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TITLE: Characterizing eHealth Behaviors Of Active Duty Service Members: A Cross-Sectional Analysis Of Patient Portal Use, Demographics, And Pre-Existing Health Conditions

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ABSTRACT

The Defense Health Agency is heavily invested in various eHealth tools to support the overall health and medical readiness of Active Duty Service Members. Initial studies discovered that the use of eHealth tools is positively associated with improved health outcomes, adherence to treatment, consumer-provider communication, and consumer satisfaction. The five chapters in this dissertation focused on characterizing the eHealth behaviors of Active Duty Service Members by evaluating patient portal use, demographics, and six pre-existing health conditions. The results provide new insight into the behaviors of using the Internet to seek information and manage health.

The eHealth Behaviors model guided the evaluation of literature and the methodology selection used in this study. The literature review evaluated the general population, retired military, and Active Duty Service Member populations using the Johns Hopkins Nursing Evidence Level scale. The methodology in this study used the novel and time-saving approach of acquiring and evaluating pre-existing audit log data from the TOL Patient Portal. Data in this study were acquired from the TOL Patient Portal 2017-2019 audit logs, and new dependent variables, guided by the eHealth Behaviors Model, were developed from these data. A cross-sectional analysis of patient portal use, demographics, and pre-existing health conditions on a sample of 198,399 Active Duty Service Members ages 18 to 65 was completed.

The results discovered were that most of the TOL Patient Portal users in 2018 were male, between the ages of 25-34, Caucasian, and married. Although, 26.58% of the total female Active Duty Service Member population used the portal compared to 13% of males. The mean age of both males and females is 31.80; the mean age of males is 32.53 and 29.98 for females. Most Active Duty Service Members used the TOL Patient Portal in Virginia, Texas, California,

Florida, North Carolina, Georgia, and Maryland in 2018. The highest patient portal use was from March to May. The top applications used were searching for appointments, viewing family member information, viewing personal health information, viewing medical encounters, and refilling medications. Being female, having at least one health condition, and sleep issues showed the most significant difference in mean use by login and actions per year. The strongest predictor of using the TOL Patient Portal three to eleven times by Active Duty Service Members is viewing family member health information and searching for appointments. The behaviors related to the use of an eHealth tool may help improve the perceptions of eHealth and may increase use of eHealth applications by Active Duty Service Members by contributing to the knowledge needed for the development of future systems, communication strategies, and military policy updates.

CHARACTERIZING EHEALTH BEHAVIORS OF ACTIVE DUTY SERVICE MEMBERS: A CROSS-SECTIONAL ANALYSIS OF PATIENT PORTAL USE, DEMOGRAPHICS, AND SIX GENERAL HEALTH CONDITIONS

by

Stephanie J. Raps

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DEDICATION

This dissertation is dedicated to my husband, Doug, and daughters, Emma, and Leah. Your unyielding love and support have inspired me to make the world a better place and complete this research. Also, Try, George, and Flash, our three dog angels, lost while in the program; I dedicate this to your endless loving souls running free in heaven.

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ABSTRACT

The Defense Health Agency is heavily invested in various eHealth tools to support the overall health and medical readiness of Active Duty Service Members. Previous researchers discovered that the use of eHealth tools improved health outcomes, adherence to treatment, consumer-provider communication, and consumer satisfaction. However, little is known about the characteristics and behaviors of Active Duty Service Members that use asynchronous eHealth tools and if having a health condition increases or decreases these behaviors. The purpose of this cross-sectional, retrospective study was to characterize the eHealth behaviors of Active Duty Service Members by evaluating the Military Health Systems Tricare Online (TOL) Patient Portal use, demographics, and six general health conditions.

The eHealth Behaviors model guided the evaluation and synthesis of literature and the methodology selection. The literature on the general population, retired military, and Active Duty Service Member populations was reviewed using the Johns Hopkins Nursing Evidence Level scale. The current study analyzed 2018 audit log data from the TOL Patient Portal. Dependent variables were developed from these data and included logins per year, actions per year, and moderate patient portal usage (i.e., three to eleven logins). A cross-sectional, retrospective analysis of patient portal use, demographics, and six general health conditions on a sample of 198,399 Active Duty Service Members ages 18 to 68 was completed. The behaviors were then compared between gender, rank, age, and six health conditions using overall frequency, data visualization, and Mann-Whitney testing. Three logistic regression models were then built to find what factors are most associated with moderate use of the portal or three to eleven logins per year.

Most of the TOL Patient Portal users in 2018 were between the ages of 25-34, Caucasian, and married. Twenty-seven percent of the total female Active Duty Service Member population used the portal compared to 13% of males. The mean age of males is 32.53 and 29.98 for females. Active Duty Service Members used the TOL Patient Portal more frequently in Virginia, Texas, California, Florida, North Carolina, Georgia, and Maryland compared to utilization in other U.S. states. The highest patient portal use was from March to May 2018. The top applications used were searching for appointments, viewing family member information, viewing personal health information, viewing medical encounters, and refilling medications. Being female, having at least one health condition, and sleep issues showed the most significant difference in mean use by login and actions per year. Active Duty Service Members with congenital health defects, anxiety, sleep issues, and depression have higher rates of moderate TOL Patient Portal use compared to users without a health condition. The strongest predictor of using the TOL Patient Portal at a moderate rate by Active Duty Service Members is viewing family member health information and searching for appointments. These results provide new insight into the behaviors of using a patient portal to seek information and manage health in the Active Duty Service Member population.

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CHAPTER ONE: INTRODUCTION

This dissertation is aimed to characterize electronic health (eHealth) behaviors of Active Duty Service Members by evaluating patient portal use, demographics, and six general health conditions. The manuscript comprises five chapters: Introduction, Literature Review, Methodology, Results, and Discussion. The first two chapters introduce eHealth behaviors and provide an in-depth description of the current online health information-seeking and patient portal literature. The last three chapters focus on the methodology used in this study, results, and a discussion of the results compared to recent literature.

INTRODUCTION

The term eHealth pertains to the utilization of information and communication technologies to enhance or deliver health services and information sharing (25). The Defense Health Agency, the U.S. Combat Support Agency that oversees the Military Health System, is heavily invested in eHealth, spending $4.3 billion in 2015 to purchase a new electronic health record (71), which includes various eHealth tools. Examples of eHealth tools include synchronous (i.e., directly interacting with healthcare team) technology like telehealth or remote monitoring and asynchronous (i.e., independent interactions of consumers) technology like patient portals, personal health records, secure messaging, and mobile health applications. This study focused on asynchronous eHealth behaviors. Common eHealth behaviors identified in the literature fall into two categories: online health information-seeking and online health management. Health information-seeking behaviors are the deliberate effort to acquire health-related information (63). The behaviors include awareness, attempt to access information, information use, and decision making (63). Health management is defined as the deliberate action to care for oneself (78) and maintain overall health or a health condition (36).

The use of eHealth tools has been linked to improved health outcomes (55; 73), enhanced adherence to treatment (34), better-quality consumer-provider communication (30), and increased consumer satisfaction (73; 89). Online health information-seeking, a standard measure of eHealth behaviors, has been associated with how consumers use other healthcare services (35). Researchers have used online health information-seeking along with sociodemographic variables of education, gender, ethnicity, income, marital status, homeownership, insurance status, and geographic location to identify possible predictors of eHealth behaviors and describe population characteristics of eHealth users (14; 15; 52; 57; 60; 61; 69; 77; 97). The online health information-seeking behaviors of populations that use eHealth tools have been evaluated using three primary research methodologies – conducting small scale surveys (45; 57; 68; 69; 74), secondary data analysis of large scale surveys (14; 15; 33; 52; 60; 61; 66; 93; 97), and retrospective analysis of eHealth utilization (9; 16; 98; 111). However, only a small body of literature exists evaluating online health information-seeking of Active Duty Service Members that use an eHealth tool. Existing research on the Active Duty Service Member population is often limited to evaluation of eHealth tools after implementation or only includes a single branch of the military.

The Military Health System facilitates Internet-based access to health information and self-care applications through the TriCare Online (TOL) Patient Portal, an asynchronous eHealth tool available since 2010. Approximately 15% of Active Duty Service Members used the TOL Patient Portal between 2017-2019 (88). A limited body of literature is available on the eHealth behaviors and characteristics of Active Duty Service Members that use a patient portal. It is also critical to understand how eHealth tools influence information seeking and self-management of Active Duty Service Members to support overall health and improve medical readiness. The background section reviews additional information on the eHealth behaviors explored in this study, followed by the problem statement and specific aims.

DEFINITION OF TERMS

Definitions of the primary terms used in this study are described below for reference.

- **Active Duty Service Member** – An individual that serves the military full-time (24 hours per day, seven days per week) in a service like the Army, Air Force, Navy, or Marine Corps, which fall under the direction of the U.S. Department of Defense (107).
- **Audit Log** – Collected to protect the information recorded and stored within an online application. Audit log data allow health organizations to fulfill the Health Insurance Portability and Accountability Act requirement to analyze how and when protected health information is accessed (1).
- **Consumer –** Consumer is associated with a more active role versus a patient as a passive role (27). A patient is a type of consumer. However, the term consumer is more encompassing and holds regardless of the individual’s health status (89).
- **Electronic Health (eHealth)** – The use of information and communication technologies to deliver or enhance health services and information (25).

- **Health Information-Seeking** – The deliberate effort to acquire health-related information.
- **Patient Portal** – A secure online resource that provides access to personal health information twenty-four hours a day through the Internet and permits consumers to message their provider, request prescription refills, schedule medical appointments, review benefits or insurance coverage, complete payments manage contact information, acquire educational materials, and download or complete forms (40).

BACKGROUND OF PROBLEM

A majority of consumers in the U.S. have access to the Internet; 90% of adults disclosed utilizing the Internet in their daily lives (83). The Active Duty Service Member population reports spending up to eight hours per week engaging in online activities like gaming, social networking, and shopping at home or in a deployed setting (12). Furthermore, researchers are reporting that consumers are increasingly engaging in the eHealth behaviors of online health information-seeking and online health management. Madrigal and Escoffery (68) found that 75.1% of adults utilize the Internet to search for health information and Lee et al. (57) discovered that 63% of adults access the Internet as an initial resource for health information. In the Active Duty Service Member Population, Bush et al. (12) found that members spend over 6 hours per week searching for various health information topics while at home and 4.2 hours in the deployed setting (12). However, little is known about the characteristics and behaviors of Active Duty Service Members that use asynchronous eHealth tools and if having a health condition increases or decreases these behaviors. The following sections provide background on asynchronous eHealth tools, online health information-seeking, and the adapted eHealth Behaviors Model that guided the development of this study.

Asynchronous eHealth Tools

Asynchronous eHealth tools are a type of electronic health tools that are largely consumer-oriented and primarily correspond with health information technology (i.e., technology that healthcare providers use) (89). A key topic to address is the use of the terms ‘consumer’ and ‘patient’ when referring to eHealth and the use of healthcare services and information. The term consumer is associated with a more active role, and the term patient is more passive (27). A patient is a type of consumer, but the term consumer is more encompassing – an individual, their family, or caregivers are all consider consumers despite their overall health status or type of healthcare services being utilized (89). Various types of asynchronous consumer tools included in eHealth literature are patient portals, personal health records, mobile health, secure messaging, and the use of wearables to track personal health data. Patient portals are the focus of this eHealth behavior study.

A patient portal is an online website accessible securely through the Internet. Patient portals connect consumers to their health information, offer convenient access to health services, and collect consumer-generated data. Patient portals allow consumers a direct link to their healthcare provider’s electronic health record to review recent doctor visits, discharge summaries, medications, immunizations, allergies, and laboratory results (41). Some portals have additional features such as secure messaging, prescription refill requests, appointment scheduling, insurance/billing features, and downloadable forms and educational material (40).

Health Information-Seeking

The seminal contribution of Longo's (2005) health information-seeking theory provides the operational definition used in this study. Health information-seeking is the deliberate effort to acquire health-related information, and the behaviors include awareness, attempt to access information, information use, and decision making (63-65). The concept of health information-seeking behavior was developed from information science in the 1980s and focused on self-monitoring, self-care, health promotion, and illness prevention in adults (54; 64). The ubiquitous growth of the Internet in the early 2000s shifted the focus from other mass media and paper-based health information resources, towards Internet-based resources and the development of eHealth tools (4; 53).

Awareness, the first concept of health information seeking, is the consumer's level of awareness of health information. Longo (63) found that "health information is not always intentionally sought" (p. 189), but the information is still useful to the consumer. Consumers are either aware or unaware of health information and this influences how a consumer actively or passively seeks information (63), which leads to a consumer's attempt to access information. At this level, the consumer is not always successful in accessing the information source (e.g., login into a website). If the consumer is able to access the information, the next behavior in this model is if the consumer used the information and did it support the user in making a personal health care decision (63).

Longo (63) also identified contextual and personal factors that predispose consumers to seek health information and the associated health information outcomes. The contextual factors include: delivery of care, healthcare structure, general environment factors, and if the consumer is seeking information for themself or someone else (63). The personal factors include: health and family history, demographic, socioeconomic, genetics, education, culture, language, attitude, and current health status (63). A short summary of literature evaluating the contextual and personal factors when seeking online health information is provided next.

Person & Environment

Various demographic factors that predispose consumers to seek health information have been identified in the literature. A consumer's gender, ethnicity, marital status, age, and education level have been found to influence the level of seeking health information. Environmental factors have been found to influence consumer behaviors and how they access health information to include Internet access (e.g., home or public access, speed of Internet), available technology (e.g., computer or smartphone), geographic location, and community (e.g., rural, metropolitan).

Women with a higher level of education have a long-standing association with seeking health-information (7; 10; 32; 43; 47; 54; 114). Age also influences the source of information used. For example, consumers younger than 45 lean towards friends as a source for health-information (48%), but the Internet is a close second at 45.8% (31). However, many researchers reported that consumers above age 60 utilize the Internet less frequently as a health information source compared to younger consumers (26; 47; 54; 109; 114). The relationship between online health information-seeking and marital status is unclear. Studies show that married consumers or consumers with a long-time partner have a higher frequency of seeking health information online (6; 102; 112). Bjarnadottir et al. (6) discovered that single or widowed consumers are not as likely to look for health information on the Internet but found no significant associations in married consumers.

Another important factor associated with utilizing the Internet for health information is ethnicity. Consumers who identify as African American and Caucasian have the highest frequency of health information seeking (15; 26; 49). Hispanic consumers are generally the least associated with utilizing the Internet for health information (6; 58; 59; 69). Geographic location is also related to the frequency of seeking health information online. African Americans, Caucasians, and Hispanics living in a rural location with Internet access report lower health information-seeking levels than consumers in metropolitan areas (85).

Finally, access to technology, speed of the Internet, type of technology, and the ability to use technology have been studied to identify associations when using the Internet to seek health information. The standard barriers to online health information-seeking are limited Internet access (73), low eHealth literacy (73; 91), and the lack of awareness of eHealth technology by consumers (73). Woods et al. (112) discovered a significantly higher rate of using an online health information resource, like a patient portal, when the consumer had access to the Internet from home, reported higher capability to use the Internet and went online frequently. The following section provides an overview of the association of online health information-seeking on health behaviors and outcomes.

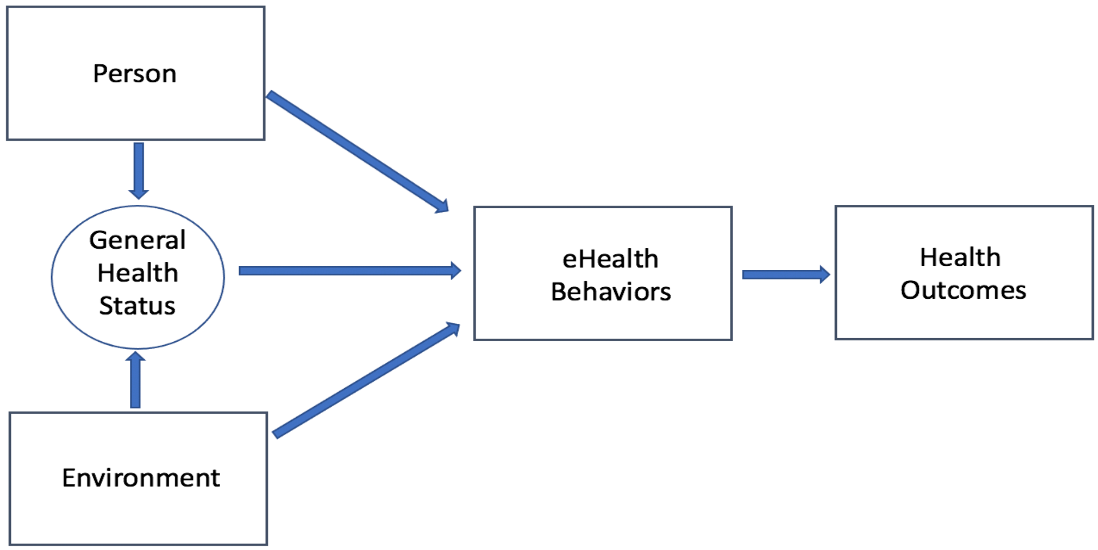
Behaviors & Outcomes

Health status influences individual behaviors. Researchers have discovered that consumers diagnosed with cancer in the last five years use the Internet to seek health-information more frequently (94). Kaphingst et al. (51) found that consumers who seek health-information from doctors, the Internet, or publications tend to follow cancer prevention guidelines compared to consumers who do not seek health information. Managing a health-threatening disease is a primary reason consumers seek health-information (114). The second most common reason for consumers to seek health-information is to maintain their overall health and wellness by searching for information, such as diet and exercise (8).

Patient portals are one resource used to study eHealth behaviors on health outcomes. The use of patient portals has been found to improve health outcomes (30; 73; 89), increase adherence to medical treatment (34), increase consumer-provider communication (30), and consumer satisfaction (30; 55; 73; 89; 110). Garrido et al. (30) reported that consumers who used a patient portal to send a message to their healthcare team had statistically significant improvements in their diabetes and hypertension outcomes. Despite the technological advances and increase in eHealth tools, further research is needed to determine the association between portal use and health outcomes and readiness in the Active Duty Service Member population.

Based on the above summary and Longo's (2005) health information-seeking conceptual model, the following eHealth Behaviors Model (see Figure 1) was adapted to illustrate how demographic, environmental, and health status variables lead to eHealth behaviors and health outcomes.

Figure 1: eHealth Behaviors Model



PROBLEM STATEMENT

Online resources, such as patient portals, are a valuable additional tool for Active Duty Service Members to manage their health (67). Connolly et al. (16) found that patient portals enhance continuity of care and increase self-management behaviors, two key factors to support medical readiness. Hogan et al. (45) found that having an excellent or good self-reported health status was a predictor of eHealth behaviors in the retired military population. Active Duty Service Members must sustain baseline medical requirements to carry out their duties and be ready to deploy 24 hours a day and seven days a week. Active Duty Service Members are an overall healthy population with health conditions often maintained in an outpatient setting. Sixty percent of outpatient Active Duty Service Member medical encounters relate to musculoskeletal issues, mental health disorders, and injury (20). This generally healthy population may be seeking information online about healthy eating, losing weight, and self-treatment. The patterns of engaging in ‘wellness’ information-seeking behaviors in the general population have only been recently studied by research teams (108). Evaluating the relationship of eHealth behaviors on common health conditions in the Active Duty Military population is an area with limited documented literature. The following problem statement describes the gap addressed in this study.

Research on eHealth behaviors has an extensive history. Still, there are limited studies that evaluate these behaviors in the Active Duty Service Member population. Anecdotally, many Military Health System healthcare providers believe that Active Duty Service Members use eHealth tools significantly lower than the general population. A knowledge gap exists on the eHealth behaviors of Active Duty Service Members and the influence of these behaviors on health outcomes and medical readiness. Multiple studies have been completed on 'retired' military populations primarily within the Department of Veterans Affairs health system (16; 45; 98; 104-106; 112; 113). However, the retired military member no longer has the requirement to maintain medical readiness, their age range is varied, and Internet access has been reported as a barrier. Thus, the relevance of these study findings to Active Duty Service Members is limited.

Researchers have completed multiple studies to identify attitudes, beliefs, and preferences when using Military Health System communication and information tools (12; 22; 24; 42; 56; 67; 90; 92) but there is limited research characterizing patient portal use, demographics, and six general health conditions among the Active Duty Service Members population. No studies were found in the literature using patient portal audit data from all three military services to evaluate eHealth behaviors and the association with identified health conditions. This study will contribute to closing these gaps in knowledge through the following specific aims.

PURPOSE & SPECIFIC AIMS

The purpose of this cross-sectional, retrospective study was to characterize the ehealth behaviors of Active Duty Service Members by evaluating the Military Health Systems TOL Patient Portal use, demographics, and six general health conditions. To accomplish the overall objective, the following specific aims were pursued:

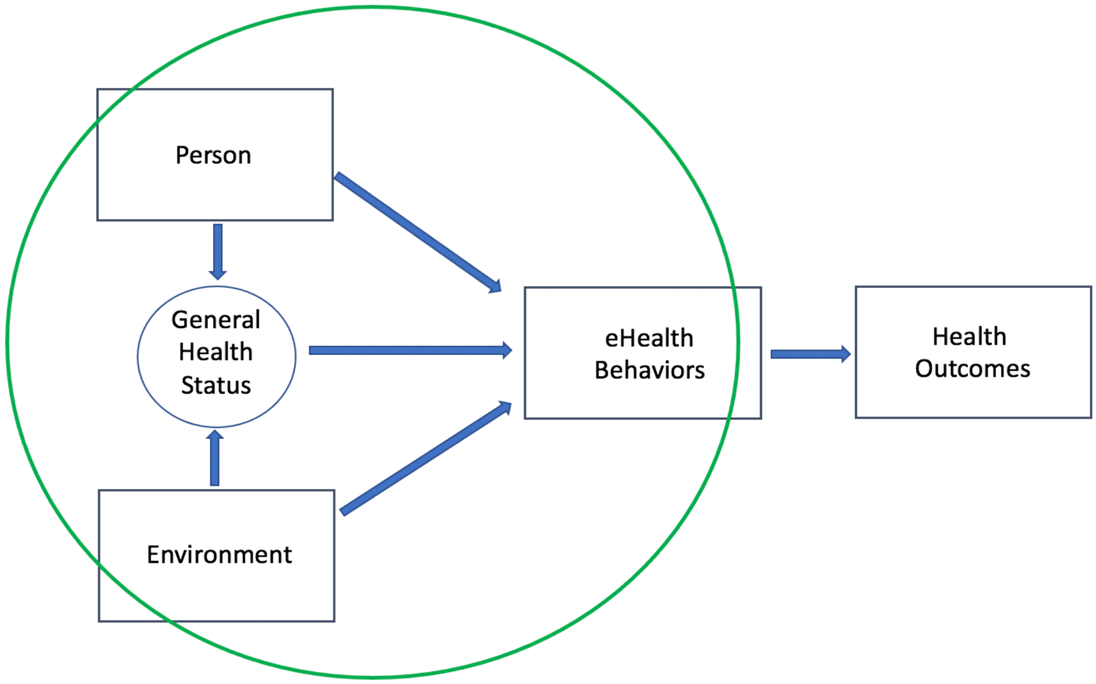
AIM (1) Describe the characteristics and eHealth behaviors of Active Duty Service Members that use the TriCare Online (TOL) Patient Portal.

AIM (2) Compare the eHealth behaviors of Active Duty Service Members that use TOL Patient Portal.

AIM (3): Identify associations between eHealth behaviors, demographic characteristics, and selected health conditions in Active Duty Service Members.

An observational study design was used to evaluate the patient portal use, demographics, and general health conditions by Active Duty Service Members between 18 and 68. The eHealth Behavior Model guided the development of the variables included in this study and aided in interpreting the results. The current study focuses on the associations between person, environment, health conditions, and eHealth behaviors. Evaluating the causal effects of how these factors are associated with health outcomes is not within the scope of this study's focus and not possible in an observational study.

Figure 2: Health Information-Seeking Variables from eHealth Behaviors Model



To evaluate the health information-seeking variables from the model, this study used the approach of collecting and evaluating pre-existing audit log data from the TOL Patient Portal and data from the Military Health System's electronic health record. A description of these Active Duty Service Member users was also provided with similarities and differences compared by assessing six health conditions. The analysis was done retrospectively by evaluating the TOL Patient Portal audit logs combined with the Military Health System electronic health record data to add the six general health conditions and demographic information. The outpatient encounters and diagnoses codes (i.e., ICD-10) of TOL Patient Portal users from 2018 data were reviewed to select available health conditions. Three health information-seeking variables were used to measure eHealth behaviors – frequency of logins, frequency of actions, and type of action completed.

SIGNIFICANCE OF STUDY

Medical readiness of Active Duty Service Members is a vital objective of the Defense Health Agency, the U.S. Combat Support Agency that oversees the Military Health System (38). The Military Health System utilizes many approaches to foster medical readiness, health promotion, and management of both acute and long-term health conditions. Yet, Active Duty Service Members continue to report various barriers to o ensure medical readiness, including extended travel distances to access care, limited hours of operation within military treatment facilities, limited availability of health services, and barriers to booking routine medical appointments (99).

Consequently, expanding the reach of care to support health, wellness, and readiness through eHealth solutions is a top priority for the Defense Health Agency (95). Advances in health information technology and eHealth provide opportunities for interactive health communication and consumer engagement making health services, like the Military Health System, more accessible and person-centered. Despite high interest from consumers and the overall growth of eHealth tools – widespread adoption remains low (5; 46; 75; 96). The Military Health System encounters comparable eHealth adoption obstacles. The overall effectiveness of eHealth can be affected by implementation barriers and facilitators (i.e., individual characteristics and behaviors, practice challenges). Identifying the relationships and comparing the eHealth behaviors between gender and general health conditions, including user characteristics of Active Duty Service Members that use the TOL Patient Portal, may provide the foundation to overcome some implementation barriers and increase adoption.

