ABSTRACT

Title of Dissertation: A MULTIDIMENSIONAL ANALYSIS OF EHEALTH LITERACY SKILLS AND CHRONIC DISEASE SELF-MANAGEMENT BEHAVIORS AMONG U.S. ADULTS WITH CHRONIC CONDITIONS

Katherine F. Raymond,
Doctor of Philosophy, 2026

Dissertation directed by: Dr. Cynthia Baur, Endowed Professor, Department of Behavioral and Community Health Department

Background: More than 140 million adults in the U.S. live with one or more chronic conditions and must engage in ongoing chronic disease self-management, increasingly within an electronic health (eHealth) environment. Effective use of eHealth tools depends on eHealth literacy skills, yet little is known about how specific eHealth literacy domains relate to health behaviors among U.S. adults living with chronic conditions. This dissertation examined the role of eHealth literacy skills in supporting chronic disease self-management behaviors among adults with common chronic conditions.

Methods: This study involved a secondary analysis of 2022 Health Information National Trends Survey data (HINTS Cycle 6) among internet-using adults with at least one chronic condition (n = 2,888). Guided by theory from public health, health communication, and information science, variables approximating six domains of eHealth literacy—basic, computer, scientific, information, health, and media literacy—were identified and operationalized. Four study aims were addressed using survey-weighted descriptive statistics, bivariate analyses, and regression models.

Results: Overall, in Aim 1, eHealth literacy skill levels varied across domains, with higher reported levels of basic and health literacy and lower levels of scientific and media literacy. In Aim 2, an eHealth use composite score showed its strongest and most consistent associations with computer, information, and health literacy, supporting the validity of these skill measures. In Aim 3, higher levels of several eHealth literacy domains were independently associated with select chronic disease self-management behaviors, although patterns varied by domain and behavior. In Aim 4, the composite eHealth literacy index was positively and significantly associated with greater engagement in chronic disease self-management behaviors after adjustment for sociodemographic factors. Self-efficacy emerged as the strongest independent predictor of chronic disease self-management behaviors but did not eliminate the association between eHealth literacy and self-management.

Conclusions: This study demonstrated that eHealth literacy skills can be meaningfully approximated using population surveillance data and that higher eHealth literacy is associated with greater engagement in chronic disease self-management behaviors among U.S. adults with chronic conditions. Findings support a multidimensional conceptualization of eHealth literacy and suggest that eHealth literacy and self-efficacy together represent important behavioral skills for effective self-management. These results have implications for theory, measurement, and the design of digital health interventions for adults living with chronic disease.

A MULTIDIMENSIONAL ANALYSIS OF EHEALTH LITERACY SKILLS AND CHRONIC DISEASE SELF-MANAGEMENT AMONG U.S. ADULTS WITH CHRONIC CONDITIONS

by

Katherine F. Raymond

Dissertation submitted to the Faculty of the Graduate School of the
University of Maryland, College Park, in partial fulfillment
of the requirements for the degree of
Doctor of Philosophy
2026

Advisory Committee:
Endowed Professor, Dr. Cynthia Baur, Chair
Assistant Professor, Dr. Héctor E. Alcalá, Committee Member
Assistant Research Professor, Dr. Devlon Jackson, Committee Member
Lecturer, Dr. Sandra L. Saperstein, Committee Member
Associate Professor, Dr. Beth St. Jean, Dean's Representative

Dedication

This dissertation is dedicated to each person I have encountered in my life who helped open doors to new learning opportunities. I never would have made it this far in my educational career without the push and support of mentors from elementary school all the way through graduate school and beyond. Thank you for seeing my potential.

I also dedicate this dissertation to my husband, Scott, without whom I would have quit 100 times over. Scott, your unwavering belief in me propelled me every single day of this experience, and your steadfast counsel provided me with the self-confidence to persevere no matter how lost I became. It is not hyperbole to say that I could not have done this without you. I am eternally grateful to you.

Lastly, to my children, I dedicate this work to you. Although you were with me every step of the way, either in utero, in my lap, or playing beside me, let this dissertation be a reminder of the commitment I have made to you to make this world a more equitable, generous, and thoughtful world for each of you and us all.

Acknowledgements

I would like to acknowledge everyone who has helped me along my doctoral journey and share my heartfelt thanks for the love and support I have been gifted throughout this long journey.

First, I am grateful to my chair and academic adviser, Dr. Cynthia Baur, who saw my potential when I applied to the program and who has since helped me through every step of this journey. Thank you for believing in me, for funding me each year, and for challenging me to strive for more and push myself further. Your attention to detail in all of my work helped me develop as a writer and refine my communication skills. I am also eternally grateful for your flexibility and kindness when I struggled to balance it all. Your commitment to supporting students like me is unwavering, and we are all lucky to have such a dedicated expert guiding us along the way.

I am also grateful to my dissertation committee: To Dr. Devlon Jackson, your scholarship in eHealth literacy and HINTS research, especially for more marginalized or understudied populations, inspired me to want to learn how to analyze these data to see what I could contribute to the field. Thank you for helping me learn how to think more comprehensively and incorporate that into my work. To Dr. Beth St. Jean, I am so thankful for your willingness to serve on my committee. Your kindness, curiosity, steadfastness, and generosity have helped me accomplish so much over the past couple of years. Thank you for supporting my growth and development as an information behavior/health communication scholar. To Dr. Sandy Saperstein, thank you for inspiring my interest in health information technologies and for always being a source of calm throughout my studies. Personally, I was often motivated by reflecting on your own motherhood and dissertation experience and how you persevered to accomplish great things. To Dr. Héctor E. Alcalá, thank you for joining my committee and for being flexible as timelines and goals have

changed. Your ability to see different angles for my research and your willingness to review drafts and answer quick questions helped me refine my methods and enhance my analytic approach.

Starting a doctoral program in the middle of the COVID-19 pandemic was challenging, but Dr. Kathy Sharp was a steadfast guide through the years, and I am so thankful for her willingness to answer the most basic questions, to support me with last-minute requests, and to always believe in me despite the ups and downs. Thank you to the Behavioral and Community Health Department and all the faculty who supported my learning over the years. To my cohortmates – Leena and Sharon – who would have thought we would end up here after a rocky start? I am so thankful that we had the opportunity to walk this path together all these years. I would also like to extend a hug and thank-you to my peers (you know who you are) and breathe a collective sigh of relief as each one of us moves towards and across that finish line.

Thank you to the National Cancer Institute and the National Institutes of Health for undertaking this important research and providing these data for researchers to explore and share back out with the public. Thank you to all who completed the H6 research and shared aspects of your lives with researchers like me.

To my friends and family members – thank you so much for supporting me and my family all these years, especially with babysitting, vacations, self-care, and more. To my beautiful children—Laila and Lucas—you two fill my heart with so much joy. The time that I got to spend with each of you while completing my studies is time that I will always cherish. I am so thankful for the love you two shower on me each day, especially during times when I struggled with this work. To my fur child, Ripley, thank you for staying by my side and keeping me company during the long, late-night hours when I would work after everyone went to bed.

Lastly, I want to thank my husband, best friend, and life partner, Scott, who counseled me, supported me, held me, and lifted me up every step along the way. He also supplied me with endless streams of candy and sunflower seeds to fuel my late-night work. Not only are you working to change the world, to reduce suffering, and to improve people's lives, you are doing it while raising a beautiful family and supporting the growth and development of your spouse. You are truly a gift to this world.

Table of Contents

Lists of Tables

List of Figures

Lists of Abbreviations and Acronyms

CDC	Centers for Disease Control and Prevention
CDSM	Chronic disease self-management
COPD	Chronic obstructive pulmonary disease
eCCM	eHealth Enhanced Chronic Care Model
eHealth	Electronic health
eHealth Literacy	Electronic health literacy
eHL	eHealth literacy
H6	6^{th} Cycle of the Health Information National Trends Survey
HeLSI	H6 eHealth Literacy Skill Index
HINTS	Health Information National Trends Survey
HIT	Health information technology
IMB	Information-Motivation-Behavioral Skills Model
mHealth	Mobile health
MRTSCI	Middle Range Theory of Self-Care of Chronic Illness
NCI	National Cancer Institute
P-HeLSI	Partial H6 eHealth Literacy Skill Index

Chapter 1. Introduction

Nearly 140 million adults in the U.S. suffer from at least one type of chronic disease, such as preventable conditions like Type 2 diabetes, hypertension, heart disease, lung disease, and cancer (Benavidez et al., 2024; Centers for Disease Control and Prevention, 2024, October). Millions more adults are expected to develop these conditions and/or develop additional conditions (i.e., comorbidities) by 2050 (Ansah & Chiu, 2022; Benavidez et al., 2024). Diseases are generally considered chronic if they persist or recur for at least 12 months or longer (Bernell & Howard, 2016; Goodman et al., 2013). For decades, chronic diseases have been responsible for most of the reported illnesses, disabilities, and death in the U.S. and have been tied to enormous health care costs (Centers for Disease Control and Prevention, 2024, July; World Health Organization, 2020, December). These diseases are complex to live with, can be debilitating, and often require a lot of information, communication, and tools to understand and complete self-management tasks (Hacker, 2024; Lorig & Holman, 2003; Mackey et al., 2016).

Managing a chronic disease according to clinical recommendations while focusing on minimizing negative health effects often requires lifestyle and behavioral adjustments to primarily mitigate the disease in the present and to establish habits to support individuals in the future as individuals age with the condition(s) (Grady & Gough, 2014). Successful chronic disease self-management varies across preventable diseases but is often measured by quantifiable, documented behaviors, such as individuals maintaining adequate physical activity levels, abstaining from smoking tobacco and drinking alcohol, managing a disease-specific health-promoting diet, and monitoring their health status, among other indicators (Centers for Disease Control and Prevention, 2024; Riegel et al., 2017; Schulman-Green et al., 2012).

The general availability of digital technologies in the U.S. is changing the meaning of chronic disease self-management. Managing a chronic condition in the present generally requires individuals to engage in self-management activities using available technology-enabled resources, such as at-home health monitoring systems like blood pressure cuffs or glucose meters, and dynamic technology-based care resources, such as online care planning platforms, mobile health (mHealth) applications, and web-based medication management tools to optimally manage their health (Adibi, 2015; Eysenbach, 2001; Istepanian et al., 2004; Li et al., 2024; Marklund et al., 2021). mHealth is usually considered mobile computing, medical sensing, and the use of other eHealth resources via web-enabled devices like smartphones or tablets (Istepanian et al., 2004).) To navigate this more technologically-connected, or electronic health (eHealth), environment, individuals with chronic diseases may benefit from electronic health literacy (eHealth literacy) skills to support successful self-management health behaviors (Brandtweiner et al., 2010; Li et al., 2024; Marklund et al., 2021; Wu et al., 2022).

In the context of chronic disease self-management, eHealth literacy skills, defined broadly as "a foundational skill set that underpins the use of information and communication technologies (ICT) for health" (Norman, 2011, p. 1), represent a common health behavior domain that may be a critical modifiable and teachable component on the pathway to target health behaviors, such as physical inactivity, poor nutrition, tobacco use, and excessive alcohol use (Hacker, 2024; Manganello Jennifer et al., 2024; van Kessel et al., 2022). eHealth use is defined as "the use of information and communications technology in support of health and health-related fields" (World Health Organization, 2019, p. ix).

Monitoring and assessing the eHealth literacy skills of an adult population in the U.S. living with some of the most common chronic conditions is critical to supporting the evidence base underpinning clinical and public health chronic disease self-management programs and services to ensure that individuals skills at disease management are well-considered. This dissertation manuscript presents findings from a multidimensional analysis of eHealth literacy skills and CDSM behaviors among a target population of adult internet users with chronic conditions. There are five chapters in this book. The following chapter presents an argument for examining eHealth literacy skills among a population of U.S. adults living with chronic illnesses and the role eHealth literacy skills play in their chronic disease self-management behaviors. The chapter begins by providing an overview of the individual behaviors associated with chronic disease self-management and the role of eHealth literacy in navigating present-day eHealth environments. The chapter also provides an overview of the rationale and justification for this dissertation research study, including a discussion of relevant theoretical and conceptual foundations. The chapter concludes with an overview of key terms used in this dissertation.

1.1. Background

Despite high prevalence rates and morbidity associated with chronic diseases, major conditions like hypertension, heart disease, cancer, Type 2 diabetes, and lung disease are largely preventable and can be mitigated through adherence to health-promoting behaviors, such as adequate physical activity, appropriate nutrition, limited or no tobacco use, and limited or no alcohol consumption (Centers for Disease Control and Prevention, 2024; Milani et al., 2016; The Lancet, 2024). Many public health approaches to addressing the chronic disease burden in the population require system-level changes focused on addressing inequities in social determinants of health (Bauer et al., 2014; Beaglehole et al., 2007; Gaziano et al., 2007), yet evidence suggests that individually-focused behavioral interventions designed to promote lifestyle changes can also effectively reduce the impact of these common conditions (Allegrante et al., 2019; Chodosh et al., 2005; Hacker, 2024).

Individual-level behavior change consists of making small adjustments to daily life while frequently monitoring trends over time for opportunities to update or modify clinical treatment plans (Corbin & Strauss, 1988; Lorig & Holman, 2003; Milani et al., 2016). While diverse clinical interventions supporting chronic disease health management exist, most chronic disease health management takes place outside of clinical settings in people's homes, highlighting an overlap between public health and clinical health and the need for at-home supportive services (Corbin & Strauss, 1985; Grady & Gough, 2014). According to the Middle Range Theory of Self-Care of Chronic Illness, "chronic disease self-management" (CDSM) is generally comprised of three separate activities—self-care monitoring (the routine behaviors), self-care maintenance (the bodily surveillance), and self-care management (the response to bodily changes)—that co-occur and represent the dynamics at play in an individual's life when managing an ongoing, long-term condition (Riegel et al., 2012; Riegel et al., 2017). Thus, chronic disease self-management is best understood as a combination of individual behaviors that span cognitive and physiological aspects of an individual's life.

1.1.1. Chronic Disease Self-Management and Electronic Health (eHealth)

Chronic disease self-management reflects ongoing investments in personal health behaviors, health behavior skills, knowledge, and motivation, because health management takes place in a dynamic context comprised of environmental and personal capacity influences throughout the ever-evolving life course context (Audulv, 2013; Miller et al., 2015; Short & Mollborn, 2015). Adults living with chronic conditions in the U.S. engage with the healthcare system at higher rates and in more locations than those without chronic conditions, such as through in-office, in-hospital, or at-home services (Davis-Ajami et al., 2019). eHealth represents one arena of healthcare in which adults with chronic conditions connect with healthcare services and wherein tools and related digital technologies are used to provide health services and information, usually through an internet-based connection (Eysenbach, 2001; Oh et al., 2005).

eHealth tools can be useful in chronic disease self-management if individuals see the value in the tools, perceive the tools as customized to their specific situation, and perceive a need to adjust their daily self-management strategies (Apolinário-Hagen et al., 2018; Nittas et al., 2023; Taylor et al., 2022). These tools can be used to provide monitoring and feedback on health metrics, health education, practical lifestyle intervention tips, clinical decision support, and assistance with medication or treatment adherence (Fan & Zhao, 2022; Li et al., 2024). In fact, adults with chronic conditions are more likely to track health indicators using technology than those individuals without chronic conditions and are more likely to use web-based health portals to manage their care (Madrigal & Escoffery, 2019). Adults also use different types of eHealth tools based on the chronicity and long-term nature of their condition, such as individuals living with Type 2 diabetes who use peer-to-peer exchanges in online health communities to supplement their disease knowledge and inform their health decisions (Ardissone et al., 2024; Ma et al., 2024). Others, like those living with arthritis, use these communities for drug management, symptom management, information, and social support (Willis & Royne, 2017).

Adoption of eHealth-based interventions to support individual chronic disease self-management grew during the COVID-19 pandemic (i.e., 2020-2023), during which telehealth (e.g., patient-to-provider virtual visits, health worker decision support systems), remote monitoring (e.g., web-enabled systems for tracking patients' health status through wearables, remote sensors, etc.), and mHealth technologies (e.g., smartphone-based self-care or health education applications) became more widely utilized (Bitar & Alismail, 2021; Fava & Lapão, 2024; Hacker, 2024; Reiners et al., 2019). eHealth tools can help patients take the lead in their self-management journeys by facilitating the sharing of patient reported outcomes with healthcare providers via electronic health records or patient portals (Penedo et al., 2020; Sülz et al., 2021). Subsets of eHealth, such as mHealth smartphone applications, can lead to more frequent touchpoints with healthcare providers related to urgent care needs such as the use of instant messaging in smartphone applications to encourage healthcare providers to fill prescriptions or provide guidance on managing acute flare-ups of conditions that may previously have been delayed due to administrative barriers or ignored until the next in-person visit (Agnihothri et al., 2020; Penedo et al., 2020).

The presence of eHealth tools and their subsequent use during the pandemic allowed patients to avoid unnecessary exposure risks to the SARS-CoV-2 virus while maintaining care visits through telemedicine and virtual care appointments (Bokolo, 2021), although not all people benefitted equally. eHealth tool use helped reduce the time and financial cost of managing a chronic condition while living in a remote area or living with physical disabilities that made regular transportation to a clinic difficult (and therefore skippable) by providing ongoing regular care at home like virtual medication counseling and lifestyle coaching (Doyle-Lindrud, 2020; Sülz et al., 2021). There are benefits related to reduced financial and time-related costs associated with the use of eHealth tools for chronic disease self-management that were realized during the COVID-19 pandemic; however, adoption of eHealth tools has not always been uniform across different demographics and healthcare systems (Keuper et al., 2024; Qian et al., 2022; Zeng et al., 2022). Some well-known disparities related to a digital divide—wherein access to the internet and knowhow of using internet-based tools varies by demographic characteristics—persisted in the COVID-19 pandemic as higher-educated, younger, higher-income earning adults continued to be more likely to use these eHealth tools for their care needs (Datta et al., 2022; Hoffman et al., 2000; Kontos et al., 2014). However, gaps in these differences based on sociodemographics may have lessened due to rapid investments in underserved areas (Datta et al., 2022). These gaps are worth now exploring and quantifying.

1.1.2. The Need for eHealth Literacy in Chronic Disease Self-Management

In addition to internet access or web-enabled devices, eHealth literacy is often seen as a prerequisite skill to effectively engage with eHealth tools (Brørs et al., 2023; Maita et al., 2024; U.S. Department of Health and Human Services, 2025). As discussed, eHealth tools are widely available and recognized, and research shows that adults living with chronic diseases now regularly engage with healthcare providers, health services, and health information through these eHealth technologies (Biancuzzi et al., 2023; Keesara et al., 2020; Madrigal & Escoffery, 2019; Shaver, 2022). Yet, despite the potential for usefulness, the design of eHealth tools can perpetuate inequities if they do not account for differing levels of eHealth literacy skills within the target population that empower individuals to first understand how to get online and then how to navigate the complex, dynamic resources (Dominick et al., 2009; Kontos et al., 2014; Veinot et al., 2018). Poorer eHealth literacy skills may also lead to consumers being more susceptible to misinformation or disinformation as well as information overload (Kim & Tandoc, 2022; Mitsutake et al., 2024). Thus, it is worthwhile to develop an updated understanding of what eHealth literacy skills are among a population with high health needs in a time when the use of eHealth tools is quickly becoming standard practice.

