the presence of reactive arrangements, this occurs in an experimental setting where participants may change their behavior due to unusual surroundings (Frankfort-Nachmias & Nachmias, 2015). No reactive arrangements were present in the study; all participants accessed the HHIE in their natural environment using usual normal business practices in which a computer or device is utilized. Access to the HHIE could have occurred in their personal or professional office settings or using any other setting typically used to access electronic health records or online applications. Further I used secondary data to calculate HHIE activity. To my knowledge there were no other studies were conducted during the dates contained in the secondary data set therefore no experimental behavior or altered behavior is contained in the study.

Internal Validity

Internal validity ensures the independent variable was a factor associated to the measurement or influence on the dependent variable (Frankfort-Nachmias & Nachmias, 2008). In my study I predicted HHIE usage based upon the independent variable of age, gender, medical specialty, and location. To address internal validity, I computed my analysis by controlling for each of these variables during the calculation of each independent variable. This allows for each factor to be represented independently without influence from the other variables under study. Controlling for these variables also minimizes the potential for an alternate explanation of predictive behavior (Frankfort-Nachmias & Nachmias, 2008)

Another threat to internal validity is the passage of time or history that has occurred since the time the data was collected (Frankfort-Nachmias & Nachmias, 2008). Being mindful of time or a history of event is important because the data may no longer apply to the study in present day or rules, laws, or regulations (Frankfort-Nachmias & Nachmias, 2015). Further, these previous societal influences may have altered previous behavior to the extent that the data is no longer applicable (Frankfort-Nachmias & Nachmias, 2008); this factor is more affluent in longitudinal studies. For my study, the data under evaluation was within the past three years and after meaningful use stage 1 and stage 2 began rewarding and penalizing providers for not meeting federal program expectations therefore time and history were excluded as a threat to the study.

Construct Validity

Construct validity determines if the study justifiably aligns with the stated theory and whether inferences can be drawn to the theory for additional studies (Bagozzi, Yi, & Phillips, 1991). I based my research questions upon the constructs of the TAM theory which has been widely used to test user intention and technology system adoption. I could not locate any studies in which the TAM was used as a theory to evaluate physician use of HIE systems specific to the independent variables of age, gender, medical specialty, or location. However, previous research on these variables have been studied using the TAM theory under the broad scope of information technology, electronic health records, internet, and telemedicine (Holden & Karsh, 2010; Legris et al., 2003; Melas et al., 2011). To ensure construct validity, my study followed similar research designs when identifying factors for PU and PEOU.

Ethical Procedures

Written consent was received by the Executive Director of the HHIE to provide the archival data set used in this study. The HHIE agreed to provide a listing of providers signed up with the HHIE, community health record login counts for users, and medical specialty, age, gender, and location as recorded from HHIE sign-up forms. All data was stored on my personal computer which contains an encrypted drive with bit-locker protection. My computer is password protected and requires biometric (fingerprint) authentication.

My study did not report any provider specific information identification in the data analysis plan. The variables of interest are able to be broadly grouped to maintain complete provider anonymity. All data will be kept from the date I complete the doctoral program as approved by Walden University governance plus the required five years. At which time, all material will be deleted from my personal computer to ensure the files are not a threat to future access of the device.

Summary

As discussed in this chapter, the constructs of the TAM for PU and PEOU were statistically evaluated using the dependent variable of HHIE use and the independent variables of medical specialty, age, gender, and location. To calculate the predictive relationships of these variables, I first conducted a binary logistic regression to calculate HHIE use as dichotomous variable of whether a physician has ever logged in to the HHIE. Next I conducted a multiple linear regression to assess the extent of HHIE use on a continuous scale by calculating differences between the total sums of logins between providers.

A number of considerations were evaluated in deciding upon the research methods. First, the data used in the study was provided to me directly by the HHIE as archival data from a date range between 2014 and 2016. No interventions had taken place to HHIE users, nor were HHIE users aware that login information would be further evaluated for use during the time the counts were collected. This makes the study and the data appropriate for descriptive research. Internal, external, and construct validity was also assessed. Threats were minimized by (a) including a HHIE user group limited to physicians (MD or DO), (b) including covariates in the regression analysis, and (c) following similar constructs from prior TAM research studies. The study also ensured that no personally identifiable physician information was reported. To accomplish this, I used broad groupings of medical specialty and age groups.

In chapter 4, I will review the HHIE archival data set in greater detail. I will also provide results from the binary logistic regression and multiple linear regression models for each independent variable and any accompanying graphical representations of the data. After the data has been completely reviewed, I further report any additional descriptive statistics retrieved from the data to better understand the predictive indicators of HHIE use.

Chapter 4: Results

Introduction

The purpose of this study was to evaluate physician factors associated with using a HIE in the state of Hawaii. I sought to investigate the predictive relationship between provider characteristics, area characteristics, and HHIE use. To accomplish this, I drew from the constructs of the TAM to perform a quantitative assessment of PU and PEOU for physician users of the HHIE. I included the physician activity of (a) logging into the HHIE and (b) the number or times a physician has logged into the HHIE. Only physicians with the credentials of MD or DO were included in the analysis to limit end-user variability.

I constructed two research questions to analyze physician use of the HHIE:

RQ1: What is the predictive relationship, if any, between any HHIE use (as measured by login vs. no login) and physician medical specialty (primary care, emergency medicine, or specialist), physician age, physician gender, and location when controlling for the other variables? and

RQ2. What is the predictive relationship, if any, between the extent of HHIE use (as measured by number of times logged in) and physician medical specialty (primary care, emergency medicine, or specialist), physician age, physician gender, and location when controlling for the other variables?

Past researchers aligned the TAM construct of PU with the variables of medical specialty and location and the construct of PEOU with age and gender. I tested whether age, gender, medical specialty, and location were predictive indicators of HHIE use and HHIE usage. The null hypothesis was that there is no predictive relationship between HHIE use and HHIE usage and the factors of age, gender, medical specialty, and location. This chapter includes (a) an explanation of the secondary the data received, dates the data was collected, and the total population size included in the study; (b) descriptive statistics for data set analyzed in the study; and (c) output findings from the binary logistic regression and the multiple linear regression analyses I conducted.

Data Collection

The data for this study was collected by the HHIE. I obtained files containing user login data from the dates of January 1, 2016, to June 30, 2017 using secure file transfer. In total, the file contained 127,839 counts of successful logins for all HHIE users. A separate HHIE participating provider file was also obtained from the HHIE to identify physician users. In total, the participating provider file listed 1,388 members. The file was closely reviewed for any duplicate entries or potential data entry errors, and all users without a credentialing of DO or MD were removed. Examples of removed data included users listed as doctors of pharmacy (PharmD), advanced practice nurse practitioners (APRN), and physician assistants (PA). Any missing gender or age information was obtained from the CMS Physician Compare website, Heathgrades.com, or other publically available websites. The resulting data set contained the total population for the study at 1034 HHIE physician users.

Population Characteristics

The study design used a purposeful sample. Supporting the purposeful sampling method, the study included the total population of users with the characteristics of MD or

DO who had signed up to use the HHIE in the state of Hawaii. The total population (N = 1034) of HHIE physicians was used to compute RQ1 when evaluating if a physician who had signed up to use the HHIE had ever logged in. The population was further defined upon evaluation of RQ2 when predicting HHIE usage. For this analysis, I excluded all users with a login count of "0." The login count "0" identified a provider who had signed up for the HHIE, but never logged in. Upon exclusion of these physicians, the total population of HHIE providers containing a login count of "1" or more was narrowed to 273 physicians. This was the total population for RQ2, which was posed to evaluate the extent of HHIE usage.

Population characteristics for RQ1. In reviewing the total population (N =1034) for RQ1, I found that the data showed a largely male dominated group with males comprising 70.3% of HHIE physicians and women representing 29.7%. Within the data set, physicians aged 35-44 (25.9%) were the largest group, followed by ages 55-64 (25.2%), ages 45-54 (22.5%), age 65 and over (19.2%), and, lastly, age 35 and under (7.1%). The majority of HHIE physicians were designated as medical specialists (49.4%) and primary care physicians (37.6%). Emergency medicine physicians made up the smallest group of physicians (13%). In terms of location, the county of Oahu also had the highest number of physicians signed up for the HHIE with 83.9% of the population; Maui was the next largest county at 9.2%, followed by Hawaii (6%) and Kauai (.9%). When comparing these numbers to the percentage of population per county who had signed up for the HHIE, based upon the data, findings indicated that 43% of Oahu county physicians had signed up for the HHIE, compared to 35% of Maui County physicians, 20% of Hawaii County physicians, and 8% of Kauai physicians.

Population characteristics for RQ2. The total population for RQ2 (*n* = 273 users) followed similar themes. There were more males in the population (70.3%) than females (29.7%). Age groups 35 to 44 and 55 to 64 constituted the same percentage of users (24.9%), followed by ages 45 to 54 (22.7%), age 65 and over (20.5%), and age 35 and younger (7.0%). Specialists also held the highest population (43.2%) closely followed by primary care (41.4%) and emergency medicine (15.4%). The highest number of users were located in the county of Oahu (82.4%), followed by Maui (9.9%), Hawaii county (7.3%), and Kauai (.4%).