ASSUMPTIONS & LIMITATIONS

The central assumption identified while completing this study was that Active Duty Service Members' use of the TOL Patient Portal represents a component of their eHealth behavior. The ability to use eHealth tools includes access to the Internet and a computer or smartphone. It was also assumed that Active Duty Service Members have adequate access to Military Health System eHealth tools. However, similar disparities (e.g., health literacy and lack of broadband Internet) found in the general population may also appear in this population.

CONCLUSION

The current study results contribute to broader eHealth research by expanding the military relevance with eHealth and the various implications and barriers. A description of eHealth behaviors and characteristics by Active Duty Service Members with multiple health conditions managed in an outpatient setting that use the TOL Patient Portal was created. The knowledge generated in this study will support the Military Health System's efforts to overcome implementation barriers and identify facilitators that promote eHealth and readiness-centric engagement by Active Duty Service Members.

CHAPTER TWO: LITERATURE REVIEW

An in-depth review of past studies was completed to build an understanding of the state of the science of eHealth behaviors on the general population, Military Veteran, and Active Duty Service Members. A total of 28 studies were reviewed, 14 general population studies, eight Military Veteran studies, and six Active Duty Service Member studies. The eHealth Behaviors Model was used to structure the literature review and guided the interpretation of the results. The following section provides an overall description of the search strategies used to review the current online health information-seeking and patient portal literature in the general, retired military, and Active Duty Service Member populations.

SEARCH DESCRIPTION

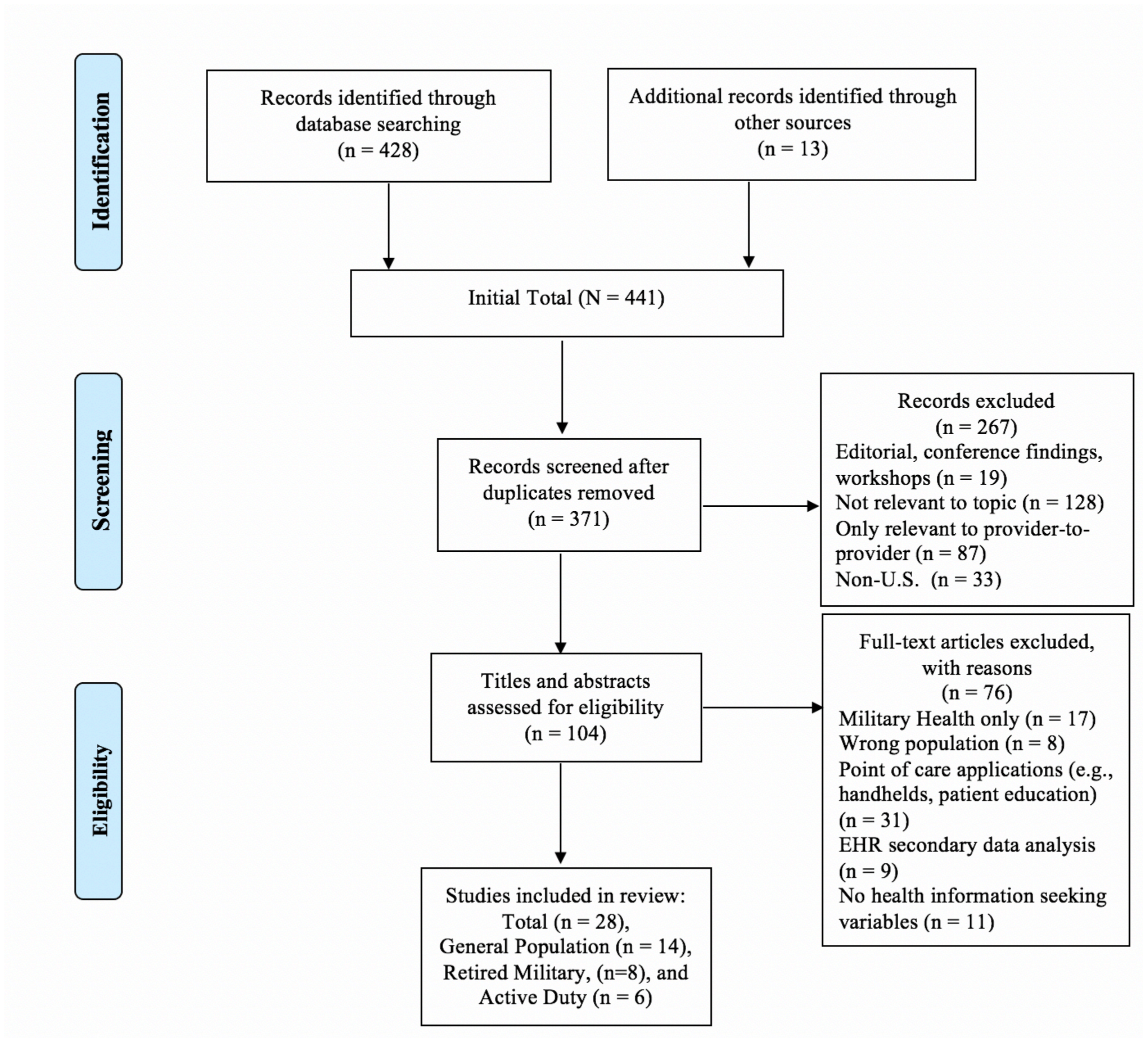
To critically analyze literature on this topic, studies in the review included evaluation of a patient portal. Then the eHealth Behaviors Model was used to create the eligibility criteria to screen articles identified in the search: (1) use of an eHealth tool and (2) evaluate at least one of the primary health information-seeking concepts: information awareness, attempt to access information, ability, and information use. The PubMed, CINAHL, and Embase databases were used to search for literature on eHealth seeking behaviors. The following terms were used to find literature on the general population: eHealth, electronic health, patient portal, personal health record, secure messaging, and health information-seeking (see Appendix 1).

The general population search did not uncover studies on the retired military or Active Duty Service Member population. Additional searches were completed to discover retired military or Active Duty Service Member literature on eHealth behaviors.

No studies were found when health information-seeking was added to the search, so this term was dropped. The articles had to be individually reviewed to find studies that matched the developed screening strategy. The term eHealth was also dropped to focus on asynchronous tools like patient portals and secure messaging in retired military or Active Duty Service Member populations. The terms military retired military, Veteran, military, Active Duty, Service Member, Army, Navy, Air Force, and Marines were then added to help find the missing literature (see Appendix 1).

Articles were then filtered to include only English and U.S. literature on all genders between 18 and 68. Studies were excluded from the literature review if they did not contain a health information-seeking measure or were an editorial. A total of 104 articles were then individually evaluated for selection using the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) guidelines (72). After review (see Figure 3), a total of 28 articles were included – 14 general population, eight retired military, and six Active Duty Service Member. For readability, details of the sample, procedures, measures, and results for the final selected articles were placed in a literature review table (see Appendix 3). All of the articles discussed in this review were approved by their organizations Institutional Review Board or were exempt due to the collection or analysis method.

Figure 3: Results of Literature Review



Note: PRISMA Diagram (72)

Review of Research

The following review provides a concise evaluation of the body of literature on eHealth in the general, retired military, and Active Duty Service Member populations. Each study was evaluated using the Johns Hopkins Nursing Evidence Level and Quality Guide (50). The Evidence Level and Quality Guide is found in Appendix 2, and the score of each article is included in the literature review table. The review is organized, first, by population and then by the type of study (i.e., mixed-methods, survey, secondary data analysis, retrospective data analysis, or qualitative).

General Population

Mixed-Methods

One study evaluated eHealth behaviors using a mixed-method design – a demographic questionnaire and short-form (SF)-36 health survey and participants were randomly assigned to a searching scenario (79). The study's purpose was to describe the process of online information searching and identify demographic characteristics of consumers using two hypothetical acute illnesses (i.e., influenza and bacterial meningitis) search scenarios (82). The study identified four online information search patterns: (1) simple or systematic searching, (2) evidence gathering, (3) hypothesis testing, and (4) action and seeking treatment.

The analysis of demographic variables uncovered that age and education had the strongest association with using a systematic searching process to search for information about specific diagnoses (82). Additionally, participants with less education were not likely to use an online search process that was systematic (82). The researchers did not find a significant association between the type of search that the participant completed and the participant's gender, race, or insurance status (82). Most participants use an "intuitive" approach when conducting an initial health information search (82).

The Perez et al. (82) study was the only non-survey or secondary data analysis study and used a unique approach to evaluate health information-seeking behaviors. However, the sample size was only 78, and the initial level of awareness for the symptom scenarios was not assessed, limiting this study's generalizability. This study had the highest Johns Hopkins Nursing Evidence Level score of II-B (see Appendix 2). The survey literature is reviewed next.

Survey

Five of the 14 studies on the general population used a survey design. Lee et al. (58), Manganello et al. (69), and Lee et al. (57) had the largest sample sizes of 2,680, 1,350, and 970. Madrigal and Escoffery (68) and Nambisan (74) had a smaller sample size of 401 and 132. Lee et al. (58) examined associations of seeking health information online and five health behaviors: physical activity, consumption of fruits and vegetables, the use of alcohol, and medication adherence. Manganello et al. (69) assessed health information-seeking patterns of media and technology use on a sample of New York State residents. Nambisan (74) evaluated which factors added to a consumer's willingness to utilize a patient portal. Madrigal and Escoffery (68) explored the difference in technology utilization, frequency of the Internet, and health information-seeking behaviors. Lee et al. (57) assessed the factors associated with communication, health information technology, and interaction with providers.

Each study found multiple demographic variables to influence eHealth behaviors. Older respondents with less education and lower-income had lower odds of utilizing the Internet (69). Income was the greatest predictor of using other health information sources (i.e., social media) (69). However, Lee et al. (57) found no association with income, race, or geographic location. Lee et al. (58) found that the demographic variables most significantly linked with seeking health information online were older in age, more educated, and U.S. born. Lee et al. (57) identified being female, overall trust of Internet sources, and higher education were most associated with having awareness about electronic health record messaging. Lastly, Madrigal and Escoffery (68) found that younger, females with a greater health literacy score were significantly associated with seeking health information online and utilizing health-related mobile applications. Health status was another independent variable evaluated in these survey studies. Participants with poor health indicators were linked with lower levels of online health information-seeking (58). The researchers pointed out that health status cannot be confirmed in these self-reported surveys (58; 69).

Internet access and high-speed access were measured; researchers found that these were not significant predictors of health information-seeking behavior, and what participants do on the Internet is varied (69). However, Nambisan (74) found that a participant's preference of health record-keeping and access to the Internet at home had the most significant influence on a participant's willingness to use a patient portal. Four studies found many participants access the Internet at home, work, or public locations (58; 68; 69; 74) and 66.7% of participants used the Internet for health-related activities (74).

Various eHealth behaviors measured as health information-seeking were applied in these survey-based studies. Behaviors included utilization of the Internet to manage or seek health information (57; 58; 74), platforms used (e.g., chat room, Website, Health application) (57; 60; 69; 74), preference of receiving health information (69), and trust of online health information (57; 68). The overall design of these survey studies were strong. However, some limitations are noted. Manganello et al. (69) used targeted sample selection to identify the subpopulations of rural, Hispanic, and cell phone users while

Nambisan (74) had a small sample size, making both results difficult to generalize to the broader population.

Secondary Data Analysis

Eight general population studies assessed eHealth behaviors using a secondary data source. The researchers in these studies used different demographics, health conditions, type of Internet access, and health management to describe or predict associations with health information-seeking behavior and eHealth tools like patient portals. Although researchers in these studies used secondary data, the average sample sizes were large. The eight studies will be reviewed by the year they were published.

Chisolm (14) examined how a participant searches for health information match the description of a behavioral model and then identified predictors of seeking health information between distinctive health concepts (e.g., diet, nutrition, and treatment). The 2006 Pew Internet and American Life Project survey data were used to create a sample of 1,880 for the final logistic regression model. Three predictors of online searching behaviors included being female, having a health crisis, and consistent use of the Internet (14). A critical point that Chisolm (14) uncovered is that the process of seeking health information online is complicated and different kinds of searches are associated with other demographic characteristics. Some of the consistent characteristics included Caucasian participants utilizing online resources to search for specific health conditions, while African Americans have higher odds of searching for sexual health topics (14). Additionally, Hispanic participants searched most for alternative medicine (14). Participants 65 and over had lower rates of searching the Internet for health information (14).

Lustria et al. (66) examined the relationship between using online tools to seek health information, managing individual health information, and provider communication. The Health Information National Trends Survey (HINTS) data from 2007 was used for analysis, and the research team used different sample sizes. Using odds ratios and logistic regression models, Lustria et al. (66) assessed participant characteristics. Lustria et al. (66) found that access to the Internet was significantly associated with online health information-seeking, but not provider communication via email. Age, gender, and education level were significant demographic predictors of using online tools to seek health information. Younger participants with a college education were more likely to search for health information online, and female participants with higher education were more likely to communicate with their provider using email (66). Lustria et al. (66) did not find that race was a significant factor.

Saulsberry et al. (93) examined eHealth and mobile health technology utilization by three different insurance types: privately insured, publicly insured, and uninsured. A sample of 3,014 participants was evaluated from the 2102 Pew Charitable Trust telephone interview data. A majority of the sample participants were privately insured: 52% private insurance, 21% Medicare, 9% Medicaid, and 18% uninsured (93). Both privately insured and Medicare insured reported using the Internet. However, most communication with healthcare teams was reported to happen offline (93). A majority of the identified Internet users searched for health information using an online source (93). Medicaid (16%) insured participants shared health information online more than other insurance groups (93). Privately (15%) insured participants used mHealth more than other insurance groups (93).

Kontos et al. (52) evaluated eHealth use and disparities by sociodemographic factors and different communication domains. This research team used the 2012 HINTS data for their analysis. Seven predictor variables were used to develop logistic regression models: birthplace, race, homeownership, education level, income, age, and gender (52). Overall, only 18.95% of the participants reported emailing their provider, 19.29% tracked health information online, and 17.67% purchased medications online (52). The highest type of eHealth behavior was utilizing the Internet to seek information on physical activity, diet, or weight (52). Kontos et al. (52) found that participants were less likely to use the Internet for health information if they did not have a college education (52). Lastly, being female and younger is a consistent predictor of increased eHealth use (52).

Chisolm and Sarkar (15) explored predictors of online health information-seeking in minority health populations. This research team used data from the 2010 Pew Internet and American Life Health Tracking Survey to build a sample of 395 survey participants. Several variables were included in the analysis gender, age, education level, income level, employment status, health insurance status, perceived health status, having a chronic condition, and a recent medical crisis (15). Compared to earlier studies in this review, participants reported higher percentages of eHealth behaviors: 71% searched for health information, 55% socialized online for health information, 24% tracked health activities online (15). Participants with higher income levels and females had higher odds of searching for health information online (15). Lower-income, lower education, and male participants were less likely to seek health information online (15). A unique finding was that participants with at least a high school education level were four times more probable to socialize online about health (15). The research design and analysis process were described well in this article.

Li et al. (62) examined and compared predictors of online health information-seeking behavior. Data from two different surveys were used – Pew Internet and American Life Project. The final sample for each year was 2,463 for 2002 and 3,014 for 2012. The 2012 participants had a higher percentage of using the Internet (62). In 2002, 64.3% of the participants searched for disease topics, compared to 56.7% in 2012 (62). Age, income, and child guardianship were significant predictors of online health information-seeking in 2012, but not 2002 (62). The strongest predictor was a participant's medical history in both years (62). Other predictors were similar to previous studies; females with more education were associated with increased health information-seeking (62).

Gonzalez et al. (33) studied online health information-seeking disparities and patient portal use in U.S.-born non-Hispanic, Caucasians, and Latinos. A secondary data analysis was completed on the 2015 and 2016 National Health Interview Survey (NHIS) data. The sample included 36,214 survey participants. The sample was 80.36% Caucasian, 21% Latino, and 40.29% between the ages of 31 and 54 (33). The independent variables included being U.S. born, age, gender, education, level of poverty, marital status, insured, employment category, ethnicity, and Internet use. The participants were mostly married (63.48%) and insured (90.16%) (33). Overall, Internet use in Latinos compared to Caucasians was low (33). Most participants looked for health information online (65.05%) (33). Thirteen percent of the participants reported using some type of Patient Portal (33). Caucasians were the most likely to engage in health information-seeking behavior, and Latinos not born in the U.S. were less likely to utilize a portal to fill a prescription or email healthcare providers (33). Younger Latinos had the lowest likelihood of using a patient portal (33). Gonzalez et al. (33) discovered continued disparities with patient portal utilization despite increased Internet access and use.

Sherman et al. (97) evaluated where diabetic and non-diabetic males seek health information and identified predictors of using online health information. In this study, demographic variables included age, education level, income level, employment status, race, ethnicity, and technology use. The health variables included smoking frequency, weekly exercise habits, vegetables and fruit consumption, heart disease, diabetes, high blood pressure, and obesity. Sherman et al. (97) found no statistically significant differences in sexual orientation, individuals with diabetes, obesity, and heart conditions, but discovered that age, education, race, and income affect eHealth scores. Seeking health information online was the strongest predictor of increased eHealth scores (97).

In summary, one mixed-method, five survey, and eight secondary data analysis studies on health information-seeking on the general population were reviewed. Gonzalez et al. (33) and Chisolm and Sarkar (15) were given the highest quality rating on the Johns Hopkins Nursing Evidence Level scale. The review of this literature uncovered some common associations. Access and use of the Internet are common environmental factors affecting consumer eHealth behaviors. As an example, having a lower income was associated with using the Internet to seek information at lower rates. The person or demographic characteristics most associated with eHealth behavior, using online health information-seeking as a measure, were Caucasian, female, higher educated, higher income, and consistent use of the Internet. The research on the general population highlighted some disparities in eHealth by race, poor health status, and lower-income. The next body of literature reviewed was on the retired military population.

RETIRED MILITARY POPULATION

Four survey, two retrospective, and two qualitative studies were reviewed on the retired military population.

Survey

Tsai and Rosenheck (105) evaluated veteran mental health consumers for patient portal enrolment and utilization. Tsai and Rosenheck (105) conducted a large-scale survey in 2010 called the National Survey of Veterans. The self-administered surveys were mailed using address-based sampling. The final sample had 195 participants. Most of the participants were Caucasian, male, between 60 and 69 (105). Additionally, most participants in the final sample have attended some college, were married, had a job, and had a household income greater than $30,000 (105). The Veterans Health Administration (VA) mental health service consumers were female and younger with lower incomes (105). Over 70% of the participants reported using the Internet (105). However, no significant difference was found between Internet utilization and mental health consumers and other veterans (105). Twenty percent of the participants utilized the My HealtheVet patient portal (105). Tsai and Rosenheck (105) found that younger, more educated, Caucasian, married, and with a higher income level were most associated with using the Internet.

The next survey examined the adoption and utilization of the 'health record' feature on the VA's patient portal (106). A random sample of four percent of the current patient portal users was created in 2012 (106). The users received an online survey, and

18,389 users participated (106). A total of 33% of the participants used the health record feature (106). A majority of the participants described that access to their personal health information in one location increased understanding of their overall health history (106). Around 20% of the participants shared their health record information with non-VA providers (106). Per the participants, most of the non-VA providers found the information useful. The factor most associated with using or sharing health record information was the participant's self-rated computer ability (106). The most significant reported barrier to using the health record feature was a lack of awareness and difficulty using the patient portal (106).

Hogan et al. (45) evaluated the associations between health information-seeking behaviors, technology use, and individual characteristics of retired military members with spinal cord injury or disorder. The self-reported survey was conducted by mail and had a 38% response rate (45). The 290-participant sample of retired military members with spinal cord injury or disorder had 97.2% males, 71.0% under the age of 65, 71.7% white, and 58.6% married (45). The participants reported that their healthcare provider was their primary health information source (91%) (45). Although, "75.5% of veterans with excellent or good health status" described using the Internet to seek health information (45). Most of the participants had a computer (64.8%) and did not use assistive equipment with a computer (67.5%) (45). Caucasian retired military members use computers and the Internet the most (45). Younger retired military members (under 65) use technology like computers, Internet resources, and text messaging more than participants over 65 (45). Lastly, the self-reported status of excellent or good health was the most associated with computer and Internet usage and mobile text messaging (45).

Woods et al. (112) prospectively surveyed and followed a group of retired military members after initial registration on the VA's patient portal. Woods et al. (112) aimed to identify factors related to short and long-term patient portal use beyond initial registration. The total sample was 260 retired military members. Baseline information was collected after patient portal registration and included these variables: demographics, health literacy, access and utilization of the Internet, patient activation, and health conditions reported by the participant (112). This study's primary outcome variable was the portal login frequency during six and 18-month intervals after initial patient portal registration. See Appendix 3 for 6-month and 18-month login categories. Ninety-seven percent of the participants reported using the Internet, and 92.5% used it at home (112). At the 6-month mark, 84.1% of participants logged on the portal and 91% at the 18-month mark (112). Woods et al. (112) found no significant differences in portal logins by gender, age, education level, marital status, ethnicity, VA facility location, or patient activation measure. The factors most associated with increased portal utilization in this study were a history of home broadband Internet use, higher capability to individually use the Internet, and regular use of the Internet (112).

Retrospective Data Analysis

The first retrospective data analysis reviewed in this section was completed by Shimada et al. (98). The goal of this study was to assess the relationship between continued use of the VA’s patient portal and management of type 2 diabetes. Data were collected from administrative records, inpatient and outpatient medical records, and patient portal registration between 2010 and 2014 to develop a cohort for analysis (98). The sample included retired military members with diabetes that used one of two patient portal features – medication refill and secure messaging (98). The final cohort was 111,686 members, and 34.13% used medication refills, while 5.75% used secure messaging (98). Overall, the members were younger females with lower economic means, making them eligible for free care from the VA (98). Shimada et al. (98) identified that retired military members with baseline uncontrolled glycated hemoglobin had higher odds of achieving glycemic control when using secure messaging than non-users at a medical follow-up (98). Members with a baseline uncontrolled blood pressure were more likely to achieve control at a follow-up compared to non-users (98). Additionally, compared to medication refills, sustained secure messaging had the most significant impact on glycated hemoglobin (98). Lastly, Shimada et al. (98) found that both features were significantly associated with improvements in LDL cholesterol levels at follow-up (98).

Connolly et al. (16) examined associations between symptom severity, demographic characteristics, and patient portal use among retired military members with depression. A retrospective analysis using data from the VA's patient portal, electronic health record, and administrative databases were acquired, and a sample of 3,053 members was included. Random sampling of comparison groups was completed. The sample included 61.4% of members with mild to moderate depressive symptoms (16). Over 38% of the sample had moderately severe to severe symptoms (16). Around 21% of the sample's retired military members had registered for the VA's patient portal. The top used features were medication refills (44.7%), viewing appointments (33.6%), use of secure messaging (20.4%), and downloading their health history (15.9%) (16). Connolly et al. (16) found that members with a medical history of severe depression were more likely to register for the portal and use it to download their medical records (16). Younger retired military members had higher portal registration rates, and African Americans had the lowest rate of portal use after initial registration (16).

Qualitative

Two studies used a qualitative method to explore retired military members' experiences using VA's patient portal (104; 113). Woods et al. (113) examined the views and experiences of retired military members while reading their health records and clinical notes by completing five focus groups. Stewart et al. (104) explored how patient portals facilitate patient engagement and self-management among consumers with diabetes through semi-structured telephone interviews. Woods et al. (113) coded the results using inductive conventional content analysis, and Stewart et al. (104) used both deductive and inductive coding.

Woods et al. (113) discovered both positive and negative experiences. Common themes in this analysis were that participants reported a perceived benefit of using a patient portal for self-care by positively influencing communication with their providers and improving the ability to participate in their care (113). However, some participants reported feeling the negative experiences of viewing information that was not disclosed to them by a provider, use of derogatory language, and inconsistent clinical notes. Stewart et al. (104) also found that patient portals improved the relationship with providers by preparing participants for appointments and reviewing laboratory results. Another critical finding of the Stewart et al. (104) study was that participants felt coordination of care with non-VA providers improved.

Research on the retired military population expanded literature on eHealth behavior and used different methodologies to collect this information. Adding the qualitative studies expanded the personal experiences of using a patient portal in this population and retrospectively evaluating patient portal generated data allowed researchers to move beyond the standard self-reported data collected from surveys. The Connolly et al. (16), Stewart et al. (104), Woods et al. (112) and Shimada et al. (98) studies were given the highest quality rating on the Johns Hopkins Nursing Evidence Level scale. The environmental factors most associated with the use of eHealth tools were having access to the Internet and high self-reported Internet ability. Being female was not reported as a significant factor in the retired military population; this may be due to the lower percentages of retired military females in the VA's health system. The Active Duty military population literature is presented next.

ACTIVE DUTY MILITARY POPULATION

One mixed-method, two surveys, two retrospective, and one qualitative study were reviewed on the Active Duty Service Member population.

Mixed-Methods

Agarwal et al. (2) evaluated how patient activation, provider satisfaction, and technology influence a consumer's intent to utilize a newly implemented personal health record. Two hundred ninety-three participants were recruited during a three month period after a new personal health record was released at a Military Treatment Facility in Elmendorf, Alaska (2). The sample included 52% Active Duty Service Members. The research team used an email survey and, with permission, connected the results with information from a Military Health System database to obtain demographic and health condition variables. Agarwal et al. (2) found that consumer satisfaction with their provider, communication strategies, tool functionality, and patient activation were all significantly associated with intent to use the new personal health record.

Survey

Do et al. (22) conducted a pilot study at Madigan Army Medical Center on a sample of 250 Military Health System beneficiaries. The sample included only 60 (24%) Active Duty Service Members (22). The aim of this study was to evaluate the functionality and usability of a newly implemented personal health record. Users were given a satisfaction survey during the month of April 2009 over the telephone (22). A local panel of providers and patients was created to collect additional feedback. Consumers experienced challenges with using the personal health record, but consumers that used the secure message feature reported 100% (60 out of 60) satisfaction with convenience (22). Consumers also desired additional features like online tutorials, the ability to correct wrong information, and faster release of laboratory results (22).