Fifteen years before the pandemic motivated telehealth and eHealth expansion, Norman and Skinner defined eHealth literacy as “the ability to seek, find, understand, and appraise health information from electronic sources and apply the knowledge gained to addressing or solving a health problem" (Norman & Skinner, 2006b, p. 2). This definition has been widely adopted across public health and health informatics fields and is accepted as an appropriate definition of the skills needed to navigate an eHealth environment (Barbati et al., 2025; Kim et al., 2023; Jiyeon Lee et al., 2021; Refahi et al., 2022). Recent updates to this definition describe eHealth literacy as "the ability to engage with digital technologies in effective, safe, and helpful ways to achieve health goals" (Milanti et al., 2025, p. 1). eHealth literacy and health literacy are related concepts that highlight the importance of fundamental literacy skills to achieve desired health outcomes; however, health literacy is just one of several other necessary literacy skillsets within eHealth literacy (Manganello et al., 2017; Monkman et al., 2017). eHealth literacy reflects an individual's ability to navigate a complex eHealth environment using six different core skills (traditional/basic literacy, computer literacy, scientific literacy, information literacy, health literacy, and media literacy) (Norman & Skinner, 2006b). These skills can be grouped into analytic skills (basic, information, media literacies) or context-specific skills (computer, scientific, health literacies). For example during the COVID-19 pandemic, analytic eHealth literacy skills were required for participating in daily informational life, like ordering prescription refills solely online or ordering food for delivery from supermarkets, while context-specific eHealth literacy skills were used to address specific issues such as scheduling online vaccination appointments or interpreting health risks based on their chronic disease health status (i.e., vulnerability) (Brørs et al., 2020).

Research shows that the role of eHealth literacy skills in navigating eHealth environments is an important part of effective health management as it relates to perceptions of health and engaging in self-care activities (Elgamal, 2024; Kyaw et al., 2024; Reiners et al., 2019; Scheerder et al., 2017; van Kessel et al., 2022). This is especially relevant because public health researchers anticipate that the need to use more complex health information technologies in a rapidly shifting health information landscape will continue to increase post-pandemic (Brørs et al., 2020; Karatas et al., 2022). Previous studies examining the health behaviors of adults with chronic conditions found that higher levels of eHealth literacy were associated with better access to health information, and more health-promoting behaviors and self-management of care (Neter & Brainin, 2012; M. Stellefson et al., 2013; Wayment et al., 2020). Other research showed that higher engagement with eHealth tools such as mHealth was also significantly associated with higher levels of eHealth literacy and better health outcomes (Bol et al., 2018; Neter & Brainin, 2012).

While in-depth information about existing levels of eHealth literacy among adults with chronic diseases in the U.S. remains limited, international research among adults with chronic diseases found that affected adults struggled with finding high quality sources of health information, staying up-to-date with the latest functions of eHealth tools, understanding jargon related to the content they encountered, and assessing the relevance of specific information they were offered virtually, highlighting possible eHealth literacy skill gaps (Tamminen et al., 2023; Wu et al., 2022). In light of the added complexities in the healthcare environment where technologies rapidly expanded and care shifted to more online formats due to adaptations made during the pandemic, there is a greater need to better understand how affected adults currently use eHealth to manage their chronic diseases, what their eHealth literacy skills are, and how eHealth literacy impacts their chronic disease self-management behaviors (Kokkinakis, 2022).

eHealth literacy research is still emerging and is oftentimes incomplete, as studies struggle to address all six domains of the eHealth literacy Lily model that represent the analytic (basic, media, and information literacy) and context-specific (health, scientific, and computer literacy) aspects of eHealth literacy (El Benny et al., 2021; Kim et al., 2023; Norman & Skinner, 2006b). For instance, El Benny and colleagues highlighted a need for future eHealth literacy research to focus on better assessing scientific, media, basic, and information literacy (2021). Meanwhile, Kim and colleagues emphasized the need for more research to examine the link between eHealth literacy and specific health-promoting, disease self-management, and health-supporting behaviors (Kim et al., 2023). The measurement and study of eHealth literacy skills vary from mainly self-reported measures, like the eHealth literacy scale (eHEALS), to computer-based assessments, because national level population assessments tend not to study eHealth literacy skills explicitly (Crocker et al., 2023; Faux-Nightingale et al., 2022; Karnoe et al., 2018; Jiyeon Lee et al., 2021; Norman & Skinner, 2006a; van der Vaart & Drossaert, 2017; C. Wang et al., 2021). Data that reflect eHealth literacy concepts exist in national datasets like the Health Information National Trends Survey (HINTS), which may yield important insights into the eHealth literacy skills of a nationally representative population. However, few studies have explored all six eHealth literacy domains using these data in the U.S. (Shaw Jr et al., 2024; Stellefson et al., 2018).

1.1.3. The Study of eHealth Literacy within this Dissertation Study

To fill a gap in the literature, this dissertation research study examined the presence of eHealth literacy skills, the relationship of eHealth literacy skills with chronic disease self-management behaviors, and the influence of varying demographic factors on that relationship, among a nationally representative sample of adults living with some of the most common chronic conditions in the U.S.—diabetes, hypertension, heart disease, lung disease, and cancer—and who were also internet users.

1.2. Problem Statement

Adults living with chronic diseases tend to be among the highest users of healthcare services and represent a high-need population for whom appropriate and timely health services can make a measurable difference in health outcomes and quality of life (Agency for Healthcare Research, 2021; Holman, 2020). Research suggests that eHealth literacy skills—as measured by the eHEALS scale and digital literacy instruments—can enable adults living with chronic diseases to better understand their personal health needs and act on these needs to achieve control over their disease, which should lead to an increased quality of life (Jang & Je, 2022; Nguyen et al., 2021). Additional research that examines the full conceptualization of eHealth literacy skills and explores all six domains of eHealth literacy is warranted to better understand the intricacies of how the overlapping components of eHealth literacy are connected with chronic disease self-management behaviors.

Previous studies have found that individuals with chronic diseases who also have low levels of eHealth literacy—which may manifest as having difficulty accessing information online, using specific digital health services, understanding webpage navigation, accessing patient portals, and more—have poorer health outcomes related to medication adherence (C. Y. Lin et al., 2020) and lower use of healthcare services than those with higher eHealth literacy levels (Neter & Brainin, 2019). Research also indicates that individuals with lower eHealth literacy are less likely to have positive attitudes towards eHealth, which may impact their ability to receive appropriate care if options are limited to technology-focused options (Elgamal, 2024; Holt et al., 2019). While eHealth literacy has been assessed in previous research typically as a unidimensional construct, few studies explore the multiple dimensions of eHealth literacy as separate domains impacting health management (El Benny et al., 2021; Griebel et al., 2018).

Fewer studies have examined the effect of the eHealth tool expansion due to COVID-19 investments on eHealth literacy skills of adults with chronic conditions (Brørs et al., 2020; Jang, 2023). Additional research is needed to understand more about the relationship of the multidimensional aspects of eHealth literacy skills within the complexity of life managing a chronic disease (Smith & Magnani, 2019).

In the U.S. during the COVID-19 pandemic, lockdowns, psychological stress, stay-at-home orders, and remote work policies led to reduced diet quality, increased sedentary behavior, inconsistencies in tobacco use behaviors, and negative impacts on psychological well-being, mental health, and sleep behaviors in adults with chronic diseases nationwide (Hacker, 2024; Laddu et al., 2023; Nour & Altintaş, 2023). Many individuals living with chronic diseases also faced periods of limited access to healthcare and technological barriers to telemedicine which impacted the frequency of visits to the doctor (Gertz et al., 2022). When people do not regularly attend healthcare visits while managing their chronic disease, they may not receive critical self-management information related to their specific condition(s) for long periods of time (Gille et al., 2021). eHealth tools related to chronic disease self-management rapidly expanded during the COVID-19 pandemic as a solution to account for COVID-related barriers to care (Adetunji et al., 2022; Tebeje & Klein, 2021), yet little is known about how expanded technology access has affected the eHealth behaviors of adults living with chronic disease in the U.S. and the requisite eHealth literacy skills to use those tools. However, many adults turning to eHealth tools for information may not have those requisite skills to effectively use these tools (Chesser et al., 2016) which may have limited their uptake of specific services to meet their ongoing health needs (Bitar & Alismail, 2021).

Establishing a baseline understanding of the multidimensional eHealth literacy skills of U.S. adults with chronic conditions post-pandemic can lead to an improved understanding of how these adults are engaging in chronic disease management efforts (Shiu et al., 2023). This understanding can also strengthen public health surveillance and response by contextualizing these activities to actual knowledge of individual skills (Lee et al., 2022) and provide insights on how to improve healthcare system efficiencies related to disease management and care engagement on the part of those with chronic conditions (Brørs et al., 2023; Hasannejadasl et al., 2022). Addressing individual eHealth literacy within the context of broader public health initiatives is also a potential way to help reduce health disparities in at-risk populations (Jacobs et al., 2016).

Because adults with chronic diseases now rely more on eHealth tools to self-manage their health, eHealth literacy skills play a new role in influencing the adoption of healthy eating, exercise, and sleep behaviors (Airola, 2021; Hsu et al., 2014; Mitsutake et al., 2016). Among a population of adults with chronic disease, Kim and colleagues found that there was a moderate correlation between eHealth literacy and chronic disease health-related behaviors, specifically for health-promoting behavior (e.g., diet, activity, stress management, etc.), health-supporting behavior (e.g., routines, dietary choices, exercise planning, etc.), and disease management behaviors related to specific conditions (e.g., medication adherence, etc.) (Kim et al., 2023). eHealth literacy skills have been described as falling along a spectrum and may be affected by the type of chronic condition an individual has and the resulting disability (Hahn et al., 2017).

In conclusion, this dissertation research study used national survey data to assess six domains of eHealth literacy skills, as well as a combined composite grouping of those eHealth literacy skill domains, among U.S. adults living with chronic conditions, examined the relationship between these skills and CDSM behaviors, and assessed the directionality of the eHealth literacy skills with the CDSM behaviors. This study fills a gap in the research about the comprehensive eHealth literacy skills of the target population, who are often a high-risk, high-healthcare user population, and informs future practice opportunities and clinical education directions (Banerjee et al., 2021; Lewis et al., 2016; Luo et al., 2022; Renzi et al., 2022).

1.3. Research Question & Specific Aims

The underlying goal of this dissertation research was to explore the role of eHealth literacy skills in chronic disease self-management among U.S. adults 18 years and older who are internet users and who reported having diabetes, high blood pressure, heart conditions, lung disease, or cancer.

My guiding research question was: What is the association between level of eHealth literacy skill with specific chronic disease self-management behaviors among U.S. internet-using adults with a chronic disease? I answered this question by conducting a secondary analysis of cross-sectional data from the 6th cycle of the National Cancer Institute's Health Information National Trends Survey (H6). The following aims guided this research.

Aim 1: To investigate the eHealth literacy skills of adults with chronic diseases using the 2022 H6 dataset.

- Descriptive statistics were used to establish a profile of the eHealth literacy skill level of the sample population using representative variables that aligned with the six domains of the eHealth Literacy Scale (eHEALS) alongside other key variables: seven sociodemographic variables, one self-efficacy variable, and six chronic disease self-management behaviors. Additional descriptive and bivariate analyses were conducted to determine the presence of eHealth literacy skills based on type of chronic condition (e.g., diabetes, high blood pressure, heart conditions, lung disease, cancer, or multiple conditions). Individual bivariate analyses compared each of the six eHealth literacy skill domains with seven distinct sociodemographic variables to determine if the eHealth literacy skill domain varied by demographic characteristics.

Aim 2: To identify eHealth use among the sample population and establish a relationship between variables representing six domains of eHealth literacy skill and eHealth use in the H6 dataset.

- Using descriptive statistics, I established a profile of eHealth use among the sample population. Then, using bivariate and multivariable analyses, I assessed the strength of the relationship between the variables representing eHealth literacy skill domains and the variables representing the application of those eHealth literacy skills (i.e., eHealth use) to determine how well these constructs aligned with one other. This step provided criterion validity for the variables representing each eHealth literacy skill domain. Based on these findings, I adapted analytic plans to examine the role of eHealth literacy skill in chronic disease self-management behaviors.

Aim 3: To examine the conceptual link between eHealth literacy skill domain and specific chronic disease self-management behaviors as reported in the H6 dataset.

- Building on the theorized relationship between eHealth literacy skill and chronic disease self-management identified using the Information-Motivation-Behavioral Skills model, I used unadjusted and adjusted logistic regression analyses to study the strength of the association between each eHealth literacy skill domain and each of the six chronic disease self-management variables, respectively.

- Aim 3 was guided by hypothesis 1 (H1): Separate unadjusted and adjusted regression models would show that variables representing each eHealth literacy skill domain would be significantly associated with each of the six chronic disease self-management variables, respectively.

Aim 4: To determine the direction and magnitude of the relationship between level of eHealth literacy skill and level of self-reported chronic disease self-management behavioral engagement, while controlling for self-efficacy.

- The six domains of eHealth literacy skill were combined into one composite variable representing eHealth literacy skill level called H6 eHealth Literacy Skill Index (HeLSI), and the six chronic disease self-management variables were also combined into another composite variable that represented disease management (CDSM Behavior Score). Using linear regression models controlling for self-efficacy, a theoretically-related construct to eHealth literacy, and relevant sociodemographic variables, I explored the direction of the relationship between levels of eHealth literacy skill and levels of chronic disease self-management behavior.
- Aim 4 was guided by hypothesis 2 (H2): Higher levels of self-reported eHealth literacy skill would be associated with higher levels of chronic disease self-management behaviors.

1.4. Theoretical Foundation

This dissertation research study examined a complex relationship—eHealth literacy skill level in chronic disease self-management—within an interdisciplinary context spanning public health, health communication, and information science. As a result, four theoretical frameworks taken from those fields guided this dissertation research.

1.4.1. Information-Motivation-Behavioral Skills Model (IMB) Defining Core Relationship

At its core, the relationship between the independent variables outlined in this dissertation—eHealth literacy skills—and the dependent variables—CDSM behaviors—was informed by the Information-Motivation-Behavioral Skills model (IMB)(Fisher & Fisher, 1992; Fisher et al., 2009). Many health behavior theories provide insights into chronic disease self-management; however, the Information-Motivation-Behavioral Skills model of adherence is a common, theoretically-based framework used to describe disease-specific activities (Fisher & Fisher, 1992; Fisher et al., 2006; Fisher et al., 2009). The IMB provides the core framework for understanding how social and psychological factors influence chronic disease health-related behaviors. Different chronic disease studies describe the roles of information, motivation, and behavioral skills in achieving specific health behaviors, indicating that health literacy affects the relationships between the constructs within the IMB (Ding et al., 2023; Nelson et al., 2018; Osborn & Egede, 2010). Relatedly, eHealth literacy is often considered a skill level (Centers for Disease Control and Prevention, 2024, June; Norman & Skinner, 2006b; Shiferaw et al., 2020). Within this framework, eHealth literacy reflects the behavioral skills that enable individuals to locate, interpret, and apply online health information to build new knowledge and to support disease management behaviors. This dissertation examined whether eHealth literacy, operationalized as a behavioral skill within the IMB framework, predicted chronic disease self-management behaviors while controlling for self-efficacy (Figure 1) (Chang et al., 2022).

The IMB model also positions health behavior skills as a necessary determinant of health behaviors where skills are both an individual's objective abilities <u>and</u> their sense of self-efficacy concerning performance of a specific health-related behavior (Fisher et al., 2009). Research links self-efficacy to chronic disease self-management; however, it is not clear how separate self-efficacy is from eHealth literacy and how independently and/or synergistically they may contribute to improved health outcomes (Darvishpour et al., 2022; Zou et al., 2024). Past studies found correlations between eHealth literacy with self-efficacy in the IMB model, which suggests they may operate as covariates (Chang et al., 2014; Filabadi et al., 2020; Huang & Fan, 2023; Park, 2024; Sögüt et al., 2022; Wang et al., 2022). Therefore, for purposes of this analysis, self-efficacy was treated as a covariate in this study.

Lastly, and importantly, because the available data in H6 primarily captured eHealth-related skills rather than the full range of informational and motivational constructs, the present analyses focus specifically on the behavioral skills component of the IMB model. Therefore, the conceptual model reflects the middle section of the IMB model—skills and behaviors—rather than the full diagram reflection motivation-information-skills-behaviors (see Figure 1).

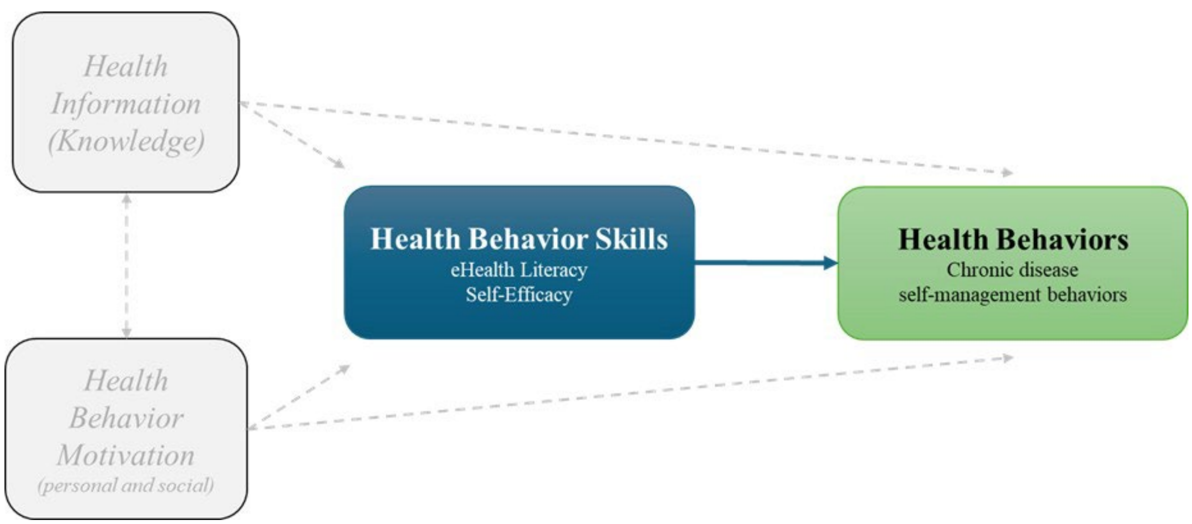

***Figure 1**. Modified Information-Motivation-Behavioral Skills Model (IMB) of health behavior (Fisher & Fisher, 1992). Grey components represent theoretical constructs not evaluated in this dissertation study.*

1.4.2. Theoretical Grounding of Key Variables

The independent variables in this dissertation study reflecting the health behavior skills as part of the IMB are the eHealth literacy skill variables. As discussed, eHealth literacy was first introduced by Norman and Skinner in the form of a six-domain lily flower model (“Lily model”) comprised of basic (or traditional) literacy, computer literacy, scientific literacy, information literacy, health literacy, and media literacy (Norman, 2011; Norman & Skinner, 2006a, 2006b). The Lily model defines eHealth literacy in a comprehensive way that accounts for the merger of the digital environment, health environment, and individual characteristics (Milanti et al., 2025). The model and the concepts are founded in Social Cognitive Theory (SCT) (Bandura, 1997, 2001; Sudbury-Riley et al., 2017) where eHealth literacy, like the SCT's key concept of self-efficacy, is often considered the application of a set of skills (Manganello et al., 2017; Norman & Skinner, 2006b; Smith & Magnani, 2019). In fact, Levin-Zamir and Bertschi describe eHealth literacy as a skillset that reflects the combined knowledge needed to complete complex health-related tasks within a digital media health environment and argue that higher levels of skills can help individuals successfully navigate this complex environment (2018). Thus, to capture these dynamic and multi-faceted eHealth literacy skills within the H6 dataset, the six domains of the Lily model were used to identify six related variables from H6 that sought to reflect each type of literacy outlined above.

The dependent variables reflecting chronic disease self-management behaviors, which reflect the "health behavior" construct of the IMB, were selected based on ideas captured in the Middle-Range Theory of Self-Care in Chronic Illness (MRTSCI) (Riegel et al., 2012). At a more fundamental, individual level, chronic disease self-management is based in behavioral theory because chronic health conditions often develop through individual behaviors (Glanz et al., 2015, pp. 7–8). The MRTSCI provides a theoretical understanding of how chronic diseases are self-managed within the context of someone's life and their environment as well as over the course of their disease experience (Riegel et al., 2019; Riegel et al., 2012; Riegel et al., 2026). At its core, this theory includes three sequential yet overlapping levels of self-care—self-care maintenance, self-care monitoring, and self-care management—that reflect the intricacies comprising chronic disease self-management behaviors. In this dissertation research study, self-management is assessed using variables that reflect self-care maintenance and self-care monitoring behaviors which respectively represent an individual's ability to maintain specific health behaviors and their ability to assess general health needs related to their conditions (Fabrizi et al., 2020; Riegel et al., 2012). These behaviors (avoiding cigarettes and alcohol, monitoring diet and overall physical status, and getting enough physical activity) are among the most frequently encouraged individual behavior across disease conditions for these preventable diseases.