Table 2

HHIE Population Characteristics for RQ1 and RQ2

Independent variables	RQ1 (*N* = 1034)		RQ2 (*n = 273)*	
Age	*N*	%	*n*	%
Under 35	73	7.10%	19	7.0%
35-44	268	25.90%	68	24.9%
45-54	233	22.50%	62	22.7%
55-64	261	25.20%	68	24.9%
65 and over	199	19.20%	56	20.5%
Medical specialty				
Primary care	389	37.60%	113	41.4%
Specialist	511	49.40%	118	43.2%
Emergency medicine	134	13%	42	15.4%
Location				
Oahu county	868	83.90%	225	82.4%
Hawaii county	62	6%	20	7.30%
Maui county	95	9.20%	27	9.90%
Kauai county	9	0.90%	1	0.4%
Gender				
Male	727	70.3%	192	70.3%

Female	307	29.7%	81	29.4%

Population characteristics of Hawaii physicians. In the latest report from Withy (2017) on the composite demographic makeup of all Hawaii physicians, the report stated that there are over 8,900 physicians licensed to practice in the state, 3,693 of whom are practicing in nonmilitary settings. Only 2,903 physicians were involved in directly caring for Hawaii residents (Withy, 2017). Included in this group were physicians licensed to practice telehealth services in the state. The 2016 Workforce Report for the Legislature also listed the average age of a physician in Hawaii as 55 and 31% of the Hawaii physician workforce as being age 55 to 65, 15% between the age of 66 and 75, and 3% 75 and over (Withy, 2017). Male physicians made up the majority of the profession in Hawaii at 69%, with female physicians constituting 31% of the profession (Withy, 2017). In reviewing differences between medical specialties reporting to practice in Hawaii, specialists made up the largest number of physicians at 55% of the population, with primary care comprising 37% of the population, and emergency medicine constituting 7% of the physician group (Withy, 2017).

In a macro view of the United States, themes remain consistent with the state of Hawaii. Although the number of female physicians are on the rise, the workforce remains predominately male holding 64.7% of the total population (Young et al., 2017). The age of the national physician workforce has also risen to 51 which is four years younger than the average Hawaii physician, yet percentages between ages holds steady with the majority of the population reported between ages 40 to 49 (23.9%) and 50 to 59 (22.5%) years of age (Young et al., 2017).

Both data sets are of interest when comparing the total population of practicing physicians across the US and in the state of Hawaii with the total population of HHIE physician users used within the research for this study. The study data further indicates that 35.6% of practicing Hawaii physicians had signed up for the HHIE community health record. Of those participating Hawaii providers, gender appears to be fairly consistent between Hawaii and national percentages of male and female groups. The age of physicians who have signed up to use the HHIE appears to be fairly equal between physicians aged 35 to 44 and ages 55 to 64. The percentages between groups of physician medical specialties also appear fairly consistent when comparing Hawaii state averages with those participating with the HHIE. Review of this information is important when comparing results from this study and applying findings to similar populations across the country. Since the representative population in (a) the study, (b) the state, and (c) the national average are very similar, external validity of the study was strengthened.

Results

In this section I will review the research questions contained in the study. I will evaluate the model created to calculate findings and also report all findings from the analysis. The descriptive statistics explains the fundamental features found in the study and serves as the foundation for the data (Trochim, 2006). The descriptive statistics for the independent variables and dependent variable can be found below.

Table 3

Descriptive Statistics: Dependent Variable for RQ 1 (N = 1034)

	Minimum	Maximum	Mean	(SE)	SD

RQ 1 login	0.00	1.00	.026	(.014)	.441

Table 4

Descriptive Statistics: Dependent Variable for RQ 2 (n = 273)

	Minimum	Maximum	Mean	(SE)	SD
RQ 2 login count	1.00	1806	44.13	(9.51)	157.160

Table 4

Descriptive Statistics: Independent Variables for RQ1 (N =1034)

	Minimum	Maximum	Mean	(SE)	SD
Female	0.00	1.00	0.30	(.014)	.457
Under age 35	0.00	1.00	0.07	(.008)	.256
Age 35-44	0.00	1.00	0.26	(.014)	.438
Age 45-54	0.00	1.00	0.23	(.013)	.418
Age 55-64	0.00	1.00	0.25	(.014)	.435
Age 65 and over	0.00	1.00	0.19	(.012)	.394
Primary care	0.00	1.00	0.38	(.015)	.485
Specialists	0.00	1.00	0.49	(.016)	.500
Emergency medicine	0.00	1.00	0.13	(.010)	.336
Oahu county	0.00	1.00	0.84	(.011)	.367
Hawaii county	0.00	1.00	0.06	(.007)	.238
Maui county	0.00	1.00	0.09	(.009)	.289
Kauai county	0.00	1.00	0.01	(.003)	.093

Table 5

Descriptive Statistics: Independent Variables for RQ2 (n =273)

	Minimum	Maximum	Mean	(SE)	SD
Female	0.00	1.00	0.30	(.280)	.458
Under age 35	0.00	1.00	0.07	(.015)	.255
Age 35-44	0.00	1.00	0.24	(.026)	.433
Age 45-54	0.00	1.00	0.23	(.025)	.420
Age 55-64	0.00	1.00	0.25	(.026)	.433
Age 65 and over	0.00	1.00	0.21	(.024)	.405
Primary care	0.00	1.00	0.41	(.030)	.493

Specialists	0.00	1.00	0.43	(.030)	.496
Emergency medicine	0.00	1.00	0.15	(.022)	.361
Oahu county	0.00	1.00	0.82	(.023)	.381
Hawaii county	0.00	1.00	0.07	(.016)	.261
Maui county	0.00	1.00	0.10	(.018)	.299
Kauai county	0.00	1.00	0.00	(.004)	.061

Research Question 1

In the first research question, I measured the use of the HHIE by using the total physician population included in the study (N = 1034). The first research question reads: What is the predictive relationship, if any, between any HHIE use (as measured by login vs. no login) and (a) physician medical specialty (primary care, emergency medicine, or specialist), (b) physician age, (c) physician gender, and (d) location when controlling for the other variables? The null hypothesis stated that there is no predictive relationship between any HHIE use (as measured by login vs. no login) and (a) physician medical specialty (primary care, emergency medicine, or specialist), (b) physician age, (c) physician gender, and (d) location when controlling for the other variables. The alternative hypothesis stated there is a predictive relationship between any HHIE use (as measured by login vs. no login) and (a) physician medical specialty (primary care, emergency medicine, or specialist), (b) physician age, (c) physician gender, and (d) location when controlling for the other variables.

Logistic regression. To approach research question one, I conducted a logistic regression analysis. The outcome of interest was whether a physician who has signed up to access the HHIE had ever logged into the system. All predictor variables were inputted into the regression model using forced entry. Assumptions met for the binary logistic regression include a dichotomous dependent variable, one or more independent variables, and an independence of observations. Correlations were checked with linear regression and resulted in a mean Variance Inflation Factor (VIF) of 1.336 which is close to a mean of 1.0; therefore, no evidence of multicollinearity was found (Field, 2013). There was one studentized residual with a value of 2.776 standard deviations, which was kept in the analysis. Hosmer-Lemeshow goodness-of-fit was not statistically significant $p = .986$ confirming the model is correctly specified. All independent variables included in the study were dichotomous; therefore, linearity was not tested as part of the assumptions. The model sensitivity was found to predict no HHIE use coded as "0" 100% of the time, and use coded as "1" 0% of the time. The fit indicates 73.6% positive classification for the model.

Of the predictor variables, medical specialty was found to be statistically significant ($p < .05$) when comparing HHIE use between specialty physicians to primary care and emergency room physicians while controlling for all other factors. The findings indicate that emergency department physicians were 57% more likely to login to the HHIE [Exp*(B)*= [1.57], 95% CI (1.026, 2.430), $p = .038$] compared to specialists. No other physician factors were found to be significant. However, a predictive relationship was found between medical specialty and HHIE use (login vs. no login) therefore the null hypothesis was rejected and the alternate hypothesis was accepted. These findings are reported in Table 3.

Table 6

Logistic Regression Predicting any HHIE Use based on Gender, Age, Medical Specialty and Location (N =1034)

				95% CI for odds ratio	
	B	*p- value*	Exp*(B)*	Lower	Upper
Gender	-0.001	0.993	0.999	0.726	1.374
Age < 35	-0.147	0.649	0.863	0.458	1.627
Age 35-44	-0.152	0.494	0.859	0.555	1.328
Age 45- 54	-0.064	0.774	0.938	0.606	1.451
Age 55-64	-0.1	0.641	0.905	0.595	1.376
Primary care	0.287	0.072	1.332	0.974	1.821
Emergency medicine	0.457	0.038	1.579	1.026	2.430
Hawaii county	0.243	0.403	1.275	0.722	2.252
Maui county	0.133	0.59	1.142	0.705	1.85
Kauai county	-1.134	0.288	0.322	0.04	2.607
Constant	-1.131	0	0.323		

Note: Gender is for males compared to females, age is compared to age group 65 and over, medical specialty is compared to medical specialists, and Hawaii counties are compared to the county of Oahu.