Hernandez et al. (42) explored consumer-to-provider communication preferences. This research team used convenience sampling at five Air Force Military Treatment Facilities to build a sample of 70 Air Force medical providers, staff, and 1,260 consumers (42). Forty percent of the consumer sample were Active Duty Service Members. A cross-sectional survey was then conducted between 2014 and 2015. The communication styles evaluated included: in-person, telephone, secure messaging, or mail (42). Consumers reported overall satisfaction with using secure messaging, but 40.3% reported being undecided (42). The analysis identified that communication preferences differ by age and military status (42). Additionally, consumers reported preferring to receive non-urgent test results through a telephone call, but medical providers preferred sending a secure message (42).

Retrospective Data Analysis

Boocks et al. (9) completed a multiphase retrospective data analysis to evaluate the medication refills, appointment booking, and the utilization of health information searches on the Walter Reed Army Medical Center's patient portal. This research team did not provide a sample size but instead presented data on the overall frequencies of each patient portal function used in the analysis. The team used a combination of analyzing data using Microsoft Excel and a Webtrends Log Analyzer to review the information search function (9). The results included 34,741 medication refills, 819 booked appointments, and 147,425 information searches (9). The most common topics searched were women's health issues (9). Boocks et al. (9) found statistically significant differences between appointment bookings in gender, age, and geographic location Boocks et al. (9). Younger (under 40) females used the appointment booking more than males, but men over 40 used the system more than females (9). Geographically, Fort Belvoir and Fort Meade had the highest use (9).

Wolcott et al. (111) evaluated how the level and type of provider secure messaging influenced consumer utilization. A sample of 81,625 Active Duty Soldiers that used the patient portal from January 2011 to November 2014 was created from the Army Medicine Secure Messaging service (111). The dependent variable used in the study was the number of messages sent by the consumer (111). The independent variables included age, deployment history, time-in-service, rank, race, marital status, body mass index, self-reported health measures, medical diagnoses, medical appointment data, prescription medications, physical fitness test scores, and tobacco use (111). Wolcott et al. (111) found that Soldiers sent 334% more messages when they interacted with "high response-messaging providers" (p. 5), making this a major predictor for consumer utilization of patient portals. It was also discovered that a patient's healthcare utilization was a predictor of secure messaging utilization – Army Members sent an average of 14% more secure messages in a month for every primary care encounter (111). Wolcott et al. (111) reported that a "musculoskeletal or dyslipidemia diagnosis in the previous three months" was related to an increase in secure messaging (p. 6). However, there was no association between mental health, hypertension, and sleep apnea and the number of secure messages sent (111).

Qualitative

Luxton et al. (67) explored the awareness, attitudes, and use behaviors of online self-care resources among Active Duty Service Members and military healthcare providers. Data were collected using self-reported survey questions. The sample included 28 Active Duty Service Members and 25 military medical providers. Luxton et al. (67) found that a majority of the participants use online health resources, primarily for self-care activities. However, if there is a health concern or question, both service members and providers prefer in-person communication (67). Additionally, Active Duty Service Members reported having an interest in using other online health resources like patient portals. In general, Active Duty Service Members prefer in-person care but are comfortable using online health resources to maintain health Luxton et al. (67).

The research on the Active Duty Service Member population mainly focused on attitudes towards using eHealth, such as preference and satisfaction. The large-scale retrospective studies mainly evaluated the frequency of using an eHealth tool and presented limited information on the person and environmental characteristics that influence eHealth behaviors. Age and gender, as a predictor of eHealth, in this population were inconsistent and could also be caused by the high numbers of males like the retired military population. No study evaluated more than one military service, and most studies only included one location. Wolcott et al. (111) and Hernandez et al. (42) were given the highest quality rating on the Johns Hopkins Nursing Evidence Level scale. The combined evaluation of the three populations of literature is discussed in the next section.

DISCUSSION AND APPLICATION

The eHealth Behaviors Model was used to guide the discussion and application of information found in the reviewed literature. The current literature on eHealth behaviors, using online health information-seeking as a measure, has various gaps in the Active Duty Military Population. The most notable literature gap is the limited information on eHealth behaviors by Active Duty Service Members, especially past initial adoption. Also, Active Duty Service Members have unique requirements for maintaining their health and medical readiness. The retired military population has similar Internet environmental factors; however, as an Active Duty Service Member, Internet access is more readily available in the work environment. Increased Internet access may affect Active Duty Service Member eHealth behaviors. Another gap identified is that most surveys and secondary data on large-scale survey research cannot confirm the health status reported by participants. This gap can be addressed by confirming the health condition with a diagnosis code in an electronic health record, such as the methodology used in this study.

Initially, studies focused on Active Duty Service Member interest in using eHealth tools and, in general, service members show interest and are already using eHealth types of tools and information for self-care support and wellness (3; 12; 13). However, despite interest, utilization remains low, and no large-scale assessment of factors associated with eHealth has been completed. Chapter 3 describes the research design and methodology used to characterize eHealth behaviors of Active Duty Service Members by evaluating patient portal use, demographics, and six general health conditions.

CHAPTER THREE: METHODOLOGY

A cross-sectional analysis of patient portal use, demographics, and general health conditions of Active Duty Service Members ages 18 to 68 was completed in this observational study. The approach of retrospectively evaluating the TOL Patient Portal's audit logs between 2017 to 2019 was used to characterize eHealth behaviors by Active Duty Service Members. Audit log data were combined with the Military Health System electronic health record data to add the six general health conditions and demographic information. The eHealth Behavior Model (see Figure 1) guided the development of the variables included in this study and aided in interpreting the results. The next sections in this chapter cover the overall concept of audit log data and the connection to big data analysis, followed by the methodological approach and steps completed to assess eHealth behaviors in Active Duty Service Members.

RESEARCH DESIGN

Many researchers utilize surveys to collect data necessary to evaluate the overall aims in a cross-sectional analysis study. As presented in the literature review section, nearly all studies evaluating eHealth behaviors used some type of survey to collect information from participants. Even the studies that used secondary data for evaluation had the limitation of the primary study data being generated from a large-scale survey. When using a survey design, researchers often report limited time to conduct the survey (69) and timing is essential when faced with constantly changing eHealth technology. This study used the scalable and time-saving approach of acquiring and evaluating pre-existing audit log data from the TOL Patient Portal. In technical terms, the use of 'pre-existing' data is considered secondary data. However, Doolan and Froelicher (23) state that a secondary analysis involves the use of an existing ‘data set’ or data collected to answer a research question (pp. 204). Data collected from an electronic health record (i.e., data not originally collected for a research purpose) is generally not considered secondary analysis (23). Hence, this study used a cross-sectional analysis versus secondary data analysis methodology. Data in this study were acquired from the TOL Patient Portal audit logs 2017-2019, and dependent variables, guided by the eHealth Behaviors Model, were developed from these data.

Audit logs are collected to protect the information recorded and stored within an online application. Like electronic health records, patient portals record all interactions or events performed within the system and when they happened (1). Audit log data allowed health organizations to fulfill the Health Insurance Portability and Accountability Act (HIPPA) requirement to analyze how and when protected health information was being accessed (1). Although audit log data is not intended for research, it provides individual behavioral data, such as frequency of use and the types of actions completed. The added benefits of using audit log data in behavioral research are that these data are collected in a natural environment, which overcomes the limitations of self-reported surveys and the influence of the unnatural experiment environment. The behavioral data collected from audit logs allow the researcher to assess huge data sets, often falling into the ‘big’ data dominion, which supports the generalization of the overall study results. These studies are also more cost-effective and time-efficient than most large-scale survey or controlled studies that evaluate usability and behaviors in a laboratory setting.

Preliminary data analysis of the TOL Patient Portal audit logs provided insight into the data's overall size, structure, and limitations. The overall size and type of data from the audit logs push this study into some levels of big data research. 'Big data' or the massive amounts of data often hold key information about the patient's overall experience not available through conventional research approaches. Big data research is frequently described by the 'Five V's of Big Data' or volume, velocity, variety, variability, and value of data (48). Volume refers to the overall size and range of the complete dataset (48). Velocity is the rapid speed and amount of time needed to analyze new data (48). Variety denotes the different or varying types of data (e.g., structured or unstructured textual information) (48; 76). The varying modes that data are collected, such as the time, setting, and context, define the data variability (48). Lastly, value of data contributes to delivering measurable improvements from accurate data. The TOL Patient Portal audit log data was acquired in March 2019 and then combined with Military Health System electronic health record data to include 77 million user interactions with the portal (volume and variety) and 1.2 million unique Military Health System consumers logged-in during this time period (value). An extended amount of time was required to combine or wrangle (i.e., a big data term) the audit log and electronic health record data and used a variety of analytic tools – SPSS and 'R' Studio. Although, velocity and variability of data limit the ability to use big data analytics in this cross-sectional analysis study. This study used the principles of big data and analyzed and interpreted the results from the TOL Patient Portal audit log data with a nursing perspective.

The analysis process included the following phases: acquiring and protecting, preparing, exploring, modeling, and analyzing (29; 100). The Open Source program 'R' Studio and SPSS were used in this study. The final SPSS syntax, 'R' Studio script, analysis phases, and pertinent notes documented during the phases have been saved for reproducibility. Each phase of the study design is explained in the next section.

Acquiring & Protecting Data

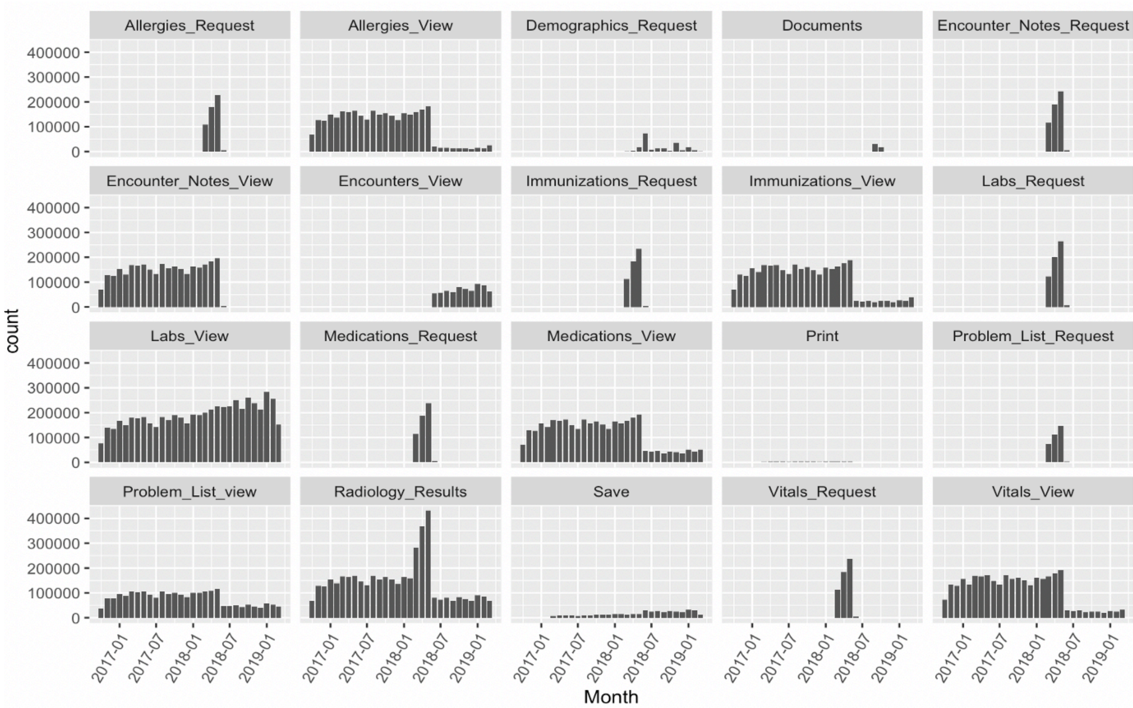
The source material or data should support or relate to the research problem and purpose. All data acquired relating to the research problem should be considered; with huge amounts of data, leaving out a small portion of data may lead the researcher to incorrect conclusions and correlations. Rationale should be provided for the removal of any data from the analysis and, ideally, the logic from removal should follow the theory guiding the study. TOL Patient Portal system audit logs are stored with an individual vendor contractor that provides this service to the Military Health System. A data-sharing agreement was established via the Defense Health Agency privacy office with the National Intrepid Center for Traumatic Brain Injury, Informatics Department in Bethesda, Maryland, to transfer these data elements. This department is the location of the informatics research laboratory supporting this research project and team. The data-sharing agreement included a description of the requested data, steps to transfer the data, and a description of where the data was stored. The storage location had multiple layers of access protection. Double authentication was the solution used in this study and data can only be accessed using a (1) password and (2) Department of Defense (DoD) Common Access Card.

Data was transferred using a Defense Health Agency secure file sharing system. Upon transfer, data were loaded and stored in the Air Force Health Services Data Warehouse (HSDW). The HSDW already receives data from the Military Health System's electronic health record to add the six general health conditions and demographic information. Protecting data is critical when analyzing large samples of data. No personally identifiable information was included in the final dataset. The unique identifiers for each record were replaced with a coded number system before analysis to decrease the potential release of private information. Approval from the Uniformed Service University of the Health Science (USUHS) Institutional Review Board (IRB) and leadership was obtained before completing building the dataset and conducting the analysis. Release of information increases when multiple copies of the same information are stored in different locations. Upon completion of this study, all data will be held in a secure location for one year and destroyed at the one-year mark.

Preparing Data

After data were received and adequately protected, the next phase began by preparing the data for analysis. The preparation of data included cleaning, creating standard terms/naming conventions, and joining datasets. Data were cleaned by assessing inconsistent values, removing duplicate records, and accounting for missing values, invalid data, and outliers. An initial descriptive analysis was completed to assess the data elements available in the TOL audit logs. The results showed that Army-affiliated consumers engage the most with the TOL Patient Portal (87). Also, the highest use was by female consumers between the ages of 35 to 39 and the most employed eHealth functionalities were viewing laboratory results, appointment searching, and viewing prescriptions (87). This initial analysis included all consumers that used the patient portal between 2017-2019. Inconsistencies were noted in the data (see Figure 4) and it was discovered due to various system updates (i.e., new features added, different naming conventions) 2018 provided the most consistent data for evaluation.

Figure 4: Initial Review of TOL Data Elements



The TOL Patient Portal generates and collects a large number of data elements in the system audit logs. The TOL Patient Portal data dictionary was obtained to understand what the various data elements represent in the audit logs. After TOL Patient Portal data elements were selected, they were combined with data from the Military Health System's electronic health record to add the six general health conditions and demographic information. The following description provides an overview of the data elements selected for this study.

Dataset Description: The initial dataset, provided by the NICoE, included the following variables on all consumers that used the TOL Patient Portal between January 2017 and May 2019.

1. **Log_ID** – New Log_ID created each time the user completes an action on the TOL Patient Portal.

2. **Person_ID** – Randomly generated, unique ID created to identify individual users.
3. **Date** – Date recorded each time the user completes an action on the TOL Patient Portal.
4. **Military_Branch** – The branch of service of the Active Duty Service Member is included for both the Service Member and their family members.
5. **Service_Category** – Identifies the consumer as Active Duty, Retiree, Guard/Reserve on Active Duty, Inactive Guard/Reserve, Depends of Active Duty, Dependents of Retiree, Dependent Survivor, Dependent of Guard/Reserve, Dependent of Inactive Guard/Reserve, Other, and Unknown.
6. **Gender** – Gender of TOL Patient Portal consumer. During this time period only male and female gender was documented.
7. **Race/Ethnicity** - Identifies the consumer as American Indian or Alaskan Native, Asian or Pacific Islander, Black not Hispanic, White not Hispanic, Hispanic, Other, and Unknown.
8. **Age** – Provides age of consumer for the date that the action was completed TOL Patient Portal.
9. **Marital Status** – Provides marital status of consumer for the date that the action was completed TOL Patient Portal.
10. **TOL Action** – The type of action completed on TOL Patient Portal is recorded and the following actions are presented in the format of the original data. The TOL Patient Portal Data dictionary was used to understand what each action represented and then the actions were renamed for analysis: APPT BOOKED,

APPT CANCELLED, APPT REFUSED – FAM, APPT REFUSED -SELF, APPT SEARCH, ATTAMPT BOOK APPT – FAM, ATTAMPT BOOK APPT – SELF, ATTAMPT CANCEL APPT – SELF, ATTAMPT OBTAIN FAM DATA, PRINT, REQUEST ALLERGIES, REQUEST DEMOGRAPHICS, REQUEST IMMNIZATION, REQUEST LAB RESULT, REQUEST MEDS, REQUEST MEDS REFILL, REQUEST MEDS STATUS, REQUEST MTF TRANSFER, REQUEST NOTE, REQUEST PROBLEM LIST, REQUEST RADIOLOGY, REQUEST VITALS, SAVE, VIEW ALLERGIES, VIEW DOCUMENTS, VIEW ENCOUNTER, VIEW IMMUNIZATION, VIEW LAB RESULT, VIEW MEDS, VIEW NOTE, VIEW PROBLEM LIST, VIEW RADIOLOGY, and VIEW VITALS.

11. **Sponsor Pay Grade** – The pay grade (e.g., E2/Airmen, O2/Major) of the Active Duty Service Member is included for both the Service Member and their family members.

12. **Zip Code** – Zip code of the consumer for the date that the action was completed TOL Patient Portal.

13. **State** – State where the consumer resides for the date that the action was completed TOL Patient Portal.

14. **Country** – Provides country where the consumer resides for the date that the active was completed TOL Patient Portal.

15. **Health Condition** – The following health conditions were added using International Classification of Disease (ICD-10) from the electronic health record:

Congenital Health Defects (CHD), Amputation, Anxiety, Sleep, Traumatic Brain Injury (TBI), and Depression.

After these data elements were reviewed, selected for analysis, and joined into one large dataset, the values within each variable had to be updated for analysis. The following section explains the process in detail and the SPSS Syntax for reproducibility can be found in Appendix 8.

1. Loaded joined dataset into SPSS.
2. Renamed variables to common names for the study.
    a. spon_svc: Changed to Military_Branch.
        i. Recoded using the Military Health System – MHS Mart (M2) Data dictionary as reference (39).
    b. ben_cat: Changed to Service_Category, recoded and labeled from M2 data.
    c. Gender recoded and labeled: (Note: Active Duty Service Members from Army, Air Force, Navy, and Marine Corps cases selected at this point)
    d. Race_Ethnicity recoded and labeled from M2 data.
    e. Marital_Status recoded and labeled.
    f. Full_spon_paygrade: changed to Rank.
    g. Age: recoded into age group categories: 18-24, 25-44, 35-44, 45-54, and 55 ≥

h. State: recoded into geographic region categories, see Appendix 8 for detail on how regions were created.

i. Patient Portal Actions: recoded into eHealth behaviors categories.

j. Health Conditions: recoded into separate categories for each condition.

3. Removed data elements that were not necessary for analysis.

4. Created new continuous variables and datasets for evaluation.

   a. Actions_PerYear: The total number of actions for Active Duty Service Members is 1,432,889, however, this number does not reflect unique users. SPSS was used to identify and count unique users to create a new variable called 'Count'. The total number of unique Active Duty Service Members that used the TOL Patient Portal in 2018 was 201,073. For analysis purposes a new dataset was created: Count_ActiveDuty_TOL2018_201073.

   b. Logins_PerYear: The total number of logins per year is different than the total number of actions per year. For example, an Active Duty Service Member could complete four actions on a single date on the TOL Patient Portal or 2 actions on two different dates. The first user would count as one login per year and the second would count as two logins per year (see Figure 5). For the purpose of this analysis, it is assumed that the user only logged in one time per day.

Figure 5*:* Example Data on Actions vs. Logins Per Year

Person ID	Date	TOL Action
11111	11/10/2018	View Labs
11111	11/10/2018	Appt Search
11111	11/10/2018	Appt Booked
11111	11/10/2018	View Meds
22222	04/16/2018	View Labs
22222	04/16/2018	View Meds
22222	02/05/2018	Appt Search
22222	02/05/2018	Appt Booked

One login per year

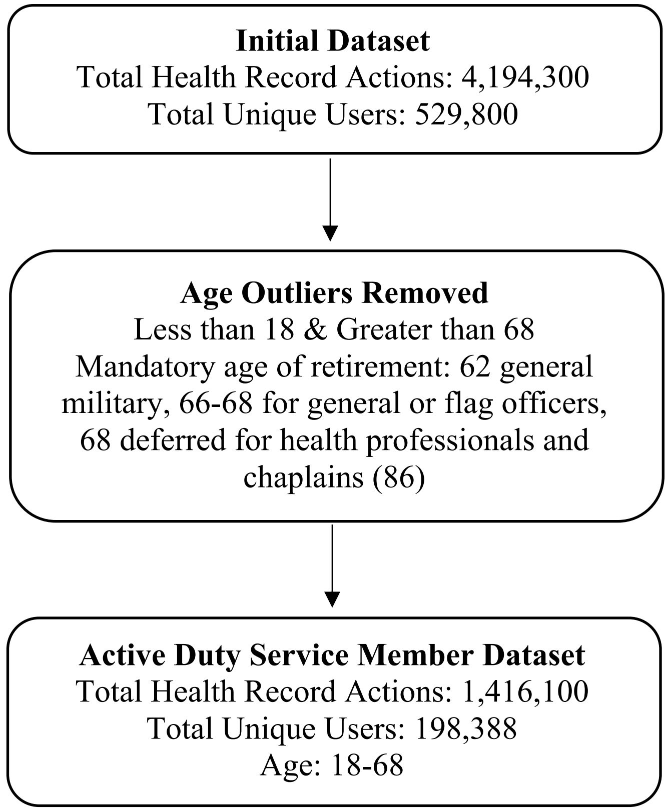
Two logins per year

Upon completion of the data cleaning process, data were explored, modeled, and analyzed following the aims developed to test the eHealth behaviors of Active Duty Service Members.

Population & Sample

A sample of data including all TOL Patient Portal Active Duty Service Member users between 18-68 years of age was created from the 2018 data. Records on non-military members and consumers under the age of 18 and over the age of 68 were excluded, making the assumption that ages outside of this range were outliers or test data. The final sample included 198,388 Active Duty Service Members from the Army, Air Force, Navy, and Marines. Figure eight depicts how the Active Duty Service Member dataset was created (see Figure 6).

Figure 6: Active Duty Service Member Dataset (January 1 to December 31, 2018)



DATA ANALYSIS

The last phase included exploring, modeling, and analyzing the data. Results of the analysis will be presented in Chapter 4. A cross-sectional was completed to characterize the ehealth behaviors of Active Duty Service Members by evaluating patient portal use, demographics, and six general health conditions. The following section describes the analysis process used for each aim and research question.

AIM (1) Describe the characteristics and eHealth behaviors of Active Duty Service

Members that use the TriCare Online (TOL) Patient Portal

RQ1: What are the demographics of Active Duty Service Members that use the TOL Patient Portal compared to the overall Active Duty population?

Variables: Gender, Age, Race, Marital Status, Service Branch, Rank, Geographic Location, and Health Conditions

Analysis: Frequency, Bar Graph, Map

RQ2: What are the eHealth behaviors by Active Duty Service Members that use the TOL Patient Portal?

Variables: Demographic variables with type of action, number of actions per year, and number of logins per year

Analysis: Frequency and Bar Graph

AIM (2) Compare the eHealth behaviors of Active Duty Service Members that use TOL Patient Portal

Research Hypothesis: It is hypothesized that there will be a difference in the mean frequency of TOL Patient Portal usage between gender, rank, age, and health condition.

RQ1: Do male and female Active Duty Service Members use the TOL Patient Portal in similar or different patterns?

Dependent Variables: Actions Per Year and Logins Per Year

Independent Variables: Gender

Analysis: Frequency, Bar Graph, and Mann-Whitney Test with Effect Size

RQ2: Do officers and enlisted Active Duty Service Members use the TOL Patient Portal in similar or different patterns?

Dependent Variables: Actions Per Year and Logins Per Year

Independent Variables: Rank

Analysis: Frequency, Bar Graph, and Mann-Whitney Test with Effect Size

RQ3: Do Active Duty Service Members under 50 and over 50 use the TOL Patient Portal in similar or different patterns?

Dependent Variables: Actions Per Year and Logins Per Year

Independent Variables: Age

Analysis: Frequency, Bar Graph, and Mann-Whitney Test with Effect Size

RQ4: Do Active Duty Service Members with a health condition use the TOL Patient Portal in similar or different patterns than Active Duty Service Members without a health condition?

Dependent Variables: Actions Per Year and Logins Per Year

Independent Variables: Health Condition

Analysis: Frequency, Bar Graph, and Mann-Whitney Test with Effect Size

AIM (3): Identify associations between eHealth behaviors, demographic characteristics, and given health condition in Active Duty Service Members

Research Hypothesis: It is hypothesized that there will a relationship three to eleven logins per year and health condition, gender, age, race, marital status, service branch, rank, geographic location, health conditions, and type of action.

RQ1: Is there an association between a health condition, demographic characteristics, and Active Duty Service Members that use the TOL Patient Portal 3-11 times per year?

Dependent Variables: 3-11 Logins Per Year

Independent Variables: Health Condition, Gender, Age, Race, Marital Status, Service Branch, Rank, Geographic Location, Health Conditions, and Type of Action

Analysis: Logistic Regression Models

Logistic regression models were completed for the main analysis of the patient portal use, demographics, and six health conditions of a sample of 198,388 Active Duty Service Members. Woods et al. (112) levels of patient portal use were used to identify a moderate usage: zero to two logins, three to 17 logins, 18 to 35 logins, and 36 or more logins in eighteen months. Before the model was built, the data assumptions of linearity, independent errors, and multicollinearity were conducted and evaluated.