The use of the MRTSCI in this dissertation study provides the theoretical connection between skills and behaviors. In the MRTSCI, Riegel, Jaarsma, and Strömberg describe functional abilities or skills as important micro-level factors that influence self-care behaviors (2026). This conceptualization aligns with how eHealth literacy is described as a prerequisite skill needed to engage in specific health behaviors in the IMB. Therefore, this theory further supports the operationalization of eHealth literacy skills as predictors of CDSM behaviors. These theoretical linkages and underpinnings are further discussed in Chapter 2.

1.4.3. Theoretical Grounding Guiding Analytic Decisions

Finally, two additional theories were used to guide the selection of variables analyzed as part of the larger relationship of interest in this secondary data analysis. First, there is a large body of research describing the context of chronic care management within the healthcare system. Much of this research utilizes the Chronic Care Model (Wagner et al., 1996) and its derivative, the eHealth Enhanced Chronic Care Model (eCCM) (Gee et al., 2015), which adopt an ecological systems perspective describing a dynamic healthcare environment that consists of relevant health system technologies, interpersonal relationships, and local community environmental influences that impact chronic disease self-management behaviors (Bronfenbrenner, 1977; Gee et al., 2015; Wagner, 2019). The eCCM connects data, information, knowledge, and wisdom with specific eHealth services related to self-management, care delivery systems, clinical decision support systems, clinical information systems, and eHealth education (Gee et al., 2015). eHealth literacy, this dissertation study's independent variable, appears under the knowledge-to-wisdom pathway in the eCCM model, reflecting the process through which individuals interpret and apply digital health information to support health decision-making and disease management (Gee et al., 2015).

The sociodemographic variables included in this study were selected to represent the broader contextual environment described at the "community–health systems–eCommunity–eHealth" level of the eCCM (Gee et al., 2015, p. 5). Factors such as age, education, income, insurance status, race/ethnicity, and locality shape individuals' access to digital resources, exposure to health information technologies, and opportunities to develop eHealth skills. Within the framework of the eCCM, these contextual characteristics are therefore expected to influence the development and distribution of eHealth literacy skills, which in turn shape individuals' ability to engage with digital health information and perform chronic disease self-management behaviors. Accordingly, these sociodemographic factors were included as contextual covariates in the present analyses.

Secondly, because all six domains of eHealth literacy skills were not directly measured using variables from the Health Information National Trends Survey (HINTS), I sought to establish criterion validity for six variables representing eHealth literacy skills by examining how well they aligned with selected eHealth use variables. The Uses and Gratifications Theory (UGT), which has previously been applied to the measurement of eHealth use among HINTS respondents (Kontos et al., 2014), informed the selection and pairing of these variables. Originating in mass communication research, UGT reflects a socio-psychological perspective in which individuals deliberately select media that satisfy specific informational or psychological needs (Cantril & Allport, 1935; Ruggiero, 2000). Contemporary applications extend this framework to digital environments, where individuals identify a need for particular types of media—including internet-based health information—and use specific technologies to fulfill that need (e.g., Lee & Cho, 2017). Guided by this framework, eHealth literacy skill variables were conceptually linked with eHealth use variables that reflected corresponding online health activities. Because eHealth literacy represents a multidimensional construct encompassing both perceived ability and functional skill, these skills were expected to shape how individuals engage with digital health technologies. Within the UGT framework, eHealth literacy skills represent the capabilities that generate or support a need for digital health engagement, while eHealth use reflects the behavioral mechanism through which that need is satisfied, ultimately supporting specific health behaviors (Rubin, 1994). A visual representation of this conceptual relationship is shown in Figure 2.

In summary, the above theoretical concepts and models were used to examine relationships of interest in this dissertation research study using the available 2022 HINTS data.

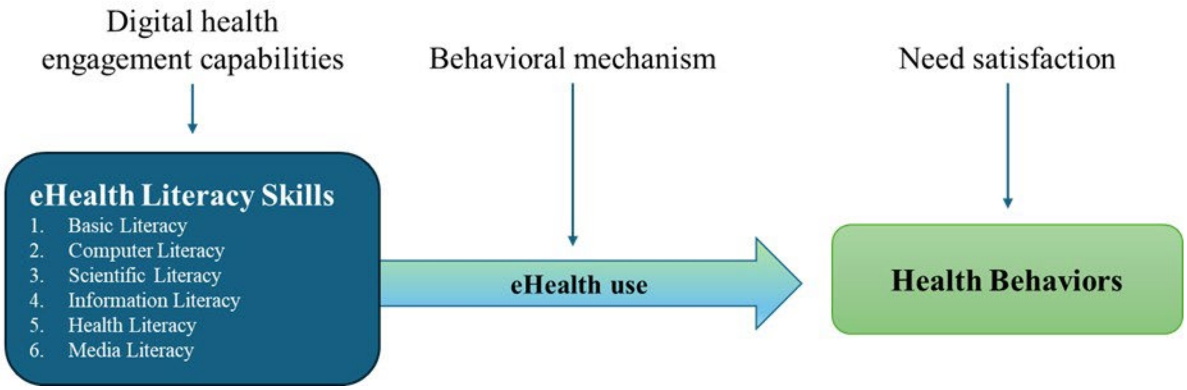

Figure 2. *Conceptual relationship informed by the Uses and Gratifications Theory (UGT) in which eHealth literacy skills represent digital health engagement capabilities, eHealth use reflects the behavioral mechanism through which those capabilities are enacted, and health behaviors represent the resulting need satisfaction.*

1.5. Conceptual Model

This dissertation used data from HINTS Cycle 6 (H6) to examine the association between eHealth literacy and chronic disease self-management. The conceptual model for this study (Figure 3) depicts the presence and direction of the hypothesized relationships between eHealth literacy skills and chronic disease self-management behaviors while accounting for covariates such as sociodemographic characteristics and self-efficacy. The IMB model informed the anticipated relationship between health behavior skills (e.g., eHealth literacy and self-efficacy) and health behaviors (e.g., chronic disease self-management behaviors). The eCCM informed the selection of key sociodemographic variables that represent the broader context in which these relationships operate. The narrow dark blue arrow represents the primary hypothesized pathway and incorporates the eHealth use variables discussed in the previous section, which were selected based on mechanisms described by UGT. Finally, the MRTSCI informed the selection of relevant self-management behaviors, including smoking status, physical activity, calorie information seeking, food discussion, alcohol consumption, and health perception. Additional details regarding the selection and operationalization of these variables is provided in Chapters 2 and 3.

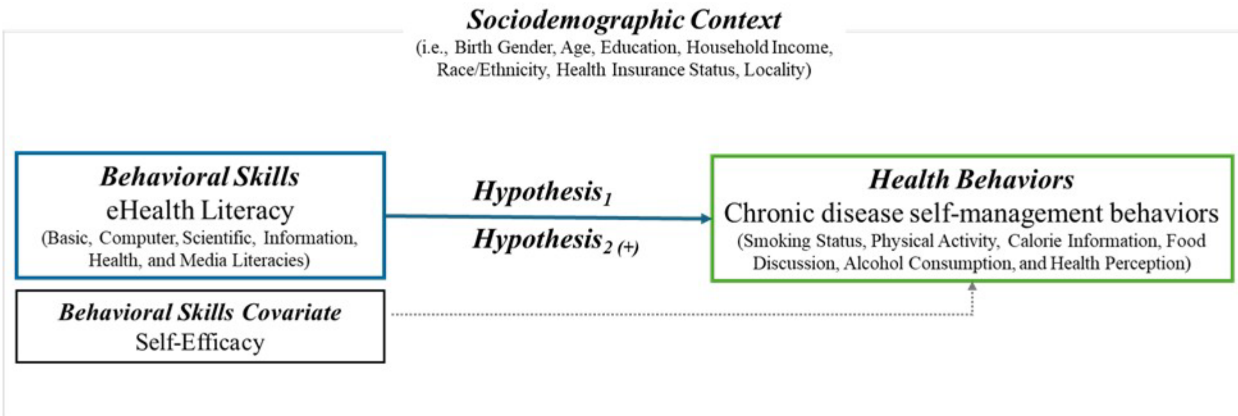

Figure 3. *Dissertation conceptual model informed by the IMB framework, illustrating the hypothesized relationship between eHealth literacy as a behavioral skill and CDSM behaviors within a broader sociodemographic context and accounting for self-efficacy as a covariate.*

1.6. Brief Justification and Rationale

Existing research on this dissertation topic suggests that adults lack key eHealth literacy skills that can foster successful engagement in eHealth activities that support lifestyle behaviors (e.g., medication management, dietary intake, physical activity, etc.), which are core aspects to chronic disease self-management (van Olmen, 2022; Verweel et al., 2023; Wu et al., 2022). There have long been calls by health literacy researchers to better define and operationalize health literacy and by extension, eHealth literacy (Institute of Medicine Committee on Health, 2004, p. 52; Norman, 2011; Paasche-Orlow & Wolf, 2007). This is due partly to the different ways literacy is operationalized within research studies. For years leading experts have also highlighted a need for better health literacy assessments within existing national population surveys (Berkman et al., 2011; Institute of Medicine Committee on Health, 2004; Kim & Xie, 2017). There have likewise been calls by eHealth literacy researchers to better understand what eHealth literacy really is and what it represents amid an ever-evolving digital health environment (Milanti et al., 2025; Norman, 2011; Paige et al., 2019).

The COVID-19 pandemic represented a paradigm shift in healthcare service and delivery for chronic and acute conditions worldwide. Due to the rapid shift of eHealth availability and the requisite necessity to quickly adopt those new tools during the COVID-19 pandemic, there is now a need to understand where the current eHealth literacy skills are of those living with chronic conditions who adapted to a new environment during the pandemic. As Brørs, Norman, and Norekvål emphasize in their 2020 editorial, using eHealth tools that were rapidly expanded during the COVID-19 pandemic required consumers to apply multidimensional motivations and skills to seek, find, internalize, and effectively use health-related content and technologies (2020). They identified these multifaceted skills, motivations, and knowledge as eHealth literacy. Scholars in the eHealth literacy field highlight the need for more studies examining the full range of eHealth literacy skills as outlined by Norman and Skinner to build a more complete understanding of current levels of eHealth literacy and their appearance in different populations (C. Wang et al., 2021). Establishing a foundation of eHealth literacy skills among U.S. adults at this time, given the advances in eHealth tool use post-pandemic, is an important way to update the existing research and evidence base to support targeted interventions, policies, and practices within public and clinical health.

Given the scope of chronic disease prevalence and the range of behavioral characteristics that influence health outcomes related to disease management (Schulman-Green et al., 2016), understanding how existing skills like eHealth literacy can support or detract from specific key behaviors may inform the design and approach of future eHealth-focused interventions. With the relative newness of eHealth as a regular aspect of care, there is an opportunity to better assess eHealth literacy skills within the existing digital communication environment captured by the 2022 version of the HINTS questionnaire. There is also an opportunity to go beyond descriptive summaries of eHealth literacy concepts from the HINTS data to test possible predictive relationships between variables that represent key elements of eHealth literacy skills and targeted health outcomes (Hesse et al., 2017).

1.7. Public Health Significance

The significance of this study was multifaceted. First, this dissertation provided updated evidence on eHealth literacy skills among U.S. adults living with chronic conditions who use the internet. To my knowledge, this was the first in-depth examination of eHealth literacy among adults with chronic disease using HINTS data and the full Lily model framework. In doing so, this study advanced theoretical understanding of how eHealth literacy functions within chronic disease self-management and contributed new evidence about the relationship between eHealth literacy and specific health behaviors.

Second, this study offered a relatively novel operationalization of eHealth literacy skills using HINTS variables. Because HINTS is a valid and reliable source of nationally representative health communication data (Finney Rutten et al., 2020), these analyses provided a credible population-level picture of how eHealth literacy skills may be represented and measured in this dataset. This approach also extended existing eHealth literacy research by examining the six Lily model domains as both independent skills and as a combined construct.

Third, this study provided a contemporary profile of how adults living with chronic conditions engaged with eHealth technologies following a period of rapid digital health expansion. The findings offered insight into how this population used eHealth resources to manage chronic conditions, navigated an increasingly complex digital health environment, and perceived their own capabilities across different eHealth literacy domains. This more nuanced understanding of eHealth literacy skills and eHealth use may help inform targeted interventions at the individual, community, and health system levels.

Fourth, this study provided updated evidence on sociodemographic disparities across eHealth literacy domains using the most recently available nationally representative HINTS data at the time of analysis. By examining variation across demographic, geographic, health, and socioeconomic characteristics, this dissertation established a useful benchmark for assessing whether previously documented disparities—such as those associated with age and education—persisted or changed in the post-pandemic digital health environment (Lane et al., 2023; Rajamani et al., 2022; Shaw Jr et al., 2024; Tennant et al., 2015; Vazquez et al., 2024).

Finally, this dissertation generated new analytic evidence linking eHealth literacy skills with both eHealth use and chronic disease self-management behaviors. Examining whether specific eHealth literacy domains were associated with specific self-management behaviors helped clarify the potential role of different types of eHealth literacy skills in supporting chronic disease management. In addition, the use of eHealth variables as indicators aligned with specific literacy domains offered a conceptually informed way to assess criterion-related support for the selected HINTS measures. Variable selection was guided by prior research on health literacy and eHealth literacy among adults with chronic disease and among HINTS respondents (Ajayi et al., 2022; Champlin & Mackert, 2016; Chew et al., 2004; Paige, Flood-Grady, et al., 2021a; Refahi et al., 2022; Shaw Jr et al., 2024; Shiferaw et al., 2020; Tennant et al., 2015). Together, these contributions provided new insight into the role of eHealth literacy skills in chronic disease self-management and offered a foundation for future intervention and measurement research.

1.8. Delimitations of the Study

This dissertation study sought to contribute new findings regarding eHealth literacy measurement among adults with chronic conditions in the U.S. to the literature base; however, the findings of this study are limited based to conclusions made using available data in H6. Other health literacy research studies using HINTS have supplemented the HINTS data with additional sources of information for more generalizable findings (Aponte & Nokes, 2017; Chu et al., 2022; Hesse et al., 2017), which could be a future direction for research. Additionally, HINTS data were collected through a cross-sectional questionnaire, so causal relationships between eHealth literacy and chronic disease self-management were not assessed. Instead, statistically significant associations and predictive relationships were analyzed. While only a snapshot of common chronic disease self-management behaviors were captured and analyzed in this data, these available variables provided insights into common patterns of self-management among adults living with chronic conditions (Brady et al., 2018). Despite these limitations, this specific research study used existing population-level data to conduct an in-depth examination of specific variables and their relationships with other variables, contributing new knowledge to the fields of eHealth literacy and broader health communication research.

1.9. Summary

Living with a chronic condition requires ongoing self-management and reflects a continual process of engaging in health behaviors facilitated through behavioral skills informed by health information and initiated through personal and social motivations (Grady & Gough, 2014; Lorig & Holman, 2003). Given this dynamic, long-term process, chronic disease self-management changes over time and requires the application of new knowledge and tools to successfully accomplish personal goals related to care management. With reduced access to “brick and mortar” healthcare facilities and providers and the rapid expansion and adoption of various eHealth technologies during the COVID-19 pandemic, people with chronic conditions had to adapt to using these new tools for their daily disease management to adhere to their care visits and related activities (Golinelli et al., 2020). Many people are still learning how best to navigate these tools. Understanding the baseline of eHealth literacy skill levels after the COVID-19 pandemic is a helpful starting point for public health educators and communicators as well as healthcare providers as we evolve together in a more technologically advanced society.

This chapter (Chapter 1) provided an overview of the background, aims, significance, research questions, and theoretical and conceptual underpinnings of this dissertation research. Chapter 2 consists of a thorough review of related literature describing what is currently known about chronic disease self-management behaviors in an eHealth context, eHealth literacy and how it is operationalized, relevant HINTS research driving methodological designs in this paper, and other relevant background literature. Chapter 3 describes the methods of the HINTS data analysis, including data acquisition, data cleaning, analytic approaches and models, variable definitions and operationalization, and other relevant methodological information. Chapter 4 presents findings organized by each of the four study aims and presents results in tables, figures, and graphics. Chapter 5 concludes this dissertation with a discussion on the implications of the findings, strengths and limitations of the research, and suggestions for future research. At the end of the dissertation is an appendix featuring additional analytic details and results.

Chapter 2. Literature Review

For decades several preventable conditions—diabetes mellitus (or Type 2 diabetes), cardiovascular disease, chronic respiratory disease, cancer, and stroke—have plagued Americans and comprised half of the 10 leading causes of disease in the U.S. (Centers for Disease Control and Prevention, 2024, October; World Health Organization, 2024, December). For the 140 million adults living in the U.S. with at least one or more chronic diseases, clinicians, public health researchers, and scientists have proposed and tested many types of health interventions to address the growing burden of chronic disease in the U.S. (Araújo-Soares et al., 2019; Newsom et al., 2012; Rahelić et al., 2024). Chief among those solutions are individual behavior self-management interventions, which are designed to help individuals adopt or cease specific behaviors to help them improve their quality of life with these diseases (Benavidez et al., 2024; Bodenheimer et al., 2002; Brownson & Bright, 2004; Grady & Gough, 2014; Megari, 2013).

In the 2010s–2020s, "electronic health" or eHealth, known as the use of information and communication technologies (ICTs) in healthcare (Eysenbach, 2001), emerged to produce a wide variety of promising tools designed to support individuals in their chronic disease self-management (CDSM) as chronic disease prevalence has continued to grow (Ansah & Chiu, 2022; Lewis et al., 2016). Use of eHealth solutions rapidly expanded during the COVID-19 pandemic as individuals sought to maintain their regular care while protecting themselves from in-person health risks due to the SARS-CoV-2 virus (Zeng et al., 2022). By leveraging digital technologies, individuals can access health information, communicate with healthcare providers, and monitor their health conditions related to their chronic disease(s). However, the effectiveness of eHealth interventions may depend on individuals' eHealth literacy, or their ability to seek, find, understand, and use health information from electronic sources (Bodie & Dutta, 2008; Kim et al., 2023; Manganello et al., 2017; Neter & Brainin, 2012; Norgaard et al., 2015; Smith & Magnani, 2019).

This chapter provides an overview of the fundamental aspects of CDSM, eHealth, and eHealth literacy discussed in this dissertation research study. Details about the role of eHealth tools in CDSM before and after the pandemic are provided. Available research about what is known about eHealth literacy among adults with chronic diseases is also discussed. This chapter also provides an overview of how CDSM, eHealth literacy, and relevant sociodemographic factors—this study's main variables—are currently studied in the Health Information National Trends Survey (HINTS) dataset. Finally, the chapter ends with a discussion of key gaps in the literature that led to the guiding research questions and approach of this dissertation study.

2.1. Chronic Disease Self-Management (CDSM)

This dissertation study uses data collected in the 2022 HINTS survey (H6) and examines the following chronic conditions: <u>diabetes</u> or high blood sugar, <u>high blood pressure</u> or hypertension, <u>heart conditions</u> like heart attack, angina, or congestive heart failure, <u>cancer</u>, and <u>lung diseases</u> like chronic lung disease, asthma, emphysema, or chronic bronchitis (National Cancer Institute, 2023a). Additionally, since many of these diseases co-occur (Schiltz, 2022), I created a variable that represented multimorbidity, which reflected instances when survey respondents reported having <u>one or more chronic conditions</u>.