Research Question 2

In the second research question, I evaluated the extent of HHIE use based upon the number of times a physician logged into the HHIE. The second research question reads: What is the predictive relationship, if any, between the extent of HHIE use (as measured by number of times logged in) and (a) physician medical specialty (primary care, emergency medicine, or specialist) (b) physician age, (c) physician gender, and (d) location when controlling for the other variables? The null hypothesis stated that there is no predictive relationship between the extent of HHIE use (as measured by number of times logged in) and (a) physician medical specialty (primary care, emergency medicine, or specialist) (b) physician age, (c) physician gender, and (d) location when controlling for the other variables. The alternative hypothesis asserted that there is a predictive relationship between the extent of HHIE use (as measured by number of times logged in) and (a) physician medical specialty (primary care, emergency medicine, or specialist) (b) physician age, (c) physician gender, and (d) location when controlling for the other variables.

Linear regression. To approach research question two a linear regression model was constructed to review the extent of HHIE usage from predictor variables of age, gender, medical specialty, and location. All users with a login count of "0" were excluded from the analysis, the resulting file contained a total of n = 273 physicians as described as in the RQ2 population for the study. Assumptions met for this study include a continuous dependent variable, multicollinearity, and an independence of residuals as assessed by a Durbin-Watson statistic of 2.048. In review of the scatter plot, the dependent variable was not normally distributed and contained significant outliers as indicated in Figure 2 below.

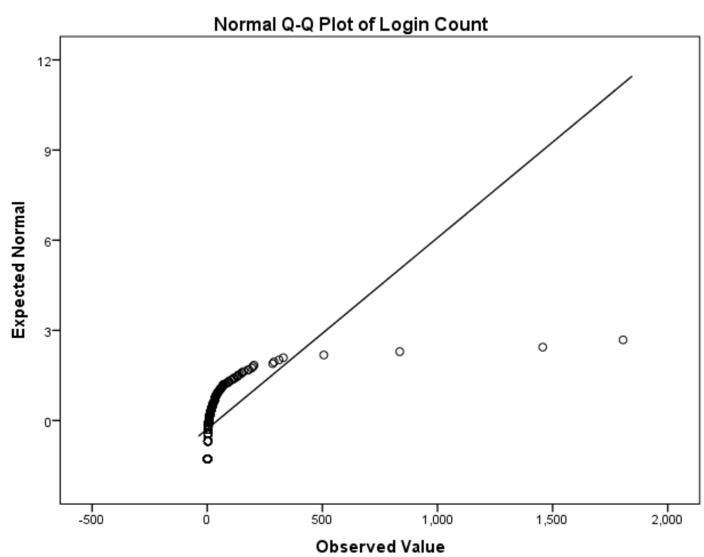

Figure 2: Linear Regression Model Before Log Transformation

The model failed the assumption of homoscedasticity, normality, and the assumption of linearity as assessed by visual inspection (Figure 2).

Transformed linear regression. As a result of these findings, I transformed the dependent variable to address the failed assumption of normality of the dependent variable. The transformation was processed by applying a log (log10) transformation within SPSS, this can be done to correct moderately skewed data (Field, 2013). I reran the model using the transformed data to improve normality as seen in the Normal Q-Q Plot show in Figure 3.

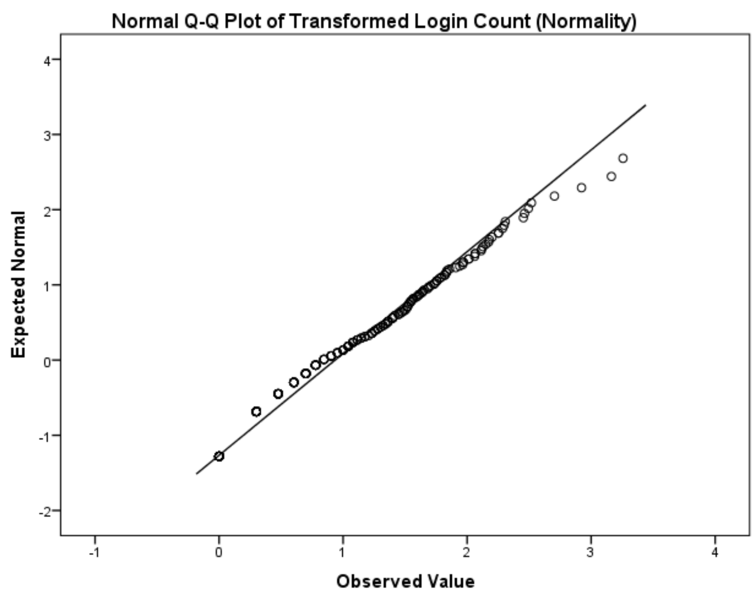

Figure 3: Linear Regression Model After Log Transformation

The updated model utilizing the transformed data (login count) maintained the assumption of a continuous dependent variable, and an independence of residuals as assessed by a Durbin-Watson statistic of 1.847. Correlations calculated a mean VIF of

1.336 which is close to a mean of 1.0 therefore no evidence of multicollinearity was found (Field, 2013). There were two studentized residuals with a value of 5.555 and 5.507 standard deviations, which was kept in the analysis. In review of the scatter plot, the dependent variable was improved, but remained not normally distributed therefore the assumptions of normality and linearity were not met. Specifically, the Kolmogorov-Smirnov[2] Test of Normality remained at $p < .001$. The model summary calculated and $R^2 = 0.63$ and an adjusted $R^2 = 0.27$ indicating the model accounts for 27% of HHIE usage based on the predictor variables. The model significance was found to be $F(10,262) = 1.757$, $p = .069$.

Results from the transformed dependent variable found the regression coefficient associated with medical specialty statistically significant. The model confirmed for every unit increase of login count, the number of logins for primary care physicians increased by 0.673, and emergency physician login counts increased by 0.684. Specifically, the model displays when compared to medical specialist while controlling for age, gender, and location, primary care physicians had a predictive relationship of HHIE usage [B = 0.673, 95% C.I. (.223, 1.123) $p = 0.004$]. Results also indicate when specialist are compared to emergency medicine physicians, statistically significant predictive relationship of usage was found [B = 0.684, 95% C.I. (.074, 1.295) $p = 0.028$]. No other variables were found to be statistically significant. These results are displayed in Table 4. Overall assumptions for linear regression model were violated therefore the results were inconclusive.

Table 7

Linear Regression: Individual predictors for the Extent of HHIE Use (n = 273)

Model	Unstandardized coefficients		Standardized coefficients		
	B	*SE*	*B*	*t*	*p-value*
(Constant)	1.656	.259		6.398	.000
Gender	-.229	.233	-.062	-.981	.328
Age <35	-.241	.463	-.036	-.521	.603
Age 35-44	.565	.321	.144	1.760	.080
Age 45-54	.349	.319	.086	1.095	.274
Age 55-64	.073	.306	.019	.239	.811
Primary care	.673	.229	.195	2.942	.004
Emergency medicine	.684	.310	.145	2.206	.028
Hawaii county	-.477	.404	-.073	-1.181	.239
Maui county	-.086	.353	-.015	-.243	.808
Kauai county	1.011	1.701	.036	.594	.553

Note: Gender is for males compared to females, age is compared to age group 65 and over, medical specialty is compared to medical specialists, and Hawaii counties are compared to the county of Oahu.

Revised transformed linear regression. An additional model was created to address the linear regression model assumptions. The model eliminated the high and low dependent variable outliers at 5% of the high and low data points and maintained the transformed dependent variable and all predictor variables. Removal of the outliers reduced the population by 77 HHIE physicians (n = 206).