ETHICS AND HUMAN SUBJECTS ISSUES

Data collected on patients from electronic health records and other eHealth applications, such as the TOL Patient Portal, can deliver huge data sets to researchers to analyze and produce new knowledge. However, the information collected from eHealth applications is intended to support clinical, administrative, and financial purposes – not research (79). Most healthcare consumers do not realize researchers can also access this information. The standard concepts in ethical research, specifically the human subject's protection, are strained in significant ways when evaluating what is considered right and wrong in big data research (70). Instead, ethical review moves away from traditional harms (e.g., physical injury or decreased lifespan) to less observable concepts like the influence of information privacy and data discrimination (70). Research using large datasets has the possibility to involve the conventional idea of a human subject as an individual or may have broader relevance to groups or communities. How data are collected and used is key to building and maintaining the trust of healthcare consumers. Metcalf and Crawford (2016) state that "data science methods create an abstract relationship between researchers and subjects" (p. 20). Often research using data from sources like patient portal audit logs is completed at a location removed from the participant and communities most concerned and consents often equate to overlooked terms of service or unclear privacy standards (70).

The primary argument supporting the use of audit logs and electronic health record data is that very specific data protection requirements, such as de-identification of consumer data, must be established before a research team can receive these data. This does not address the issue that most consumers are not aware their information can be used for research or how, in recent studies, the unknowing participants are re-identified when joining different large datasets (70). When evaluating a military population, one must evaluate how the release of this information will affect the military population. The technology industry is competitive, and the primary driver is increased income. Keeping the trust of Military Health System healthcare consumers and possible research participants are vital.

Limitations of Study

When using data from an audit log or electronics health record, initial collection of data cannot be controlled. Healthcare teams attempt to enter accurate and timely information in the electronic health record, but due to the often high-paced environment, data are not always entered correctly. The data preparation phase can account for identifying various outliers, inaccurate data, and missing data but when dealing with large datasets weakness of the data can be overlooked. It is also important to remember that the information collected from eHealth applications is intended to support clinical, administrative, and financial purposes (79). Additionally, this method does not provide context to the overall experience and satisfaction of the eHealth experience. Follow-on studies such as surveys or in-person interviews will be valuable to assess the Active Duty Service Member population eHealth behaviors further.

Additionally, the results of the current study do not account for the causal effects of how these factors are associated with health outcomes because of the observational study design. Only six general health conditions were available to evaluate the effect of how having a health condition increase or decreases eHealth behaviors of Active Duty Service Members that use asynchronous eHealth tools. Lastly, because the Military Health System eHealth tools are not yet a single electronic health system, the TOL Patient Portal Audit log data only represented a portion of available asynchronous eHealth tools. Secure messaging and nurse advice line texting data were not included in this study.

CONCLUSION

A cross-sectional analysis of patient portal use, demographics, and six general health conditions of Active Duty Service Members ages 18 to 68 was completed to identify associated eHealth behaviors. This study will fill the gap in knowledge of how these tools can support Active Duty Service Members in meeting military medical requirements and what drives members to utilize these tools. Data collected on patients from electronic health records and other eHealth applications, such as the TOL Patient Portal, can deliver huge data sets to researchers to analyze and produce new knowledge. The methodology used to evaluate this topic is also relevant to the Military Health System, because it represents a scalable and time-saving strategy to evaluate eHealth applications and build the knowledge needed for future design strategies and policy updates.

CHAPTER FOUR: RESULTS

The results of the cross-sectional analysis of patient portal use, demographics, and six general health conditions on a sample of 198,399 Active Duty Service Members ages 18 to 68 are presented in this chapter. The characteristics and identified behaviors of Active Duty Service Members that use the TOL Patient Portal are presented first, followed by the comparative analysis and logistic regression results.

CHARACTERISTICS AND EHEALTH BEHAVIORS

The first aim of this study focused on describing the characteristics and eHealth behaviors of Active Duty Service Members that use the TOL Patient Portal. This was done by describing the Active Duty Service Members population and then comparing the results with the overall Active Duty population. The variables of gender, age, race, marital status, service branch, rank, geographic location, and six health conditions were analyzed with the SPSS Version 27 statistical software package. The variables developed from the audit log data (note: process described in Chapter 3) were used to identify the eHealth behavior of Active Duty Service Members. The variables used in this analysis included demographic variables along with the type of action, number of actions per year, and number of logins per year.

A majority of the TOL Patient Portal users in 2018 were male (71.2%), between the ages of 25 and 34 (43%), Caucasian (55.7%), and married (72.1%) (see Table 1). Army (42.8%) and Enlisted (71%) members had the highest number of TOL Patient Portal users. However, it is important to note three population variables; there are generally more men in the military, Army is the largest branch, and most military members are enlisted. In 2018, there were 1,086,740 male Active Duty Service Members compared to 214,781 females (21). Also, the Army made up 36.25% of the total Active Duty Service Member population, and 81.44% were Enlisted members (21). This information was used to calculate the percentage of TOL Patient Portal use within the overall military population in 2018 (see Table 1). Viewing the percentage of use shows that 26.58% of females used the portal compared to 13% of male Active Duty Service Members. Additionally, the Air Force (22.64%) had the highest population use and only 13.32% of enlisted members used the portal in 2018. Chi-Square calculations were completed to evaluate the association between gender, service branch, and rank and the use of the TOL Patient Portal (see Appendix 4). A significant association between each independent variable (gender, service branch, and rank) and use of the TOL Patient Portal was found.

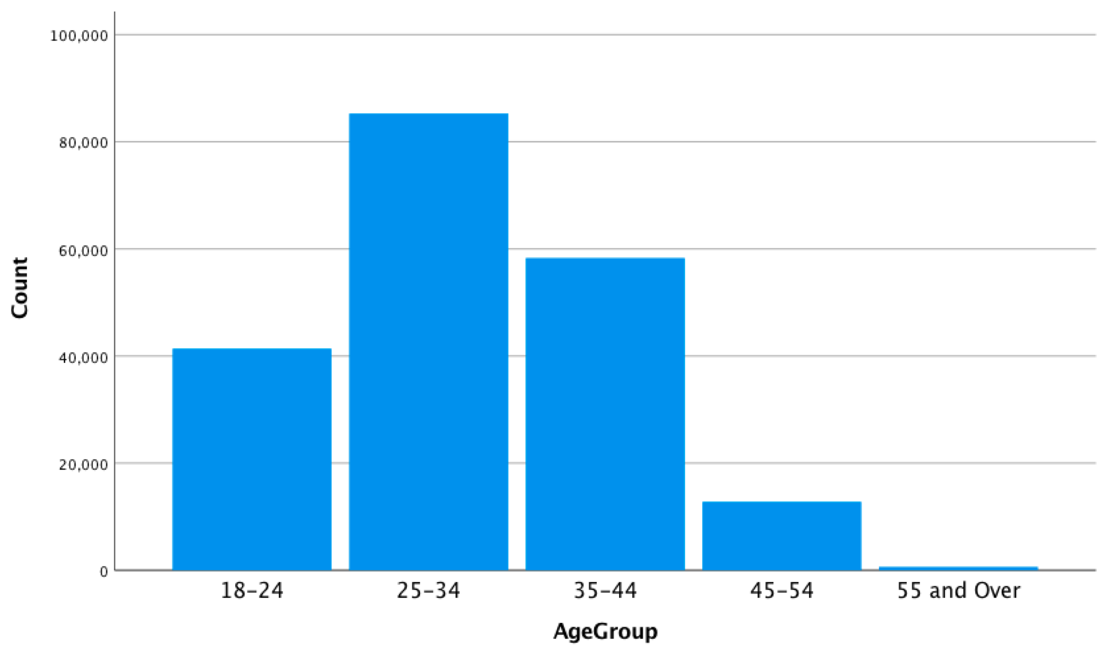
Table 1: Demographic Characteristics of Active Duty Service Members

Demographic Categories	Frequency	Percentage	
Gender			
Male*	141,293	71.2	13.0
Female	57,095	28.8	26.58
Age			
18-24	41,374	20.9	---
25-34	85,279	43.0	---
35-44	58,319	29.4	---
45-54	12,776	6.4	---
55 ≥	640	0.3	---
Ethnicity			
American Indian/Alaskan Native	2,319	1.2	---
Asian or Pacific Islander	12,932	6.5	---
Black, not Hispanic	36,889	18.6	---
White, not Hispanic	110,539	55.7	---
Hispanic	28,156	14.2	---
Other	6,913	3.5	---
Unknown	639	0.3	---
Marital Status			
Single	55,267	27.9	---
Married	143,121	72.1	---
Military Branch			

Army*	84,823	42.8	17.84
Air Force	73,659	37.1	22.64
Navy	31,344	15.8	9.5
Marines	8,563	4.3	4.6
Military Rank			
Cadet	1,227	0.6	9.2
Enlisted*	142,708	71.0	13.32
Officer	51,726	25.7	24.35
Warrant Officer	5,412	2.7	29.55

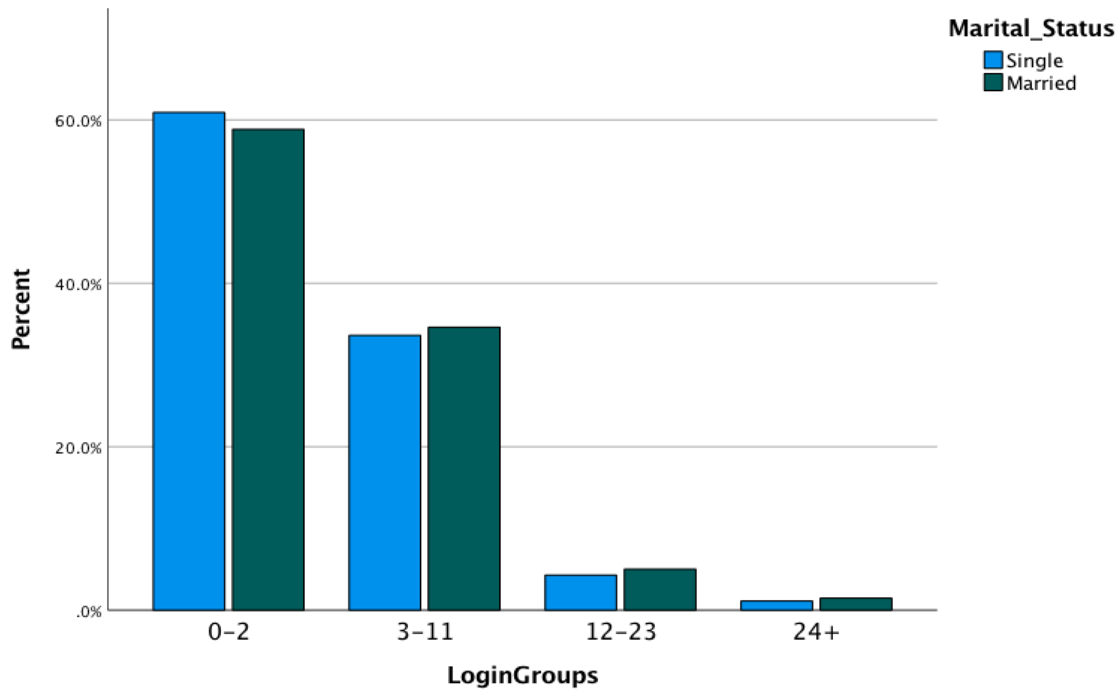
The mean age of this population is 31.80 and Active Duty Service Members show higher usage in the 24 to 34 age group (see Figure 7).

Figure 7: Active Duty Service Member by Age



Despite a majority of Active Duty Service Members being married, the overall percentage of TOL Patient Portal use is fairly equal (see Figure 8).

Figure 8: Active Duty Service Member by Age and Marital Status



The most extensive use of the patient portal is seen in Texas (11.5%), Virginia (11.1%), California (7.3%), North Carolina (5.5%), Florida (5.0%), Georgia (4.4%), and Maryland (4.3). The Southeast Region of the U.S. has the most Active Duty Service Member users (35.9) followed by the West Region (20.3%) and the Southwest Region (17.0%). Over half of the Active Duty Service Members used the patient portal one to two times in 2018 (see Table 2). The mean number of logins per year was 3.83 and the mean number of completed actions was 7.14 per year.

Table 2: Login Groups of Active Duty Service Members

Logins Groups	Frequency	Percentage
0-2	11,7903	59.4
3-11	68,179	34.3
12-23	9,565	4.8
24+	2,741	1.4

The top actions completed were searching for appointments, viewing family member information, viewing personal health information, viewing medical encounters, and refilling medications (see Table 3).

Table 3: Frequency of eHealth Behaviors by Active Duty Service Members

eHealth Behavior	Frequency	Percentage
Booking Appointments	30,984	15.6
Cancelled Appointments	11,067	5.6
Searching for Appointments	74,702	37.7
Viewing Health Information	100,121	50.5
Viewing Family Information	139,386	70.3
Viewing Medical Encounter	60,363	30.4
Saving/Printing	294	0.1
Request MTF Transfer	7,961	4.0
Medication Refill	82,515	41.6

The highest use of the TOL Patient Portal was seen between the months of March and May (see Figure 9). The results of AIM (2) are presented in the next section.

Figure 9: Frequency of eHealth Behaviors by Active Duty Service Members

The frequencies and percentages of the six health conditions can be found in Table Four.

Table 4: Frequency & Percentage of Health Conditions

Health Condition	**Frequency**	**Percentage**
CHD	582	0.3%
Amputation	23	<0.0%
Anxiety	7,354	3.7%
Sleep	60,611	30.6%
TBI	25,176	12.7%
Depression	10,377	5.2%

Active Duty Service Members with CHD, anxiety, sleep issues, and depression have higher rates of moderate TOL Patient Portal use (see Table 5).

Table 5: Frequency & Percentage of Health Conditions

Logins by Health Condition	**Frequency**	**Percentage**
CHD		
0-2	246	42.3
3-11	248	42.6
12-23	61	10.5
24+	27	4.6
Amputation		
0-2	14	60.9
3-11	7	30.4
12-23	2	8.7
24+	--	--
Anxiety		
0-2	2,982	40.5
3-11	3,175	43.2
12-23	805	10.9
24+	392	5.3
Sleep		
0-2	29,567	48.8
3-11	24,283	40.1
12-23	4,941	8.2
24+	1,820	3.0
TBI		
0-2	13,554	53.8
3-11	9,281	36.9
12-23	1,728	6.9

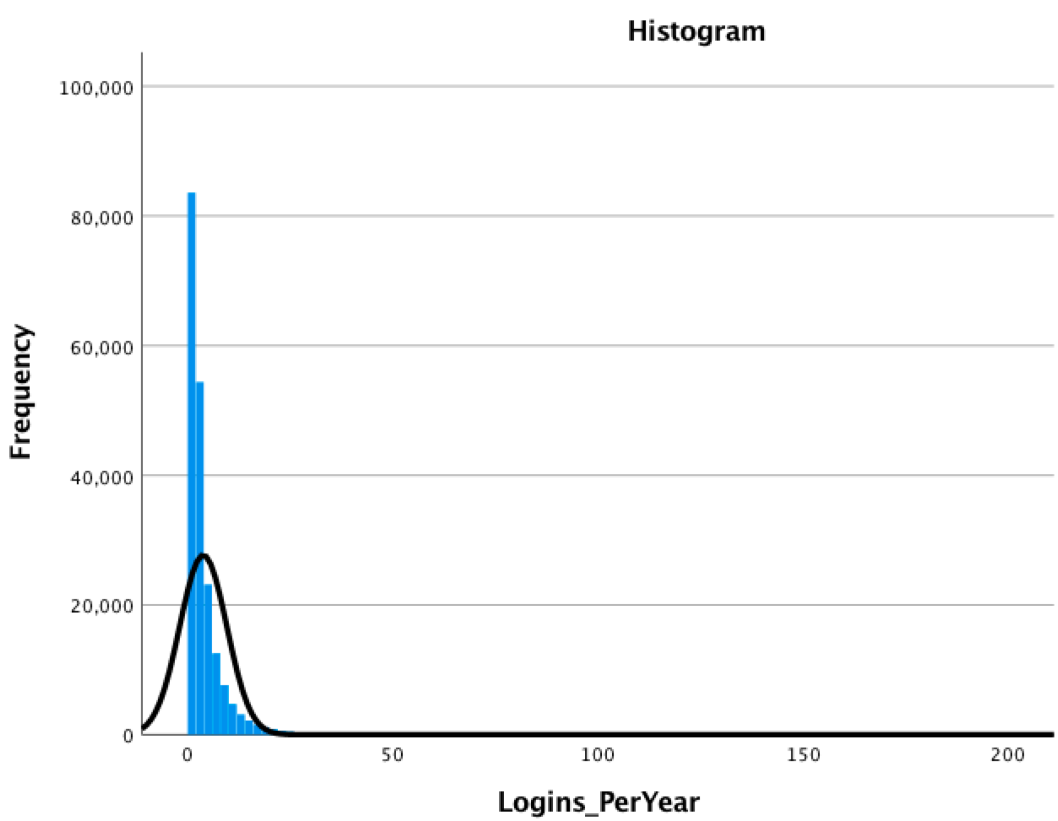
24+	613	2.4
Depression		
0-2	4,477	43.1
3-11	4,319	41.6
12-23	1,108	10.7
24+	473	4.6

The results of AIM (3) are presented in the next section.

COMPARING EHEALTH BEHAVIORS

The second aim of this study focused on comparing eHealth behavior by evaluating four different independent variables: gender, rank, age, and health condition. Logins and actions per year were the dependent variables used to compare the means between the independent groups. The dependent variables do not follow a normal distribution (see Figure 10) therefore Mann-Whitney non-parametric testing was used.

Figure 10: Histogram of Logins Per Year



Most of the results had a significant *p-value*; however, this is common when testing is completed on large samples (see Appendix 5). The effect size is calculated to find the extent of the differences between the means (80). The effect size equation commonly used with the Mann-Whitney Test is r = z/square root of the total number of cases (Cohen 1988, as cited in 28). Cohen recommended that "d = 0.1 be considered a 'small' effect size, 0.3 represents a 'medium' effect size and 0.5 a 'large' effect size" (Cohen 1988, as cited in 28). The largest effect size results were gender, members with at least one health condition, and members with sleep issues. Although, all three of these still had a minimal effect size based on Cohen's 1988 guidelines (as cited in 28). The highest mean use by logins and actions per year were seen in members over 50 and members with CHD, anxiety, sleep issues, and depression (see Table 6). There were no significant differences between rank by logins per year and members with amputations (see Appendix 5).

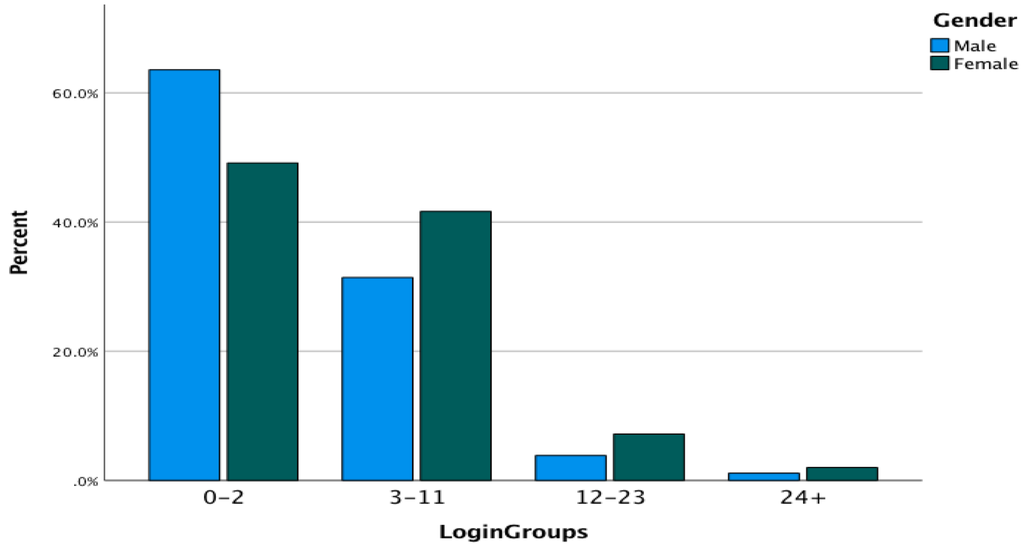
Table 6: Mean Logins & Actions Per Year by Active Duty Service Members

Variable		**Mean**	**Std. Deviation**
Gender			
Male	Logins	3.46	5.433
	Actions	6.44	12.919
Female	Logins	4.75	6.272
	Actions	8.87	14.565
Rank			
Cadet	Logins	2.38	2.337
	Actions	3.74	5.097
Enlisted	Logins	3.89	5.874
	Actions	7.29	13.817
Officer	Logins	3.65	5.194
	Actions	6.65	12.251
Warrant	Logins	4.45	15.583
	Actions	3.74	6.587
Age			
Over 50	Logins	5.18	7.642

	Actions	9.60	17.581
Under 50	Logins	3.81	5.684
	Actions	7.10	13.390
Health Condition			
CHD	Logins	6.64	10.029
	Actions	13.06	23.747
Amputation	Logins	3.57	5.264
	Actions	6.26	11.083
Anxiety	Logins	6.99	10.391
	Actions	13.68	25.335
Sleep	Logins	5.31	7.897
	Actions	10.10	18.511
TBI	Logins	4.74	7.493
	Actions	9.04	17.926
Depression	Logins	6.46	9.694
	Actions	12.41	22.98

Male Active Duty Service Members use the portal more consistently between the ages of 25 to 40 compared to females (see Figure 11). The mean age of males is 32.53 and 29.98 for females. Females logon to the TOL Patient Portal and complete more actions that male Active Duty Service Members (see Table 3). Using a bar graph to visualize the percentage of logins by groups (see Figure 11), female Active Duty Service Members login at a moderate rate of three to eleven logins compared to males.

Figure 11: Logins Per Year by Gender



Active Duty Service Members over 50 have a higher mean use, however, the overall effect size is very small. The results of AIM (2) are presented in the next section.

ASSOCIATIONS OF EHEALTH BEHAVIORS

The third and final aim of this study evaluated possible associations between eHealth behaviors, demographic characteristics, and six health conditions in Active Duty Service Members. Logistic regression models were used to assess portal users that logged-in at moderate rates or 3-11 times (112). Logistic regression is an effective multivariate analysis technique that produces a predictive equation and can be used with both continuous and binary independent variables (84), which matches the dataset used in the current study. The independent variables included health condition, gender, age, race, marital status, service branch, rank, geographic location, health conditions, and action type. Although, prior studies found the geographic location was not a factor, military members frequently move, making geographic location a possible predictor of moderate portal utilization. Each independent variable bivariate relationship was tested individually; the odds ratios of these are found in Appendix 6. The logistic regression model was built using an iterative process that was based on the bivariate results and previous eHealth behavior literature. The software package used to complete the logistic regression models was ‘R’ Studio Version 1.3.1073. The script created for the regression model can be found in Appendix 9.

The first step in the logistic regression process was to convert variables into factors. The full dataset was then randomly split into training, validation, and test data. The ‘set.seed’ function was used to allow for reproducibility. The training dataset included 70% of the original data, the validation dataset 15%, and the test dataset 15%. Using training, validation, and test data supports avoiding overfitting a model by obtaining the model coefficients using the training dataset, identifying an optimal cutoff point using the validation data, and testing the model’s strength using the test data. Using a training dataset allows the researcher to “learn patterns from the data” without the model evaluating all available data (81). Test data is then used to evaluate the final developed logistic regression model and see how the model will perform on “real world scenario” data (81). The first iteration of the logistic regression model included all available independent variables. The most significant variables discovered in this model included gender, age, military branch, anxiety, depression, booking or searching for appointments, viewing family members or personal health information, viewing encounter notes, and refilling medication. A second model was built using the most significant values from the first model. Rank was added because it is the best representation of income and education in this dataset and a common predictor from previous literature. The final model used for evaluation included the following variables: gender, age, military branch, depression, booking or searching for appointments, viewing family members or personal health information, viewing encounter notes, and refilling medication.

The model was built on the training data and tested on the final 30% test data. The model has a misclassification error rate of 0.2389; lower error rates are associated with better models. The Receiver Operating Characteristics (ROC) curve was completed for this model. The ROC curve provides a visual of the model's accuracy and the larger area under the curve, supports greater predictive ability. The model's area under the ROC curve was 84.21% (see Appendix 7). Lastly, the Concordance (i.e., actual positives are greater than actual negatives) was 84.21% and is considered a good quality model. Table 7 shows the results of the logistic regression model. The 'B' column represents the coefficient for the constant and is sometimes referred to as the intercept (80). The standard error (S.E) is reported in the third column. The Wald column represents the Wald Chi-Square test which evaluates the null hypothesis (80), interruption of these results is often combined with the significance results in column six.

Table 7: Predicting the Likelihood of TOL Patient Portal Moderate Use

Variable	B	S.E.	Wald	df	Sig.	Exp(B)	95% C.I. for Exp(B) Lower	Upper
Gender (F)	0.183	0.013	208.326	1	0.000	1.2	1.171	1.23
Age	0.006	0.001	75.2	1	0.000	1.006	1.005	1.008
Depression	-0.182	0.025	52.618	1	0.000	0.833	0.793	0.867
Booked Appointment	0.543	0.016	1131.587	1	0.000	1.722	1.668	1.777
Searcher for Appointment	1.166	0.012	8993.243	1	0.000	3.211	3.134	3.289
Viewed Family Health Information	1.764	0.015	13102.811	1	0.000	5.834	5.661	6.013
Viewed Personal Health Information	0.960	0.013	5641.361	1	0.000	2.612	2.547	2.678

Viewed Encounter Notes	0.14	0.013	108.363	1	0.000	1.151	1.121	1.182
Refilled Medication	1.061	0.012	7766.018	1	0.000	2.889	2.822	2.958
Constant	-3.865	0.029	17990.763	1	0.000	0.021	---	---

Note: Moderate use equals 3-11 logins per year. Logistic Regression used for analysis.

A logistic regression model was completed to assess the factors that could possibly predict moderate TOL Patient Portal use in the Active Duty Service Member Population. The two strongest predictors of moderate TOL Patient Portal use were viewing family member health information, recording an odds ratio of 5.834, and searching for appointments (OR=3.211). Female Active Duty Service Members were 20% more likely to login in at a moderate rate than male members. Moderate utilization increases slightly in Active Duty Service Members increase in age. Active Duty Service Members with depression are negatively associated with using the patient portal at a moderate rate, meaning 16.7% decrease in odds of using the portal at a moderate rate.