As context, millions of Americans live with at least one of the chronic diseases measured in HINTS. It is estimated that about 42% of Americans, or 140 million people, have reported having one or more chronic conditions (i.e., multimorbidity) (Buttorff et al., 2017). Based on 2021 data from the National Health and Nutrition Examination Survey (NHANES), 14.7% of adults 18 years old or older (38.1 million) had diabetes (Centers for Disease Control and

Prevention, 2024, May). According to data from 2020-2023, about 47% of U.S. adults (158 million) had hypertension (or high blood pressure) (Fryar et al., 2024). Between 2019-2023, national health data showed that about 11.4% (38 million) of American adults had a heart condition such as heart attack, angina, or congestive heart failure, 9.8% (33 million) had any type of cancer, and 13.2% (44 million) had a lung disease such as chronic lung disease, asthma, emphysema, or chronic bronchitis (National Center for Health Statistics, 2025). Given the high prevalence of these conditions nationwide and their contribution to premature mortality in U.S. adults (Garcia et al., 2019; García et al., 2024), health experts have spent decades studying these conditions and exploring how best to treat them by adjusting care services and adopting frameworks of chronic care to focus on disease prevention and management.

2.1.1. Guiding Frameworks of Chronic Care

In the early 2000s, scholars documented that the paradigm of healthcare began shifting from a paternalistic model to a more patient-centered care model for chronic disease management, and patients were encouraged to adopt a more active role in their healthcare management (Barlow et al., 2002; Lee, 2020). This was largely due to the need for healthcare services to shift from primarily addressing acute illnesses to more chronic conditions (Michael Stellefson et al., 2013; Wagner et al., 1996). As a result, researchers developed several chronic care models. The Chronic Care Model (CCM) is one of the most frequently used models of chronic disease management using a clinical, healthcare system perspective (Allory et al., 2024; Grover & Joshi, 2014). The CCM was developed to illustrate how individual behaviors can be informed through productive interactions with clinical care providers who provide self-management health education within a larger healthcare system comprised of clinical information systems, decision support systems, and clinical delivery systems (Wagner, 2019, 1996). This model has successfully been incorporated into clinical care for different disease states for decades, leading to improved health outcomes for those suffering with chronic conditions (Coleman et al., 2009; Goh et al., 2022). Programs that have incorporated the CCM framework in targeting Type 2 diabetes, hypertension and cardiovascular disease, and chronic obstructive pulmonary disease (COPD) were found to improve individual patients' medical outcomes and their adherence with medical treatment plans, among other health benefits (Adams et al., 2007; Yeoh et al., 2018).

Health experts have built upon the CCM to develop more sophisticated and comprehensive versions of a chronic care model, such as the Expanded Chronic Care Model (Expanded CCM) (Barr et al., 2003), the Health Literate Care Model (Koh et al., 2013), and the eHealth Enhanced Chronic Care Model (Gee et al., 2015). The Expanded CCM was designed to better integrate aspects of population health, disease prevention, and health promotion into the CCM that takes place outside of clinical settings (Barr et al., 2003), and has seen some success in this broader, more community-based chronic care approach (Lopez et al., 2024). The Health Literate Care Model (Koh et al., 2013) positions the role of individual and organizational health literacy as critical to successful patient-provider interactions and an essential foundational element of a healthcare system, emphasizing a health literate network of providers, care systems, and patients who work together to manage chronic conditions. Health literacy is seen as an organizational value that should be infused in disease self-management approaches through techniques such as shared decision-making and "teach back" methods that allow for information to be better received and internalized by patients (Harris et al., 2019). Another related model, the eHealth Enhanced Chronic Care Model (eCCM), was developed as a "child" theory of the CCM that emphasizes the importance of eHealth education to orient the patient to available eHealth resources, eHealth technical and conceptual support to build self-efficacy among patients for eHealth-based self-management activities, and a complete feedback loop between the patient and the provider to ensure that the use of the technology is productive (Gee et al., 2015). This model, while relatively new, highlights the updated context in which chronic care management takes place where eHealth tools are used to complement in-clinic services (da Silva Lopes et al., 2023).

The focus of the CCM and its derivatives is mainly on adjusting a health system to provide the infrastructure to support individuals in their self-management largely through patient-provider relationships. This dissertation research study uses the eCCM as a guide for positioning the concept of eHealth literacy within a broader chronic care context that consists of eHealth services and highlights the value and importance of applying individual-level skills, such as eHealth literacy, to successfully manage chronic conditions within an individual's personal environment.

The following section discusses the theoretical foundation of <u>individual</u> self-care management as conceptualized through the Middle Range Theory of Self-Care in Chronic Illness (MRTSCI).

2.1.2. The Foundational Elements of Disease Management

Chronic care models represent the broader system in which individual care management takes place. Individual care management is often described as "self-management". The term "self-management" related to chronic diseases first gained traction in the academic vernacular in the 1960s through the work of Creer, Renne, and Christian (1976). Early descriptions of self-management emphasized the role that individuals suffering from a medical condition, acute or chronic, adopt in their day-to-day health management (Lorig & Holman, 2003; Wagner, 1996). This role, as conceptualized by Lorig and Holman, reflects an individual's behavior, or set of behaviors, they undertake to manage their health, with the emphasis that deciding *not* to take care of one's health is also one form of self-management (2003)(emphasis added). Thus, self-management represents a spectrum of day-to-day behaviors over the length of an illness that may or may not lead to positive health outcomes.

Additional research has expanded the scientific description of self-management to reflect more of a process or phases. For instance, the Middle Range Theory of Self-Care of Chronic Illness (MRTSCI) discusses different phases within the chronic care experience that may co-occur or stem from one another (Jaarsma et al., 2021; Riegel et al., 2025; Riegel et al., 2012; Riegel et al., 2026). These phases are self-care maintenance, self-care monitoring, and self-care management, where maintenance refers to overall behaviors that stabilize physical and mental health, monitoring refers to behaviors that assess whether or not physical changes are occurring, and management reflects the ongoing cognition management of the disease and response to signs and symptoms that arise over time (Jaarsma et al., 2021). Many individuals live with chronic conditions for decades (DuGoff et al., 2014), so they engage in each of these types of behaviors based on the current needs of their diseases and in response to new or recurrent symptoms (Fabrizi et al., 2020). The chronic disease self-management behaviors utilized in this research study focus on self-care maintenance and self-care monitoring behaviors, although this dissertation uses the more general term "self-management" to describe these behaviors for simplicity.

Some common behaviors associated with self-management include medical management, such as adhering to certain medication regimens, adhering to special diets, or engaging in clinical activities like blood pressure monitoring or therapeutic treatments (Corbin & Strauss, 1985; Corbin & Strauss, 1988; Grady & Gough, 2014; Lorig & Holman, 2003; Wagner et al., 1996), engaging in meaningful behaviors that foster wellness such as reducing consumption of harmful substances or adopting supportive behaviors like adequate physical activity (Corbin & Strauss, 1985; Corbin & Strauss, 1988; Grady & Gough, 2014; Lorig & Holman, 2003), and learning how to manage the cognitive and mental health aspect of tracking daily symptoms and perceiving changes in one's health status (Corbin & Strauss, 1985; Corbin & Strauss, 1988; Grady & Gough, 2014; Lorig & Holman, 2003; Riegel et al., 2026). Other descriptions of self-management broaden the use of the term to include descriptions of the individual's process of self-management, the types of behavioral interventions designed to promote individual self-management, and the outcomes generated through effective self-management behaviors (Grady & Gough, 2014; Miller et al., 2015; Riegel et al., 2026; Ryan & Sawin, 2009). At a fundamental level, self-management should be considered part of a process that impacts and generates health outcomes (Miller et al., 2015).

Because chronic diseases are so widespread and addressing them is critically important to improve health outcomes at a population level, there are many ways that chronic disease self-management behaviors are studied and influenced. While there is no one accepted definition of a chronic disease self-management program, a simple definition refers to this type of program as a "systematic intervention that is targeted toward patients with chronic disease" (Chodosh et al., 2005, p. 428). These types of programs focused on individual care management typically appear in clinical settings and are often comprised of self-management educational programs and activities, treatments and medications, or strategies that support individuals along their journey of chronic disease self-management (Allory et al., 2024; Davis et al., 2022; Riegel et al., 2017; Rock et al., 2020). Generally, self-management education focuses on giving up behaviors that can cause or exacerbate chronic conditions—such as smoking or alcohol use—and begin or optimize behaviors that could help alleviate chronic disease symptoms—such as maintaining a healthy body mass index, meeting physical activity recommendations, eating a diet that supports their disease management, maintaining normal blood pressure, and maintaining normal blood glucose levels (Davis et al., 2022; Riegel et al., 2017; Rock et al., 2020). While chronic disease self-management programs evolve as new technologies emerge (Al Mahmud et al., 2026; Chen et al., 2024; Rossmann et al., 2026), the underlying target behaviors reflecting an increase in health-promoting behaviors and a decrease in health-harming behaviors tend to be evergreen health recommendations across programs.

To conclude, self-management is comprised of different behaviors that impact the trajectory of someone's chronic disease and represents their personalized experience managing it over time. As a result, different types of measurements exist to track these types of behaviors based on disease type or intended goal.

2.1.3. Measuring Disease Management Behaviors

The study of successful chronic disease self-management is wide-ranging, which has led to the development of many types of measurement tools to assess whether someone is achieving adequate disease management. These instruments most often measure perceived self-efficacy; perceived skill at certain behaviors; knowledge/awareness of disease-specific target behaviors; emotional or psychological health; actual engagement in specific behaviors; and other relevant psychometric properties related to either the disease or individual characteristics required for disease self-management (Hibbard et al., 2004; Lorig et al., 1989; Riegel et al., 2025; Ritter & Lorig, 2014; Schmitt et al., 2013; Schwarzer, 1995; Wigal et al., 1991). These tools may measure disease-specific factors that affect individual behavior or disease-management skills such as self-efficacy, a commonly measured factor and contributor to health behaviors as operationalized in the Information-Motivation-Behavioral Skills Model (IMB) (Fisher et al., 2009). Self-efficacy is explored in this dissertation study as a covariate of eHealth literacy skills and is defined as an individual's belief in their capacity to organize and perform the behaviors necessary to produce specific performance attainments, such as meeting health goals (Bandura, 1977, 1997, 2001).

Examples of self-efficacy measures include the Diabetes Management Self-Efficacy Scale (Schmitt et al., 2013), the Arthritis Self-Efficacy Scale (Lorig et al., 1989), and the COPD Self-Efficacy Scale (Wigal et al., 1991). Tools may also measure broader concepts such as general self-efficacy or patient activation through tools like the General Self-Efficacy Scale (Schwarzer, 1995), the Patient Activation Measure (Hibbard et al., 2004), and the Self-Efficacy to Manage Chronic Disease Scale (Ritter & Lorig, 2014). Still other measures exist to capture a range of self-care behaviors for each disease condition: the Self-Care of Heart Failure Index (Riegel et al., 2004), the Self-Care of Coronary Heart Disease Inventory (Dickson et al., 2022), the Self-Care of Hypertension Inventory (Warren-Findlow et al., 2013), the Self-Care of Diabetes Inventory (Ausili et al., 2017), the Self-Care of Chronic Obstructive Pulmonary Disease Inventory (Matarese et al., 2020), the Self-Care of Chronic Illness Inventory (Riegel et al., 2018), and the Self-Care Inventory (Luciani et al., 2022). There are still countless other measures available that were developed as part of behavioral interventions, experimental studies, pilot studies, and more designed to track CDSM among different populations (Allegrante et al., 2019). Because there are many validated tools, it can be difficult to select the best instrument to assess these complex self-management behaviors.

The following section describes how specific variables were operationalized to describe chronic diseases self-management behaviors using the MRTSCI and related measures from instruments that aligned with items from H6. The items used to measure these behaviors were selected to provide a range of some of the most common self-management behaviors that are captured in HINTS and were informed by related research that links these specific behaviors to specific diseases or health outcomes.

2.1.4. Disease Management Variable Operationalization

I drew on the conceptualization of self-care maintenance and self-care monitoring from the MRTSCI to effectuate the disease management variables used in this study as dependent variables (Riegel et al., 2012). These variables were selected based on symptom monitoring and treatment adherence, such as those items measured in the Self-Care of Heart Failure Index (e.g., physical activity and dietary awareness) (Riegel et al., 2004; Riegel et al., 2009) and the Self-Care of Diabetes Inventory (e.g., limiting alcohol consumption and avoiding cigarette smoking) (Ausili et al., 2017) as well as checking in with one's health status (e.g., perceived general health) as measured in the Self-Care of Chronic Illness Inventory (Riegel et al., 2018).

Several available chronic disease self-management behaviors—smoking status, physical activity, dietary awareness, alcohol consumption, and perception of health—captured in HINTS served as indicators of successful chronic disease self-management based on existing research linking these behaviors to positive health outcomes (Anderson & Durstine, 2019; Chiva-Blanch & Badimon, 2019; Jansen et al., 2013; Prochaska et al., 1985). While each of these behaviors manifest differently based on disease type—such as the impact of smoking for someone with lung disease as compared to hypertension—these behaviors are critical elements on the pathway to positive health outcomes because of their connection to premature mortality (Loprinzi et al., 2016; Lushniak et al., 2014; Reedy et al., 2014; Reinwarth et al., 2023; Sohi et al., 2021). The following paragraphs provide details on how each of these behaviors is typically measured and the benefits of achieving satisfactory levels of these behaviors for each type of behavior.

Smoking status has been identified as an important indicator of adherence to chronic disease self-care behaviors. For instance, in a study examining the smoking behaviors of adults living with COPD and asthma, researchers found that smokers, as compared to disease-affected non-smokers, were less likely to keep track of medication refills for their conditions, were less likely to engage in preventive behaviors like receiving the annual flu shot, and were most likely having difficulty alleviating their symptoms (Hayes-Watson et al., 2017). Thus, remaining a non-smoker is an important element of chronic disease self-management for those living with different chronic conditions (United States Public Health Service Office of the Surgeon et al., 2020). This item appears in many self-management scales but specifically is captured in the Self-Care of Hypertension Inventory (Warren-Findlow et al., 2013).

Like tobacco consumption, alcohol consumption can negatively impact individuals living with chronic conditions. Alcohol consumption above light drinking thresholds (7-14 drinks per week for women and men, respectively) is problematic for health and can negatively impact chronic disease self-management behaviors by making it harder to reach treatment goals and exacerbating disease symptoms (Centers for Disease Control and Prevention, 2025; Mudd et al., 2020). Abstention from alcohol consumption is ideal for chronic disease management, although low consumption of alcohol is also not as damaging as higher levels of consumption (Müller et al., 2023; Shield et al., 2013). Individuals with chronic conditions who report lower levels of consumption are less likely to experience adverse health events than those who report higher levels of alcohol consumption (Sterling et al., 2020). Limited research suggests that maintaining levels of alcohol consumption at or below the light drinking thresholds can also represent effective self-management behaviors (Barbería-Latasa et al., 2022). Like measures of smoking status, this item appears in many self-management scales but was most informed by the MRTSCI and by research conducted by Rockwell, Funk, Huffstetler, et al (2024).

Adopting new health behaviors can consist of behaviors where an individual chooses not to engage in a specific activity such as smoking cigarettes or consuming alcohol. Engaging in health behaviors can also include activities where an individual adopts new behaviors or maintain behaviors at target levels. The remaining three variables generally refer to adopting or maintaining behaviors.

Physical activity with a chronic condition usually implies meeting recommended activity level thresholds, which typically consist of an individual engaging in at least 150 minutes of moderate or 75 minutes of vigorous activity each week (Piercy et al., 2018). Special interest groups and voluntary health organizations for each disease (e.g., American Cancer Society, American Diabetes Association, American Heart Association, and American Lung Association) provide specific guidelines on how individuals living with a disease related to each of those special interests should incorporate physical activity into their lifestyles that generally align with the national recommendations (Riegel et al., 2017; Rock et al., 2020; Zhang & Yang, 2024) with exceptions as needed for those living with COPD (Demeyer et al., n.d.; Hartman et al., 2014). Getting adequate physical activity while living with each of these diseases can lead to better cardiovascular health, musculoskeletal benefits, mental health benefits, and an improved quality of life which has positive effects on other behaviors (Piercy et al., 2018). While guidelines recommend a threshold for “adequate” physical activity, individuals experience benefits from that physical activity in unique ways that match their current health status (i.e., physical activity is generally beneficial for all regardless of how their disease manifests) (Anderson & Durstine, 2019). Reporting adequate physical activity levels is a sign of effective chronic disease self-management because of the benefits of having become physically active and maintaining that level of activity (Durstine et al., 2013; Myers et al., 2021). This item appears in many self-management scales but specifically is captured in the Self-Care of Hypertension Inventory (Warren-Findlow et al., 2013) and the Self-Care of Diabetes Inventory (Ausili et al., 2017).

Another variable that is often linked with physical activity is dietary behavior. Previous versions of HINTS measured fruit and vegetable consumption for dietary behavior; however, in H6, dietary awareness was measured instead of actual self-reported consumption (Restrepo, 2024). This seems to align with existing guidelines for nutrition in chronic disease worldwide that focus on overall dietary patterns rather than specific consumption levels (Gropper, 2023). Dietary awareness is often considered the first factor within an overall dietary pattern that is followed by 1) an understanding of what is healthy and 2) actions to consume healthy foods (Brown et al., 2011). Generally, dietary awareness may consist of an individual understanding of the importance of consuming different macronutrients (fiber, fat, carbohydrates), acknowledging the importance of adequate vitamin intake, and being able to recognize elements of what a healthy diet is comprised of (Żarnowski et al., 2022). While research linking dietary awareness and behavior is still limited, some studies have found an association between noticing calorie information and making consumption behaviors based on what is observed, usually in favor of healthier choices (Jia et al., 2023; Petimar et al., 2021; Salvia et al., 2024). Dietary awareness was measured using two items—calorie information and food discussion—that were informed by the Diabetes Management Self-Efficacy Scale (Schmitt et al., 2013).

Finally, and perhaps more controversially due to how cognitive aspects of disease management are typically operationalized, there are important health beliefs and risk perceptions about chronic disease management that have long been studied, such as the connection between perception of general health and health status where poorer perceptions of health are connected with higher risk of premature mortality (Idler & Kasl, 1991; Kaplan & Camacho, 1983; Wang et al., 2009). As it relates to chronic disease health behaviors, perceptions of health can be considered a biobehavioral or mental health behavior because the process of assessing one's own health and making adjustments is tied to a feedback system where individuals may be noticing aspects of their health and fearing a decline, or they may be forecasting a future state where their disease condition deteriorates (Masterson Creber et al., 2013; Riegel et al., 2019; Riegel et al., 2026; Shahid et al., 2025; Williams, 2008). This regular engagement with perceptions of health is a key part of self-care monitoring (Corbin & Strauss, 1985; Grady & Gough, 2014; Lorig & Holman, 2003; Riegel et al., 2019; Riegel et al., 2012; Riegel et al., 2026). High levels of perceived health are associated with more stable health outcomes than lower levels of perceived health among those with chronic conditions (Ferrer & Klein, 2015; Frostholm et al., 2007; Lee et al., 2019; Rañó-Santamaría et al., 2022). These higher levels of perceived health are linked with sufficient health-related quality of life, which is also associated with better chronic disease health outcomes related to treatment and management (Dresden et al., 2019; Megari, 2013; Schuler, 2015). While an association exists, it is difficult to pinpoint the exact causality and direction of this relationship. However, the variable in H 6 measuring health perception provide a helpful datapoint that represents health-related quality of life, which has been linked with effective chronic disease self-management in the literature (Alzarea et al., 2024; Singh & Dixit, 2010). Its inclusion as a CDSM behavior is supported by similarly worded items found in the Patient Activation Measure (Hibbard et al., 2004), the Self-Efficacy to Manage Chronic Disease Scale (Ritter & Lorig, 2014), and the Self-Care of Chronic Illness Inventory (Riegel et al., 2018).