Table 8

Revised RQ2 Population (n = 206)

Independent variables	RQ1 (*N* = 1034)		RQ2 (*n* = 273)		RQ2 revised (*n* = 206)	
Age	*N*	%	*n*	%	*n*	%
Under 35	73	7.1%	19	7.0%	13	6.3%
35-44	268	25.9%	68	24.9%	46	22.3%
45-54	233	22.5%	62	22.7%	50	24.3%
55-64	261	25.2%	68	24.9%	55	26.7%
65 and over	199	19.2%	56	20.5%	42	20.4%
Medical specialty						
Primary care	389	37.6%	113	41.4%	90	43.7%
Specialist	511	49.4%	118	43.2%	82	39.8%
Emergency medicine	134	13%	42	15.4%	34	16.5%
Location						
Oahu county	868	83.90%	225	82.4%	172	83.5%
Hawaii county	62	6%	20	7.30%	13	6.3%
Maui county	95	9.2%	27	9.9%	20	9.7%
Kauai county	9	0.90%	1	0.4%	1	0.5%
Gender						
Male	727	70.3%	192	70.3%	146	70.9%
Female	307	29.7%	81	29.4%	60	29.1%

The assumptions from the study upheld a continuous independent variable and an independence of residuals as assessed by a Durbin-Watson statistic of 1.872. Similar to the previous linear regression models the distribution of residuals remained skewed and the model failed the assumption of linearity and normality as assessed by visual inspection. VIF values were calculated above the threshold of 10 for Hawaii counties suggesting collinearity within the data. The model summary calculated $R^2 = 0.061$ and adjusted $R^2 = 0.013$ indicating the model accounts for 1.3% of HHIE usage based on the predictor variables. The model significance was $F(10, 195) = 1.275$, $p = .247$.

Findings from the updated model indicate the regression coefficient associated with medical specialty predicts in comparison to specialists, primary care physicians have slightly higher HHIE usage. Specifically for every one unit increase in login count, an increase of .196 logins for primary care physicians [*B* =.196, 95% C.I. (.0.29, .364) *p* = .022] were found. Results further indicate higher predictive usage when specialist are compared to emergency medicine physicians. For every one unit of increase of login counts an additional .234 logins by emergency medicine physicians could be predicted [*B* = 0.234, 95% C.I. (0.006, 0.462) *p* = .044]. No other variables were found to be statistically significant, these results are displayed in Table 5. The model violated the assumption of linearity, collinearity, and normality and was found inconclusive.

Table 9

Linear Regression: Individual predictors for the Extent of HHIE Use with the Removal of Outliers (n = 206)

Model	Unstandardized coefficients		Standardized coefficients		
	B	*SE*	*B*	*t*	*p-value*
(Constant)	.990	.097		10.232	.000
Gender	-.069	.087	-.058	-.794	.428
Age <35	-.030	.179	-.014	-.169	.866
Age 35-44	.061	.124	.047	.496	.620
Age 45-54	.032	.117	.025	.270	.788
Age 55-64	-.086	.112	-.070	-.768	.443
Primary care	.196	.085	.179	2.311	.022
Emergency medicine	.234	.116	.160	2.024	.044
Hawaii county	-.242	.160	-.108	-1.519	.131
Maui county	.000	.133	.000	-.001	.999
Kauai county	.384	.551	.049	.696	.487

Note: Gender is for males compared to females, age is compared to age group 65 and over, medical specialty is compared to specialists, and Hawaii counties are compared to the county of Oahu.

Additional analysis logistic regression. Since the normality assumption with linear regression was violated, a final model based on logistic regression was constructed to test whether there was a non-linear relationship between the factors and the extent of HHIE use. The linear regression dependent variable (n = 206, login count > 0) was recoded to identify HHIE users above and below the median login count of 7. The new dependent variable was coded as login count < 7 = "0" and login count 7 > = "1". The logistic regression model maintained all prior predictor variables of age, gender, medical specialty, and location. Assumptions met for the binary logistic regression include a dichotomous dependent variable, one or more independent variables and an independence of observations. Correlations calculated a mean VIF of 1.349 which is close to a mean of 1.0 therefore no evidence of multicollinearity was found (Field, 2013). There were no studentized the residuals above 2 standard deviations. All independent variables included in the study were dichotomous therefore linearity was not tested as part of the assumptions. The Hosmer-Lemeshow goodness-of-fit was not statistically significant p = .144 confirming the model is correctly specified. The -2 log Likelihood = 263.149 and the Nagelkerke R2= .083 indicating the model predicted 8.3% of the median physician usage of the HHIE. The model sensitivity is 88.0%, specificity is 22.2%, and the fit indicates 62.1% positive classification resulting from the logistic model.

Of the predictor variables, medical specialty was found statistically significant (p < .05) when comparing HHIE use between specialty physicians to primary care and emergency room physicians while controlling for age, gender, and location. The findings indicate that primary care physicians had a 2.011 higher odds, or twice as likely to use the HHIE [Exp*(B)* = [2.011], 95% CI (1.055, 3.803), *p* = .034] compared to specialists. No other predictor variables calculated significance. The model proved significance for the physician factor of HHIE usage between medical specialties. Due to this finding, the null hypothesis was rejected and the alternate hypothesis was accepted stating there is a predictive relationship between medical specialty and HHIE usage (number of logins). These findings are reported in Table 6.

Table 10

Logistic Regression Recoded at Above the Median Number of Logins: Individual predictors for the Extent of HHIE Use with the Removal of Outliers (n = 206)

				95% CI for odds ratio	
	B	*p-value*	Exp*(B)*	Lower	Upper
Gender	-.046	.892	.955	.489	1.864
Age < 35	.313	.661	1.367	.338	5.534
Age 35-44	.446	.358	1.562	.604	4.043
Age 45- 54	.211	.641	1.236	.508	3.003
Age 55-64	-.416	.329	.660	.286	1.520
Primary care	.698	.034	2.011	1.055	3.830
Emergency medicine	.761	.104	2.140	.855	5.354
Hawaii county	-.678	.265	.508	.154	1.673
Maui county	-.267	.598	.765	.283	2.068
Kauai county	20.249	1.000	622422081.009	0.000	
Constant	.044	.905	1.045		

Note: Gender is for males compared to females; age is compared to age group 65 and over, medical specialty is compared to specialists, and Hawaii counties are compared to the county of Oahu.

Summary

In this quantitative study I constructed two research questions to analyze physician use, the first examined whether a provider who has signed up to view the HHIE community health record had ever logged into the system as determined by login or no login. Secondly, for those who had logged in, how many times have they accessed the HHIE as determined by login count. The variables extracted from HHIE login data were physician age, gender, medical specialty, and practice location.

To address the first research question I created a logistic regression model to evaluate differences between physician factors and HHIE use. The logistic regression model passed assumptions, yet the model fit only explained 1.3% of the variation of HHIE use. Due to this low percentage findings could not be generalized well. In review of the statistical findings, the regression model indicated a significant relationship (p = .038) between HHIE use and emergency medicine physicians when compared to medical specialists and controlling for all other variables. Specifically, emergency medicine physicians had 1.6 higher odds of using the HHIE, no other physician factors were found to be significant. The significant finding for medical specialty caused me to reject the null hypothesis and accept the alternate hypothesis for HHIE use (login vs. no login).

The second research question reviewed HHIE usage by evaluating login counts as the continuous dependent variable. A multiple linear regression model was initially constructed with all login counts of 1 and greater (n = 273). The model was found to be a poor fit and did not maintain the assumptions of linearity and normality. To correct these assumptions a second linear regression model was constructed, the model used a transformed (log10) dependent variable and retained all independent variables. The model continued to find significance for medical specialty groups of emergency medicine physicians and for primary care providers. However, the model was a poor fit and failed the assumptions of linearity, normality, and contained outliers. The model was rejected and proved inconclusive.

A third multiple regression model was ran using the transformed dependent variable and all previous predictor variables. The model eliminated login counts at 5% of the high and low continuum, the resulting model contained $n = 206$. Consistent with the previous model, the updated calculations also predicted an increase of .234 logins for every one unit increase for emergency medicine physicians and an increase of .196 logins for primary care physicians. However, tests for multicollinearity, linearity, and normality failed assumptions and the model was found bias and inconclusive.

A final logistic regression model was created to evaluate previous findings and confirm results. Using the multiple linear regression data with removed outliers ($n = 206$), the dependent variable was recoded to record data above and below the median number of logins. Logins less than seven were coded as "0" and logins seven and greater were coded as "1". All previous independent variables were used in the model. Assumptions for the model were maintained to include a dichotomous dependent variable, an independence of observations, and multicollinearity. The model predicted 8.3% of the median physician usage of the HHIE. Results from the regression indicate for every unit increase, primary care physicians had 2.011 higher odds of using the HHIE compared to specialists when controlling for all other variables. No other predictor variables calculated significance. The significant finding for medical specialty caused the rejection of the null hypothesis and acceptance of the alternate hypothesis. This finding confirmed a predictive relationship for the extent of HHIE usage based on medical specialty.

Chapter 5 provides a working interpretation of key findings collected from the regression models. I will relate these findings to existing literature and to the TAM framework used as the theoretical model for the study. A discussion of the study limitations will be fully reviewed, and I will also explore recommendations for future research and social change.

Chapter 5: Discussion, Conclusions, and Recommendations

Introduction

In this study, I researched physician use of the HHIE by evaluating the total population of Hawaii physicians signed up for the HHIE community health record. To accomplish this, I first used a logistic regression model to evaluate whether medical specialty, age, gender, and location were significant predictors of any use. I then used multiple linear regression to assess the same predictor variables to determine extent of use, as calculated from the continuous number of logins. To address violations in the linear regression model assumptions, an additional logistic regression model was created using the transformed dependent variable to evaluate use above and below the median number of logins. The independent variables aligned with the previous research conducted on the TAM regarding PU, as represented in this study by medical specialty and location, and PEOU, as represented in this study by age and gender.