CONCLUSION

In summary, majority of the TOL Patient Portal users in 2018 were male, between the ages of 25-34, Caucasian, and married. Although, 26.58% of the total female Active Duty Service Members used the portal compared to 13% of males. Over half of the TOL Patient Portal Active Duty Service Members users in 2018 utilized one to two times. The mean age of both males and females is 31.80; the mean age of males is 32.53 and 29.98 for females. Most Active Duty Service Members used the TOL Patient Portal in Virginia, Texas, California, Florida, North Carolina, Georgia, and Maryland in 2018. The highest patient portal use was during the months of March to May. The top actions or applications used were searching for appointments, viewing family member information, viewing personal health information, viewing medical encounters, and refilling medications. Being female, having at least one health condition, and sleep issues showed the most significant difference in mean use by login and actions per year. Females logon (M=4.75, SD=6.272) to the TOL Patient Portal and complete more actions (M=8.87, SD=4.565) compared to males (Logins: M=3.46, SD=5.433; Actions: M=6.44, SD=12.919) Active Duty Service Members. Females have a greater percentage of using the patient portal moderately (i.e., three to eleven logins) than males. The strongest predictor of using the TOL Patient Portal three to eleven times by Active Duty Service Members is viewing family member health information and searching for an appointment. Active Duty Service Members with CHD, anxiety, and sleep issues have higher rates of three to eleven logins. Although, Active Duty Service Members with depression have a negative associated with using the patient portal at a moderate rate. The general application and review of these results, compared to previous literature, are presented next in the final chapter.

CHAPTER FIVE: DISCUSSION

The current study focused on characterizing the eHealth behaviors of Active Duty Service Members by evaluating patient portal use, demographics, and six general health conditions. The results provide new understanding into the behaviors of using the online, asynchronous tools, like patient portals, to seek information and manage health. The eHealth Behaviors model, developed from health information-seeking historical literature, guided the evaluation of literature and the methodology selection used in this study. The literature review evaluated the general population, retired military, and Active Duty Service Member populations using the Johns Hopkins Nursing Evidence Level scale. The methodology for this study used the scalable and time-saving approach of acquiring and evaluating pre-existing audit log data from the TOL Patient Portal. Data in this study were acquired from the TOL Patient Portal audit logs 2017-2019, and new dependent variables, guided by the eHealth Behaviors Model, were developed from these data. A cross-sectional analysis of patient portal use, demographics, and six general health conditions on a sample of 198,399 Active Duty Service Members ages 18 to 68 was completed. The summary of these findings presented in the Results section will be discussed with the results from the previous studies cited in the literature review. Contributions of this study will be discussed from the conceptual and methodological perspective, followed by the implications for future research and practice.

DISCUSSION

The current study expanded Longo's (2005) seminal health information-seeking theory by developing an eHealth Behaviors Model that may assist future researchers in evaluating patient portals and other asynchronous eHealth resources. Additionally, this study was one of the first to operationalize measurement of health information-seeking using patient portal audit log data versus a survey method. Use of audit log data not only highlighted the value of existing data for research, but also the value of the clinical or nursing perspective to evaluate big data in research. Specifically, using big data in nursing research provides a unique opportunity for large amounts of healthcare data to be analyzed and interpreted with the crucial nursing perspective, versus a data scientist that may overlook trends related to a specific consumer population or disease type (11; 76). Brennan and Bakken (11) further expand the concept of "data-informed nursing practice" where the consumer experience is better comprehended with the support of data science by a "more comprehensive view of the person to devise creative approaches to interventions and monitor the effectiveness of the interventions" (p. 483).

The current study fills the gaps identified in the literature review by (1) evaluating eHealth behaviors of Active Duty Service Members across all Military Branches, (2) past initial adoption of a patient portal, and (3) assessing these behaviors in six general health conditions. Initial evaluation of the frequency of TOL Patient Portal users in 2018 found that most users were male, between the ages of 25 and 34, Caucasian, and married. In previous studies on the general population, users were mainly Caucasian (14; 33), female (14; 57; 66; 68) and married (33). It appears that in the Active Duty Service Member population, more males use the patient portal, but with further investigation and comparing the frequency with the general population, 26.58% of the total female population used the portal compared to 13% of males. This is more consistent with previous literature. Additionally, being female, having at least one health condition, and sleep issues had the most significant difference in mean use by login and actions per year compared to all other TOL Patient Portal Users in 2018. Females also logon to the TOL Patient Portal and complete more actions compared to males. The last critical discovery is that females Active Duty Service Members use the patient portal at a moderate rate (i.e., three to eleven logins) more frequently than male Active Duty Service Members.

When comparing race in the Active Duty Service Member population, an interesting discovery is that only 55.7% of the users were Caucasian. In a sample of 36,214 survey respondents, Gonzalez et al. (33) found that 80.36% of the study's sample was Caucasian. In the retired military population African Americans had the lowest portal use rate after initial registration (16). The current study found that there are more non-Caucasian patient portal users, compared to the general population: Black 18.6%, Hispanic 14.2%, Asian or Pacific Islander 6.5%, and American Indian or Alaskan Native 1.2%. Geographic location, like the general population, did not significantly influence patient portal use. However, the highest frequencies were found in Virginia, Texas, California, Florida, North Carolina, Georgia, and Maryland. These locations have large medical centers and military populations, which most likely accounts for the higher use. No other studies on the general population evaluated the highest usage by month. In the Active Duty Service Member population, the highest patient portal use was during the months of March to May. Future studies could evaluate the cause of this increase. An anecdotal reason for the increase, is that military members move at higher rates during these months and may seek health services prior to their move.

The retired military population has slightly higher patient portal enrollment rates, around 21% (16) compared to 15% of Active Duty Service Members between 2017-2019 (88). The top used features in the retired military population were medication refills, viewing appointments, secure messaging, and downloading their health history (16; 98). In the Active Duty Military Population, very few users saved or downloaded their information, but, like the retired population, the top features used were searching for appointments and refilling medications. Additionally, the Active Duty Service Members have a very high rate of viewing family member and personal health information. Active Duty Service Members often live long distances from family and have limited support systems, which may account for the importance of maintaining family health and wellness. The strongest predictors for moderate TOL Patient Portal use were viewing family member health information and searching for an appointment. However, Active Duty Service Members with depression are negatively associated with using the patient portal at a moderate rate. In the retired military population, Connolly et al. (16) found that members severe depression were more likely engage with the patient portal (16). The findings in the current study have multiple implications for future research and practice.

RECOMMENDATIONS FOR FUTURE RESEARCH & PRACTICE

The current study provides a baseline of the characteristics of Active Duty Service Members that use a patient portal and their associated behaviors and used a methodology outside of the common survey. Completing this study using audit log data supports this methodology's effectiveness to study large samples of a population in a natural setting. Nearly 200,000 Active Duty Service Members were evaluated, and the process was documented for replication and use on other large samples collected from audit log data. In fact, audit logs are not limited to consumers. Audit logs are also collected from the healthcare team when they use electronic health records in their daily practice. Just this year, Adler-Milstein et al. (1) highlighted how the nearly ubiquitous utilization of electronic health records throughout the U.S. provides an untapped resource to observe behavioral data and interactions at a very granular level. Future studies could use audit log data to evaluate clinical eHealth behaviors by Military Health System provider and healthcare teams.

Additionally, audit log studies are more cost-effective and time-efficient than most large-scale survey or controlled studies that evaluate usability and behaviors in a laboratory setting. The time and money savings support the development of future comparison and longitudinal studies of these behaviors over several years. Currently, the Military Health System has seen a surge in the utilization of online health resources during the COVID-19 pandemic (101). Future studies evaluating behaviors over a several years or comparing predictors of eHealth behaviors, like pandemic eHealth use, will benefit from the results and methodology found in this study. The current study's results provide a baseline understanding of eHealth behaviors and characteristics of Active Duty Service Members and specify a scalable and time saving framework to evaluate how behaviors changed or stayed consistent.

Nursing practice in the military and the general population will benefit from the information found in this study. Use of eHealth tools improves the relationship with healthcare teams by preparing consumers for appointments and reviewing laboratory results (104). It is essential to disseminate that the Active Duty Service Member population uses the TOL Patient Portal from March to May and searches for appointments, refills medication, and seeks health information the most to healthcare teams. Military healthcare teams should also know that Active Duty Service Members have a very high propensity to seek and view family member health information. These pattern and preference results contribute to the knowledge needed for future systems and communication strategies used by nurses and healthcare teams. The results can be utilized to improve the overall perceptions of eHealth and may increase the subsequent use of eHealth applications by Active Duty Service Members.

MILITARY POLICY

The use of these eHealth tools has the potential to support improved medical readiness or the overall health, wellness, and fitness status of Active Duty Service Members and their ability to deploy worldwide (19). Widespread use of these eHealth applications remains low in the Military Health System. Still, the Defense Health Agency continues to invest millions of dollars toward implementing, upgrading, and maintaining eHealth technologies for consumers, mainly in Primary Care Clinics. Adopting eHealth tools in the Military Health System is further reinforced through Congressional directives (18; 37; 95). Past initiatives have established procedures (i.e., returning secure messages in 24 hours and answering before telephone consults) to drive eHealth adoption in the Military Health System. Several eHealth tools to support patient engagement in primary care clinics were released and updated over the last twelve years. In 2006, the TOL Patient Portal was deployed to the Military Health System enterprise, and in 2012, a secure messaging application was purchased and released. In 2014, multiple patient engagement application updates and redesigns were released to enhance the TOL Patient Portal, including a mobile version of the patient portal released in 2017. The TOL Secure Messaging system can be accessed from the TOL Patient Portal but is technically another application with a different username and password. The TOL Patient Portal is available to all 9.4 million Military Health System beneficiaries, but for full functionality of those tools, beneficiaries must be Direct Care patients connected to a Military Health System clinic. The Military Health System Nurse Advice Line, a toll-free line that links beneficiaries to Registered Nurses, is one non-Internet based tool available for use. Military Health System is presently in a five-year process of implementing a new electronic health record that features a tethered or directly connected patient portal. The new patient portal, called Military Health System GENESIS Patient Portal, is a consolidated portal with telehealth options and secure messaging. This effort started in February of 2017, and the system is only available to a small number of the Military Health System beneficiaries.

Despite recent studies identifying a growing interest by Active Duty Service Members in electronic health tools (17; 103), the Military Health System still struggles with enterprise-wide adoption of these tools. The Military Health System has led various efforts to optimize patient engagement and use of eHealth tools. In May 2016, a small, multi-disciplinary group led a multi-layered effort to develop strategies to change how the organization utilized its existing eHealth tools. The effort included improving the patient experience, consolidating multiple eHealth tools, creating a Tri-Service Brand, rebuilding and launching a communication package, increasing functionality, and initiating Defense Health Agency policy to support new functionality. The redesigned patient portal launched in November 2016.

The Military Health System often supports Active Duty Service Member healthcare needs in outpatient Primary Care settings and sees the importance of expanding how services are delivered by purchasing and managing millions of dollars of eHealth applications and implementing policies to support their use. The Military Health

System reports 70.5 million annual visits across 375 outpatient clinics, yet minimal information was known about how Active Duty Service Members interact with the current Military Health System eHealth resources. This study expanded this knowledge, which is critical as the Defense Health Agency is shifting to a new electronic health record and health system structure (19). This study also fills the gap in Military Health System knowledge past implementation and initial adoption research and can influence policy to developed more tailored eHealth tools that support coordination of care. Researchers evaluating retired military populations have discovered that participants felt coordination of care between non-VA providers improved (104). Military members move every two to four years, making coordination of care vital. Lastly, the knowledge gained in this study may expanded eHealth use and support Active Duty Service Members to meet military medical requirements.

CONCLUSION

The results of this cross-sectional analysis on a sample of 198,399 Active Duty Service Members ages 18 to 68 contributes to the knowledge needed for future design strategies and policy updates that can improve the perceptions of eHealth. This study's results can positively affect large numbers of military members across all military branches, which maximizes benefit. Data collected on consumers from electronic health records and other eHealth applications, such as the TOL Patient Portal, can deliver huge data sets to researchers to analyze and produce new knowledge. Most importantly, this knowledge may support top military initiatives improving the overall health, wellness, and readiness of Active Duty Service Members while decreasing the Military Health System's overall cost. The long-term goal of this study is to build knowledge that provides the foundation for delivering tailored health information to promote health and readiness-centric patient engagement.

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Appendix 1: Literature Review Search Strategy

General Population Search Strategy

Database	Search Strategy	Results
PubMed	("eHealth" OR "electronic health" OR "personal health record" OR "patient portal" OR "secure messag*") AND "health information seek*"	82
CINAHL	("eHealth" OR "electronic health" OR "personal health record" OR "patient portal" OR "secure messag*") AND "health information seek*"	48
Embase	("eHealth" OR "electronic health" OR "personal health record" OR "patient portal" OR "secure messag*") AND "health information seek*"	86
		216

Retired Military Search Strategy

Database	Search Strategy	Results
PubMed	("patient portal" OR "secure messag*") AND (military OR "active duty" OR service member* OR servicemember* OR army OR navy OR "air force" OR marines)	12
CINAHL	("patient portal" OR "secure messag*") AND (military OR "active duty" OR service member* OR servicemember* OR army OR navy OR "air force" OR marines)	4
Embase	("patient portal" OR "secure messag*") AND (military OR "active duty" OR service member* OR servicemember* OR army OR navy OR "air force" OR marines)	23
		39

Active Duty Service Member Search Strategy

Database	Search Strategy	Results
PubMed	("patient portal" OR "secure messag*") AND ("military Veteran" OR Veteran OR "retired military")	80
CINAHL	("patient portal" OR "secure messag*") AND ("military Veteran" OR Veteran OR "retired military")	35
Embase	("patient portal" OR "secure messag*") AND (military OR "active duty" OR service member* OR servicemember* OR army OR navy OR "air force" OR marines)	58
		173

Appendix 2: Johns Hopkins Nursing Evidence Level and Quality Guide

Evidence Levels	Quality Ratings
Level I Experimental study, randomized controlled trial (RCT) Explanatory mixed method design that includes only a level I quaNtitative study Systematic review of RCTs, with or without meta- analysis	**<u>QuaNtitative Studies</u>** **A <u>High quality</u>**: Consistent, generalizable results; sufficient sample size for the study design; adequate control; definitive conclusions; consistent recommendations based on comprehensive literature review that includes thorough reference to scientific evidence. **B <u>Good quality</u>**: Reasonably consistent results; sufficient sample size for the study design; some control, fairly definitive conclusions; reasonably consistent recommendations based on fairly comprehensive literature review that includes some reference to scientific evidence. **C <u>Low quality or major flaws</u>**: Little evidence with inconsistent results; insufficient sample size for the study design; conclusions cannot be drawn.
Level II Quasi-experimental study Explanatory mixed method design that includes only a level II quaNtitative study Systematic review of a combination of RCTs and quasi-experimental studies, or quasi-experimental studies only, with or without meta-analysis **Level III** Nonexperimental study Systematic review of a combination of RCTs, quasi-experimental and nonexperimental studies, or nonexperimental studies only, with or without meta-analysis Exploratory, convergent, or multiphasic mixed methods studies Explanatory mixed method design that includes only a level III quaNtitative study QuaLitative study Meta-synthesis	**<u>QuaLitative Studies</u>** No commonly agreed-on principles exist for judging the quality of quaLitative studies. It is a subjective process based on the extent to which study data contributes to synthesis and how much information is known about the researchers' efforts to meet the appraisal criteria. *For meta-synthesis, there is preliminary agreement that quality assessments of individual studies should be made before synthesis to screen out poor-quality studies[1].* **A/B <u>High/Good quality</u>** is used for single studies and meta-syntheses[2]. The report discusses efforts to enhance or evaluate the quality of the data and the overall inquiry in sufficient detail; and it describes the specific techniques used to enhance the quality of the inquiry. Evidence of some or all of the following is found in the report: • Transparency: Describes how information was documented to justify decisions, how data were reviewed by others, and how themes and categories were formulated. • Diligence: Reads and rereads data to check interpretations; seeks opportunity to find multiple sources to corroborate evidence. • Verification: The process of checking, confirming, and ensuring methodologic coherence. • Self-reflection and scrutiny: Being continuously aware of how a researcher's experiences, background, or prejudices might shape and bias analysis and interpretations. • Participant-driven inquiry: Participants shape the scope and breadth of questions; analysis and interpretation give voice to those who participated. • Insightful interpretation: Data and knowledge are linked in meaningful ways to relevant literature. **C <u>Low quality</u>** studies contribute little to the overall review of findings and have few, if any, of the features listed for high/good quality.

Appendix 3: Literature Review Table

Author, Year Title (Evidence Rating)	Purpose/Specific Aims/Questions	Analysis Technique	Method/Sample	Theory/Measures	Results	Conclusions
		1) Statistical Methods 2) Data analysis described	1) Type of study 2) Description of procedural steps 1) Subjects and selection criteria 2)Appropriateness of design 3) Threats to validity	1) Description 2) Reliability & Validity	1) Data fully presented 2) Findings logically presented	1) Findings 2) Limitations 3) Generalization
General Population						
(1) Author(s): Chisolm, D. J. (2010). **Title: "**Does Online Health Information Seeking Act Like a Health Behavior?: A Test of the Behavioral Model" **Evidence Rating** (Level III: B – Good Quality)	(1) examine whether search for online health information can be described in the framework of the behavioral model, (2) test whether predictors of health information seeking are consistent across health topics	- Dependent variable: search of Internet for health information Independent variables from the model: predisposing – age, sex, race, education Enabling – high-speed Internet, Internet access at home, regularity of Internet use - hierarchical logistic regression - significance of variable contribution was tested using a likelihood ratio test - chi-square and Wald chi-square - model tested with pseudo-r^2	Method: 1) Secondary data analysis Sample: - Data from Pew Internet and American Life Project (Aug 2006) - N=2,928, 18 and older: only N=1,990 respondents answered 'yes' for Internet use N=1,880 used for hierarchical logistic regression	- Behavioral Model for online information search – a person's tendency to use health services can be predicted by three factors: predisposing, enabling, and need] - this model has been used to test a variety of health behaviors – this study compared predictors of online health information seeking with other health behaviors	- 64% looked for specific disease or medical problem, 49% looked for diet, nutrition, vitamins or nutritional supplements, 25% alternative treatment/medicines, 27% mental health issues, and 11% sexual health -White respondents used the Internet to find information on specific diseases or conditions, compared to blacks that search for sexual health and Hispanics that search for alternative medicine - age 65 and over had significantly lower rates of search for health information on the Internet	- most consistent predictors of search behavior: female gender, having a health crisis, and regular utilization of the Internet resources - seeking health information can be complicated – different types of searches are associated with different types of patient characteristics - education was not significant in any model

(2) Author(s): Lustria, M. L. A., Smith, S. A., & Hinnant, C. C. (2011) **Title:** "Exploring Digital Divides: An Examination of Ehealth Technology Use in Health Information Seeking, Communication and Personal Health Information Management in the USA" **Evidence Rating** (Level III: B – Good Quality)	(1) examine the relationships of online tools to seek health information, (2) manage personal health information, (3) communicate with their provider	- Used post-stratification weights to account for survey design and sampling - Independent dichotomous variables created for generational variables - Odds ratio for internet exposure, health information seeking, online health information seeking - multivariable logistic regression for five characteristics of behaviors - SAS 9.2 software used for analysis	Method: - Secondary data-analysis using Health Information National Trends Survey (HINTS) data from 2007 Sample: - varied based on analysis: 3523 for socio-economic characteristics, 2497 for summary of dependent variables, 3295 for model of 'do you ever go online to send or receive email?', 2349 for model of 'have you ever looked foe health topics from any source?', 2117 for model of 'did you use the Internet for your most recent health information search', 2336 for 'have you ever used the Internet to track personal health information?', and 2338 for 'in the past 12 months, have you used email or Internet to communicate with a doctor?'	- No theory used in this study but evaluated online health information seeking, personal health information management, use of web technologies for patient-provider communication, and access to and use of eHealth technologies	- Males were less likely to use the internet (OR=0.665, CI – 0.523-08.46) - Caucasians were x3 more likely to access the Internet (OR=2.999, CI=2.218-4.054 - Baby Boomers were less likely than Generation Y to have ever accessed the Internet (OR= 0.405, CI=0.246-0.668 - Silent Generation less likely than Baby Boomers to access the Internet (OR=0.118, CI=0.071-0.198) - Urban residents more likely that rural residents to have Internet access (OR=1.741, CI=1.338-2.265)	- Internet access is a significant predictor of online health information seeking but not significantly related to e-mail communication with healthcare teams - Age and education significant predicators of online health information seeking -- younger with college education -- female and more educated more likely to communicate with provider via email - No significant racial disparities observed - Unclear picture of rural vs urban access and Internet use Limitations: - secondary data analysis and development of health information seeking variables - manipulation of data for analysis
(3) Author(s): Saulsberry, L., Price, M., & Hsu, H. (2014) **Title:** "Insurance Coverage and Whither Thou Goest For Health Information In 2012" **Evidence Rating**	(1) examine use of the eHealth and mobile health technologies by privately insured, publicly insured and uninsured adults	- logistical regression to examine the association between insurance type and online health information seeking - use unadjusted and adjusted regression analysis	Method: - Secondary data-analysis using Pew Charitable Trust telephone interviews data from 2012 Sample:	- No theory used in this study	- 52% private insurance, 21% Medicare, 9% Medicaid, and 18% uninsured - 93% privately insured and 56% Medicare reported Internet use	- Most communication with healthcare provider occurred offline - Medicaid respondents share their information online more than privately insured respondents - Privately insured used the cell phone and

(Level III: B – Good Quality)			N=3,014 U.S. residents, age 18 and older		- 62% private, 60% Medicaid, 75% Medicare, 45% uninsured communicated with healthcare teams 'offline' - 50% of self-reported Internet users looked for health information online - 16% of Medicaid, compared to 6-7% of other insured, shared information online - 15% of private insured, compared to 3% Medicare, used mHealth	mHealth tools more than other insured - Medicare respondents are more likely to text healthcare professionals - Results show that use of eHealth remains low despite access to the Internet and cell phones → access alone doesn't not explain differences in utilization by insurance type - Disparities remain in access to technology-based care
(4) Author(s): Kontos, E., Blake, K. D., Chou, W. S., & Prestin, A. (2014) **Title:** "Predictors of Ehealth Usage: Insights on the Digital Divide From the Health Information National Trends Survey 2012" **Evidence Rating** (Level III: B – Good Quality)	(1) examine eHealth use and disparities by sociodemographic factors and different communication domains	- predictor variables included in each model: place of birth, race, home ownership, education, income, age, and sex - all models adjusted for occupational status, marital status, children, health information-seeking, regular access to healthcare provided, status of insurance, history of cancer in self and family - odds ratios - multivariable, logistic regression model used: education, income, race, age, and gender	Method: - secondary data-analysis using Health Information National Trends Survey (HINTS) data from 2012 Sample: - all respondents that reported 'yes' to ever going online or sending/receiving an email - N=2358	- only 18.95% of online US adults reported engaging in emailing providers, tracking health information (19.29%), and buying meds online (17.67%) - 57.04% of respondents reported using the Internet to seek health information for someone else - 42.98% utilized the Internet within the last year on topics like: diet, weight, or exercise - Online users with lower education used the Internet for health less than users with at least a college degree or more (OR 0.50 and 95% CI 0.33-0.76)	- developed health communication domains using a combination of gratification and the Affordable Care Act and Healthy People 2020	- prevalence of eHealth usage is generally low - being female and younger is consistently predictor of increase use of eHealth Limitations: - secondary data analysis

				- ages 18-34 had a x2 more odds of engaging in online provider searchers compared to 65 and older - women were more likely than men to search for a provider online (OR 1.53, 95% CI 1.14-2.04)		
(5) Author(s): Lee, Y. J., Boden-Albala, B., Jia, H., Wilcox, A., & Bakken, S. (2015) **Title:** "The Association Between Online Health Information-Seeking Behaviors and Health Behaviors Among Hispanics in New York City: A Community-Based Cross-Sectional Study" **Evidence Rating** (Level III: A – High Quality)	- Examined associations of five health behaviors and online health information-seeking behaviors - The five behaviors included "physical activity, fruit/vegetable consumption, alcohol use, and hypertension medication adherence"	- bivariate analysis of demographic, situational variables, and online health information seeking - binomial logistic regressions - hypotheses: "online health information-seeking behaviors would be (1) positively associated with fruit consumption, (2) positively associated with vegetable consumption, (3) positively associated with physical activity, (4) negatively associated with alcohol consumption, and (5) positively associated with hypertension medication adherence"	Method: - community survey of Washington Heights Inwood of northern Manhattan - community health workers led 45-60 minute in-person interviews - interviewers were bilingual - consent obtained in language of choice - $25 gift card for participation Sample: - over 18, English or Spanish speaking, and Hispanic - N=2680 - probability sampling to snowball and convenience recruitment	- Integrative Model of eHealth Use: demographic data, situation factors, health and computer literacy - online health information-seeking and health behavior variables - used to support choice of correlate and health outcomes and health information-seeking behaviors from the survey variables - model also guided the data analysis - health literacy and computer literacy the focus of measurement	- mean age 50 (SD 17.1, range 18-100), 71.60% female, 87.65% immigrants, 63.17% unemployed, 64.33% not married , 49.81% less than high school education, 75.82% Medicare or Medicaid - 74.40% reported good health, 92.20% no serious health conditions - 29.0% reported using the Internet but 7.38% reported using the Internet for seeking health information	- older age, higher education levels, and U.S. born were the most significant variables associated with Internet based health information-seeking - older age was inconsistent with existing studies - a poor health status and no hypertension also had an association - discovered that consumers that seek health information online may improve their overall health behaviors - online health information-seekers consumer were more likely to eat more fruits and vegetables and also have an increased level physical activity - population was well below the average Center for Disease Control guidelines and model only explained a small portion of the variance