While other indicators of chronic disease self-management exist, the six variables above represent different types of health behaviors that many individuals undertake to manage their disease conditions, both in the positive (adopt) and negative (cease). These variables formed an adequate summary profile of the chronic disease self-management behaviors of those adults living with chronic conditions in H6.

2.1.5. Gaps in the Literature & Summary

There are important gaps in the literature related to chronic disease self-management and the eHealth context related to health management that this dissertation seeks to address. Firstly, existing research indicates that eHealth use for chronic disease self-management will continue to be valuable and essential for effective care management, white it also acknowledges that there are gaps in the knowledge base related to the use of the eHealth Enhanced Chronic Care Model (eCCM) and how eHealth literacy is used in care management for those with chronic conditions (Al Mahmud et al., 2026; Catapan et al., 2021; Institute of Medicine Roundtable on Health, 2009). eHealth literacy exists within a context, yet existing research does not always discuss nor develop the theoretical implications and ties of eHealth literacy with the broader eHealth chronic care environment. Using the eCCM to identify relevant sociodemographic characteristics related to eHealth literacy and CDSM behaviors fills a gap in current research that links eHealth literacy with the chronic care literature.

Secondly, chronic disease self-management behaviors changed during the COVID-19 pandemic, for better or worse depending on the individual and how they were able to adapt to increased eHealth use in chronic care management amid the threat of contracting the SARS-CoV-2 virus (Yu et al., 2023). There are important contextual gaps in the literature exploring what post-pandemic chronic disease self-management now looks like and how it is associated with eHealth use; the findings in this dissertation study provide new insights into late-pandemic chronic disease self-management activities.

Thirdly, there are important methodological gaps in the literature linking the six specific chronic disease self-management behaviors identified in this dissertation study with eHealth literacy and eHealth use (Ghotbi et al., 2021). By explicitly focusing on several types of chronic disease self-management behaviors at once, this dissertation provides new evidence that links individual health behaviors across some of the most prevalent chronic conditions. The in-depth examination of each of these CDSM behaviors individually and as a composite measure provide a more nuanced perspective on how eHealth literacy may relate to general CDSM behaviors, regardless of disease type.

In summary, individual chronic disease self-management behaviors have long been studied as part of chronic disease care models. This dissertation research study draws on the eCCM and the MRTSCI to guide my research questions and analytic objectives related to describing chronic disease self-management behaviors. The variables selected as the dependent variables in this research study represent key behaviors largely under an individual's control that have important contributions to health outcomes across disease type. Information on how these variables were operationalized using the exact wording and coding from H6 is discussed in Chapter 3 (Methods). The following section provides an overview of eHealth, the costs and use of eHealth in chronic care, the impact of the COVID-19 pandemic on eHealth availability and adoption, and the variables used to represent eHealth use in this dissertation study.

2.2. Electronic Health (eHealth)

This dissertation research study examined the eHealth literacy of U.S. internet-using adults living with and managing their chronic conditions. To understand how eHealth literacy is measured and studied, it is important to review what *eHealth* is, how it was introduced into chronic care systems, and how it supports chronic disease self-management. Additionally, details regarding how the COVID-19 pandemic changed the eHealth landscape for many U.S. adults are presented in the following section. Details on how specific eHealth use behaviors were assessed are also presented.

2.2.1. eHealth Use for Disease Management

Chronic care requires an individual to engage in ongoing physiological monitoring and treatment activities for optimal health outcomes. As new technologies developed in society in the late 1900s and early 2000s, policymakers and healthcare industry leaders noticed the opportunity for technology to enhance primary and disease-specific care options for individuals living with these chronic conditions (Gee et al., 2015). While many care institutions began independently adopting electronic health (eHealth) technologies, policy advances such as the Patient Protection and Affordable Care Act (ACA) and the Health Information Technology for Economic and Clinical Health Act (HITECH Act) of 2009 endorsed the use of these technologies in patient care and led to their subsequent expansion (Adler-Milstein & Jha, 2017; Gee et al., 2015; Neiman et al., 2021). As a result, the use of eHealth in chronic disease self-care also expanded as options such as electronic health records, patient portals, online scheduling, and other eHealth services connected to the internet became more widely utilized in the delivery of healthcare services to address health needs of different populations (da Fonseca et al., 2021; Hinrichs & Zarcone, 2013; Kominski et al., 2017; Pagliari et al., 2005).

Modern conceptualizations of eHealth encompass the use of mobile devices, electronic diaries, or adherence monitors for telemonitoring or behavioral reminders; asynchronous or synchronous telemedicine consultations via video, phone, or SMS communication; social media platforms; informatics systems-electronic health records (patient portals) and clinical decision support systems, among other tools (Boogerd et al., 2015; Eysenbach, 2001; Keuper et al., 2024; Renzi et al., 2022). Specifically for people living with chronic diseases, eHealth tool use ranges from simple interventions, such as telehealth counseling, to more complex interventions with multiple layers and devices involved in eHealth care (Wannheden et al., 2022). This dissertation study uses Eysenbach's definition of eHealth:

> *"e-health is an emerging field in the intersection of medical informatics, public health and business, referring to health services and information delivered or enhanced through the Internet and related technologies. In a broader sense, the term characterizes not only a technical development, but also a state-of-mind, a way of thinking, an attitude, and a commitment for networked, global thinking, to improve health care locally, regionally, and worldwide by using information and communication technology"(Eysenbach, 2001, p. 1).*

And an oft-cited definition of eHealth use, found in Oh, Rizo, Enkin, and Jadad (2005) and Briones (2015), describes eHealth use as

> *"The use of emerging information and communication technology, especially the Internet, to improve or enable health and healthcare thereby enabling stronger and more effective connections among patients, doctors, hospitals, payors, laboratories, pharmacies, and suppliers" (Briones, 2015, p. 4).*

When introduced to patients with chronic conditions, new eHealth resources have been shown to lead to positive increases in self-care behaviors (e.g., medication management, personalized goal-setting, etc.) (Ma et al., 2019; Renzi et al., 2022; Thakkar et al., 2016; Triantafyllidis et al., 2019). For example, one study found that a patient-family-focused telehealth program with remote intervention by healthcare providers for adults living with congestive heart failure (CHF) was effective and satisfactory to participants when managing aspects of their follow-up care (Guo et al., 2019). Another study examining the impact of a pharmacist-led remote blood pressure monitoring in combination with a web-based communication program with adults with hypertension found that participants in the remote-monitoring arm experienced higher percentages of controlled blood pressure after 12 months (Green et al., 2008). A different study using a multidimensional intervention for adults with Type 2 diabetes that consisted of patient-reported glucometer readings uploaded to a portal, patient-specific diabetes care summary reports, nutrition and exercise logs, insulin records, online messaging with patient care teams, remotely delivered nurse manager and dietitian medication and dietary advice, and personalized text and video educational content, led to reductions in A1C levels at the end of the 6-month intervention compared to the control group (Tang et al., 2013).

Use of eHealth tools like patient portals for patient-provider communication, care planning, and medication management has been linked with significant improvements in patients' CDSM as well as increased quality of care, despite concerns on the patients' part regarding security and privacy (Kruse et al., 2015). One study found that individuals who tend to have more complicated medical histories and longer-lasting health conditions are more likely to engage in online health information seeking behaviors at greater rates than in those with less complicated medical histories and shorter-duration health conditions (Li et al., 2016).

While chronic disease self-management across disease conditions has many similar elements, the use of eHealth in CDSM is not always uniform across disease type. For instance, those with diabetes and COPD report more frequent engagement with eHealth than those with cardiovascular disease due to the perceived effect of the disease on their daily life (Huygens et al., 2016). Additionally, even within samples of adults with the same chronic disease, such as COPD, interventions focused on digital remote maintenance inhaler adherence have varied impacts on patient adherence from none to moderate effects (Aung et al., 2024). For some diseases, like hypertension that requires more frequent monitoring of symptoms and exacerbations, at-home remote monitoring activities (e.g., blood pressure and weight monitoring) can lead to highly effective CDSM behaviors that lead to better health outcomes (Lv et al., 2017). Previous HINTS research from before the COVID-19 pandemic indicated that those adults living with lung disease and cancer were more likely to use health information technology (HIT) tools as compared to individuals without chronic conditions, whereas adults with Type 2 diabetes, hypertension, or heart disease used HIT tools at about the same rate as patients without chronic conditions (Rajamani et al., 2022).

The studies above highlight the variation in eHealth tool use that exists within specific disease populations as well as across disease populations. Yet, across all chronic diseases, there are still relatively high rates of self-reported information seeking and use of eHealth technology among affected adults, according to some research (Madrigal & Escoffery, 2019).

2.2.2. Costs Associated with eHealth Use

Despite known advantages of the use of eHealth in CDSM, factors outside of disease diagnosis may influence engagement with eHealth or HIT (Rajamani et al., 2022), and individual adoption may be affected by ethical concerns on the part of the end user leading to a cost-benefit analysis. Different types of costs—financial, opportunity, and access-related—may affect eHealth access and adoption by groups of affected patients. Previous HINTS research found that lower socioeconomic status (i.e., lower education and lower income) contributed to lower likelihood of individuals engaging in specific eHealth activities, such as going online to look for a health care provider, using email to communicate with a doctor, tracking personal health information online, using web-based resources to track diet, weight, and physical activity, and using a smartphone for health-related activities (Kontos et al., 2014). Generally, younger adults and females with chronic conditions tend to be higher uses of eHealth overall, although within-group differences are still present and affected by other demographic variables like education and income (Ajayi et al., 2022; Haluza & Wernhart, 2019; Huang et al., 2023).

Demographic differences might also be influenced by personal perspectives on the importance of eHealth use in their lives. Many end users (i.e., patients) may have concerns about who has access to their health information, how private it is, how it is used in different ways, who owns their data, and how it may be used against them in other settings of their personal or professional lives (Jokinen et al., 2021; Wilkowska & Ziefle, 2012). This may limit adoption of specific clinical health tools, like electronic medical records, online messaging with providers, and more (Keshta & Odeh, 2021). Concerns about privacy and security may limit individual interaction with eHealth technologies or services, but the need to access quality care, the availability of this care only through digital means, and the assurance that their privacy will be upheld may reduce those concerns for those managing chronic illnesses (Alhammad et al., 2024; Chow et al., 2024).

Differences in eHealth tool use are not only affected by individual-level characteristics. There are important contextual factors that create a "digital divide" in healthcare access related to eHealth that is often acknowledged as an influence on adoption and use. In areas where there is less supportive built environment infrastructure (e.g., online banking, telemedicine, online shopping, and reliable cell phone or broadband service) that also can support eHealth activities, individuals do not have as many opportunities to engage in eHealth (Kontos et al., 2014; Latulippe et al., 2017; Sieck et al., 2021). The digital divide can impact all aspects of life and most importantly, quality of life, as many describe it as a social determinant of health that can worsen or improve health disparities (Alkureishi et al., 2021; Jackson et al., 2021; Office of Disease Prevention and Health Promotion, 2000). One review study found that specific demographic factors were associated with lower eHealth use, such as older ages, lower incomes, less education, living alone, and living in rural areas, corroborating previous research that indicates that there is a digital divide related to eHealth use among individuals living with chronic diseases (Reiners et al., 2019).

Many of these differences related to eHealth use existed before the COVID-19 pandemic due to the digital divide; however; advances like expanded telecommunications infrastructure, telehealth offerings for more remote or underserved areas, and remote monitoring tools during the pandemic helped reduce some of the divide among disadvantaged individuals worldwide (Abbott et al., 2021; Connolly et al., 2025). The following section provides more details on what investments were made during the pandemic to support individuals in their care management while shifting to a more remote healthcare environment.

2.2.3. COVID-19 Pandemic-related Changes to Care

The use of eHealth tools during the COVID-19 pandemic rapidly expanded worldwide in the form of communication with healthcare offices and providers, follow-up care via virtual appointments or asynchronous messaging, health education and disease training for specific treatments (e.g., at-home blood pressure monitoring), medication support via e-prescribing or virtual counseling, caregiver support for those caring for others with chronic conditions such as Alzheimer’s or Parkinson’s diseases, and telemedicine consultations for acute or chronic conditions (Bitar & Alismail, 2021; Citoni et al., 2022; Raj et al., 2022; U.S. Department of Health and Human Services, 2023, May). However, adoption across health systems was not uniform as many groups had to first develop the eHealth tools prior to making them available or develop and launch the tools simultaneously (Giansanti, 2022; Hunt et al., 2023). Once these tools were available, individuals also had to learn how to use them effectively, so individual eHealth literacy remained an important element in the adoption and use of these tools during the pandemic (Brørs et al., 2020; Fagherazzi et al., 2020).

Post-COVID-19 data are still emerging, but trends suggest that chronic conditions worsened due to the effects of the COVID-19 pandemic (Centers for Medicare & Medicaid Services, 2024), which could lead to higher rates of care visits related to chronic conditions. Prior to this, about 30-40% of primary care visits between 2001-2015 were focused on chronic care management and closer to 40% by 2019 (Ashman et al., 2023) (Bensken et al., 2021). However, during the COVID-19 pandemic, in-person primary care office visits dropped by about 25% while telemedicine appointments increased by about 35% (Alexander et al., 2020; Shaver, 2022). Engagement in telemedicine appointments varied by geography (rates were much higher in the Pacific region as compared to the Midwest), race (White Americans had higher levels of engagement than Black Americans), and age (19–55-year-olds engaged at higher rates that <19 year-olds and 56+ year-olds) (Alexander et al., 2020). While telemedicine appointments provided necessary health services for many adults during the pandemic, the ability to assess key biomarkers (e.g., blood pressure or cholesterol) important in disease management was limited, highlighting how chronic clinical care could not be easily replicated in an online setting without additional focus on collecting relevant biological data (Alexander et al., 2020; Shaver, 2022).

Overall, engagement in eHealth services during the COVID-19 pandemic was largely seen as a step forward for care management among different populations because of the ability to provide care while minimizing the risk of infectious disease spread, reach hard-to-reach individuals in a more timely manner, utilize personalized management tools available through the eHealth platforms, and contextualize care plans based on more information about the surrounding, more visible home environment (Doraiswamy et al., 2021). Furthermore, many systems of care were transferred to digital environments to accommodate the needs of the healthcare providers and patients during the pandemic; the eHealth infrastructure is now built and can now be improved as needed (Greiwe, 2022). Finally, some research suggests that individuals with chronic conditions who had to adjust to the eHealth environment during the pandemic became more engaged in their care and more knowledgeable about how to manage their health (Duffy et al., 2021). There is an opportunity to better understand what eHealth use looks like after these big changes occurred during the pandemic, and the following section on eHealth Literacy provides more details on how eHealth use was operationalized using H6 variables.

2.2.4. eHealth Use Variable Operationalization

This dissertation research study examined patterns in eHealth use among a nationally representative population of U.S. adults during a period of time when eHealth resources rapidly expanded and were quickly adopted from 2020-2022. There are many different types of eHealth resources available to individuals living with chronic conditions, as enumerated in previous sections of this chapter. However, the HINTS dataset collects a limited amount of cross-sectional data on actual eHealth use, specifically in H6 (National Cancer Institute, 2023a). Since HINTS does not explicitly include items measuring eHealth literacy, I conducted analyses to operationalize eHealth literacy skills along the six domains outlined in the eHEALS Lily model (e.g., media literacy, basic literacy, computer literacy, health literacy, scientific literacy, and information literacy) (Norman & Skinner, 2006a) by connecting these variables to actual eHealth use to establish criterion validity (Lotto et al., 2023). This connection between eHealth literacy skill and eHealth use supports the theorized connection between eHealth literacy skills and chronic disease self-management behaviors. The following variables were selected to represent a type of eHealth use that most closely aligned with the specific domain of the eHealth literacy skill. More details on these specific operationalizations are in Chapter 3.

The first variable is traditional/basic ("basic") literacy which, in this context, relates to basic reading, writing, and meaning-making skills used to navigate eHealth environments (Norman & Skinner, 2006b). One variable in HINTS provides a partial representation of basic literacy eHealth use, or "Basic eHealth Use" was "SharedHealthDeviceInfo", which asks if an individual shared health information from an electronic monitoring device or smartphone with a health professional in in the last 12 months (National Cancer Institute, 2023a). Individuals with chronic conditions are more likely to use electronic monitoring devices than those without chronic conditions and more likely to have to share that information with a healthcare provider due to the frequency of interactions with those providers (Griffin & Chung, 2019). This type of electronic communication may be considered a basic element of disease management in an eHealth context, which requires fundamental reading, writing, and meaning-making skills (Langford et al., 2020). While there is not a specific study linking this variable with the concept of basic literacy, there is evidence suggesting that the behavior is associated with higher eHealth engagement overall and higher subsequent eHealth literacy (Neter & Brainin, 2012; Ramachandran et al., 2023). Thus, it was considered an adequate variable to represent basic literacy in this context.

The next eHealth literacy domain was computer literacy, which refers to the ability to engage with specific technologies such as operating systems, software, applications, and other technical elements of an internet-connected device (Norman & Skinner, 2006b). The variable representing computer literacy eHealth use, or "Computer eHealth Use", was "UsedHealthWellnessApps2", which asked participants if they used a health or wellness application on their tablet or smartphone in the last 12 months (National Cancer Institute, 2023a). Individuals who use mobile applications tend to have higher levels of overall eHealth literacy because of their ability to translate behavior change techniques covered in the apps with actual behaviors (Ernsting et al., 2019; Shaw Jr et al., 2024). Therefore, this variable represented engagement with a specific format of eHealth that was likely associated with the skill necessary to effectively use these types of devices and technological platforms.

The next three eHealth literacy domains—scientific literacy, information literacy, and health literacy —contained variables that were part of a matrix in the H6 questionnaire. There is a precedent set by other studies to examine these items separately (Kontos et al., 2014; Vazquez et al., 2024). Scientific literacy is often broadly defined in health communication or science communication contexts (Li & Guo, 2021), and Norman and Skinner adopt some of that broadness in their definition (Norman & Skinner, 2006b). Scientific literacy eHealth use, or "Scientific eHealth Use", was reflected by the "Electronic2_TestResults" variable that asked if individuals had used the internet to view medical test results in the past 12 months (National Cancer Institute, 2023a). This item represented a knowledge-building activity that took place in a science-informed manner, which related to concepts of scientific literacy that reinforce understanding how the scientific discovery process influences health information (Briones, 2015; Rosenthal, 2020).

Information literacy generally reflects a need for information, seeking of information, and use of information to make good health choices (Huhta et al., 2018; Norman & Skinner, 2006b). Information literacy eHealth use, or "Information eHealth Use", was captured using "Electronic2_HealthInfo", which asked respondents if they had used the internet to look for health or medical information in the past 12 months. Strong information literacy skills are associated with the ability to engage with medical processes in the intended way by identifying an information need and accessing the appropriate platform to achieve a specific aim (Wang et al., 2023).

Lastly, Norman and Skinner consider health literacy within the Lily model as an individual being able to act on health information and perform basic tasks using eHealth tools (2006b). Health literacy eHealth use, or “Health-Related eHealth Use”, was assessed via the question “Electronic2_MessageDoc”, which assessed a respondent’s use of the internet to send a message to a healthcare provider or a provider’s office in the past 12 months (National Cancer Institute, 2023a). Individuals with lower health literacy tend to have lower odds of engaging with medical services online, such as electronic messaging platforms (Chen et al., 2018).

In the Lily model, media literacy skills refers to being able to critically assess how media shapes messaging and information dissemination related to health information or health behaviors (Norman & Skinner, 2006b). The variable representing media literacy eHealth use, or “Media eHealth Use”, was “SocMed_WatchedVid”, which measures the frequency of how often the respondent watched a health-related video on a social media site such as YouTube or others (National Cancer Institute, 2023a). Using social media to watch health-related videos has been found to be positively and significantly associated with eHealth literacy skills as well as actual intention to engage in a health-related activity (Kim et al., 2024). This eHealth use variable is a strong variable to represent media literacy skill because there is a positive and significant relationship between high uses of this type of eHealth (Web 2.0) and high levels of eHealth literacy (Tennant et al., 2015).