The total population for the study consisted of 1034 HHIE physician users, or 36% of Hawaii physicians directly involved in delivering patient care. The subpopulation of physician users who had signed up for the HHIE and had logged into the HHIE at least one time consisted of 273 users or 26% of the physician population included in the study. Medical specialty was found to be a statistically significant predictor when reviewing use and usage among primary care and emergency medicine physicians compared to specialists. Due to this finding, the alternate hypothesis was retained for the research questions in the study. The independent variables of age, gender, or location were not statistically significant predictors of use or the extent of use.

However, in reviewing the data, I found subtle outcomes that could be used in future studies on HIEs. In this chapter, I will review key discoveries and discussion points from the research study.

Interpretation of Findings

The broad findings from this study confirm findings from earlier research that HIEs continue to have limited utilization by the physician population (Rudin et al, 2011; Vest et al., 2015). The study results indicate that only 36% of Hawaii physicians have signed up to use the HHIE community health record, and of those who have signed up, only 26% have logged into the system. The independent variables included in the study of age, gender, and location were not significant predictors of HHIE use. Medical specialty was found to be statistically significant. Therefore, this variable can be used as a predictor of HHIE use and usage. As a result of this finding, the alternate hypothesis was accepted and RQ1 (use) and RQ2 (extent of use).

Technology Acceptance Model

Davis (1989) introduced the TAM to evaluate end-user acceptance of new technologies. Davis targeted end-user acceptance of health communication technologies, a focus which aligned with my evaluation of HIEs. The main constructs of the TAM include PU and PEOU to measure BI of actual use. Previous researchers conducted many studies to focus on health information system implementation and adoption, while very few studies clearly outline how physicians are actually using the technology in practice (Holden & Karsh, 2010). PU relates to the degree that a system is thought to improve job performance while PEOU is defined as the extent to which a user believes that a system is free of effort (Davis, Bagozzi, & Warshaw, 1992). For this study, PU and PEOU were operationalized as use (whether or not a user logged in) and extent of use (number of times logging in). I assessed whether physician specialty, location, age, or gender were predictive of HHIE use or extent of use.

Medical specialty as a predictor. In researching medical specialty, I compared specialists to primary care and emergency medicine physicians to evaluate use of the HHIE between groups. Previous researchers using the TAM model to assess differences between medical specialties found statistically significant differences between primary care and specialists using EHR systems (Gagnon et al., 2013), and a moderating factor for surgeons and pathologists using clinical technology systems (Melas et al., 2011).

For my study, the regression model compared primary care and emergency medicine physicians to physician specialists in terms of use. When compared to specialists, emergency medicine physicians were found to have a statistically significant relationship for using the HHIE. The data suggests they were 57% more likely or had significantly higher odds to login in at least once. In reviewing the multiple regression model to evaluate usage (login counts), for every unit increase in login counts emergency medicine physicians predicted an additional 0.684 logins and primary care predicted an increase of 0.673 logins compared to specialists.

The multiple linear regression model was run again removing participants with logins above and below 5% of study outliers. The model continued to calculate significance for emergency medicine and primary care physicians. A final logistic regression model was used to evaluate logins above and below the median login count of seven. Primary care physicians were found to have significantly higher odds of using the HHIE above the median login when compared to specialists. As a collective result of these findings, the analysis included in the research indicates that emergency medicine physicians have a higher likelihood of logging into the HHIE, and primary care physicians have a higher likelihood of frequenting the system compared to specialists. This finding is congruent with previously conducted research on electronic medical record use and medical specialties (Gagnon et al., 2013). These findings can also be further aligned with previous research conducted directly on emergency departments' use of HIEs (Vest 2010; Vest et al., 2011; Yaraghi, 2015).

Location as a predictor. Differences in physician location was studied by evaluating HHIE use between the counties of Hawaii. The state of Hawaii's unique composition is geographically challenging when trying to truly understand use in terms of location as each island is divided by miles of Pacific Ocean. For this study, I compared HHIE use between the four Hawaii counties to evaluate any predictive physician behaviors. One limited study using the TAM model on a small group of Hawaii pediatricians to evaluate BI through a mailed questionnaire found the theoretical aspects surrounding PEOU were not supported within the population of physician users (Chismar & Wiley-Patton, 2003). However, the study did not discern study demographics beyond age and gender. Withy (2017) found that physician shortages affect each county based on supply, demand, and population. Understanding the distinctive challenges for each county is an important aspect in researching predictive relationships to use technology which is addressed in this study. I could not locate any other studies in which the TAM was applied to the state of Hawaii or technology use between state counties.

For the study HHIE use was compared against the county of Oahu, this was based on Oahu having the highest number of HHIE users. Compared with physicians in Oahu county, Hawaii county physicians were 27% more likely to login, Maui physicians were 15% more likely to login, and Kauai physicians were 68% less likely to login. Although not statistically significant, results from the multiple linear regression predicted a slightly higher number of logins for Kauai county and for Maui County. Collectively the results also show in comparison to Oahu slight tendencies for higher HHIE participation on the islands of Hawaii and Maui and higher login counts for the counties of Maui and Kauai. Of interest, Withy (2017) cites that specialty care is often sought on the island of Oahu, yet HHIE use and usage proved lower within this county compared to the neighbor islands. Further studies on primary care physicians within Oahu, Hawaii, Maui, or Kauai counties may be warranted to understand their care coordination needs and if the HHIE is fulfilling gaps in communication.

Age as a predictor. In previous studies age was widely used as an independent variable within the TAM theory. In terms of behavioral intention to use information systems, age was found to predict computer self-efficacy among adults (Chung et al., 2010). Another study specific to physicians, age quantified by 50 years of age and older was also proven to have statistical significance ($p = 0.032$) with limited computer use (Gagnon et al., 2013). The association of older physicians to lower EHR system adoption was also confirmed in a number of prior studies (Bae & Encinosa, 2016; Decjer et al., 2012; Hamid & Cline; 2013). Conversely, in other studies age was found to hold no predictive relationship with EHR adoption (Hudson et al., 2012) or HIE use (Gadd et al., 2011) similar to the outcomes in this study. The logistic regression, although not statistically significant, pointed towards a decrease use and extent of use with an increase in age. Results indicate when compared to the age group of 65 and over, a 4% decline in likeliness to login. Similarly, HHIE usage (number of logins) reported similar for physicians age 35 to 64, then trended downward for physicians aged 65 and over. Taken together, these results indicate that HHIE use decreased with age.

Gender as a predictor. Gender has also been extensively studied within the framework of the TAM to extend knowledge on differences between male and female users. In this study, gender was found to have no predictive relationship with use or amount of use of the HHIE. This is consistent with previous research findings on HIE use (Furukawa et al., 2014; Gadd et al., 2011). According to the Association of American Medical Colleges (2016) the number of women enrolled in medical school increased by 6.2% in 2016 which is a start to leveling the gender distribution in the profession. As female medical school enrollees continue to rise, gender may continue as a variable of interest to predict behavior related to using health information technology. Although findings from this study were not statistically significant, it is important to note that there was almost no difference between HHIE physicians who have signed up for the HHIE with behavior to login. Perhaps future studies may reveal differences in gender as females appear to have a marginally higher system usage (number of logins) than their male counterparts for the data collected.

Limitations of the Study

The total population of physicians included in this study had similar characteristics to the overall population of physicians practicing in the state of Hawaii as well as the demographic composition to national averages in the United States. However, the use of the HHIE by office staff or clinical support personnel on behalf of the physician is not indicated within the physician's login activity. The total file of HHIE user activity contained 127,839 logins between the months of January 1, 2016 to June 30, 2017. This study only contained 9% of those logins, indicating that the majority of the logins were by non-physician participants in the HHIE. Inclusion of the non-physician population in future studies could assist in determining the complete range of first hand and second hand information physicians are retrieving from the HHIE.

A second limitation of the study is the limited data available for analysis. The HHIE is relatively new to the state and data collection processes are improving as the system matures. The study was limited to the information available through the HHIE and public resources. In the future, improved reported analytics from the HHIE may help understand which screens are frequented and in what order. In a prior study Vest and Jasperson (2012) reviewed session information from and user patterns within an HIE application, and they were able to report on whether clinical information was accessed or viewing was limited to demographic or visit data. Information on the screens viewed and information sought within the HHIE may help identify the needs of the physician when using an HIE to coordinate care.