						- discovered that skills related to online health literacy must be strengthened; understandability of health information needs to improve for this population
(6) Author(s): Chisolm, D. J., & Sarkar, M. (2015) **Title:** “E-Health Use in African American Internet Users: Can New Tools Address Old Disparities?” **Evidence Rating** (Level III: A – High Quality)	(1) explored predictors of online health information-seeking, (2) focusing on informing design and implementation of Internet-based intervention in minority health promotion and to reduce health disparities	- sociodemographic variables: gender, age, education, income, employment status, and health insurance status - health related variables: perceived health status, living with a chronic condition, family member with a chronic condition, medical crisis in the past 12 months, and or family member with medical crisis - eHealth information seeking variables: search, socialize, track - univariate chi-squared tests to examined relationships - multivariate logistic regression models were than developed for each e-health behavior → using only variables that were statistically significant in the univariate analysis - adjusted for survey weights using SAS SURVEYFREQ and SURVEYLOGISTIC procedures	Method: - Secondary data-analysis using Pew Internet and American Life Health Tracking Survey 2010 Sample: N=395, age 18 and older, African American, and responded yes to using the Internet occasionally or sending and receiving email occasionally	- created a eHealth information-seeking behavior indexes: (1) Search – used Internet to search for information about diseases, medical treatment, health insurance, pregnancy and drug safety (2) Socialize – signed up to receive emails about health issues, gone online to find others with similar health concerns, posted health comments in online discussions, (3) Track – tracked weight and diet, tracked other health indicators	- 63% used the Internet to send emails, 80% engaged in eHealth behaviors → 71% searched for health information, 55% socialized online for health information, 24% tracked health activities - univariately, searching online was significantly associated with income, education, age, gender, having health insurance, having health members with chronic conditions	- respondents with higher income, female, and had been helped by searching for health information online - low-income less likely than middle and high income to search for health information - males also less likely - respondents with high school education were four times likely to socialize online about health than less than high school education

(7) Author(s): Perez, S. L., Paterniti, D. A., Wilson, M., Bell, R. A., Chan, M. S., Villareal, C. C., . . . Kravitz, R. L. (2015) **Title:** "Characterizing the Processes for Navigating Internet Health Information Using Real-Time Observations: A Mixed-Methods Approach" **Evidence Rating** (Level II: B – Good Quality)	(1) describe the process of online information searching and (2) identify demographic characteristics of consumers using two hypothetical acute illness (i.e., influenza and bacterial meningitis) search scenarios	Analysis (1) - discovered differences between system 1&2 respondents in demographics and characteristics -- *t* Test: to make two-group comparison for age, SF-36 (physical function, body pain, overall health, vitality, social status, emotional status, and mental health -- categorical variables included race, gender, type of treatment, location, and education evaluated with chi-square tests Analysis (2) - multivariate logistic regression model to evaluate dominate search strategy -- model using independent variables from analysis (1) with a P value $\leq$ 0.1: physical functioning, site, gender, race, and education - SAS 9.3 software used for analysis	Method: - Mixed-method: observational and survey - demographic questionnaire and short-form (SF)-36 health survey - randomly assigned to a searching scenario: influenza – fever, mild headache, dry cough, and myalgia; or bacterial meningitis – fever, severe headache, and stiff neck - then searched the internet and "think out loud" during their search process - research team collected videos and computer log files Sample: - N= 78, age 21-35 that reported searching of health information in the last 12 months - reported barriers to accessing healthcare services	Theory: - Dual-processing theory (cognitive systems 1&2) - two systems implored in decision making (1) biases and heuristics, (2) evaluation of information	- Age and education were found to have the strongest association with systematic processing choice -- for 1-year age increase the odds of processing declined by 13.3% was a P value of 0..02 - less educated participant we less likely to use a systematic approach for online information searching - No association was found with gender, race, or insurance status	Findings/ Generalization: - identified four online information search patterns: (1 simple search, (2) evidence gathering, (3) hypothesis testing, (4) action and seeking treatment - results demonstrated a preferences towards system 2 thinking or evaluation of information and many participants relied on intuitive approaches to initial searches (i.e., system 1) - younger and more educated participants used system 2 approaches Limitations: - generalizability is limited because of sample size, only focused on young adults from a convenience sample - level of awareness for symptom scenarios was not assesses - unnatural experiment environment may influence searching strategies - no control – exploratory in nature

(8) Author(s): Li, J., Theng, Y., & Foo, S. (2016) **Title:** "Predictors of Online Health Information Seeking Behavior: Changes Between 2002 and 2012" **Evidence Rating** (Level III: B – Good Quality)	(1) explores and compares the effects of the predictors of online Health Information Seeking Behavior (HISB)	- independent variables: age, gender, education level, race, employment, income, marital status, and child guardianship; overall health condition (reported health status & medical history); Internet usage (asked if used the Internet frequently) - dependent variable: created a score of online HISB for each individual - descriptive statistics, chi-square to investigate changes in HISB between 2002 & 2012 - two hierarchical regression models examine socio-demographic variables, health condition, and Internet use on HISB - SPSS software used for analysis	Method: - Secondary data analysis - use of two datasets Sample: - Data from Pew Internet and American Life Project (Dec 2006 and Sep 2012) - Data collected using Princeton Survey Research Associates International - N=2,463 (2002); N=3014 (2012)	- No theory used in this study	- 2012 respondents has a higher percentage of frequent Internet use - 64.3% in 2002 and 56.7% in 2012 searched for disease topics the most - 2012 preformed fewer online searches, leading to a significant decrease in HISB score 2.3 to 1.9 (t=8.078, p<0.001) - age, income, and child guardianship were significant in 2012 but not 2002 - health condition as a single predictor contributed to increasing HISB - medical history was the strongest predictor of HISB in 2002 and 2012	- females with a higher level of education led to increased HISB - overall health condition became a more significant predictor of online HISB over time - individuals with more extensive medical history, also exhibited a greater number of online HISB
(9) Author(s): Manganello, J. A., Gerstner, G., Pergolino, K., Graham, Y., & Strogatz, D. (2016) **Title:** "Understanding Digital Technology Access and Use Among New York State Residents to Enhance Dissemination of Health Information" **Evidence Rating** (Level III: A – High Quality)	- Examine use of technology, and patterns of health information seeking - research questions: (1) "What is the level of access to digital technologies, including computers, the Internet, cell phones,	- weighted analysis conducted to adjust for sampling procedures and the distribution of socio-demographic characteristics - chi-square teste were conducted to compare groups through bivariate analysis for key variables: education, sex,	Method: - Mobile and landline based cross-sectional survey Sample: - N=1,350 - New York State residents – "to ensure a sufficient number of rural respondents, a component of the landline sample	- No theory used in this study	- 82% had as least one computer at home, 91% had high-speed internet - 85% reported using the Internet sometimes, 53% reported using the Internet several times per day - 62% accessed with a computer, 29% with a cell phone	- high Internet and cell phone use and access to high-speed Internet by respondents in the sample - older respondents, with less education, and lower income were less likely to use the Internet - incomes was the biggest predictor of using social media for health; lower incomes were more likely

	smartphones, and texting?" (2) "What is the frequency of use of various media channels including email, search engines, online newspapers/ magazines, social networking sites, online videos, video chat, Twitter, online bulletin boards, text messaging, and smartphone apps?" (3) "What channels are preferred for receiving health information?" (4) "How do the answers to questions 1 through 3 vary by education, age, sex, ethnicity, race, income, and geographic area?"	ethnicity, race, income, geographic area - media and technology variables: number of computers at home, type of Internet access, type of phone access (landline, cell, smartphone), frequency of Internet and phone related activities, preference for receiving health information - Logistic regression model to examine information seeking patterns	targeted the 24 New York State counties not situated in a Metropolitan Statistical Area. - Oversampling of Hispanic/Lation - 18 years and older		- lower education, younger, non-white, and non-rural were all more likely to use their cell phone as the main way to access the Internet - 90% das cell phones: of these 63% were smartphones, 70% had unlimited texting but 8% reporting not having cell service throughout the year - the most common online activities were email or search engines - other activities included: Facebook, watching videos, reading newspapers and video chat → however, 75% of reported never using social media for health purposes - 49% preferred health information form websites, then 35% from TV, 35% from mail, 29% from email	to use social media for health - despite high access to the Internet and technology, what respondents actually do on the Internet is varied - "Given the variation among Internet and mobile phone activities, it is recommended that the public health groups seeking to disseminate health information should consider specific technology access and use pattern and preferences of the target population when developing a commutation plan." Limitations: - limited time to conduct survey - constantly changing technology - sample selection was intended to target subpopulations: rural, Hispanic, cell phone users

(10) Author(s): Nambisan, P. (2017). **Title: "**Factors that Impact Patient Web Portal Readiness (PWPR) Among the Underserved" **Evidence Rating** (Level III: B – Good Quality)	- evaluate which factors contribute to a patient's readiness to use a patient web portal	- dependent variables: personal health information management, attitude toward personal record keeping, and use of the Internet for health information -independent variables: access to the Internet, demographics, presence of chronic disease - descriptive statistics, multi-collinearity analysis, and simple linear regression	Method: - questionnaire-based survey, 5th grade reading level in English, Spanish, and Arabic - graduate student with training in structed interviewing administered the survey to participants who could not read Sample: N=132 - five free clinics in the Northern Virginia	- developed a new model: Patient Web Portal Readiness (PWPR) - used constructs of Personal Health Information Managements, Internet access, health status and demographic variables	- 64% income below $20,000 - 40% Hispanic - 81.8% had some form of Internet access (home, work, mobile, and public library - 66.7% reported using the Internet for health-related activities or search for health information	- many factors may influence PWPR among the underserved - demographic factors of age, gender, ethnicity, education, and income did *not* impact PWPR - attitude towards health record keeping, use of the Internet to seek health information were most likely to influence PWPR
(11) Author(s): Gonzalez, M., Sanders-Jackson, A., & Wright, T. (2019) **Title:** "Web-Based Health Information Technology: Access Among Latinos Varies by Subgroup Affiliation" **Evidence Rating** (Level III: A – High Quality)	- Examine disparities in Web-based health information-seeking behavior and patient portal use in US born non-Hispanic whites and Latinos	- dependent variable: reporting use of the Internet, emailing a healthcare provider, engaged in using the Internet to seek health information, or used an online patient portal in the last 12 months - independent variables: US born, age, gender, education, poverty level, marital status, insured, employment category - multivariable binary logistic regression to test relationship between ethnicity/nativity and internet use - binary logistic regression to test the relationship between ethnicity/nativity and health information	Method: - Secondary data analysis using the National Health Interview Survey (NHIS) - data from 2015 and 2016 Sample: N=49,251 - US born - Caucasian and Latinos N=36,214 - survey participants that reported using the Internet	- No theory used in this study	- 82.6% used the Internet with 65.05% to look for health information - 13% reported using a Patient Portal - 80.36% white, 21% Latino - 40.29% age 31-54 - 31.53% some college education - 63.48% married - 58.12% white collar - 90.16% insured - 85.6% of whites used the Internet compared to 53.76% Latino - less than 50% of the Latinos not born in the U.S. reported looking for health information - whites had the highest odds for engaging in health information-seeking behavior	- disparities continue in patient portal use, although Internet access and use is increasing - found low Internet use in Latinos compared to whites - Latinos less likely to use patient portals - younger Latinos have an even lower likelihood to use a patient portal Limitations: - secondary data analysis of cross-sectional data - causal analysis not possible - self-reported

		seeking and patient portal dependent variables			- no difference in using a portal to schedule an appointment - foreign-born Latinos were less likely to use a portal to fill a prescription or email a healthcare provider compared to whites	
(12) Author(s): Madrigal, L., & Escoffery, C. (2019) **Title:** "Electronic Health Behaviors Among US Adults with Chronic Disease: Cross-Sectional Survey" **Evidence Rating** (Level III: B – Good Quality)	- explore the difference utilization of technology and health information-seeking behaviors - attitudes towards seeking health information online, and the level of literacy of adults with a chronic disease	- 109 survey items included: ownership of different devices, online access, utilization frequency AND - eHealth and health seeking behaviors include: health indicator tracking, utilization of mobile application, and other online-based health actions - descriptive statistics for chronic disease prevalence & type, demographics, and health monitoring, and eHealth behaviors - *t*-tests and chi-square used to test differences in eHealth seeking and having a chronic disease - compared the categorical variables of frequency of participants with or without health condition using chi-square tests - evaluated continuous variables using *t*-tests	Method: - cross-sectional Internet survey in 2017 - email/SurveyMonkey Sample: N=401 - US adults 18 or older, with Internet access, English speaking	- No theory used in this study - survey questions developed from the Pew Health & Internet Surveys and the Health Information National Trends Survey - used eHEALS to measure eHealth literacy	- 71.8% owned a laptop or smart phone - 99.3% reported access to the Internet - 51.1% used the Internet several times a day - 75.1% reported searching for health related information on the Internet with 42.9% in the last month; top searches included: exercise and nutritional search, medications, and rapid self-care solutions - participants with a chronic disease were more likely to search for information about medicine - 14.0% use a mobile app, 12% use a website, 9% use a wearable, and 8.2% use a computer program to track health information - top mobile tracking apps: exercise, diet, and weight - 46.9% had access to a patient port and	- adults with and without a chronic disease use the Internet for health information - adults with a chronic disease have a slightly higher likelihood to participate in eHealth behaviors such as looking for health related information online, tacking health markers and utilizing a patient portal - younger, female, and a greater eHEALS score were the most associated with seeking health information on the Internet and use of mobile related health application Limitations: - self-reported - small sample size - could not medically verify diagnosis

		- calculated the descriptive statistics for perceived eHealth literary and Cronbach alpha to measure reliability - SAS software used for analysis			28.4% used in the last 12 months - 40.9% of participants with chronic disease accessed a portal in the last 12 months	
(13) Author(s): Lee, J. L., Rawl, S. M., Dickinson, S., Teal, E., Baker, L. B., Lyu, C., . . . Haggstrom, D. A. (2020) **Title:** "Communication about Health Information Technology Use Between Patients and Providers" **Evidence Rating** (Level III: B – Good Quality)	(1) explore how patient communicate with their providers when using health information technology, (2) prevalence of in-person discussion about technology, and (3) factors that are associated with communication and health information technology	- assessed attitudes, concerns about quality of information, frustration with finding information and able to understand the information; health information technology platforms used to communicate with healthcare providers - independent variables: age, race, education, employment status, home ownership, geographic location, and income - descriptive statistics for sociodemographic characteristics, technology use, and overall health information seeking behaviors - multivariable logistic regression to assess communication with providers abut health information technology	Method: - cross-sectional self-administered survey - survey consisted of evaluation of health information seeking behaviors, use of health information technology, and sociodemographic characteristics - questions developed from Health Information National Trends Survey (HINTS) Sample: - adults age 18-75 in the state of Indiana - 7,979 surveys mails, 970 completed, 12% response rate - prepaid postage and $1 incentive included in mailed survey package	- No theory used in this study	- 63% used the Internet as a first source of health information, 19% from providers, and family as 5% - 31% used an electronic health record messaging, 24% email, and 18% text to communication with their provider - only 21% reported having a conversation about electronic health record messing	- female, trust in the Internet and higher education were associated the most with having a conversation about electronic health record messing - preference for the Internet and providers as first sources of health information was consistent across ages groups - no race, geographic, or income differences were found - more research is needed in understanding effective electronic communication behaviors and the impact on patient outcomes Limitations: - self-reported - 12% response rate - sample from academic healthcare system

		- weights used in descriptive and regression analysis - SAS 9.4 software used for analysis				
(14) Author(s): Sherman, L. D., Patterson, M. S., Tomar, A., & Wigfall, L. T. (2020) **Title:** "Use of Digital Health Information for Health Information Seeking Among Men Living with Chronic Disease: Data From the Health Information National Trends Survey" **Evidence Rating** (Level III: B – Good Quality)	(1) tested a conceptual model, (2) investigated where male participants seek or look for health-related information, (3) identified predictors of use of digital health information diabetic males, (4) compared this information with non-diabetic males	- used demographic variables: age, education, income, employment status, race, and ethnic: cardiovascular-related health behaviors: smoking, weekly exercise, consumption of fruits and vegetables; comorbidities: heart disease, diabetes, high blood pressure, and obesity; and technology use: device to track health-related goal or seek health information - completed a chi-square to compare differences and hierarchical linear regression build three models predicting eHealth scores among - SPSS 24 software used for analysis	Method: - cross-sectional study, secondary data analysis - collected January and February of 2018 Sample: - Health Information National Trends Survey (HINTS) data from 2017 - Included self-identified males N=1,254 - eHealth technology users N=1,002 compared to non-users N=195	- Structural Influence Model (Viswanth et al., 2007) to develop a conceptual model of factors related to men's eHealth scores	- found statistically significant differences between eHealth users and non-users in age,, races, income, marital status, education, employment, fruit consumption, vegetable consumption, smoking status, exercise, blood pressure, use of digital sources for health information, use of a smartphone, and use of device to track health information - no statistically significant differences in sexual orientation, individual with diabetes, obesity, and heart conditions - linear regression model suggests education, income, age, Hispanic, smoking, using a device to track and seek health	- demographics variables suggest a relationship between age, education, race, income, and eHealth scores - digitally seeking health information is the strongest predictor of eHealth scores. Limitations: - secondary data analysis, self-reported data - unable to confirm disease status with medical chart data - Large sample but HINTS data has a higher number of educated, retired, older, and higher income respondents

					information are related to eHealth sum scores	
Military Veteran						
(1) Author(s): Tsai, J., & Rosenheck, R. A. (2012) **Title:** "Use of the Internet and an Online Personal Health Record System by US Veterans: Comparison of Veterans Affairs Mental Health Service Users and Other Veterans Nationally" **Evidence Rating** (Level II: B – Good Quality)	- This study focused veterans "who provided information about VA enrolment and mental health service use"	- Logistic regression to examine characteristics associated with internet use and My HealtheVet - Dichotomous measure of Internet use and My HeatheVet: 'Do you use the internet, at least occasionally?' 'Have you ever used the 'My HealtheVet' website to obtain information related to your personal VA healthcare?' - Additional questions regarding Internet use: frequency of internet use, places where the Internet was used, whether email was used and frequency	Method: - Large scale survey - National Survey of Veteran, is a series of comprehensive nationwide surveys designed to help the VA plan future programs and service for veterans - 2010 was first time to ask about internet use - conducted using a mailed, self-administered questionnaire using address-based sampling Sample: - Nationally representative sample from 2010 National Survey of Veterans N=195	- No theory used in this study	- Most participant were white, male, 60-69, had some college education, were employed, had a household income of >$30 000, and were married or in a civil union - 7.2% reported recent service in Iraq or Afghanistan -VA mental health service users were significantly younger, female, and had lower incomes than other veterans - 5111 (70.83%) use the Internet - No significant difference in Internet use between mental health service users and other veterans	Findings: - 71% of veterans use the internet - a fifth of the sample used My HealtheVet - Being younger, more educated, white, married, and with a higher income were most associated with Internet use - No association was found between background characteristics and use of My HealtheVet - Mental health users has no difference in use of the Internet and My HealtheVet Limitations/ Generalization - self-reported survey
(2) Author(s): Woods, S. S., Schwartz, E., Tuepker, A., Press, N. A., Nazi, K.	- examine the views and experiences of	- results from interviews were coded	Method: - Qualitative	- No theory used in this study	- both positive and negative experiences	Findings:

M., Turvey, C. L., & Nichol, W. P. (2013) **Title:** "Patient Experiences with Full Electronic Access to Health Records and Clinical Notes Through the My HealtheVet Personal Health Record Pilot: Qualitative Study" **Evidence Rating** (Level II: B – Good Quality)	Veterans reading the health records and clinical notes	by use of a content analysis method - themes emerged inductively once data collection was complete	- Five focus groups, groups included both patients and family members that were already enrolled in My HealtheVet - 60-90 minute interviews. Audio recorded and transcribed Sample: - purposeful sampling - Portland Veterans Administration Medical Center, Oregon N=30		and themes were discovered - participants described positive effect of viewing their records - increased comm. – both during and after medical visits - access to the health information improved participant knowledge on their personal health - encouraged increased appeal to completed self-care activities - participants described access to the health record enhanced participation of care - participants reported some challenges while viewing health record information, specifically clinical notes	- broad themes included perceived benefits to self-care and to participation in care - patients that seeing health information on the portal (1) "positively affected communication with providers and the health system" (2) "enhanced knowledge of their health and improved self-care" (3) "allowed for greater participation in the quality of their care" (i.e., follow-up of abnormal test results) - some patients felt that information on the portal was (1) "undisclosed information" (2) "used derogatory language" (3) "had inconsistencies in their notes" - overall patient felt " having more, rather than less, of their health record information provided benefits"
(3) Author(s): Turvey, C., Klein, D., Fix, G., Hogan, T. P., Woods, S., Simon, S. R., . . . Nazi, K. (2014) **Title:** "Blue Button Use by Patients to Access and Share Health Record Information Using the Department of Veterans Affairs' Online Patient Portal" **Evidence Rating** (Level II: A – Good Quality)	- Examined the adoption and use of the Blue Button (or health record) feature health record on My HealtheVet – VA's patient portal	- Multivariate analyses were conducted on demographics, self-rated computer ability, health status, use of a system for organizing health information, and the perceived value of access to health records - results were compared across the three Blue Button use categories using the $\chi 2$ test	Method: - online survey - assess characteristics associated with portal use - identify the perceived value of use - examine how "Veterans with non-VA providers use the Blue Button to share information with their non-VA providers" - bivariate relationships characteristics and	- No theory used in this study	- 33% of the random sample used the Blue Button feature - 73% reported a better understanding of their health history because all health information was in one place -21% percent users shared Blue Button information with a non-VA provider - 87% reported that the non-VA	- Self-rated computer ability was the most associated with Blue Button use and sharing information with non-VA providers - comparing Blue Button users and non-users, barriers to adoption were low awareness of the feature and difficulty using the Blue Button

		- single multivariate logistic regression model to determine respondent characteristics that were independently associated with sharing health information generated by the Blue Button with non-VA providers - Multivariate logistic regression models generated determine respondent characteristics that were independently associated with Blue Button use - Preparatory stepwise regression determine medical conditions (15) were independently associated with Blue Button current users - Only those illnesses remaining in the preparatory model with a p value of 0.05 or lower were included in the final logistic regression models SAS V.9.3 software used for analysis	Blue Button use were examined Sample: - 4% random portal users between March and May 2012 N = 18,398		provider found the information somewhat or very helpful	
(4) Author(s): Shimada, S. L., Allison, J. J., Rosen, A. K., Feng, H., & Houston, T. K. (2016) **Title:** "Sustained Use of Patient Portal Features and Improvements in Diabetes Physiological Measures" **Evidence Rating**	- Evaluate the association between sustained use of specific patient portal features and management of type 2 diabetes	- Calculated the odds of attaining control of each measure by the year 2013 by the years of utilizing each patient portal feature - adjusted odds for demographic and clinical aspects related to patient portal use	Method: - five-year retrospective cohort design - assessed portal use between 2010 and 2014 - features evaluated online medication refill and secure messaging Sample:	- No theory used in this study	- 34.13% of the cohort was using Web-based refills - 15.75% using secure messaging - users were somewhat younger, likely not probable to be qualify for free healthcare based on economic	- Refilling meds was the highest used function but showed no influence on outcomes - sustained SM had the greatest impact on HbA1c - future research should what individual components may have