The goal of operationalizing specific examples of eHealth use from the H6 dataset alongside each eHealth literacy skill domain was to assess the degree to which these variables correlate with one another. While these were not perfect measures of the skill domain of interest, they presented an opportunity for me to use existing data to assess the eHealth literacy phenomenon within this dataset. More details on how eHealth literacy skills were operationalized can be found in section 2.3.5 of this chapter and in Chapter 3.

2.2.5. Gaps in the Literature & Summary

Over the last 30 years, eHealth use for disease management has increasingly become more common and expected as technologies evolve and individuals become more familiar with how to use these platforms to engage in their care management (Barker et al., 2024). The COVID-19 pandemic rapidly influenced the availability and use of specific eHealth tools such as remote monitoring, telemedicine and telehealth visits, online messaging, medication refills, and more (Renzi et al., 2022). Many telehealth policies and eHealth tools introduced during the COVID-19 remain available and in-use post-pandemic (Health Resources Service Administration (HRSA), 2023, December; U.S. Department of Health and Human Services, 2023, May).

However, adoption and utility of eHealth tools for those with chronic diseases is still an understudied topic, as research suggests that there may be important differences across disease type, type of eHealth use, individual characteristics, and more that are important to study as eHealth remains a frequently offered aspect of chronic care (Yu et al., 2023). With this comes the need to better understand the role of eHealth literacy in this adoption and use as well, as it can predict the perceived usefulness and ease of use of eHealth tools (Katsaliaki, 2024). Furthermore, little is known about the effectiveness of the various types of eHealth deployed during the pandemic given how quickly access and use of these tools expanded (Bitar & Alismail, 2021). Further research is warranted to better describe the current state of eHealth and the application of eHealth literacy skills to achieve target health outcomes related to chronic disease self-management. eHealth tools are expected to remain relevant in patient care and may continue to replace in-person options as healthcare shortages continue in different areas in the U.S. (Giacalone et al., 2022).

In summary, it is important to understand how people with chronic diseases engage with different eHealth resources when managing their care because of how interconnected eHealth literacy is with eHealth use. Developing an understanding of how eHealth literacy is associated with chronic disease self-management behaviors also requires an understanding of the surrounding eHealth context in which eHealth literacy skills are applied. The following section provides more details on eHealth literacy, how it differs from health literacy, and how it was measured and analyzed in this dissertation research study using H6 variables.

2.3. eHealth Literacy

eHealth use and eHealth literacy are inextricably linked; the ability to use and navigate eHealth services requires a level of eHealth literacy skills and knowledge (Centers for Disease Control and Prevention, 2024, June; Institute of Medicine Roundtable on Health, 2009). This section provides details on how eHealth literacy deviated from health literacy to emerge as a separate and important concept related to eHealth use. This section also discusses how eHealth literacy skills are used in health management for different populations and across different disease settings. The section provides details about how eHealth literacy has been measured and how it was operationalized and measured using H6 variables in this dissertation research study.

2.3.1. eHealth Literacy and Health Literacy

As covered in previous sections of this chapter, research studying the role and impact of eHealth on health outcomes and chronic disease management has expanded steadily.

Accompanying that research has been eHealth literacy research highlighting eHealth literacy skills as the necessary skills to optimally utilize eHealth resources (Chen et al., 2024). It is well-documented that adequate health literacy plays an important role in chronic disease self-management across disease type (Koh et al., 2013; Magnani et al., 2018; Mantwill et al., 2015; Simmons et al., 2017), but gaps remain in the literature about the role of eHealth literacy in CDSM, especially for those in the U.S. (Refahi et al., 2022; Verweel et al., 2023). The concepts of *health literacy* and *eHealth literacy* are related but separate concepts. Health literacy describes skills related to general literacy, numeracy, comprehension, critical thinking, and information seeking without specifying channel, format, or technology type, whereas eHealth literacy describes a specific skill set related to computer use, media literacy, and information literacy related to evaluating sources of digital information (Levin-Zamir & Bertschi, 2018; Smith & Magnani, 2019).

Some measures of health literacy may yield different results than measures for eHealth literacy, sometimes referred to as digital health literacy, which is part of the challenge with effectively identifying these skills in individuals (Monkman et al., 2017). eHealth literacy is defined in different ways, such as "The skills to search, select, appraise, and apply online health information and health care-related digital applications" (van der Vaart & Drossaert, 2017, p. 2) or "[…] the ability of people to use emerging information and communications technologies to improve or enable health and health care" (Neter & Brainin, 2012, p. 1). In the eHealth literacy Lily model, health literacy is considered more acutely focused on interactions with the healthcare system and individual self-care, and it appears as just one component of eHealth literacy, representing an important contextual factor that influences eHealth literacy (Norman & Skinner, 2006b).

There is ambiguity in health literacy research as the health literacy construct is operationalized and studied in different ways, and there is no universal definition of health literacy that is accepted by all (Sørensen et al., 2012). Some experts see health literacy as an element that represents complementary skills of patients and health care providers (Rudd, 2015; Rudd et al., 2012). For others, health literacy is described in terms of human potential and capacity (Doak et al., 1996). This nebulousness also exists within the eHealth literacy literature where eHealth literacy may be described as a skill, an ability, or a level (Norman & Skinner, 2006b). eHealth literacy may also be referred to as something broader, such as digital health literacy, which represents a complex, multilayered series of competencies related to functional, communicative, critical, and transactional literacies (Arias López et al., 2023; Paige et al., 2019; van Kessel et al., 2022). There are key differences between eHealth literacy and digital health literacy, although these terms have been used interchangeably. eHealth literacy refers largely to how an individual interacts with eHealth services, whereas digital health literacy represents a broader capacity to engage with health activities through digital means, whether or not they are explicitly described as eHealth (van der Vaart & Drossaert, 2017; Xie & Mo, 2023). Norman, co-creator of the Lily model, and colleagues have indicated that an updated definition of eHealth literacy might be necessary as the types of technology used in health management and promotion change, and digital health literacy may begin to meet that need for more encompassing language (Milanti et al., 2025; Norman, 2011). In fact, eHealth literacy may be considered a subset of digital health literacy. Digital health literacy represents this broader understanding of health-related services that accounts for the evolving nature of digital health resources and interconnected, dynamic health services (Web 2.0 user-generated content and beyond) (Ban et al., 2024; Jackson et al., 2021). Digital health literacy represents the future of conceptualizing the ability to live and engage in health-related activities in an internet-connected world as researchers describe it as a super determinant of health (Hanebutt & Mohyuddin, 2023; van Kessel et al., 2022). While digital health literacy is a newer, more comprehensive concept, eHealth literacy has dominated the field over the last 20 years and remains the most relevant and defined concept when discussing the specific skills of individuals to navigate eHealth services (Yang et al., 2022).

2.3.2. Definition of eHealth Literacy in this Dissertation Study

While further research is required to identify a tool that best measures eHealth literacy (Jiyeon Lee et al., 2021), the domains of the Norman & Skinner Lily model provide a helpful foundation for exploring eHealth literacy. Thus, this dissertation research study conceptualizes eHealth literacy as a set of skills in the six domains popularized in the Lily model: basic literacy, computer literacy, scientific literacy, information literacy, health literacy, and media literacy (Milanti et al., 2025; Norman & Skinner, 2006a, 2006b). Researchers have looked at the six domains of eHEALS and found them to be considered knowledge, skills, and confidence (Foote et al., 2023; Sudbury-Riley et al., 2017). Others like the Centers for Disease Control and Prevention (CDC) and Stellefson and colleagues describe eHealth literacy as a skill level or set of skills (Centers for Disease Control and Prevention, 2024, June; Stellefson et al., 2011).

For the purposes of this dissertation research study, I have revised Norman & Skinner's definition of eHealth literacy ("the ability to seek, find, understand, and appraise health information from electronic sources and apply the knowledge gained to addressing or solving a health problem" (Norman & Skinner, 2006b, p. 2)) to:

> *A multidimensional set of skills that can be measured at different levels and that represent successful engagement in eHealth behaviors associated with basic literacy, computer literacy, scientific literacy, information literacy, health literacy, and media literacy.*

This operationalization of eHealth literacy keeps the main knowledge and skill-building-related concepts and ideas of the eHealth literacy framework derived from Social Cognitive Theory intact while also incorporating aspects of how it is measured and associated with other health behaviors (Bandura, 1997, 2001; Norman & Skinner, 2006b). How this definition was used to describe eHealth literacy skills among a population of adults with chronic conditions in the U.S. from the H6 dataset is further expanded upon in Chapter 3.

The subsequent section provides some examples of how eHealth literacy skills are measured, with an emphasis on how eHEALS describes eHealth literacy using the six different domains Norman and Skinner developed.

2.3.3. Measurement of eHealth literacy

Scholars emphasize that given the relative newness of eHealth literacy as a concept and the ever-evolving nature of the eHealth landscape, measuring eHealth literacy lacks a "gold standard" approach (Griebel et al., 2018). There are several different ways to measure eHealth literacy through performance-based metrics (e.g., website-based tests, task-related activities, knowledge assessments), such as the eHealth Literacy Assessment Toolkit (eHLA) (Karnoe et al., 2018) and the Research Readiness Self-Assessment (Ivanitskaya et al., 2004), among others that tend to all align with the concepts of eHealth literacy introduced by Norman & Skinner (Crocker et al., 2023; 2006b). It can also be measured through self-reported metrics, such as the eHealth Literacy Scale (eHEALS) (Norman & Skinner, 2006a), the electronic Health Literacy Scale (e-HLS) (Seçkin et al., 2016), the Digital Health Literacy Instrument (DHLI) (van der Vaart & Drossaert, 2017), the eHealth Literacy Questionnaire (eHLQ) (Kayser et al., 2018), and the Transactional eHealth Literacy Instrument (TeHLI)(Paige et al., 2019).

The eHEALS scale has been frequently used in the literature and has been found to be highly comprehensible for those who complete the questionnaire (Jiyeon Lee et al., 2021). In terms of the impact of the eHEALS measurement, higher levels of self-reported health and more regular engagement in clinical care visits were associated with higher eHEALS scores than those with lower levels of self-reported health and fewer clinical care visits (James & Harville, 2016; Xu et al., 2021); higher rates of news or online media (i.e., news content) consumption was also associated with higher eHEALS scores (James & Harville, 2016; Li & Liu, 2020); and those who reported searching for health information related to specific health behaviors (e.g., nutrition/dieting, medication use, stress/anxiety/depression, and tobacco/alcohol/drugs) also had higher eHEALS scores than those who did not search online for those health topics (James & Harville, 2016).

The 8-item eHEALS was developed and validated using a younger population of adolescents and adults (13-21 years old) and demonstrated strong internal consistency ($\alpha = .88$) and moderate test-retest reliability over six months ($r = .40$ to $.68$) (Norman & Skinner, 2006a). Convergent validity was supported by item-scale correlations ranging from .51 to .76 (Norman & Skinner, 2006a). In a population of older adults (mean age 62.8), the eHEALS demonstrated high internal consistency ($\alpha = .94$) and acceptable test-retest stability (Chung & Nahm, 2015). In another study, the eHEALS scale had sufficient internal consistency (Cronbach's alpha = .93 in study 1 and .92 in study 2) and the eight items loaded on one single component (representing 67% and 63% of variance, respectively) (van der Vaart et al., 2011). Thus, eHEALS is considered a unidimensional scale.

In summary, while there are other reliable and valid tools to measure eHealth literacy, eHEALS is one of the most commonly used measures of eHealth literacy and provided a clear and comprehensive framework for measuring eHealth literacy in this dissertation study The following section provides examples of how these specific eHealth literacy skills are linked with health management.

2.3.4. eHealth Literacy and Health Management

As the healthcare world grows increasingly digital through the diffusion of telehealth, patient portals, and other eHealth platforms, eHealth literacy skills are increasingly needed to engage fully in healthcare (Jackson et al., 2021; Price & Simpson, 2022). Research linking eHealth literacy skills with chronic disease health outcomes has been studied more on a global scale than in the U.S. For example, among general adult internet users in Japan, users with high eHealth literacy were significantly more likely to engage in recommended physical activities and have balanced nutrition than individuals with low eHealth literacy (Mitsutake et al., 2016). In South Korea, higher eHealth use, combined with strong eHealth literacy skills and informational support, was shown to be positively and significantly associated with high levels of health self-efficacy, which can lead to better health-promoting behaviors (Choi, 2020). In a Chinese population of older adults with chronic diseases, eHealth literacy skill levels were positively associated with greater engagement in chronic disease self-management behaviors related to exercise, communicating effectively with healthcare providers, and cognitively managing their conditions (Wu et al., 2022). This relationship was also mediated by self-efficacy. Research with Type 2 diabetics in Thailand indicated that there was a relationship among health literacy, self-efficacy, and self-care behaviors related to Type 2 diabetes management (Ong-Artborirak et al., 2023).

However, eHealth literacy skills for health management are not always uniformly beneficial. Among college students in Pakistan, higher eHealth literacy scores were associated with higher levels of online health information seeking about specific health conditions; but physical activity levels and social media use were not associated with higher eHealth literacy (Tariq et al., 2020). Other research examining eHealth literacy among relatively technologically literate Finnish adults with chronic diseases found that participants struggled with finding high quality sources of health information, staying up-to-date with the latest functions of eHealth tools related to their chronic disease management, understanding jargon related to the content they encountered, and assessing the relevance of specific information they were offered virtually (Tamminen et al., 2023). Participants also indicated that self-efficacy and confidence in navigating eHealth environments contributed to their chronic disease self-management experience (Tamminen et al., 2023). Another study led by Neter & Brainin in Israel showed that individuals with high levels of eHealth literacy were able use the information they searched for more effectively than those with lower levels of eHealth literacy, specifically related to cognitions of health, self-management of health care needs, and interpersonal interactions with healthcare providers (2012). However, in this same study, they found that individuals with chronic illnesses had lower levels of eHealth literacy than those with no chronic illnesses, which they attributed to possible opportunity costs related to less time and energy to develop expertise at searching for health information or inability to access certain health care services that appeared in searches (Neter & Brainin, 2012).

Overall, evidence across studies suggests that eHealth literacy is associated with health-related behaviors and the degree to which they are associated depends on type of disease, type of behavior, and different individual demographic factors. Data from a meta-analysis conducted by Kim and colleagues from 29 studies examining the role between eHealth literacy (measured mostly using the eHEALS scale) and health-related behaviors worldwide found that a majority of the studies (n=22) showed that individuals with higher eHealth literacy scores were reported to engage in more regular eating and exercise, smoking cessation, alcohol abstinence, medication adherence, and self-care activities related to heart failure and diabetes (Kim et al., 2023), among other health-promoting activities. However, the populations of these studies were quite varied, ranging from adolescents to college students to older adults, and some were conducted with well individuals while others were conducted with individuals living with chronic conditions (Park et al., 2014; Tsukahara et al., 2020).

In summary, this international evidence presents a strong case for the theoretical connection between eHealth literacy skills and chronic disease self-management behaviors. This evidence shows that higher eHealth literacy skill levels are associated with better CDSM behaviors. When eHealth literacy skill levels are lower, individuals may not be as effective or successful in their chronic disease self-management behaviors. In a study of U.S. adults (18-65+ years-old), researchers found that eHealth literacy related to COVID-19 was low, which resulted in low engagement in health-promoting activities, especially as it related to confidence in finding reliable informing and using it effectively, trust in sources of information, skill in navigating and evaluating online health resources, and awareness of available resources (An et al., 2021). Another study that used some HINTS questions in surveys of Baby Boomer adults (50+ years old) ranging from self-reported “fair to excellent” health living in Florida found that there were important eHealth literacy skill differences among this group based on age, sex, and education (Tennant et al., 2015). More engagement with interactive websites (e.g., social media like Facebook, YouTube, etc.), more use of electronic devices, and more frequent use of the internet for health information was associated with higher eHealth literacy scores than those who engaged in these activities less often (Tennant et al., 2015).

Based on the available research linking eHealth literacy skills with chronic disease self-management above, the conceptualization of eHealth literacy positions it as a latent construct that can be used to predict specific behaviors. Further research is needed to establish a more causal relationship between these two domains (eHealth literacy and chronic disease self-management behaviors); this dissertation research study aims to provide additional evidence on this previously observed relationship using new variables and a new study population. The following section provides a brief overview of how eHealth literacy was measured in this study using HINTS variables, which is also expanded upon in Chapter 3.

2.3.5. eHealth Literacy Variable Operationalization

As discussed, many studies look at eHealth literacy using the eHEALS framework; however, few studies independently look at each of the six domains of the Lily model that underpins the eHEALS instrument (El Benny et al., 2021). In related eHealth literacy research, some studies focus on only one of the domains. For example, in one article exploring media health literacy and eHealth literacy, media literacy is described as skills utilized to identify, extract, and understand health information from different media sources (media literacy) to build health knowledge, engage in health tasks, and navigate resources (Levin-Zamir & Bertschi, 2018). Another study in Ethiopia looked more narrowly at computer literacy within the context of eHealth literacy skills and found that computer literacy is a particularly important part of larger eHealth literacy skills when it comes to managing a chronic condition due to the impact of successfully utilizing a technology to achieve health-related activities (Shiferaw et al., 2020).

This dissertation research study draws on available research using HINTS data to measure the underlying constructs of each type of literacy from eHEALS alongside other research examining these constructs using other datasets. Each eHealth literacy domain was represented by one variable from the H6 questionnaire that best aligned with the main concept covered for each one, as informed by Norman & Skinner's definitions in the Lily model (Milanti et al., 2025; Norman, 2011; Norman & Skinner, 2006a). Definitions of each of these literacies are drawn directly from the Lily 3.0 Model (Milanti et al., 2025, p.3):

- Basic literacy is defined as "reading, writing, and speaking skills".
- Computer literacy is defined as "the skills to learn, adapt to, and engage with digital technologies to actively promote and support health, care and well-being".
- Scientific literacy is defined as "the ability to understand the nature, objectives, methods, practice, limitations, perspectives and opportunities of science and/or knowledge".
- Information literacy is defined as "the ability to seek, find, understand, appraise, filter, use, and create information ethically and safely".
- Health literacy is defined as "the ability to understand and engage with health source material and the health system, make appropriate and safe health decisions, and act upon them".
- Media literacy is defined as "Critical thinking and conscious thinking skills to analyze, evaluate, and use media content to form a judgment and guide actions".

These variables were transformed and recoded to best align with the analytic plan, and further details on these procedures are provided in Chapter 3.

2.3.6. Gaps in the Literature & Summary

Although there is myriad research evidence highlighting the important role of eHealth literacy in CDSM (Kim et al., 2023), further research on the U.S. context is needed to understand how advancements made in eHealth tool use during the COVID-19 pandemic may be affected by eHealth literacy skill level, especially given what is known about how eHealth literacy significantly impacts the perceived ease of use, perceived usefulness, and individual intention to use eHealth services such as telemedicine (Jang, 2023). Some cross-sectional evidence shows results connecting eHealth literacy to health outcomes in those with chronic conditions, but further statistically significant empirical evidence is needed to verify these relationships (Neter & Brainin, 2019). Despite progress during the pandemic, important gaps in eHealth literacy among the adult population in the U.S. may remain, especially for those with ongoing chronic conditions. Existing research also highlights the connection between *health* literacy and CDSM, indicating that lower health literacy is associated with lower CDSM self-efficacy (Mackey et al., 2016); however, fewer research studies examine the relationship between *eHealth* literacy and CDSM, highlighting a need for future research. Some studies examining the impact of eHealth on health behaviors and health outcomes among certain groups of individuals with chronic diseases lack adequate sample sizes to draw meaningful conclusions from the data (Aung et al., 2024). This dissertation research study presents an opportunity to address this important gap through a robust analysis of nationally representative data.