Recommendations

Overall there remain very few studies on HIEs, particularly how they are being used in practice and the impact of health care exchanges to health care delivery. This study was a first in two respects: it was the first study on HIEs to be conducted in the state of Hawaii and it was the first to evaluate specific HIE physician characteristics based upon archival data from login activity under the constructs of the TAM. My initial recommendation is to continue to review the variables in this study over longer periods of time as HIEs mature and becomes fully understood in practice. Longitudinal studies lend valuable insight into how systems mature and develop (Frankfort-Nachmias & Nachmias, 2008). Time studies could be of interest as gender gaps between the percentage of male and female physicians level. In the future generational gaps will also be normalized when physicians 65 and over start to retire, and physicians 35 and younger continue to enter the workforce. For Hawaii, HIE use between counties will also dynamically change longitudinally while new areas on the islands develop causing the population to shift geographically.

Although this study was quantitative approach, further studies expanding upon the variables of medical specialty, age, and gender may also prove supportive to understand factors of HIE use among physicians. Previous research sought qualitative methods of interviewing end users (Gadd et al., 2011; Politi et al., 2015; Unertl, Johnson, & Lorenzi, 2011; Yeager et al., 2014) as a means to understand HIE use. A mixed method approach may match quantitative analysis findings with qualitative outcomes to fully understand barriers of use beyond login activity. Previously Frisse et al. (2012) conducted a mixed-methods study to review HIE usage within emergency departments. The study included login data as well as semi-structured interviews and direct observation. Another quantitative method could be the development of a questionnaire as done by previous HIE researchers (Adler-Milstein, Bates, & Jha, 2011).

Meaningful use programs and federal mandates continue as an important factor in understanding how HIEs are influencing health care communication. CMS (2017) released final rules on MU stage three objectives; contained in these measures is the ongoing requirement to participate in a health exchange to communicate patient centric information. Although providers are able to choose a transmission method to send and retrieve information, HIEs remain as a suitable option for satisfying this measure. Future studies should continue to take federal incentive program participation into account when reviewing provider activity within HIEs. If providers are not involved in an incentive program, it may decrease their willingness to participate in an exchange leaving gaps in the continuity of care for the patient.

The focus of this study was to exclusively review physician factors of HHIE use therefore only physicians with an MD or DO were included in the analysis. The inclusion of a limited population was a strength of the study because findings could be applied to similar physician populations. Future studies may be able to use the same data set to evaluate all user activity between medical specialties, role, and HHIE use between Hawaii counties. If users are able to be mapped back to a health care provider or practice, a better depiction of how a physician is using the HHIE in its entirety may be realized. Additional mid-level credentialed providers such as physician assistants, nurse practitioners, and pharmacists have also signed up to view the HHIE community health record. A separate analysis of this population using the same variables could be a potential area of concentration to evaluate HHIE utilization.

Implications

Although age, gender, or location did not prove to be statistically significant predictors of HHIE use, results from the study continue to add to the body of knowledge on the role of HIEs in health care. Foremost, the study revealed the continued trend of HIE underutilization, even in a state where care coordination is geographically challenging. Health care providers in underserved areas like Hawaii must continue to use technology as a way to coordinate care and close gaps in health care coverage. Similar to nationwide physician shortages, Hawaii's shortage is forecasted as 800 to 1500 full-time providers by year 2020 (Withy et al., 2017). Progressive tracking of how well Hawaii physicians are using technology and addressing current barriers will be imperative to consistently providing for the growing health care needs of the community. From the results of the study, it is discovered that very few providers have signed up for the HHIE in the counties of Hawaii, Maui, and particularly Kauai. The limited amount of physicians who have signed up may be an opportunity for onboarding efforts within these counties. Another implication of the study is to seek additional variables outside of age, gender, and medical specialty for evaluation as barriers to HIE use since these factors were not statistically significant. Previous studies have used practice size and attestation for federal programs as incentives to participate in health exchanges (Furukawa et al., 2012). As government mandates evolve year after year, so will the focus of many providers. Incentives and barriers to using technology like HIEs will need to be constantly evaluated for continued participation.

Future implications for positive social change as a result of the study centered on the state of Hawaii shows differences in the use of the HHIE based on medical specialty. The study indicated emergency medicine physicians were more likely to login to the HHIE compared to specialists and primary care physicians. This is a positive implication for emergency and critical care for the islands because critical care is often sought on the island of Oahu where majority of the state's health care resources are located (Withy et al., 2017). Greater information sharing using the HHIE for emergency medicine providers could indicate an increased opportunity to retrieve critical information while the patient is in transit from another island, or while consulting a neighbor island provider prior to a patient transfer. An additional area of future research could evaluate Hawaii emergency room visit outcomes due to the information sharing using an HIE in comparison to those visits where an HIE was not accessed.

The TAM was used as the theoretical basis of this study measuring PU and PEOU to predict the intention to use an HIE. I could not locate any other studies that used the TAM in the research design employed within this study. Future studies can draw from this research design and the variables used to test further iterations of the TAM such as the TAM2 model or the Unified Theory of Acceptance and Use of Technology (UTAUT).

In terms of policy, the low use of HIEs appears troubling in achieving the outcomes of interoperability that federal incentive programs hoped to accomplish. One of the major aims of meaningful use attainment was to first adopt an EHR to capture structured data, then to exchange the data during care transitions to allow providers to reconcile a subset of critical information (Cohen & Adler-Milstein, 2015). An additional finding noted from this study is the consistency between the percentage of providers that have signed up for the HHIE and those that have demonstrated Meaningful Use. The Office of the National Coordinator (2016) states that 34% of Hawaii office-based physicians have demonstrated meaningful use, which is consistent with the finding from this study that 36% of Hawaii practicing physicians have signed up for the HHIE. Yet, in terms of actual use, only 26% of those who have signed up have ever logged in. A policy implication for future consideration is the potential requirement of active participation evidenced by use.

Conclusions

In this study, I evaluated factors for using the HHIE for Hawaii physicians. Using archival data, I analyzed the predictive relationship between HHIE utilization and the variables of medical specialty, age, gender, and location. The first logistic regression model measured whether a provider who has signed up to the use the HHIE ever logged in. The study concluded a statistically significant relationship between the predictor variable of medical specialty and use. It was found that emergency medicine physicians were more likely to login to the HHIE compared to specialists therefore the null hypothesis was rejected and the alternate hypothesis was accepted.

Next, the study also concluded a predictive relationship between the variables of medical specialty and HHIE usage. Emergency medicine physicians and primary care physicians calculated a predictive increase in login counts when compared to specialists. Emergency medicine physicians were also found to be statistically significant in the revised logistic regression model evaluating login counts above the median. This is important aspect when evaluating implications of the study as emergency medicine physicians are using the system more than their physician counterparts. Having historical patient information readily available at any time is vital in a state where most of the critical care resources are located on the island of Oahu. A final logistic regression was created to address failed assumptions from the multiple linear regression models to assess HHIE usage. The model determined a significant relationship between primary care physicians and HHIE usage.

The aim of the study was to evaluate predictive relationships to better comprehend physician patterns of using health exchanges for care coordination. If predictive patterns were present in the study, barriers of use within the focus of age, gender, or location could also be addressed and outreach programs could be assembled to onboard physicians to health exchanges. Ultimately medical specialty was the only variable with a predictive relationship for HHIE use and usage leaving future research to expand on the role of physician specialty and HIE use and seek additional physician factors. Overall this study adds to the body of knowledge known on HIE use within the state of Hawaii, findings could be applied to similar physician populations nationally for future studies on health exchanges and health care coordination.

References

Adler-Milstein, J., Bates, D. W., & Jha, A. K. (2011). A survey of health information exchange organizations in the United States: Implications for meaningful use. *Annals of Internal Medicine*, *154*(10), 666-671. doi:10.7326/0003-4819-154-10-201105170-0000

Adler-Milstein, J., & Jha, A. K. (2014). Health information exchange among U.S. hospitals: Who's in, who's out, and why? *Healthcare 2*(1), 26-32. doi:10.1016/j.hjdsi.2013.12.005

Alicata, D., Schroepfer, A., Unten, T., Agoha, R., Helm, S., Fukuda, M., . . . & Michels, S. (2016). Telemental health training, team building, and workforce development in cultural context: The Hawaii experience. *Journal of Child and Adolescent Psychopharmacology, 26*(3), 260-265. doi:10.1089/cap.2015.0036

Association of American Medical Colleges. (2016). *Number of female medical school enrollees reaches 10-year high* [Press release]. Retrieved from https://news.aamc.org/press-releases/article/applicant-enrollment-2016/

American Academy of Family Physicians. (2017). *Primary care*. Retrieved from http://www.aafp.org/about/policies/all/primary-care.html#use

American Hospital Association. (2015). *Rethinking the hospital readmissions program.* Retrieved from http://www.aha.org/research/reports/tw/15mar-tw-readmissions.pdf

Bae, J., & Encinosa, W. E. (2016). National estimates of the impact of electronic health records on the workload of primary care physicians. *BMC Health Services Research*, *16,* 172-194. doi:10.1186/s12913-016-1422-6

Ben-Assuli, O., Shabtai, I., & Leshno, M. (2013). The impact of EHR and HIE on reducing avoidable admissions: Controlling main differential diagnoses. *BMC Medical Informatics and Decision Making*, *13,*49-59. doi:10.1186/1472-6947-13-49