(Level III: A – High Quality)		- "covariates included age, gender, race or ethnicity, urban, suburban, or rural residence, educational attainment, and income" - "multivariable models, adjusted for age, gender, race, comorbidities, and available measures of socioeconomic status"	- Veterans with diabetes registered for the My HealtheVet N=111,686		status, and mostly female - participants with uncontrolled HbA1c and utilized secure messaging were the most likely achieve glycemic control than consumers that did not use the patient portal - participants with uncontrolled baseline blood pressure that utilized the online medication refill, were significantly more likely to achieve control during a follow-up appointment compared to non-patient portal users	differential effects on health improvements - both patient portal features were associated with improvements in low-density lipoprotein cholesterol levels
(5) Author(s): Hogan, T. P., Hill, J. N., Locatelli, S. M., Weaver, F. M., Thomas, F. P., Nazi, K. M., . . . Smith, B. M. (2016) **Title:** "Health Information Seeking and Technology Use Among Veterans with Spinal Cord Injuries and Disorders" **Evidence Rating** (Level II: B – Good Quality)	- Evaluate health information seeking among veterans with spinal cord injury or disorder SCI/D - Examine the associations between technology use and the characteristics of veterans with SCI/D	- Frequencies of computer use, test messaging, the Internet and sources of information - t-tests for continuous variables and x2 test for categorical variables - Multiple logistic regression: associations between veteran characteristics and computer, Internet, and text messaging use - multiple linear regression for eHEALS score - Stata 12.0 software used for analysis	Method: - mail survey, 38% response rate - questions developed to assess participant patterns of computer and Internet use, information preferences, and an 8-item e-Health Literacy Scale (eHEALS) Sample: - N=290, 18 or older, veterans, with SCI/D and utilized healthcare services within the past 12 months at one of two Veterans Health Administration SCI/D centers in the Midwestern United States	- No theory used in this study - eHEALS survey for eHealth literacy	- 97.2% male, 71.0% under 65, 71.7% white, 58.6% married - 51.4% had paraplegia, 53.9% with less than 10 years of having injury - 64.8% had a computer, 67.5% did not use assistive equipment with computer - 91% used health professionals as a primary source of information - eHEALS mean score 27.3 (SD =7.2) - 75.5% of veterans with excellent or good health status reported Internet use	- Veterans are comparable to other studies for high level of computer use - veterans also use the Internet for an information resource - self-reported excellent of good health status was associated with more computer, Internet, and text messaging use - self-reported excellent of good health status was associated with higher eHEALS scores - white veterans use computers and the Internet more than other races - veterans younger than 65 use computers, Internet, and text messaging more than older veterans - veterans use healthcare professionals as the most

						frequent source of information Limitations: - only veterans from to facilities - did not assess availability, quality, or trustworthiness of information - did not collect socioeconomic information
(6) Author(s): Woods, S. S., Forsberg, C. W., Schwartz, E. C., Nazi, K. M., Hibbard, J. H., Houston, T. K., & Gerrity, M. (2017) **Title:** “The Association of Patient Factors, Digital Access, and Online Behavior on Sustained Patient Portal Use: A Prospective Cohort of Enrolled Users” **Evidence Rating** (Level III: A – High Quality)	- Distinguish factors that relate to short and long-term patient portal utilization beyond initial registration	- Information collected at baseline: demographics, health literacy, access and utilization of the Internet, patient activation, and health conditions reported by the participant - primary outcome was the frequency of portal logins during six and 18-month time intervals after study enrollment - 6 months, categories included: 0 or 1 login, 2 to 5 logins, 6 to 11 logins, and 12 or more logins - 18 months the categories included: 0 to 2 logins, 3 to 17 logins, 18 to 35 logins, and 36 or more logins - 4 categories of logins corresponded to portal use frequencies of never/rare use, less than monthly, once or twice per month, and	Method: - survey - prospectively followed a cohort of VA patients that recently registered for the My HealtheVet - conducted a health literacy assessment - survey questions were completed on paper at the time of enrollment or within 30 days, and returned by mail - 6 months survey email link to the follow-up survey Sample: N= 260	- No theory used in this study	- 97.0% using the Internet - most Internet use was at home 92.5% - at six months, 84.1% of participants logged on to the patient portal - at 18 months, 91% participants had utilized to the patient portal	- No significant differences in patient portal logins by gender, age, education level, marital status, ethnicity, VA facility location, or patient activation measure - participants home broadband Internet use, higher capability to individually use the Internet, and regular use of the Internet and going online frequently where significantly associated with increased portal use Limitation: - self-reported patient portal use

		more than twice per month				
(7) Author(s): Stewart, M. T., Hogan, T. P., Nicklas, J., Robinson, S. A., Purington, C. M., Miller, C. J., . . . Shimada, S. L. (2020). **Title:** “The Promise of Patient Portals for Individuals Living with Chronic Illness: Qualitative Study Identifying Pathways of Patient Engagement” **Evidence Rating** (Level III: A – High Quality)	- Evaluate how patient portals facilitate patient engagement - diabetic patients - identify how patients living with diabetes use an online health portal to support diabetes self-management.	- Analyzed using an inductive approach - interviews were logged, then recorded, and coded twice for several themes, utilizing an established coding scheme - thematic coding: utilized both deductive and inductive - 8 codes picked that were related to using a portal and patient engagement: “(1) patient-team relationship (portal use impact on the patient-healthcare team relationship)” (2) empowerment (patients feeling empowered through portal use) (3) care collaboration (patients using the portal to coordinate care with their healthcare teams) (4) impact on care plan (how portal use changes patients’ care plans between visits) (5) clarification (patient-initiated communication through the portal for explanations of information). (6) secure messaging challenges (7) medication refill challenges	Method: - qualitative study - semi-structured telephone interviews, recorded, transcribed, coded - deductive coding: used firstly to make a list of initial codes from the interview guide - inductive codes: coders examined developed narrative and fresh themes materialized from the transcribed records Sample: - patients uncontrolled diabetes since 2011 - utilized secure messaging at a minimum of 4 times over 18 months N=40	- Patient Activation Measure (PAM) (44) as a measure for patient engagement	- Patients who used the portal reported feeling engaged in their health care - reported that the portal helped improve the patient-provider relationship - reported challenges with both secure messaging and access to medical records. - “benefits for patient engagement were described by many types of portal users with varying degrees of diabetes control”	- Better understand their health by asking questions about new symptoms, notes, or labs - prepare for medical appointments by reviewing labs and notes - coordinate care between VA and non-VA healthcare teams - reach out to providers to request help between visits

		(8) Blue Button challenges"				
(8) Author(s): Connolly, S. L., Etingen, B., Shimada, S. L., Hogan, T. P., Nazi, K., Stroupe, K., & Smith, B. M. (2020) **Title:** "Patient Portal Use Among Veterans with Depression: Associations with Symptom Severity and Demographic Characteristics" **Evidence Rating** (Level III: A – High Quality)	- Evaluated the "associations between symptom severity, demographic characteristics and patient portal adoption and use among Veterans with depression diagnoses"	- Random sampling of the comparison weighted groups - Used logistic regression models - evaluated factors of patient portal use in Veterans - factors included: "appointment views, prescription refills, secure messages read, secure messages sent, and medical record content downloads" - covariates included: "depressive symptom severity, age, sex, race, and ethnicity" Used STATA MP Version 14.2 software for analysis	Methods: - retrospective analysis Sample: - excluded if deceased, younger than 18 or older than 104, had less than two encounters before or after their index date, and/or had missing data on any study covariates. N=3053	- No theory used in this study	- "61.4% had mild to moderate depressive symptoms and 38.6% had moderately severe/severe symptoms" - "55.4 years old on average" - "9.7% female" - "7.3% African American" - "9% Hispanic" - 21.9% of the sample registered for the patient portal - 33.6% used the appointment view feature - 44.7% refilled a medication - 20.4% used or read a secure message - 24.9% sent a secure message - 15.9% downloaded personal health information	- Veterans with higher depression had higher odds of registering for the patient portal and also downloading their medical record - older Veterans the lowest rates of patient portal registration - African American Veterans had lower rates of using patient portal features after initial registration Limitations: - "restriction to a Veteran population who first used MHV in FY2013 as opposed to prior or subsequent years"
Military Studies						
(1) Author(s): Boocks, C. E., Sun, Z., Boal, T. R., Poropatich, R. K., & Abbott, K. C. (2003) **Title:** "Walter Reed Army Medical Center's Internet-Based Electronic Health Portal" **Evidence Rating** (Level II: B – Good Quality)	- Multiphase retrospective analysis to to evaluate the medication refills, appointment booking, and the utilization of health information searches completed using the Internet and compared these to other non-Internet and	- Med Refill/Appt data - Statistical methods includes linear regression along with exponential growth equations - X2 (categorical) and t test used to compare demographics of online users and total users - Data were analyzed using Microsoft Excel Search & Learn data	- Retrospective analysis from October 2000 to June 2002 of online med refill data and online appointments - appointment booking and online medication refill data were utilized - Software: spreadsheets used for analysis - Webtrends software used to assess log files	- No theory used in this study	- Data was fully presented with findings logically presented in article: - 34,741 medication refills and 819 appointments via the Internet compared to traditional methods 2,252,112 and about 500,000 appts - 147,425 unique visits	Findings - most search phrases in the Search & Learn application related to women's health - statistically significant differences for appts data were discovered for sex, age, and geographic location - Women under 40 use the system more than men - Men over 40 use the system more than women

	conventional resources	- log files analyzed using Webtrends Log Analyzer	for the ‘Search & Learn’ medical information application - Study completed at the Walter Reed Army Medical Center Sample: - The overall sample size was not clearly stated - No exclusion criteria; all consumers who used the system between 2000 and 2002 were included - Incomplete demographic information was provided			- Highest use is by consumers directly surrounding large military facilities (Fort Belvoir, Fort Meade) Limitations/ Generalization - study did not account for the Military Health System (MHS) being a “male-dominated military establishment” - Only one MHS military treatment facility (MTF) used, may not reflect total population - unable to determine reasons for statistical differences because of using retrospective data, future studies will include optional survey questions to assess satisfaction and obtain feedback - simplification of user interfaces has potential to improve adoption and use of eHealth tools - technological infrastructure must be established to support reliability of eHealth tools - More consumers searched for information after the September 11th event - More consumers used the online appointing application - Location of consumer important (awareness)

(2) Author(s): Luxton, D. D., Armstrong, C. M., Fantelli, E. E., & Thomas, E. K. (2011) **Title:** “Attitudes and Awareness of Web-Based Self-Care Resources in the Military: A Preliminary Survey Study” **Evidence Rating** (Level II: B – Good Quality)	- Our goal with this study was to conduct a preliminary survey assessment of self-care Web site awareness, general attitudes about use, and usage behaviors of Web-based self-care resources among service members and military healthcare providers.	- Descriptive statistics, data analysis was not described - Data fully presented - Findings were logically presented	- Exploratory study - Data collected using self-reported survey questions - Questions focused on “(1) Internet usage and purpose, (2) attitudes about the values and utility of Web-based resources, and (3) comfort/ willingness to use Web-based self-care resources Sample: - (N=28) Service members recruited at an in-processing personal facility on a large military installation; this helps avoid bias of only surveying participants that are seeking care at MTFs - (N=25) Military medical providers - IRB approved - No power analysis complete, exploratory study	- Preliminary survey; developed by research team - No model or theory used to guide		Findings - majority of service members and providers use Internet-based health resources; mostly for self-care - Both service members and providers prefer in-person care - Almost all service members have web-cameras at home Limitations/ Generalization - limited sample size and low survey response by providers - preliminary surveys, not validated - Service members have interest in using other Internet-based resources - Service members still prefer in-person care; but will to use Internet-based tools as accessory tools to maintain health - Internet-based self-care resources are valuable as an adjunct resource in healthcare; more research is needed
(3) Author(s): Do, N. V., Barnhill, R., Heermann-Do, K. A., Salzman, K. L., & Gimbel, R. W. (2011) **Title:** “The Military Health System's Personal Health Record Pilot with Microsoft HealthVault And Google Health”	- Goal of project was to evaluate a personal health record after implementation - Evaluate the functionality and usability of various personal health records	- (N=250) MHS beneficiaries assigned to Madigan Army Medical Center - Convenience sample - Recruitment open to active duty, family members, retirees, and family members of retirees	- This was a pilot study - Location was Madigan Army Medical Center - Consumers recruited to use personal health record options: MICARE, HealthVault, and Google Health	- Measured using satisfaction survey, panel feedback, system usage data, and system implementation documentation	- Used Google Analytics for analysis of usage data - Descriptive statistics; analysis was not described - Limited results were displayed and finding were not logically presented	Findings - large data transfer slow down system performance - discovered timing of sensitive labs is important - accessing personal health record was disruptive to provider workflow

Evidence Rating (Level II: B – Good Quality)		- Printed advertisement in base and local community newspaper; posters on base at stores and electronic sign when entering military base gate; hospital staff encouraged to promote enrollment, and registrations booths setup in MTF - No rationale for study size or power analysis provided, may introduce bias	- Users surveyed via telephone in April 2009 - Received rolling feedback from a panel of providers and patients			- consumer exclusion of information may lead to patient safety issues Limitations/ Generalization - the study has the appearance of being completed post implementation of the MICARE system, the flow between implementation information, surveys and, utilization logs do not flow; as an example, the overall sample size for the study was N=250 but only N=60 participants were surveyed, and 3304 utilization metrics were evaluated but provided not demographic information - design and implementation issues are important and must be considered to support adoption of eHealth - only 20 active duty family members, 20 active duty, and 20 retirees Air Force participants at on MTF location were surveyed; this limits generalization to the target population of the total Air Force and total MHS - Consumers appreciate faster system performance - Discovered timing of sensitive labs is important - Consumers requested an option to exclude sharing information with providers; want to feel in

						"control of health information"
(4) Author(s): Agarwal, R., Anderson, C., Zarate, J., & Ward, C. (2013) **Title:** "If We Offer It, Will They Accept? Factors Affecting Patient Use Intentions of Personal Health Records and Secure Messaging" **Evidence Rating** (Level II: B – Good Quality)	- Assessed how patient activation, provider satisfaction, technology, and the organization are related intentions to use a personal health record by patient that are early technology adopters	- (N=293) Participants were recruited after enrolling and using the personal health record and secure messaging application; sampling participants from the actual uses of the system is effective in evaluating the target population for this study - No power analysis completed	- Cross-sectional analysis of data collected in the field at Elmendorf Air Force Base (AFB), Alaska; during a three-month period after a personal health record and secure messaging was released	- PHR acceptance model developed from the social cognitive theory - Factors: - technology perceptions - employer communication strategies - individual characteristic - patient activation - provider satisfaction	- Moderated multiple regression - SPSS used for analysis - Data fully presented - Findings were logically presented	Findings - satisfaction with their provider, communication strategies, tool functionality, and patient activation were found to be associated with behavioral intentions to use the personal health record tool - variance was explained by independent behavioral intentions variables, around 42% Limitation - only one Air Force facility was used in this study which limits generalizability Generalization - Provided insight on the importance of "employers, insurer, and providers" sponsoring PHR technology - Perceived usefulness and communication strategies are predictors of utilization

(5) Author(s): Wolcott, V., Agarwal, R., & Nelson, D. A. (2017) **Title:** "Is Provider Secure Messaging Associated with Patient Messaging Behavior? Evidence from the US Army" **Evidence Rating** (Level III: A – High Quality)	- Evaluated the relationship between provider and patient secure messaging	- (N=) 81,000 US Army Soldiers secure messaging records - received an exempt from the University of Maryland Institutional Review Board - also reviewed and exempt by the Human Protection Office on Research in the Defense Health Agency	- Used Army Medicine Secure Messaging Service secure messaging data - Data evaluated included "message their primary care and medical teams to request medical advice, appointments, lab results, referrals, and prescription renewals; record medical information; and access educational materials" - the primary dataset was de-identified and secured - available data elements: "age, deployment history, time-in-service, rank, race, marital status, body mass index, self-reported health measures, medical diagnoses, medical appointment data, prescription medications, physical fitness test scores, and tobacco use" - Dependent variable: number of messages sent by consumer	- Secondary data analysis of secure messaging records; over a four-year time period	- Negative binomial regression model - Analysis completed using Stata 13 software - Data fully presented - Findings were logically presented	Findings - providers responding to patient messages at a high rate was the most associated with high patient response - leading to the link between a provider's level of messaging possibly predicting patient follow-on communication behavior Limitations/Generalization - only one evaluated Army data ; which limits generalizability to all Service Members - however, the data analysis is a good representative of the Army medical services target population - Provider behavior affect consumer behavior with secure messaging
(6) Author (s): Hernandez, B. F., Morgan, B. J., Ish, J., Agbator, L. O., Lindo-Moon, S., Stotler, F. F., & Gardner, C. L. (2018) **Title:** "Communication Preferences and Satisfaction of Secure Messaging Among Patients and Providers in the Military Healthcare System"	- Goal to build and knowledge for patient–provider communication preferences in the military healthcare consumers	- Convenience sampling used (N=70) Air Force providers and staff - Inclusion criteria: providers and staff assigned to one of the five designated MTFs - Providers and staff recruited with flyers	- Cross-sectional survey between 2014 and 2015 - Evaluated communication variables: in person visits, telephone, secure messaging, or postal mail	- Survey developed by research team - No validity or reliability provided - No theory used to develop survey	- Patients, providers, and staff differences in communication preferences by were evaluated with Chi-square and Fisher's exact tests - Satisfaction responses frequencies completed	Findings - Consumers were satisfied with secure messaging; although 40.3% were undecided - Providers believed secure messaging improved "efficiency (58.0%) and communication with

Evidence Rating (Level III: A – High Quality)		and email; link to the survey provided (N= 1,260) MHS consumers - Inclusion criteria: Age 18 to 65; linked with a primary care manager at one of the chosen military treatment facilities - Recruited with letter of information before appointment check-in - Power analysis not provided for either population - IRB exempt; study considered a quality improvement project	- Five Air Force MTFs used - Five to ten minute anonymous surveys - participants completed surveys in the waiting rooms before primary care visits - completed surveys places in confidential holding box - surveys then were sent via postal mail back to research team - data were entered and into an electronic database then cleaned before analysis		- Data fully presented - Findings were logically presented	patients (72.3%)" but 65% of the staff and providers felt secure messaging increased their overall workload Limitations/Generalization - study considered a quality improvement project - only one evaluated Air Force data; which limits generalizability to all Service Members - however, the data analysis is a good representative of the Air Force medical services target population - Convenience sampling used; may not be generalizable to other AF MTFs - Provider and staff sample size was small - Outside factors such as access to the internet, eHealth/health literacy, or the utilization frequency were not collected internet access - Age, military status (i.e., active or retired), type of duty, the years of clinical experience all supported different communication preferences

Appendix 4: Chi-Square Test Results

Count

		TOL_Use Yes	No	Total
Gender	Male	141293	945447	1086740
	Female	57095	156686	213781
Total		198388	1102133	1300521

329,809

Chi-Square Tests

	Value	df	Asymptotic Significance (2-sided)	Exact Sig. (2-sided)	Exact Sig. (1-sided)
Pearson Chi-Square	25957.607[a]	1	.000		
Continuity Correction[b]	25956.547	1	.000		
Likelihood Ratio	22908.229	1	.000		
Fisher's Exact Test				.000	.000
Linear-by-Linear Association	25957.587	1	.000		
N of Valid Cases	1300521				

a. 0 cells (0.0%) have expected count less than 5. The minimum expected count is 32611.23.

b. Computed only for a 2x2 table

Count

		TOL_Use Yes	No	Total
Branch	Army	57095	475367	532462
	Air Force	73659	325208	398867
	Navy	31244	329809	361053
Total		161998	1130384	1292382

Chi-Square Tests

	Value	df	Asymptotic Significance (2-sided)
Pearson Chi-Square	19358.448[a]	2	.000
Likelihood Ratio	18552.538	2	.000
Linear-by-Linear Association	199.589	1	.000
N of Valid Cases	1292382		

a. 0 cells (0.0%) have expected count less than 5. The minimum expected count is 45257.41.

Note: Chi-Square for Branch – Only Army, Air Force, and Navy Included

Rank * TOL_Use Crosstabulation

Count

		TOL_Use yes	no	Total
Rank	Enlisted	141614	1070811	1212425
	Officer	50259	212397	262656
	Warrant Officer	5289	18313	23602
Total		197162	1301521	1498683

Chi-Square Tests

	Value	df	Asymptotic Significance (2-sided)
Pearson Chi-Square	12298.180[a]	2	.000
Likelihood Ratio	11252.987	2	.000
Linear-by-Linear Association	12036.345	1	.000
N of Valid Cases	1498683		

a. 0 cells (0.0%) have expected count less than 5. The minimum expected count is 3105.00.

Note: Chi-Square for Rank – Only Enlisted, Officer, and Warrant Officer Included

Appendix 5: Comparison Tables

Comparison of Active Duty Service Members eHealth Behaviors by Gender

		Male (n=141,293)		Female (n=57,095)				
	n	**Mean (SD)**	**Median**	**Mean (SD)**	**Median**	**Z**	***p***	**Effect Size**
Age	198,388	32.53 (7.9)	32	29.97(7.5)	29	-68.029	*.000	-0.1527342
Logins	198,388	3.46(5.43)	2	4.75(6.2)	3	-65.942	*.000	-0.1480486
Actions	198,388	6.44(12.92)	3	8.87(14.66)	4	-59.211	*.000	-0.1329366

Note: Results of Mann-Whitney U Test and effect size. (*p < 0.05)

Comparison of Active Duty Service Members eHealth Behaviors by Rank

		Enlisted (n=142,840)		Officer (n=55,548)				
	n	**Mean (SD)**	**Median**	**Mean (SD)**	**Median**	**Z**	***p***	**Effect Size**
Logins	198,388	3.89(5.87)	2	3.65(5.2)	2	-1.888	0.59	-0.00423881
Actions	198,388	7.29(13.82)	3	6.65(12.25)	3	-7.437	*.000	-0.01669706

Note: Results of Mann-Whitney U Test and effect size. (*p < 0.05)

Comparison of Active Duty Service Members eHealth Behaviors by Age

		Over 50 (n=2,664)		Under 50 (n=195,724)				
	N	**Mean (SD)**	**Median**	**Mean (SD)**	**Median**	**Z**	***p***	**Effect Size**
Logins	198,388	5.18(7.642)	3	3.81(5.684)	2	-13.925	*.000	-0.0275523
Actions	198,388	9.6(17.581)	4	7.14(13.458)	3	-12.272	*.000	-0.0312635

Note: Results of Mann-Whitney U Test and effect size. (*p < 0.05)

Comparison of Active Duty Service Members eHealth Behaviors by CHD

		CHD (n=582)		Non-CHD (n=197,806)				
	N	**Mean (SD)**	**Median**	**Mean (SD)**	**Median**	**Z**	***p***	**Effect Size**
Logins	198,388	6.64(10.03)	3	3.82(5.7)	2	-9.914	*.000	-0.0222583
Actions	198,388	13.06(23.75)	6	7.12(13.41)	3	-9.638	*.000	-0.0216386

Note: Results of Mann-Whitney U Test and effect size. (*p < 0.05)

Comparison of Active Duty Service Members eHealth Behaviors by Amputation

		Amputation (n=23)		Non-Amputation (n=197,806)				
	N	**Mean (SD)**	**Median**	**Mean (SD)**	**Median**	**Z**	***p***	**Effect Size**
Logins	198,388	3.57(5.26)	2	3.83(5.72)	2	-0.649	0.516	-0.0014571

Actions	198,388	6.26(11.08)	3	7.14(13.46)	3	-0.415	0.678	-0.0009317

Note: Results of Mann-Whitney U Test and effect size. (*p < 0.05)

Comparison of Active Duty Service Members eHealth Behaviors by Anxiety

		Anxiety (n=7,354)		**Non-Anxiety (n=191,034)**				
	N	**Mean (SD)**	**Median**	**Mean (SD)**	**Median**	**Z**	***p***	**Effect Size**
Logins	198,388	6.99(10.39)	4	3.71(5.42)	2	-40.294	*.000	-0.0904654
Actions	198,388	13.68(25.34)	6	6.89(12.71)	3	-37.551	*.000	-0.084307

Note: Results of Mann-Whitney U Test and effect size. (*p < 0.05)

Comparison of Active Duty Service Members eHealth Behaviors by Sleep

		Sleep (n=60,611)		**Non-Sleep (n=137,777)**				
	N	**Mean (SD)**	**Median**	**Mean (SD)**	**Median**	**Z**	***p***	**Effect Size**
Logins	198,388	5.31(7.9)	3	3.18(4.27)	2	-74.252	*.000	-0.1667057
Actions	198,388	10.1(18.51)	4	5.83(10.22)	3	-72.125	*.000	-0.1619303

Note: Results of Mann-Whitney U Test and effect size. (*p < 0.05)

Comparison of Active Duty Service Members eHealth Behaviors by TBI

		TBI (n=25,176)		**Non-TBI (n=173,212)**				
	N	**Mean (SD)**	**Median**	**Mean (SD)**	**Median**	**Z**	***p***	**Effect Size**
Logins	198,388	4.74(7.49)	2	3.7(5.39)	2	-23.184	*.000	-0.0520512
Actions	198,388	9.04(17.93)	4	6.86(12.65)	3	-22.881	*.000	-0.0513709

Note: Results of Mann-Whitney U Test and effect size. (*p < 0.05)

Comparison of Active Duty Service Members eHealth Behaviors by Depression

		Depression (n=25,176)		**Non-Depression (n=173,212)**				
	N	**Mean (SD)**	**Median**	**Mean (SD)**	**Median**	**Z**	***p***	**Effect Size**
Logins	198,388	6.46(9.694)	3	3.69(5.38)	2	-41.267	*.000	-0.09265
Actions	198,388	12.41(22.98)	5	6.85(12.66)	3	-38.8	*.000	-0.0871112

Note: Results of Mann-Whitney U Test and effect size. (*p < 0.05)

Comparison of Active Duty Service Members eHealth Behaviors by Health Condition

		Health Condition (n=78,366)		**No Health Condition (n=120,022)**				

	N	Mean (SD)	Median	Mean (SD)	Median	Z	*p*	Effect Size
Logins	198,388	5.01(7.484)	2	3.07(3.996)	2	-74.438	*.000	-0.1671233
Actions	198,388	9.51(17.719)	4	5.59(9.398)	3	-71.958	*.000	-0.1615554

Note: Results of Mann-Whitney U Test and effect size. ($*p < 0.05$)

Appendix 6: Odds Rations

Logistic Regression Model: Training Data, Odds Rations of All Variables

Characteristic	**OR**[1]	**95% CI**[1]	**p-value**
Gender			
Female	—	—	
Male	0.84	0.82, 0.87	<0.001
Age	1.01	1.00, 1.01	<0.001
Race_Ethnicity			
American Indian/Alaskan Native	—	—	
Asian or Pacific Islander	1.07	0.93, 1.22	0.3
Black, not Hispanic	1.09	0.96, 1.24	0.2
Hispanic	1.06	0.93, 1.20	0.4
Other	1.09	0.94, 1.26	0.3
Unknown	1.26	0.97, 1.64	0.083
White, not Hispanic	1.04	0.92, 1.18	0.5
Marital_Status			
Married	—	—	
Single	1.02	0.99, 1.06	0.15
Military_Branch			
Air Force	—	—	
Army	0.93	0.90, 0.96	<0.001
Marine Corps	0.80	0.74, 0.85	<0.001
Navy	0.87	0.83, 0.90	<0.001
Geographic_Location			