Conceptually, it was important to better understand how each of the six domains of the eHEALS framework combine to form the full six domains of eHealth literacy given the paucity of research on all six domains (El Benny et al., 2021). The findings from this dissertation research study yields new insights into how to assess eHealth literacy and how eHealth literacy skills relate to eHealth use in the context of chronic disease self-management, addressing an important gap in the literature related to the psychometric properties of eHEALS and the Lily model (Sudbury-Riley et al., 2017). To summarize, not much is known about eHealth literacy skill levels among Americans post-pandemic, so this study offers an opportunity to describe skill levels using representative variables from a nationally representative dataset. More details on what makes HINTS unique and how the data have been used to describe these types of relationships appears in the next section.

2.4. Health Information National Trends Survey

There are a variety of population-based surveys designed to capture trends in American health behaviors, health statuses, and health coverage (Centers for Disease Control and

Prevention & National Center for Health Statistics, 2024, Sept.). The HINTS program is the population survey designed to assess the status of health communication in the U.S. adult English and Spanish speaking population and afford researchers an opportunity to test new theories related to health communication (National Cancer Institute, n.d.–a). It is an authoritative and frequently used dataset designed to capture trends in health communication, and later versions of HINTS have evolved to also capture trends in eHealth use and behaviors (Blake et al., 2024). HINTS data can provide helpful insights into the behavioral trends and eHealth activities of adults with chronic disease (Hesse et al., 2017; Kontos et al., 2014; Nelson et al., 2004).

The HINTS survey was also designed in part to assess functional health literacy, or the degree to which individuals use eHealth tools within a new media environment (Hesse et al., 2017). Over the years, researchers have explored the concept of *health literacy* using HINTS data and its relation to various health outcomes or health behaviors (Jiang & Hong, 2018; Jiao et al., 2023; H. Y. Lee et al., 2021; Persoskie et al., 2017). Some authors use engagement in a specific behavior as a measure of health literacy within the HINTS data (Jiang & Beaudoin, 2016; Wigfall & Tanner, 2018). Much of the health literacy research using HINTS used subjective items (i.e., self-reported assessments of specific behaviors) to measure health literacy where it appeared at the intersection of personal experience and the information environment (Hesse et al., 2017). Other studies have found linkages between patient-centered communication (i.e., comfort, ease, and satisfaction of health information interactions) behaviors with private eHealth use (i.e., using clinical services at home) (Asan et al., 2019; Knowles et al., 2023; Paige, Bunnell, et al., 2021). While eHealth literacy is not a specific construct conceptualized and incorporated into the HINTS questionnaire, this dissertation research study sought to use a series of related variables in the data to provide information about possible patterns in domains of eHealth literacy among the sample population. The following section provides details on how this has been done in other studies using HINTS.

2.4.1. HINTS' Role in eHealth Literacy Research

While some HINTS studies have examined eHealth behaviors among chronically ill HINTS respondents (Bhatla et al., 2024; A. W. Lin et al., 2020; Sun & Jiang, 2021; Vazquez et al., 2024; Yang et al., 2021), eHealth literacy research using HINTS data is still in the nascent stages. As of January 2026, there are more than 1,000 publications listed on PubMed.gov that report on findings using HINTS data or the survey instrument since its launch in 2003. From that list, 79 of those publications examine health literacy, and, even more narrowly, only three publications measure eHealth literacy explicitly (Liao et al., 2025; Shaw Jr et al., 2024; Tennant et al., 2015). Three additional studies discuss eHealth literacy in the context of eHealth behaviors that can be assessed from the HINTS dataset and associated with eHealth literacy (Ghani et al., 2021; Hong et al., 2020; Kontos et al., 2014). Even still, none of these studies look individually at the six different domains of eHealth literacy described using the eHEALS framework.

From this eHealth literacy research using HINTS, evidence shows that adults who used Web 2.0 websites and applications (e.g., Facebook, Instagram, TikTok, etc.) and similar web-based support groups for health-related purposes had higher eHealth literacy than those who did not (Tennant et al., 2015). Adults representing younger ages, higher education, and greater total number of electronic devices used to seek out health information predicts higher levels of eHealth literacy in certain populations (Tennant et al., 2015). Findings also show that eHealth literacy plays an important role in specific aspects of chronic care management, such as using mHealth to manage obesity via regular weight management, dietary intake, and exercise tracking

(Shaw Jr et al., 2024). Research using variables from the HINTS dataset to examine eHealth literacy among obese smartphone owners measured eHealth literacy as the application of an eHealth literacy skill (Shaw Jr et al., 2024). They found that those with higher self-reported application of eHealth literacy skills had higher mHealth use, indicating a potential area for intervention related to diet, weight, and physical activity self-management via smartphone applications and other eHealth tools (Shaw Jr et al., 2024).

Additionally, some studies have used HINTS questions in conjunction with other questionnaires to assess eHealth literacy. However, as stated previously, assessing eHealth literacy is complicated and is often not comprehensively conducted for each of the six domains of the eHEALS scale (El Benny et al., 2021; J. Lee et al., 2021). For instance, previous HINTS research has examined health literacy—one of the six domains of eHEALS—in different ways over the years. HINTS research examining the role of *health* literacy among disabled adults (HINTS 4 Cycle 3) defined health literacy among the available variables as 4 items: "It took a lot of effort to get the information you needed"; "You felt frustrated during your search for information"; "You were concerned about the quality of the information"; and "The information you found was hard to understand" (Nguyen & Gilbert, 2019). This measurement of health literacy can help inform one aspect of this larger eHealth literacy measurement this study seeks to accomplish.

There are also important demographic elements to explore within the HINTS data related to eHealth literacy and its role in CDSM, such as understanding the role of locality in the relationship between eHealth literacy and CDSM (Chesser et al., 2016). Racial and ethnic differences in eHealth use and health information technology adoption during the COVID-19 pandemic emerged; therefore, there is an opportunity to contribute to health disparities research by using nationally representative data to describe current eHealth use and eHealth literacy among racial and ethnic minorities with chronic conditions (Ojinnaka & Adepoju, 2021). There are gaps in the literature about eHealth literacy among populations who may be affected by the digital divide due to inadequate evidence or lack of focus on specific aspects of the digital divide within vulnerable populations (Chesser et al., 2016).

Finally, there are also important temporal aspects to examine from a period that was at the end of the COVID-19 pandemic to see if there emerged any important disease-specific distinctions between eHealth use and eHealth literacy among HINTS respondents (Rajamani et al., 2022). Further research is also needed to understand if the type of chronic condition an individual has plays a role in eHealth use, eHealth literacy level, and CDSM behaviors.

2.4.2. Gaps in the Literature & Summary

As noted above, the full conceptual definition of eHealth literacy using six skill domains has not yet been studied using HINTS data. HINTS captures important variables that represent eHealth literacy in action, so there is an opportunity to use this existing dataset to map eHealth literacy skills to specific items in the questionnaire. This dissertation study seeks to leverage the scope of a nationally representative dataset to explore an important potential health behavior skill in the context of chronic disease self-management and relevant individual characteristics. This study produced additional evidence linking all six domains of eHEALS together while connecting it to tangible eHealth use and CDSM behaviors.

2.5. Chapter Summary

In this chapter, I presented information about common chronic diseases in the U.S. and their prevalence rates for adults. I discussed how these conditions are managed through the concept of chronic disease self-management. Models of disease management were presented to showcase the context in which care management takes place and where the role of individual skills, such as eHealth literacy, appears. This chapter provided details about what eHealth use is of and how it will be assessed alongside variables representing eHealth literacy to describe the mechanism through which eHealth literacy is associated with chronic disease self-management behaviors. Details about the influence of the COVID-19 pandemic on eHealth use and eHealth literacy research were provided. An explanation of how eHealth literacy was conceptualized and measured was also provided. Information about the HINTS study and how researchers have used this dataset to look at eHealth literacy behaviors was discussed. Finally, throughout the chapter, gaps in the literature were presented to provide additional details on the relevance of this dissertation research study and the potential research contributions it may offer to the field of eHealth literacy and chronic disease self-management.

Chapter 3. Methods

This chapter provides details about the Health Information National Trends (HINTS) data, including background information from the National Cancer Institute (NCI), data collection, cleaning, and analytic procedures. This chapter also provides a detailed description of the secondary analysis methodology, including sampling strategy, missing data procedures, descriptions of variables, preliminary analyses, and final data analyses. The chapter finishes with information describing the protection of human subjects.

3.1. Conceptual Framework

As outlined in Chapters 1 and 2, this study was guided by several key conceptual frameworks that contextualized the surrounding environment, the individual characteristics, the use of technology for certain purposes, and the accompanying individual skills and behaviors associated with eHealth literacy and chronic disease self-management. These integrated ideas reflect a multidimensional framework that conceptualizes eHealth literacy as a set of distinct but interrelated skills influencing technology use and engagement in digital health behaviors and, ultimately, chronic disease self-management. This framework informed the selection and operationalization of eHealth literacy skill domains, the specification of eHealth use as a proximal behavioral outcome, and the modeling of self-management behaviors as downstream outcomes. Accordingly, analyses were structured to first explore descriptive statistics for each set of variables, including eHealth literacy skills and CDSM behaviors (Aim 1), then evaluate associations between individual eHealth literacy skills and eHealth use (Aim 2), followed by an examination of relationships between eHealth literacy and chronic disease self-management behaviors (Aims 3 and 4). To empirically evaluate these theoretically informed relationships within a nationally representative sample of U.S. adults, the present study utilized data from HINTS Cycle 6 (H6). The design and scope of this dataset are described in the following section.

3.2. Data Source – Health Information National Trends Survey (HINTS)

National-level population surveillance datasets are designed to provide insights into population-level patterns in the U.S. to identify areas for interventions, programming, and/or policies (Andersen, 2008). HINTS is a nationally representative survey routinely administered since 2003 by the U.S. National Institutes of Health National Cancer Institute (NCI). HINTS provides a comprehensive assessment of non-institutionalized, civilian adults' access and use of cancer care and information (Nelson et al., 2004). Additionally, HINTS collects data about current trends in health information seeking among respondent adults related to the current public information environment (Blake et al., 2024; National Cancer Institute, n.d.–a). NCI makes the questionnaires and datasets publicly available through its website (https://hints.cancer.gov).

The survey is currently administered in two ways, a web-based questionnaire or paper-based questionnaire, that are either sequentially or concurrently offered to one adult per household, drawn from a random sample of U.S. households (Finney Rutten et al., 2020; Finney Rutten et al., 2012; National Cancer Institute & Westat, 2023, April). NCI aims to collect responses from several thousand adults each iteration, and usually has a response rate that hovers between 30-40% of invited households (Finney Rutten et al., 2020; National Cancer Institute, n.d.–a; National Cancer Institute & Westat, 2023, April). NCI partners with a contract research organization (e.g., Westat) to collect the data; clean the data through procedures to de-identify information, re-code levels, derive new variables using imputation, and more; add sampling weights to allow for population-level estimates to be conducted; and publish the data for public analysis alongside accompanying methodological reports (National Cancer Institute, n.d.–a; National Cancer Institute & Westat, 2023, April).

The following sections outline information regarding the study design and specific sample of HINTS data used to answer the research question and meet the aims of this dissertation research study. Details on the specifics of the sample are provided. Information about data transformation to facilitate the analytic procedures planned with this dissertation research study are also provided. Each type of variable is described in detail, including how the specific study variables are written in the H6 questionnaire. Finally, details outlining each step of the analysis aligning with each study aim are provided.

3.2.1. HINTS Study Design and Data

While eHealth literacy has been studied extensively in international settings, available data examining eHealth literacy in the U.S. is limited, especially regarding eHealth literacy of those living with preventable chronic diseases (e.g., Choi & DiNitto, 2013; Elgamal, 2024; Kim et al., 2023; Xie, 2011). Available data from H6 collected near the end of the COVID-19 pandemic, between March 7, 2022 and November 8, 2022, provides a new opportunity to examine behaviors and concepts related to eHealth use, eHealth literacy, and chronic disease self-management.

The target sample population of HINTS are adults 18 years or older in the civilian non-institutionalized population of the U.S. The sampling strategy consisted of a two-stage approach where a stratified sample of addresses were selected from a larger list of residential addresses (stage 1), followed by the selection of one adult within each sampled household to be contacted (stage 2) (National Cancer Institute & Westat, 2023, April). The sampling strategy also included greater emphasis on selecting a strata of high minority households at both urban and rural levels to increase the number of potentially high-need respondents and rural respondents (National Cancer Institute, n.d.–a). Data for H6 were collected through the same questionnaire delivered in mixed modes: a paper- and web-based questionnaire. Participants contacted to complete the survey were randomly assigned to receive the option of using one of the two modes (concurrently) or they were first offered one mode followed by the other mode later (sequentially) (National Cancer Institute & Westat, 2023, April). Participants were contacted a few times by mail to encourage participation in the survey (National Cancer Institute, n.d.–a; National Cancer Institute & Westat, 2023, April). Participants received a small pre-paid incentive in the mail when asked to complete the survey and may have received additional incentives in subsequent mailings to encourage a response (National Cancer Institute & Westat, 2023, April). While HINTS does not employ simple random sampling, it is considered a nationally representative dataset due to the extensive survey weighting procedures the NCI team incorporates into the public dataset. Further details on weighting procedures are discussed in NCI's H6 Methodology report (National Cancer Institute & Westat, 2023, April). More information regarding HINTS methodology, sampling design, mode of collection, and response rates is published elsewhere (Finney Rutten et al., 2012; Hesse et al., 2006; Nelson et al., 2004).

Most items in HINTS questionnaires—which are usually around 122 close-ended questions organized into 15 sections—have now been analyzed and accepted and replicated in hundreds of papers suggesting acceptable test-retest reliability and construct validity (National Cancer Institute & Westat, 2023, April; Paige, Flood-Grady, et al., 2021b). When developing the questionnaire, NCI engages content experts called "champions" who lead working groups to conduct background research on potential items for inclusion in the questionnaire (National Cancer Institute, n.d.–b). Once a pool of valid and evidence-based questions are identified, the research team conducts cognitive interviews to assess how well individuals can understand the words, phrases, and concepts used in the study and to assess if they have any difficulties answering the questions and uses the interview results to finalize the questionnaire (National Cancer Institute, n.d.–b).

The HINTS study provides data about specific types of health information behaviors online and through various technologies that do not exist in other surveys (National Cancer Institute, n.d.–a; Taksler et al., 2022). Most versions of the HINTS questionnaire capture data about sociodemographic characteristics, health information-seeking, cancer prevention and screening knowledge and behavior, cancer-related behavior, cancer risk perceptions, health care use and access, and technology use and access (Blake et al., 2024; Finney Rutten et al., 2020; Hesse et al., 2017; Nelson et al., 2004). Special topics available in H6 include issues with health information, such as misinformation, conflicting information, health literacy, and telehealth, such as use of telehealth and satisfaction with telehealth appointments, among other topics (National Cancer Institute & Westat, 2023, April). HINTS questions are answered through self-report, a method that has been shown to have moderate associations with individual perceptions and/or behaviors and that are deemed acceptable when capturing data from large, diverse samples (Kormos & Gifford, 2014; Short et al., 2009; Thornberry & Krohn, 2002). Although HINTS is a cross-sectional study, the periodic administration and repeated use of questions can help identify emerging trends in health information seeking and health information use, including changes in eHealth literacy (Ajayi et al., 2022; Hesse et al., 2017; Kontos et al., 2014).

3.3. Study Population and Analytic Sample

H6 yielded 6,252 total respondents, of which 6,185 were complete and 67 were partial responses. Questionnaires were considered complete if at least 80% of the required questions pertaining to health information activities in the first two sections of the survey were answered (for reference, there are 17 sections in H6). The target population for this dissertation study were adult internet users with chronic conditions, which was a subset of the overall sample. Details on the makeup of this subset and how it was restricted are provided in the following sections.

3.3.1. Restriction to Internet Users

The dissertation analysis was restricted to H6 respondents who reported current internet use. This decision was guided by the study's focus on eHealth literacy and eHealth use, both of which presuppose access to and engagement with internet-based technologies. In H6, the majority of respondents reported using the internet ("UseInternet", 82.6%; n = 5,166), consistent with national estimates of internet use among U.S. adults (National Telecommunications and Information Administration, 2024). Prior research has demonstrated that internet use is associated with higher levels of eHealth literacy and greater engagement with digital health tools (Kyaw et al., 2024; Xiang & Stanley, 2017). Restricting the analytic sample to internet users therefore allowed for a more focused examination of eHealth-related behaviors among individuals for whom such technologies are relevant.

3.3.2. Defining and Selecting Chronic Conditions

In addition to restricting the sample to individuals who reported using the internet, the sample was further restricted to those internet users with chronic conditions. The five chronic conditions included in this study—diabetes, high blood pressure, heart conditions, lung disease, and cancer—were selected based on their availability in the H6 dataset and their relevance as leading causes of morbidity and preventable mortality in the United States (Blake et al., 2024; Centers for Disease Control and Prevention, 2024, October; National Cancer Institute & Westat, 2023, April). Chronic condition status was determined using self-reported items in the H6 questionnaire that asked respondents whether a doctor or other health professional had *ever* told them that they had these specific health conditions.

The wording of these items did not assess current disease status; therefore, affirmative responses were interpreted as indicating a history of diagnosis for the purposes of this study. Additionally, individuals could report having had one or more conditions. The specific questionnaire items were as follows:

- **Diabetes (MedConditions_Diabetes):** "Has a doctor or other health professional ever told you that you had diabetes or high blood sugar?" (Yes/No)
- **High blood pressure (MedConditions_HighBP):** "Has a doctor or other health professional ever told you that you had high blood pressure or hypertension?" (Yes/No)
- **Heart condition (MedConditions_HeartCondition):** "Has a doctor or other health professional ever told you that you had a heart condition such as heart attack, angina, or congestive heart failure?" (Yes/No)
- **Lung disease (MedConditions_LungDisease):** "Has a doctor or other health professional ever told you that you had chronic lung disease, asthma, emphysema, or chronic bronchitis?" (Yes/No)
- **Cancer (EverHadCancer):** "Have you ever been diagnosed as having cancer?" (Yes/No)

Prior to subgroup selection, the proportion of H6 respondents reporting each condition (non-mutually exclusive) was as follows: diabetes (16.7%), high blood pressure (35.7%), heart conditions (7.3%), lung disease (11.3%), and cancer (9.5%).

Finally, consistent with prior research, a composite indicator of multimorbidity was created to identify respondents who reported having been diagnosed with more than one of the selected chronic conditions (Ajayi et al., 2022; Manning et al., 2023). This variable was used in subsequent analyses to assess whether the presence of multiple chronic conditions influenced relationships between eHealth literacy and self-management behaviors.

3.3.3. Total Analytic Sample

In total, of the 5,166 H6 respondents who reported current internet use, 2,888 met eligibility criteria for inclusion in the analytic sample by reporting a history of at least one of the selected chronic conditions and having sufficient data on key study variables. Detailed sample characteristics are presented in Chapter 4.

3.4. Measures and Variable Operationalization

Guided by the study's conceptual framework and prior HINTS-based research, specific survey items and composite measures were selected to operationalize the primary constructs of interest (e.g., Lai et al., 2024; Olvera et al., 2025; Shaw Jr et al., 2024; Vazquez et al., 2024). This section details the measures used to assess chronic disease self-management (CDSM) behaviors, eHealth literacy skills, eHealth use, sociodemographics, and self-efficacy, along with their construction and coding procedures because variable transformation was necessary for complex survey analysis (Kindratt, 2022).