Charles, D., Gabriel, M., & Searcy, T. (2015). Adoption of electronic health record systems among U.S. non-federal acute care hospitals. *ONC Data Brief, 23*, 1-10. Retrieved from https://www.healthit.gov/sites/default/files/data-brief/2014HospitalAdoptionDataBrief.pdf

Chen, R. F., & Hsiao, J. L. (2012). An investigation on physicians' acceptance of hospital information systems: A case study. *International Journal of Medical Informatics*, *81*(12), 810-820. doi:10.1016/j.ijmedinf.2012.05.003

Chin, B. J., & Sakuda, C. M. (2012). Transforming and improving health care through meaningful use of health information technology. *Hawai'i Journal of Medicine & Public Health*, *71*(4 Suppl 1), 50-55. doi:10.1016/j.ijmedinf.2012.05.003

Centers for Disease Control and Prevention. (2016). *Meaningful use: Introduction.* Retrieved from https://www.cdc.gov/ehrmeaningfuluse/introduction.html

Centers for Medicare and Medicaid Services. (2016.). *National health expenditures 2015 highlights*. Retrieved from https://www.cms.gov/research-statistics-data-and-systems/statistics-trends-and-reports/nationalhealthexpenddata/downloads/highlights.pdf

Centers for Medicare and Medicaid Services. (2015). Meaningful Use. *Stage 2 specification sheet table of contents for eligible hospitals and CAHs*. Retrieved from https://www.cms.gov/Regulations-and-Guidance/Legislation/EHRIncentivePrograms/Downloads/Stage2_MeaningfulUseSpecSheet_TableContents_EligibleHospitals_CAHs.pdf

Centers for Medicare and Medicaid Services. (2015). Meaningful Use. *Stage 3 program requirements for providers attesting to their state's medicaid EHR incentive program.* Retrieved from https://www.cms.gov/Regulations-and-Guidance/Legislation/EHRIncentivePrograms/Stage3Medicaid_Require.html

Centers for Medicare and Medicaid Services. (2017). Meaningful Use. *Medicaid EHR incentive program health information exchange objective stage 3*. Retrieved from https://www.cms.gov/Regulations-and-Guidance/Legislation/EHRIncentivePrograms/Downloads/HealthInformationExchange_Stage3Medicaid.pdf

Chismar, W. G., & Wiley-Patton, S. (2003). Does the extended technology acceptance model apply to physicians. In *Proceedings of the 36th Annual Hawaii International Conference* (pp. 8-pp). Washington, DC: IEEE Computer Society.

Creswell, J. W. (2012). *Qualitative inquiry and research design: Choosing among five approaches*. Thousand Oaks, CA: SAGE Publications.

Cohen, G. R., & Adler-Milstein, J. (2015). Meaningful use care coordination criteria: Perceived barriers and benefits among primary care providers. *Journal of the American Medical Informatics Association*, *23*(e1), e146-e151. doi:10.1093/jamia/ocv147

Daniel, O. E., & Mensah, E. K. (2015). Effects of HIE/HIT implementation and coordination of care on health outcomes and quality. *AMIA Annual Symposium Proceedings,* 2015, 532. Retrieved from https://www.ncbi.nlm.nih.gov/pmc/articles/PMC4765664/

Davis, F. D. (1989). Perceived usefulness, perceived ease of use, and user acceptance of information technology. *MIS Quarterly*, *13*(3), 319-340.

Davis, F. D., Bagozzi, R. P., & Warshaw, P. R. (1989). User acceptance of computer technology: A comparison of two theoretical models. *Management science*, *35*(8), 982-1003. doi:10.1287/mnsc.35.8.982

Davis, F. D., Bagozzi, R. P., & Warshaw, P. R. (1992). Extrinsic and intrinsic motivation to use computers in the workplace. *Journal of Applied Social Psychology, 22*(14), 1111-1132. doi:10.1111/j.1559-1816.1992.tb00945.x

Decker, S. L., Jamoom, E. W., & Sisk, J. E. (2012). Physicians in nonprimary care and small practices and those age 55 and older lag in adopting electronic health record systems. *Health Affairs*, *31*(5), 1108-1114. doi:10.1377/hlthaff.2011.112

Dullabh, P., Moiduddin, A., Nye, C., & Virost, L. (2011). *The evolution of the State Health Information Exchange Cooperative Agreement Program: State plans to enable robust HIE*. NORC at the University of Chicago.

Egea, J. M. O., & González, M. V. R. (2011). Explaining physicians' acceptance of EHCR systems: An extension of TAM with trust and risk factors. *Computers in Human Behavior, 27*(1), 319-332. doi:10.1016/j.chb.2010.08.010

Esmaeilzadeh, P., & Sambasivan, M. (2016). Health information exchange (HIE): A literature review, assimilation pattern and a proposed classification for a new policy approach. *Journal Of Biomedical Informatics*, *64,*74-86. doi:10.1016/j.jbi.2016.09.011

Field, A. (2013). *Discovering statistics using IBM SPSS Statistics* (4th ed.). Thousand Oaks, CA: SAGE Publications.

Fingar, K., & Washington, R. (2015, November). *Trends in hospital readmissions for four high-volume conditions, 2009-2013* [Statistical brief 196]. Rockville, MD: Agency for Healthcare and Research Quality. Retrieved from https://www.hcup-us.ahrq.gov/reports/statbriefs/sb196-Readmissions-Trends-High-Volume-Conditions.pdf

Fishbein, M., & Ajzen, I. (1975). *Belief, attitude, intention, and behavior: An introduction to theory and research*. Reading, MA: Addison-Wesley.

Frisse, M. E., Johnson, K. B., Nian, H., Davison, C. L., Gadd, C. S., Unertl, K. M., ... & Chen, Q. (2012). The financial impact of health information exchange on emergency department care. *Journal of the American Medical Informatics Association, 19*(3), 328-333. doi:10.1136/amiajnl-2011-000394

Frankfort-Nachmias, C., & Nachmias, D. (2008). *Research methods in the social sciences* (7th ed.). New York, NY: Worth.

Furukawa, M. F., King, J., Patel, V., Hsiao, C., Adler-Milstein, J., & Jha, A. K. (2014). Despite substantial progress in EHR adoption, health information exchange and patient engagement remain low in office settings. *Health Affairs, 33*(9), 1672-1679. doi:10.1377/hlthaff.2014.0445

Gadd, C. S., Ho, Y., Cala, C. M., Blakemore, D., Chen, Q., Frisse, M. E., & Johnson, K. B. (2011). User perspectives on the usability of a regional health information exchange. *JAMIA*, *18*(5), 711-716. doi:10.1136/amiajnl-2011-000281

Gagnon, M. P., Ghandour, E. K., Talla, P. K., Simonyan, D., Godin, G., Labrecque, M., ... & Rousseau, M. (2014). Electronic health record acceptance by physicians: testing an integrated theoretical model. *Journal of Biomedical Informatics*, *48*, 17-27. doi:10.1016/j.jbi.2013.10.010

Gerber, S. B., & Finn, K. V. (2013). *Using SPSS for Windows: Data analysis and graphics*. Springer. New York, NY.

Gorski, J. K., Batt, R. J., Otles, E., Shah, M. N., Hamedani, A. G., & Patterson, B. W. (2016). The impact of emergency department census on the decision to admit. *Academic Emergency Medicine*, *24*(1), 13-21. doi:10.1111/acem.13103

Hamid, F. & Cline, T. (2013). Providers' acceptance factors and their perceived barriers to electronic health record (EHR) adoption. *Online Journal of Nursing Informatics, 1*(3).

Hawaii Island Beacon Community. (2013). *Care coordination*. Retrieved from http://www.hibeacon.org/indexphp/initiatives/care_coordination/

Hawaii Health Information Exchange. (n.d.). *About us*. Retrieved from https://www.hawaiihie.org/content/about-us

Hawaii Health Information Exchange. (2016). *A year of growth for the Hawai'i health information exchange*. Retrieved from https://hawaiihie.org/sites/default/files/sites/default/files/Map%20Infographic%205.pdf

HealthIT. (2013). *Health information exchange governance*. HealthIT.gov. Retrieved from https://www.healthit.gov/policy-researchers-implementers/health-information-exchange-governance

HealthIT. (2014). *State health information exchange.* HealthIT.gov. Retrieved from https://www.healthit.gov/policy-researchers-implementers/state-health-information-exchange

HealthIT. (2016). *What is an electronic health record.* HealthIT.gov. Retrieved from https://www.healthit.gov/providers-professionals/electronic-medical-records-emr

Holden, R. J., & Karsh, B. T. (2010). The technology acceptance model: Its past and its future in health care. *Journal of Biomedical Informatics*, *43*(1), 159-172. doi:10.1016/j.jbi.2009.07.002

Hsiao, J., & Chen, R. (2016). Critical factors influencing physicians' intention to use computerized clinical practice guidelines: An integrative model of activity theory and the technology acceptance model. *BMC Medical Informatics and Decision Making*, *16*(1), 3. doi:10.1186/s12911-016-0241-3

Hsiao, C. J., King, J., Hing, E., & Simon, A. E. (2015). The role of health information technology in care coordination in the United States. *Medical Care*, *53*(2), 184-190. doi:10.1097/MLR.0000000000000276.