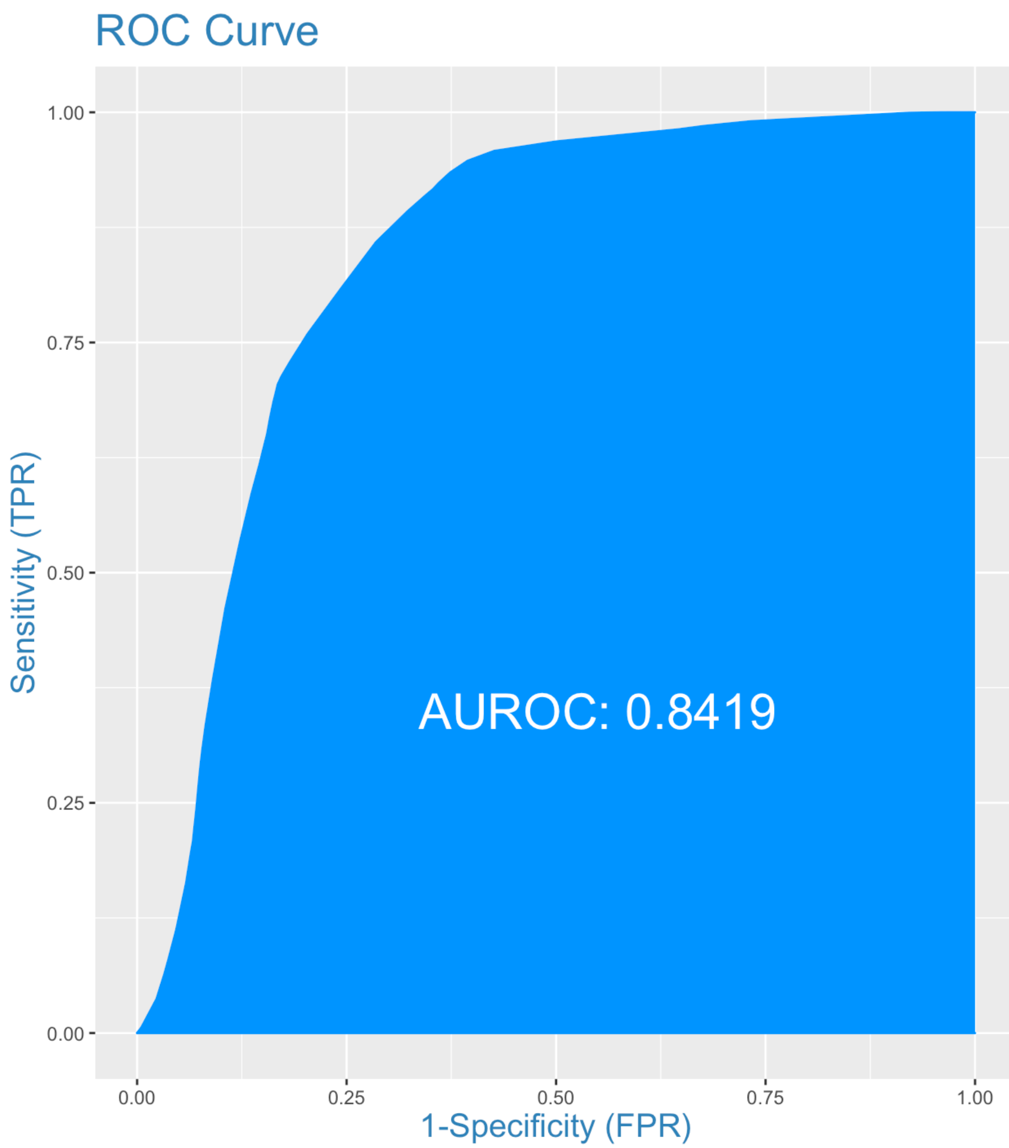
Characteristic	OR[1]	95% CI[1]	p-value
Armed Forces Europe	—	—	
Armed Forces Pacific	0.22	0.04, 1.07	0.071
Midwest	1.09	0.48, 2.64	0.8
Northeast	1.16	0.51, 2.82	0.7
Southwest	1.05	0.46, 2.54	>0.9
Unknown	1.13	0.50, 2.74	0.8
US Territories	1.29	0.55, 3.20	0.6
West	1.03	0.45, 2.49	>0.9
CHD			
No	—	—	
Yes	0.90	0.71, 1.14	0.4
Amputation			
No	—	—	
Yes	0.91	0.28, 2.74	0.9
Anxiety			
No	—	—	
Yes	0.88	0.82, 0.94	<0.001
Sleep			
No	—	—	
Yes	0.99	0.96, 1.02	0.5
TBI			
No	—	—	
Yes	0.99	0.95, 1.04	0.8

Characteristic	OR[1]	95% CI[1]	p-value
Depression			
No	—	—	
Yes	0.83	0.79, 0.89	<0.001
BookYesNo			
No	—	—	
Yes	1.71	1.65, 1.78	<0.001
CancelledYesNo			
No	—	—	
Yes	1.04	0.98, 1.11	0.15
SearchYesNo			
No	—	—	
Yes	3.17	3.08, 3.26	<0.001
ViewFamilyYesNo			
No	—	—	
Yes	5.86	5.65, 6.08	<0.001
ViewHealthInformationYesNO			
No	—	—	
Yes	2.63	2.55, 2.71	<0.001
EnconterYesNo			
No	—	—	
Yes	1.16	1.12, 1.20	<0.001
SavePrintYesNo			
No	—	—	

Characteristic	OR[1]	95% CI[1]	p-value
Yes	0.64	0.46, 0.88	0.006
MTF_YesNo			
No	—	—	
Yes	1.43	1.33, 1.54	<0.001
RefillYesNo			
No	—	—	
Yes	2.92	2.84, 3.00	<0.001

[1] OR = Odds Ratio, CI = Confidence Interval

Appendix 7: ROC Curve for Model Three



Appendix 8: SPSS Syntax

5. Loaded joined dataset into SPSS.

6. Renamed variables to common names for the study.

    a. spon_svc: Changed to Military_Branch

        i. Recoded using the Military Health System – MHS Mart (M2) Data dictionary as reference (39):

```
SPSS SYNTAX
SAVE OUTFILE='/Users/jillraps/Dropbox/Fall 2020(Final
Semester)/TOL2018_FULL(AUG_2020).sav'
  /COMPRESSED.
RECODE Military_Branch ('A'='1') ('C'='2') ('D'='3') ('F'='4') ('H'='5') ('M'='6')
('N'='7')
   ('O'='8').
EXECUTE.
```

Military_Branch

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	Army	1918659	23.1	23.1	23.1
	Coast Guard	32178	.4	.4	23.4
	Office of the Secretary of Defense	1	.0	.0	23.4
	Air Force	1350319	16.2	16.2	39.7
	The Commissioned Corps of the Public Health Service	14370	.2	.2	39.8
	Marine Corps	184871	2.2	2.2	42.1
	Navy	621961	7.5	7.5	49.5
	The Commissioned Corps of the National Oceanic and Atmospheric Administration	696	.0	.0	49.5
	NA	4200096	50.5	50.5	100.0
	Total	8323151	100.0	100.0	

    b. ben_cat: Changed to Service_Category

        i. Recoded and labeled from M2 data:

SPSS SYNTAX

```
RECODE ben_cat ('ACT'='1') ('RET'='2') ('GRD'='3') ('IGR'='4') ('DA'='5') ('DR'='6')
('DS'='7')
   ('DGR'='8') ('IDG'='9') ('OTH'='10') ('Z'='11').
EXECUTE.
```

Service_Category

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	Active Duty	1432980	17.2	17.2	17.2
	Other	38760	.5	.5	17.7
	Unknown	3	.0	.0	17.7
	Retirees	1033617	12.4	12.4	30.1
	Guard/Reserve on Active Duty	139871	1.7	1.7	31.8
	Inactive Guard/Reserve	59360	.7	.7	32.5
	Dependents of Active Duty	830527	10.0	10.0	42.5
	Dependents of Retiree	520064	6.2	6.2	48.7
	Dependent Survivor	21255	.3	.3	49.0
	Dependent of Guard/Reserve on Active Duty	34376	.4	.4	49.4
	Dependent of Inactive Guard/Reserve	12242	.1	.1	49.5
	NA	4200096	50.5	50.5	100.0
	Total	8323151	100.0	100.0	

c. Gender recoded and labeled: (Note: Active Duty Members, Army, Air Force, Navy, and Marine Corps cases selected at this point)

SPSS SYNTAX

```
RECODE Gender ('M'='1') ('F'='2').
EXECUTE.
```

Gender

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	Male	141293	71.2	71.2	71.2
	Female	57095	28.8	28.8	100.0
	Total	198388	100.0	100.0	

d. Race_Ethnicity recoded and labeled:

Recoded and labeled from M2 data:

SPSS SYNTAX
RECODE Race_Ethnicity ('A'='1') ('B'='2') ('C'='3') ('D'='4') ('E'='5') ('X'='6') ('Z'='7').
EXECUTE.

Race_Ethnicity

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	American Indian/Alaskan Native	36386	.9	.9	.9
	Asian or Pacific Islander	189426	4.5	4.5	5.4
	Black, not Hispanic	630378	15.0	15.0	20.4
	White, not Hispanic	1898283	45.3	45.3	65.7
	Hispanic	329224	7.8	7.8	73.5
	Other	97817	2.3	2.3	75.9
	Unknown	282801	6.7	6.7	82.6
	NA	729985	17.4	17.4	100.0
	Total	4194300	100.0	100.0	

e. Marital_Status recoded and labeled:

SPSS SYNTAX
RECODE Marital_Status ('S'='1') ('M'='2').
EXECUTE.

Marital_Status

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	Single	55267	27.9	27.9	27.9
	Married	143121	72.1	72.1	100.0
	Total	198388	100.0	100.0	

f. Full_spon_paygrade: changed to Rank
   i. Recoded and labeled from M2 data:

RankGroup

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	Cadet	1226	.6	.6	.6
	Enlisted	141614	71.4	71.4	72.0
	Officer	50259	25.3	25.3	97.3
	Warrant Officer	5289	2.7	2.7	100.0
	Total	198388	100.0	100.0	

g. Age: recoded into age group categories:

AgeGroup

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	18-24	41374	20.9	20.9	20.9
	25-34	85279	43.0	43.0	63.8
	35-44	58319	29.4	29.4	93.2
	45-54	12776	6.4	6.4	99.7
	55 and Over	640	.3	.3	100.0
	Total	198388	100.0	100.0	

h. State: recoded into geographic region categories:

SPSS SYNTAX

```
RECODE State ('CA'=1)('OR'=1)('WA'=1)('MT'=1)('ID'=1)('WY'=1)('NV'=1
)('UT'=2)('CO'=1)('AK'=1)('HI'=1)
('AZ'=2)('NM'=2)('TX'=2)('OK'=2)
('MI'=3)('OH'=3)('IN'=3)('IL'=3)('WI'=3)('MN'=3)('MO'=3)('IA'=3)('ND'=3
)('SD'=3)('NE'=3)('KS'=3)
('AL'=4)('AR'=4)('LA'=4)('MS'=4)('TN'=4)('FL'=4)('GA'=4)('NC'=4)('SC'=4
)('VA'=4)('WV'=4)('DC'=4)('KY'=4)('DE'=4)
('PA'=5)('CT'=5)('MA'=5)('MD'=5)('ME'=5)('NH'=5)('NJ'=5)('NY'=5)('RI'=
5)('VT'=5)
('AP'=6)
('AE'=7)
('GU'=8)('MH'=8)('PR'=8)('UM'=8)
('NA'=9)('WW'=9)('ZZ'=9) INTO Geographic_Location.
```

Geographic_Location

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	West	40354	20.3	20.3	20.3
	Southwest	33807	17.0	17.0	37.4
	Midwest	13709	6.9	6.9	44.3
	Southeast	71263	35.9	35.9	80.2
	Northeast	15101	7.6	7.6	87.8
	Armed Forces Pacific	27	.0	.0	87.8
	Armed Forces Europe	57	.0	.0	87.9
	US Territories	787	.4	.4	88.3
	Unknown	23283	11.7	11.7	100.0
	Total	198388	100.0	100.0	

i. Patient Portal Actions: recoded into eHealth behaviors categories:

   i. Recoded and labeled from M2 data:

Old Value	New Value
Appt Booked (1)	1 = Booked Appointment
Appt Cancelled (2)	2 = Cancelled Appointment
Appt Refused – Fam (3) Appt Refused – Self (4) Appt Search (5) Attempt Book Appt – Fam (6) Attempt Book Appt – Self (7) Attempt Cancel Appt – Self (8)	3 = Searching for Appointments
Attempt Obtain Fam Data (9)	4 = Viewing Family Member Health Informatic
Request Allergies (11) Request Demographics (12) Request Immunization (13) Request Lab Result (14) Request Radiology (21) Request Vitals (22) View Allergies (24) View Immunization (27) View Lab Result (28) View Radiology (32) View Vitals (33)	5 = Viewing Health Information

Request Note (19) View Note (30) View Documents (25) View Encounter (26) View Problem List (31) Request Problem List (20)	6 = Viewing Encounter Notes
Print (10) Save (23)	7 = Save/Print
Request MTF Transfer (18)	8 = Request MFT Transfer
View Meds (29) Request Meds (15) Request Meds Refill (16) Request Meds Status (17)	9 = Medication Refill

SPSS SYNTAX

```
DATASET ACTIVATE TEST.
DATASET CLOSE DataSet11.
GET
  FILE='/Users/jillraps/Dropbox/Fall 2020(Final
Semester)/Actions_Logins_2018_ActiveDuty.sav'.
DATASET NAME DataSet12 WINDOW=FRONT.
RECODE ActionCoded (1=1) (2=2) (9=4) (10=5) (23=5) (18=6) (3 thru 8=3) (11 thru
14=4) (19 thru
   22=4) (24 thru 33=4) (15 thru 17=7) INTO eHealth_BehaviorGroup.
EXECUTE.
```

a. Health Conditions: recoded into separate categories for each condition:

Health Condition	Total	Percent
Amputation	23	0.0001%
Anxiety	7,354	3.7%
CHD	582	0.3%
Depression	10,377	5.2%
Sleep	60,611	30.6%

TBI	25,176	12.7%

7. Removed data elements that were not necessary for analysis.

   a. spon_status: Only provides Active Duty Service Member's status for all family members.

   b. hasDemographics: Variable created to identify which users have a complete set of dempographic data.

   c. race: Race data element only shows if member is "White, Asian or Pacific Islander, Black, American Indian or Alaskan Native, Other, or Unknown". More detail is needed and can be found in M2 Race/Ethnicity and Ethnicity data elements.

8. Created new continuous variables and datasets for evaluation.

   a. Actions_PerYear: The total number of actions for Active Duty Service Members is 1,432,889, however, this number does not reflect unique users. SPSS was used to identify and count unique users to create a new variable called 'Count'. The total number of unique Active Duty Service Members that used the TOL Patient Portal in 2018 was 201,073. For analysis purposes a new dataset was created: Count_ActiveDuty_TOL2018_201073.

SPSS SYNTAX

```
EXECUTE.
DATASET COPY  Count.
DATASET ACTIVATE  Count.
FILTER OFF.
USE ALL.
SELECT IF (PrimaryLast = 1).
EXECUTE.
```

```
DATASET ACTIVATE  ActiveDuty_TOL2018.
DATASET ACTIVATE Count.
FREQUENCIES VARIABLES=Gender
  /ORDER=ANALYSIS.
```

b. Logins_PerYear: The total number of logins per year is different than the total number of actions per year. For example, an Active Duty Service Member could complete four actions on a single date on the TOL Patient Portal or 2 actions on two different dates. The first user would count as one login per year and the second would count as two logins per year (see Figure 10). For the purpose of this analysis, it is assumed that the user only logged in one time per day.

Example Data on Actions vs. Logins Per Year

Person_ID	Date	TOL_Action
11111	11/10/2018	View Labs
11111	11/10/2018	Appt Search
11111	11/10/2018	Appt Booked
11111	11/10/2018	View Meds
22222	04/16/2018	View Labs
22222	04/16/2018	View Meds
22222	02/05/2018	Appt Search

One login per year

Two logins per year

22222	**02/05/2018**	**Appt Booked**	

Appendix 9: Logistic Regression Model 'R' Studio Script

```
##import data - TOLRegression1 (41.5MB, 24 OCT 2020)

##install packages for analysis
library(caret)
library(e1071)
library(ISLR)
library(tibble)
library(GGally)
library(tidyverse)
library(reshape2)
library(aod)
library(ggplot2)
library(InformationValue)
library(car)
library(coefplot)
library('fastDummies')
library(ResourceSelection)
options(scipen=999)##removed scientific notation

##change to factors for analysis (note: there are faster ways to do this)

#dependent variable 0=did not login 3-11 times in one year and 1=logged in 3-11 times
in one year
TOLRegression1$Logins3_11 <-as.factor(TOLRegression1$Logins3_11)

#other categorical variables, change to factors for analysis
TOLRegression1$RefillYesNo <-as.factor(TOLRegression1$RefillYesNo)
TOLRegression1$MTF_YesNo <-as.factor(TOLRegression1$MTF_YesNo)
TOLRegression1$SavePrintYesNo <-as.factor(TOLRegression1$SavePrintYesNo)
TOLRegression1$EnconterYesNo <-as.factor(TOLRegression1$EnconterYesNo)
TOLRegression1$ViewHealthInformationYesNO <-
as.factor(TOLRegression1$ViewHealthInformationYesNO)
TOLRegression1$ViewFamilyYesNo <-
as.factor(TOLRegression1$ViewFamilyYesNo)
TOLRegression1$SearchYesNo <-as.factor(TOLRegression1$SearchYesNo)
TOLRegression1$CancelledYesNo <-as.factor(TOLRegression1$CancelledYesNo)
TOLRegression1$BookYesNo <-as.factor(TOLRegression1$BookYesNo)

TOLRegression1$Depression <-as.factor(TOLRegression1$Depression)
TOLRegression1$TBI <-as.factor(TOLRegression1$TBI)
TOLRegression1$Sleep <-as.factor(TOLRegression1$Sleep)
TOLRegression1$Anxiety <-as.factor(TOLRegression1$Anxiety)
TOLRegression1$Amputation <-as.factor(TOLRegression1$Amputation)
```

```
	TOLRegression1$CHD <-as.factor(TOLRegression1$CHD)

	TOLRegression1$Geographic_Location <
	as.factor(TOLRegression1$Geographic_Location)
	TOLRegression1$RankGroup <-as.factor(TOLRegression1$RankGroup)
	TOLRegression1$Military_Branch <-as.factor(TOLRegression1$Military_Branch)
	TOLRegression1$Marital_Status <-as.factor(TOLRegression1$Marital_Status)
	TOLRegression1$AgeGroup <-as.factor(TOLRegression1$AgeGroup)
	TOLRegression1$Race_Ethnicity <-as.factor(TOLRegression1$Race_Ethnicity)
	TOLRegression1$Gender <-as.factor(TOLRegression1$Gender)

	##dummy variables
	TOLRegression1 <- dummy_cols(TOLRegression1, select_columns = 'Gender')

	TOLRegression1 <- dummy_cols(TOLRegression1, select_columns = 'RankGroup')
	names(TOLRegression1)[names(TOLRegression1) == "RankGroup_Warrant Officer"]
<- "RankGroup_WarrantOfficer"

	TOLRegression1 <- dummy_cols(TOLRegression1, select_columns =
'Military_Branch')
	names(TOLRegression1)[names(TOLRegression1) == "Military_Branch_Air Force"]
<- "Military_Branch_AirForce"
	names(TOLRegression1)[names(TOLRegression1) == "Military_Branch_Marine
Corps"] <- "Military_Branch_MarineCorps"


	TOLRegression1 <- dummy_cols(TOLRegression1, select_columns =
'Race_Ethnicity')

	##used the set.seed() function to allow same random split
	set.seed(115)

	splitSample <- sample(1:3, size=nrow(TOLRegression1), prob=c(0.7,0.15,0.15),
replace = TRUE)
	train_data <- TOLRegression1[splitSample==1,]
	valid_data <- TOLRegression1[splitSample==2,]
	test_data <- TOLRegression1[splitSample==3,]



	##Dependent variable is Logins3_11 (this is all the service members that logged-in 3-
11 times)
	##start with a single predictor in model and build up using literature and bivariate
results (see excel spreadsheet)

	##glm() function is used in linear but to change to logic family = "binomial" which
indicates a two-class categorical response
```

```
###################################################################
########## Model #1 (logitMod1) with all variables ###############
###################################################################


####1### first the training data are used to obtain the coefficients of the model
logitMod1 = glm(Logins3_11 ~ Gender + Age + Race_Ethnicity + Marital_Status + 
Military_Branch + RankGroup + Geographic_Location + 
                CHD + Amputation + Anxiety + Sleep + TBI + Depression + BookYesNo 
+ CancelledYesNo + SearchYesNo + ViewFamilyYesNo + 
                ViewHealthInformationYesNO + EnconterYesNo + SavePrintYesNo + 
MTF_YesNo + RefillYesNo, data = train_data,
               family = "binomial")

##summary of model
summary(logitMod1)

####2### the validation data are used to obtain the best cut off point for prediction
# predicted scores using validation data
predicted1 <- predict(logitMod1, valid_data, type="response")

#optimal score to minimize the model's mis-classification error
optCutOff1 <- optimalCutoff(valid_data$Logins3_11, predicted1) ##0.3716

##check multicollinearity
vif(logitMod1)Z##only for models with more than one predictor

#lower misclassification error is ideal
misClassError(valid_data$Logins3_11, predicted1, threshold = optCutOff1) ##0.21Z18


####3#### test data are used to report the model metrics
logitMod1 = glm(Logins3_11 ~ Gender + Age + Race_Ethnicity + Marital_Status + 
Military_Branch + RankGroup + Geographic_Location + 
                CHD + Amputation + Anxiety + Sleep + TBI + Depression + BookYesNo 
+ CancelledYesNo + SearchYesNo + ViewFamilyYesNo + 
                ViewHealthInformationYesNO + EnconterYesNo + SavePrintYesNo + 
MTF_YesNo + RefillYesNo, data = test_data,
               family = "binomial")

predictedtest1 <- predict(logitMod1, test_data, type="response")
##Receiver Operating Characteristics Curve
plotROC(test_data$Logins3_11, predictedtest1)
```

```
	##Sensitivity (or True Positive Rate) is the percentage of 1's correctly predicted by the
model,
	#Specificity is the percentage of 0's (actuals) correctly predicted
	##ConfusionMatrix: columns are actuals, while rows are predicteds
	sensitivity(test_data$Logins3_11, predictedtest1, threshold = optCutOff1)
	specificity(test_data$Logins3_11, predictedtest1, threshold = optCutOff1)
	confusionMatrix(test_data$Logins3_11, predictedtest1, threshold = optCutOff1)


	## Exponentiate the coefficients, interpret as odds-ratios
	# tell R  to exponentiate (exp) and the object to exponentiate
	#-called coefficients, it's part of logitMod1 (coef(logitMod1)).
	# To put it all in one table, use cbind to bind the coefficients
	# and confidence intervals column-wise
	exp(cbind(OR = coef(logitMod1), confint(logitMod1)))

	## test the overall effect using wald.test, terms must follow order of output
	##testing effect of Rank Terms = 4:9
	wald.test(b = coef(logitMod1), Sigma = vcov(logitMod1), Terms = 2:3)

	## plot coefficients
	coefplot(logitMod1)

	##Concordance or model-calculated-probability-score --> a perfect model would be
100%
	Concordance(test_data$Logins3_11, predicted1)

	#################################################################
	########## Model #2 (logitMod1)  ###############
	#################################################################

	####1### first the training data are used to obtain the coefficients of the model
	logitMod2 = glm(Logins3_11 ~ Gender + Age + RankGroup + Military_Branch +
Anxiety
			+ Depression + BookYesNo + SearchYesNo + ViewFamilyYesNo +
			  ViewHealthInformationYesNO + EnconterYesNo + RefillYesNo
			, data = train_data,
			family = "binomial")

	summary(logitMod2)

	####2### the validation data are used to obtain the best cut off point for prediction
	predicted2 <- predict(logitMod2, valid_data, type="response")

	optCutOff2 <- optimalCutoff(valid_data$Logins3_11, predicted2) ##0.3824
```

```
vif(logitMod2)

misClassError(valid_data$Logins3_11, predicted2, threshold = optCutOff2) ##0.2157

####3#### test data are used to report the model metrics

logitMod2 = glm(Logins3_11 ~ Gender + Age + RankGroup + Military_Branch +
Anxiety
          + Depression + BookYesNo + SearchYesNo + ViewFamilyYesNo +
            ViewHealthInformationYesNO + EnconterYesNo + RefillYesNo
          , data = test_data,
          family = "binomial")

predictedtest2 <- predict(logitMod2, test_data, type="response")
plotROC(test_data$Logins3_11, predictedtest2)

sensitivity(test_data$Logins3_11, predictedtest2, threshold = optCutOff2)
specificity(test_data$Logins3_11, predictedtest2, threshold = optCutOff2)
confusionMatrix(test_data$Logins3_11, predictedtest2, threshold = optCutOff2)

exp(cbind(OR = coef(logitMod2), confint(logitMod2)))


coefplot(logitMod2)

Concordance(test_data$Logins3_11, predictedtest2)

######################################################################
########## Model #3 (logitMod1)  ###############
######################################################################

####1### first the training data are used to obtain the coefficients of the model
logitMod3 =  glm(Logins3_11 ~ Gender_Female + Age
                + Depression + BookYesNo + SearchYesNo + ViewFamilyYesNo +
                ViewHealthInformationYesNO + EnconterYesNo + RefillYesNo
               , data = train_data,
               family = "binomial")

summary(logitMod3)

####2### the validation data are used to obtain the best cut off point for prediction
predicted3 <- predict(logitMod3, valid_data, type="response")

optCutOff3 <- optimalCutoff(valid_data$Logins3_11, predicted3) ##0.3824

vif(logitMod3)
```

```
misClassError(valid_data$Logins3_11, predicted3, threshold = optCutOff3) ##0.2156


####3#### test data are used to report the model metrics

logitMod3 =  glm(Logins3_11 ~ Gender_Male + Age
            + Depression + BookYesNo + SearchYesNo + ViewFamilyYesNo +
              ViewHealthInformationYesNO + EnconterYesNo + RefillYesNo
            , data = test_data,
            family = "binomial")

predictedtest3 <- predict(logitMod3, test_data, type="response")

plotROC(test_data$Logins3_11, predictedtest3)

sensitivity(test_data$Logins3_11, predictedtest3, threshold = optCutOff3)
specificity(test_data$Logins3_11, predictedtest3, threshold = optCutOff3)
confusionMatrix(test_data$Logins3_11, predictedtest3, threshold = optCutOff3)

exp(cbind(OR = coef(logitMod3), confint(logitMod3)))

coefplot(logitMod3)

Concordance(test_data$Logins3_11, predictedtest3) ##8413
```