Hudson, J. S., Neff, J. A., Padilla, M. A., Zhang, Q., & Mercer, L. T. (2012). Predictors of physician use of inpatient electronic health records. *The American Journal of Managed Care*, *18*(4), 201-206. doi:10.1111/acem.13103

Jones, S. S., Friedberg, M. W., & Schneider, E. C. (2011). Health information exchange, health information technology use, and hospital readmission rates. In *AMIA Annual Symposium Proceedings* (Vol. 2011, p. 644). American Medical Informatics Association.

Kohn, L. T., Corrigan, J., & Donaldson, M. S. (2000). *To err is human: Building a safer health system*. Washington, DC: National Academy Press.

Kripalani, S., LeFevre, F., Phillips, C. O., Williams, M. V., Basaviah, P., & Baker, D. W. (2007). Deficits in communication and information transfer between hospital-based and primary care physicians: Implications for patient safety and continuity of care. *JAMA*, *297*(8), 831-841. doi:10.1001/jama.297.8.831

Laerd Statistics (2015a). *Binomial logistic regression using SPSS Statistics*. [Statistical tutorials and software guides]. Retrieved from https://statistics.laerd.com

Laerd Statistics (2015b). *Simple linear regression using SPSS Statistics*. [Statistical tutorials and software guides]. Retrieved from https://statistics.laerd.com/

Legris, P., Ingham, J., & Collerette, P. (2003). Why do people use information technology? A critical review of the technology acceptance model. *Information & Management*, *40*(3), 191-204.

Melas, C. D., Zampetakis, L. A., Dimopoulou, A., & Moustakis, V. (2011). Modeling the acceptance of clinical information systems among hospital medical staff: An extended TAM model. *Journal of Biomedical Informatics*, *44*(4), 553-564. doi:10.1016/j.jbi.2011.01.009

Morganti, K. G., Bauhoff, S., Blanchard, J. C., Abir, M., Iyer, N., Smith, A., … & Kellermann, A. L. (2013). The evolving role of emergency departments in the United States. *Rand Health Quarterly*, *3*(2), 3.

Morton, S., Shih, S. C., Winther, C. H., Tinoco, A., Kessler, R. S., & Scholle, S. H. (2015). Health IT-enabled care coordination: A national survey of patient-centered medical home clinicians. *Annals of Family Medicine*, *13*(3), 250-256. doi:10.1370/afm.1797

Palinkas, L. A., Horwitz, S. M., Green, C. A., Wisdom, J. P., Duan, N., & Hoagwood, K. (2015). Purposeful sampling for qualitative data collection and analysis in mixed method implementation research. *Administration and Policy in Mental Health*, *42*(5), 533-544. doi:10.1007/s10488-013-0528-y

Patel, V., Abramson, E. L., Edwards, A., Malhotra, S., & Kaushal, R. (2011). Physicians' potential use and preferences related to health information exchange. *International Journal of Medical Informatics*, *80*(3), 171-180. doi:10.1016/j.ijmedinf.2010.11.008

Politi, L., Codish, S., Sagy, I., & Fink, L. (2015). Use patterns of health information exchange systems and admission decisions: Reductionistic and configurational approaches. *International Journal of Medical Informatics*, *84*(12), 1029-1038. doi:10.1016/j.ijmedinf.2015.06.012

Randall, D. (2014). Policy challenges of electronic health records and meaningful use. *Health Med Information, 5(165),* 1-2. doi:10.4172/2157-7420.1000165

Rudin, R. S., & Bates, D. W. (2014). Let the left hand know what the right is doing: A vision for care coordination and electronic health records. *JAMIA*, *21*(1), 13-16. doi:10.1136/amiajnl-2013-001737

Rudin, R. S., Motala, A., Goldzweig, C. L., & Shekelle, P. G. (2014). Usage and effect of health information exchange: A systematic review. *Annals of Internal Medicine*, *161*(11), 803-811. doi:10.7326/M14-0877

Rudin, R., Volk, L., Simon, S., & Bates, D. (2011). What affects clinicians' usage of health information exchange? *Applied Clinical Informatics*, *2*(3), 250-262.

The Office of National Coordinator for Health Information Technology. (n.d.). *A 10-year vision to achieve an interoperable health IT infrastructure.* Retrieved from https://www.healthit.gov/sites/default/files/ONC10yearInteroperabilityConceptPaper.pdf

Thompson, B., Diamond, K. E., McWilliam, R., Snyder, P., & Snyder, S. W. (2005). Evaluating the quality of evidence from correlational research for evidence-based practice. *Exceptional Children*, *71*(2), 181-194. doi:10.1177/001440290507100204

Trochim, W. (2006). Research methods knowledge base. *Descriptive Statistics*. Retrieved from https://www.socialresearchmethods.net/kb/statdesc.php

Unertl, K. M., Johnson, K. B., & Lorenzi, N. M. (2011). Health information exchange technology on the front lines of healthcare: Workflow factors and patterns of use. *JAMIA*, *19*(3), 392-400. doi:10.1136/amiajnl-2011-000432

U.S. Department of Health & Human Service. (n.d.). HITECH act enforcement interim final rule. Retrieved from https://www.hhs.gov/hipaa/for-professionals/special-topics/HITECH-act-enforcement-interim-final-rule/index.html?language=es

Venkatesh, V., & Davis, F. D. (2000). A theoretical extension of the technology acceptance model: Four longitudinal field studies. *Management Science*, *46*(2), 186-204.

Vest, J. R. (2010). More than just a question of technology: Factors related to hospitals' adoption and implementation of health information exchange. *International Journal of Medical Informatics*, *79*(12), 797-806. doi:10.1016/j.ijmedinf.2010.09.003

Vest, J. R., & Jasperson, J. (2012). How are health professionals using health information exchange systems? Measuring usage for evaluation and system improvement. *Journal of Medical Systems, 36*(5), 3195–3204. doi:10.1007/s10916-011-9810-2

Vest, J. R., Kern, L. M., Campion, T. R., Silver, M. D., & Kaushal, R. (2014). Association between use of a health information exchange system and hospital admissions. *Applied Clinical Informatics*, *5*(1), 219-231.

Vest, J. R., Kern, L. M., Silver, M. D., & Kaushal, R. (2015). The potential for community-based health information exchange systems to reduce hospital readmissions. *JAMIA*, *22*(2), 435-442. doi:10.1136/amiajnl-2014-002760

Vest, J. R., Zhao, H., Jasperson, J., Gamm, L. D., & Ohsfeldt, R. L. (2011). Factors motivating and affecting health information exchange usage. *JAMIA*, *18*(2), 143-149. doi:10.1136/jamia.2010.004812

Withy, K. (2015). *University of Hawai'i system annual report. Report to the legislature 2016*. Retrieved from https://www.hawaii.edu/offices/eaur/govrel/reports/2016/act18-sslh2009_2016_physician-workforce_annual-report.pdf

Withy, K. (2017). *University of Hawai'i system annual report. Report to the legislature 2017*. Retrieved from https://www.hawaii.edu/govrel/docs/reports/2017/hrs304a-1704_2017_hmec_annual-report.pdf

Withy, K., Mapelli, P., Perez, J., Finberg, A., & Green, J. (2017). Hawai‘i physician workforce assessment 2016: Improvement in physician numbers but physician suicides of concern. *Hawai'i Journal of Medicine & Public Health*, *76*(3 Suppl 1), 3-9.

Yeager, V. A., Walker, D., Cole, E., Mora, A. M., & Diana, M. L. (2014). Factors related to health information exchange participation and use. *Journal of Medical Systems*, *38*(8), 78-95. doi:10.1007/s10916-014-0078-1

Yaraghi, N. (2015). An empirical analysis of the financial benefits of health information exchange in emergency departments. *Journal of the American Medical Informatics Association: JAMIA*, *22*(6), 1169-1172. doi:10.1093/jamia/ocv068

Yarbrough, A. K., & Smith, T. B. (2007). Technology acceptance among physicians: a new take on TAM. *Medical Care Research and Review*, *64*(6), 650-672. doi:10.1177/1077558707305942

Appendix A: Data Use Letter

[redacted]

January 27, 2017

[redacted]

Kris K. Wilson

[redacted]

Dear Kris K. Wilson:

The [redacted] has agreed to share with you the following information for your doctoral study at Walden University.

- Count of log-in's to the [redacted] by user
- Number of [redacted] documents transmitted to the [redacted] participating healthcare organizations
- List of providers participating [redacted]

All usernames and/or personally identifiable information must be removed from your reported findings.

Sincerely,

[redacted]

Director [redacted]

[redacted]