3.4.1. Dependent Variables: Chronic Disease Self-Management (CDSM) Behaviors

Managing chronic diseases can be complex and dependent on multiple factors; however, among the different ways to mitigate the impact of a chronic condition, there are several key behaviors that worsen or exacerbate chronic diseases— tobacco use, physical inactivity, poor dietary awareness and nutrition, excessive alcohol consumption, and/or maladaptive cognitive appraisals of one's self-management efforts (Centers for Disease Control and Prevention, 2024; Hacker, 2024; Hocking et al., 2013; Miller et al., 2015; Riegel et al., 2026). These behaviors represent some of the most commonly identified individual-level practices associated with effective chronic disease management and *health* literacy (Ajayi et al., 2022; Grady & Gough, 2014; Mackey et al., 2016; Schulman-Green et al., 2012), so they were chosen to also be examined alongside *eHealth* literacy skills.

In total, six items from the H6 questionnaire were selected to represent these common CDSM behaviors. For clarity, the names of study variables are capitalized when referenced in the text to distinguish analytic constructs from general descriptive language. Additionally, the item names from the H6 codebook are reflected in quotations and parentheses next to the variable name for this study. Finally, target behaviors reflected the "healthy" condition, that is, if individuals conformed to the recommended guideline for each behavior. Behaviors were considered not reaching the target behaviors if they fell outside of those guidelines.

Smoking Status ("SmokeStat")

Non-smoking is key to chronic disease self-management outcomes (Hayes-Watson et al., 2017). Engagement in this activity was assessed using a variable NCI generated during data cleaning to designate current-, former-, and non-smokers. This variable contained data from responses to two questions: 1) "SmokeNow"- *How often do you now smoke cigarettes? 1-Every day, 2-Some days, 3-Not at all* and 2) "Smoke100" - *Have you smoked at least 100 cigarettes in your entire life? 1-Yes, 2-No.* About 11.2% of the total H6 sample were considered current smokers, 20.8% former smokers, and 61.7% never smokers. This variable ("SmokeStat") was recoded into a binary indicator where 0 = Smokes and 1 = Does not smoke (i.e., never or former smoker), consistent with prior HINTS and tobacco control research that contrasts smokers with current non-smokers (Shahab et al., 2014). Non-smoking status, including cessation among former smokers, is widely recognized as a key behavioral component of effective chronic disease self-management and risk reduction because negative smoking status (i.e., non-smokers or former smokers) is considered a behavior that supports chronic disease self-management (Gritz et al., 2007; United States Public Health Service Office of the Surgeon et al., 2020).

Physical Activity ("WeeklyMinutesModerateExercise")

The second CDSM variable was Physical Activity. The U.S. Office of Disease Prevention and Health Promotion encourages adults with chronic conditions to engage in at least 150 minutes of moderate intensity activities per week, preferably spread across several days (U.S. Department of Health and Human Services, 2018). While limited to the available variables in H6, I used a variable NCI generated during data cleaning called "WeeklyMinutesModerateExercise" to capture this recommendation. This variable is comprised of averaged responses to two questions: 1) "TimesModerateExercise" - *In a typical week, how many days do you do any physical activity or exercise of at least moderate intensity, such as brisk walking, bicycling at a regular pace, and swimming at a regular pace? 1-1 day per week to 7-7 days per week* and 2) "HowLongModerateExerciseMinutes" - *On the days that you do any physical activity or exercise of at least moderate intensity, how long do you typically do these activities? 0 to 750 minutes.* Individual values for the derived variable fall between 0 minutes – 5,250 minutes per week. In line with other HINTS studies and national exercise recommendations, I recoded this into a binary variable based where 0 = Does not meet physical activity recommendations (i.e., <150 minutes/week) and 1 = Does meet physical activity recommendations (i.e., ≥150 min/week) (Shahab et al., 2014; U.S. Department of Health and Human Services, 2018).

Dietary Awareness – Calorie Information and Food Discussion

While nutrition-related behaviors can be difficult to capture accurately among individuals with chronic conditions (Bailey, 2021), prior iterations of HINTS included more detailed measures of fruit and vegetable consumption (Skiba et al., 2022). However, comparable dietary variables were limited in H6. As a result, dietary aspects of chronic disease self-management were operationalized using indicators related to attention to calorie information and communication about food access, both of which have been linked to nutrition knowledge and health-related food behaviors in prior research (Green et al., 2015; Ibecheozor et al., 2024; Rising, McKinnon, et al., 2021).

The first variable was **Calorie Information ("NoticeCalorieInfoOnMenu)**, which reflected responses to the question: "*Think about the last time you ordered food in a fast food or sit-down restaurant—did you notice calorie information listed next to the food on the menu or menu board?" (1 = Yes, 2 = No)*. The Food and Drug Administration (FDA) requires most fast food and sit-down restaurants to provide calorie information regarding the content of their menus to patrons, and research shows that more awareness of calorie information in restaurants is associated with better dietary decisions (Rummo et al., 2023; U.S. Food and Drug Administration, 2023). Previous national research also suggests that individuals with chronic conditions tend to be more aware of calorie labeling due to the nutrition requirements of their diseases than those without chronic conditions (Lewis et al., 2009). Based on this research, this item was recorded as a binary indicator, with values of 0 = Not aware and 1 = Aware.

The second variable, **Food Discussion ("HCPShare_FoodIssues")**, was designed to reflect more of someone's ability to access food as well as their comfort with communicating food access concerns within the healthcare setting: *"If you were experiencing issues with affording or accessing healthy food, how comfortable would you be with your health care providers sharing that information with each other for treatment purposes?"* Responses ranged from *1-Very comfortable* to *4-Very uncomfortable.* Following previous research, this item was dichotomized as 0 = Uncomfortable (includes "very" or "somewhat uncomfortable") and 1 = Comfortable (includes "somewhat" or "very comfortable") (Olvera et al., 2025).

Alcohol consumption ("AvgDrinksPerWeek")

Measuring alcohol consumption is not always straightforward in research (Dawson, 2003), so the HINTS questionnaire measures alcohol consumption in several ways. However, for purposes of this study, alcohol consumption was measured using the results from one derived variable reflected average alcohol-related behaviors (National Institute on Alcohol Abuse and Alcoholism, 2024, Dec.; Ramos-Vera et al., 2022). This derived variable was called "AvgDrinksPerWeek", and values ranged from 0 to 84 drinks per week and was comprised of answers to two other questions 1) "DrinkDaysPerWeek" - *During the past 30 days, how many days per week did you have at least one drink of any alcoholic beverage? 0-None to 7-7 days per week* and 2) "DrinksPerDay" - *During the past 30 days, on the days when you drank, about how many drinks did you drink on average?0 to 30.* The "AvgDrinksPerWeek" variable was recoded into a binary indicator calculated and designated for each individual based on sex-specific alcohol consumption guidelines, which differ for males and females (i.e., >8+ drinks per week for females and >15+ drinks per week for males). This approach aligns with national recommendations for average weekly alcohol intake and resulted in a classification as 0 = Above guidelines and 1 = Below guidelines (United States Department of Agriculture & U.S. Department of Health and Human Services, 2024).

Health Perception ("GeneralHealth")

The final CDSM behavior variable was Health Perception, conceptualized as a cognitive appraisal that reflects how individuals interpret and evaluate their overall health status in the context of living with chronic illness (Miller et al., 2015; Riegel et al., 2012; Riegel et al., 2026). While this variable is sometimes connected with general health status, general health perceptions are a core component of health-related quality of life models and capture individuals' active and ongoing thought processes about how well they are managing their conditions and functioning in daily life (Anthony et al., 2024; Wilson & Cleary, 1995). Consistent with prior work using HINTS, this construct was represented by a single item: *In general, would you say your health is… 1 = Excellent to 5 = Poor* and dichotomized for analytic purposes into 0 = Poor (fair/poor) and 1 = Good (good/very good/excellent) (Anthony et al., 2024).

3.4.2. Independent (Predictor) Variables

As outlined in the conceptual model guiding this dissertation (Chapter 1), health-related skills such as eHealth literacy are theorized to precede and shape engagement in health-promoting, health-supporting, and disease self-management behaviors (Fisher et al., 2003; Kim et al., 2023). Within this framework, eHealth literacy is understood as a multidimensional construct encompassing a set of interrelated skills that enable individuals to seek, evaluate, and apply digital health information.

Although the eHealth Literacy Scale (eHEALS), which guides this research, is widely used to assess perceived eHealth literacy, there is no broad consensus in the literature that each individual eHEALS item maps unambiguously onto a single, fixed eHealth literacy domain across populations. In general, eHealth literacy is usually assessed as a combined, unidimensional score that encompasses each of the six domains (Crocker et al., 2023; Foote et al., 2023; Kim et al., 2023; Norman & Skinner, 2006a; Sudbury-Riley et al., 2017).

While H6 does not include a validated eHealth literacy instrument such as eHEALS or the Digital Health Literacy Instrument (DHLI), eHEALS remains one of the most widely cited and conceptually influential frameworks for understanding eHealth literacy as an individual's perceived ability to find, evaluate, and apply electronic health information (Barbati et al., 2025; Norman & Skinner, 2006b). A recent scoping review of digital health literacy measures found that the eHEALS questionnaire has been the most commonly used tool to assess components of digital health literacy, reflecting core functional skills such as understanding and confidence in engaging with digital health resources (Faux-Nightingale et al., 2022). Because eHEALS captures the central functional dimensions of eHealth literacy that are theoretically relevant to this dissertation, it was used to guide the selection and conceptual alignment of HINTS items representing similar skill domains.

H6 items were selected based on their conceptual alignment with functional aspects reflected in clusters of eHEALS items, such as information access and seeking, evaluation and credibility appraisal, and application of information to health decisions. This approach allowed HINTS items to be interpreted as indicators of specific eHealth literacy–related skills without asserting rigid domain mapping (Table 1). A panel of health literacy, health communication, information science, and health behavior researchers (i.e., members of this dissertation research committee) reviewed these items and agreed with their general conceptualization.

Table 1

Conceptual Alignment of eHEALS Items with HINTS eHealth Literacy Items

eHealth Literacy Scale (eHEALS)	Items in H6 Chosen to Represent eHealth Literacy
• How useful do you feel the Internet is in helping you in making decisions about your health? • How important is it for you to be able to access health resources on the Internet? • I know what health resources are available on the Internet • I know where to find helpful health resources on the Internet • I know how to find helpful health resources on the Internet • I know how to use the Internet to answer my questions about health • I know how to use the health information I find on the Internet to help me • I have the skills I need to evaluate the health resources I find on the Internet • I can tell high quality health resources from low quality health resources on the Internet • I feel confident in using information from the Internet to make health decisions	• In general, how easy or hard do you find it to understand medical statistics? *(Basic Literacy)* • In the past 12 months have you used the Internet to make an appointment with a health care provider? *(Computer Literacy)* • How much do you agree or disagree: There are so many different recommendations about preventing cancer, it's hard to know which ones to follow. *(Scientific Literacy)* • How confident are you that you can find helpful health resources on the Internet? *(Information Literacy)* • How confident are you filling out medical forms by yourself? *(Health Literacy)* • How much do you agree or disagree - I find it hard to tell whether health information on social media is true or false? *(Media Literacy)*

Note. eHEALS items are reproduced from Norman, C. D., & Skinner, H. A. (2006). eHEALS: The eHealth Literacy Scale. *Journal of Medical Internet Research, 8*(4), e27. https://doi.org/10.2196/jmir.8.4.e27, under the terms of the Creative Commons Attribution License (CC-BY 2.0), which permits unrestricted use and reproduction. HINTS Cycle 6 were reproduced from the HINTS questionnaire, and items are available in the public domain.

Because HINTS did not directly measure eHealth literacy using a validated scale, this dissertation examined whether selected HINTS items could serve as theoretically informed indicators of distinct eHealth literacy skill domains. Thus, each eHealth literacy skill domain was first examined independently to assess domain-specific relationships with eHealth use and chronic disease self-management behaviors as an initial assessment of construct validity. Subsequently, a composite eHealth literacy variable was created to represent respondents' overall eHealth literacy skill level. The operationalization of each eHealth literacy domain as an independent variable are outlined as follows. Again, variable names are capitalized to distinguish the variables from related concepts.

Basic Literacy ("UndMedicalStats")

The first eHealth literacy skill domain examined was Basic Literacy. Basic Literacy represents a fundamental aspect of understanding numbers (numeracy) and information (Andreadis et al., 2025; Manganello & Clayman, 2011; Norman & Skinner, 2006b). In H6, one variable captures this sentiment well: "UndMedicalStats" - *In general, how easy or hard do you find it to understand medical statistics? 1-Very easy to 4-Very hard.* This variable was reported using its original categories in Aim 1 and later dichotomized into 0 = Lower (includes "hard" and "very hard") Basic Literacy and 1 = Higher Basic Literacy (includes "easy" and "very easy") for analysis in the other aims (Manganello & Clayman, 2011).

Computer Literacy ("Electronic2_MadeAppts")

Computer Literacy generally relates to the ability to use physical or actual computer/technological elements to solve problems; more specifically, it can relate to the ability to use specific types of technology to achieve online health-related goals (Norman & Skinner, 2006b). In the context of chronic disease self-management, the completion of an act, such as scheduling appointments online, could represent an individual's skill at navigating an eHealth environment (Kelly et al., 2025; Li et al., 2023). Thus, one item in H6 that reflected a specific health-related behavior indicative of underlying computer and digital literacy skills in applied health contexts was: "Electronic2_MadeAppts" - *In the past 12 months have you used the Internet to make an appointment with a health care provider? 1-Yes and 2-No*. This item was recoded as 0 = Low Computer Literacy – has not used internet to make an appointment and 1 = High Computer Literacy – has used internet to make an appointment.

Scientific Literacy ("TooManyRecommendations")

Scientific Literacy represents the ability to understand scientific guidance that has been generated through the scientific process and designed for public consumption, and translate that guidance into knowledge (Arora et al., 2008; Milanti et al., 2025; Norman & Skinner, 2006b). Recent conceptualizations of higher levels of Scientific Literacy reflect an ability to discern scientific information from competing or complex ideas (Mede et al., 2026). Therefore, one variable in H6 that represented this was "TooManyRecommendations" - *How much do you agree or disagree: There are so many different recommendations about preventing cancer, it's hard to know which ones to follow. 1-Strongly agree to 4-Strongly disagree*. Results are reported along the original categories in Aim 1 and then the variable was dichotomized in subsequent aims to reflect 0 = Lower Scientific Literacy (includes "strongly agree" and "somewhat agree") and 1 = Higher Scientific Literacy (includes "somewhat disagree" and "strongly disagree") (Plante et al., 2024).

Information Literacy ("ConfidentInternetHealth")

There are different ways to measure Information Literacy in the context of eHealth literacy, which indicates a knowing of how information is organized, how to find information, and how to use that information to create knowledge in addition to being able to navigate different information environments (Norman & Skinner, 2006b; Paige, Flood-Grady, et al., 2021b; Tanaka et al., 2020). One variable in H6 that represented this type of Information Literacy behavior was "ConfidentInternetHealth"- *How confident are you that you can find helpful health resources on the Internet? 1-Completely confident to 5-Not confident at all.* In Aim 1, Information Literacy results were reported using these original categories. Then, dichotomized results were presented where 0 = Lower Information Literacy (includes "somewhat confident", "a little confident", and "not confident at all") and 1 = Higher Information Literacy (includes "very confident" and "completely confident")(Plante et al., 2024).

Health Literacy ("ConfidentMedForms")

Health Literacy is measured in different ways using HINTS data; however, for the purposes of parsimony in this study, the most commonly used item in health literacy research to reflect this skill was: "ConfidentMedForms" - *How confident are you filling out medical forms by yourself? 1-Very to 4-No at all* (Benyahia et al., 2025; Chew et al., 2004; Wallace et al., 2006). Responses were reported along categorical lines in Aim 1 and then the variable was recoded as 0 = Lower Health Literacy (includes "not confident at all" and "a little confident") and 1 = Higher Health Literacy (includes "somewhat confident" and "very confident")(Chew et al., 2008).

Media Literacy ("SocMed_TrueFalse")

Media Literacy is defined in different ways but is primarily described as a skill related to a combination of exercising critical thinking, applying cognitive processes, and assessing beliefs when confronted with health information communicated through media (Austin et al., 2023; Brørs et al., 2020; Levin-Zamir & Bertschi, 2018; Norman & Skinner, 2006b). Associations between those individuals who are better able to discern accurate health information than not indicate higher levels of general eHealth literacy based on eHEALS scores, which by extension, may relate to Media Literacy (de Oliveira Collet et al., 2024). In this study, Media Literacy skills were operationalized using one variable that included a personal reflection of how well individuals could assess the veracity of health information on one form of media—social media: "SocMed_TrueFalse" - *How much do you agree or disagree - I find it hard to tell whether health information on social media is true or false?" 1-Strongly agree to 4-Strongly disagree or 5-N/A.* Like Scientific Literacy, the less someone agreed that it was hard to discern the veracity of information online, the higher their expected Media Literacy levels were. This variable reflected Media Literacy because social media literacy and media literacy have been linked together based on their connection to cognitive competencies (such as critical thinking) related to engaging in an activity within a certain medium (Polanco-Levicán & Salvo-Garrido, 2022; Scherer & Pennycook, 2020). In Aim 1, results were presented along categorical lines. Then, following previous research, this variable was recoded as 0 = Lower Media Literacy (includes "strongly agree", "somewhat agree", and "not applicable") and 1 = Higher Media Literacy (includes "somewhat disagree" and "strongly disagree")(Stimpson & Ortega, 2023). The "not applicable" category was included in Lower Media Literacy due to a crosstabulation that showed that non-users of social media were older, and older adults have been shown to exhibit lower levels of eHealth literacy, including media literacy (Heiss et al., 2023; C. Zhang et al., 2025).

This operationalization of each domain of the eHealth literacy Lily model sought to capture the functional essence of each domain while using available variables in the H6 dataset. The next section provides details on the accompanying covariate variables that were analyzed in this dissertation research study.

3.4.3. Covariates – eHealth Use Variables

Specific variables were utilized as covariates in the descriptive and multivariable regression analyses to better contextualize the relationship between eHealth literacy skills and chronic disease self-management behaviors. The following sections provide details on how the variables chosen to reflect eHealth use as an application of eHealth literacy skills were measured, what they represented, and how they were recoded for analysis.

As discussed in previous chapters, HINTS questions do not directly measure eHealth literacy, but there is a precedent for correlating engagement with specific eHealth use with eHealth literacy using the eHealth Literacy Scale (eHEALS) (Del Giudice et al., 2018)(Stephan et al., 2025). In Chapter 2, descriptions and definitions regarding what eHealth use is, how it is operationalized, and which variables represent this concept in the analysis related to each eHealth literacy domain were introduced. Coding and reorganizational procedures for these variables are discussed herein. All items were dichotomized in line with similar HINTS research (Kontos et al., 2014). See Table 2 for a side-by-side comparison of the eHealth literacy skill variables in use and their corresponding eHealth use variable.

Table 2

Select HINTS Items Representing eHealth Literacy Skill Variables and Corresponding eHealth Use Variables

eHealth Literacy Skill HINTS Item & Wording	eHealth Use HINTS Item & Wording
BASIC LITERACY	
UndMedicalStats *In general, how easy or hard do you find it to understand medical statistics?*	SharedHealthDeviceInfo *Have you shared health information from either an electronic monitoring device or smartphone with a health professional within the last 12 months?*
COMPUTER LITERACY	
Electronic2_MadeAppts *In the past 12 months have you used the Internet to make an appointment with a health care provider?*	UsedHealthWellnessApps2 *In the past 12 months, have you used a health or wellness app on your tablet or smartphone?*
SCIENTIFIC LITERACY	
TooManyRecommendations *How much do you agree or disagree: There are so many different recommendations about preventing cancer, it's hard to know which ones to follow.*	Electronic2_TestResults *In the past 12 months have you used the Internet to view medical test results?*
INFORMATION LITERACY	
ConfidentInternetHealth *How confident are you that you can find helpful health resources on the Internet?*	Electronic2_HealthInfo *In the past 12 months have you used the Internet to look for health or medical information?*
HEALTH LITERACY	
ConfidentMedForms *How confident are you filling out medical forms by yourself?*	Electronic2_MessageDoc *In the past 12 months have you used the Internet to send a message to a health care provider or health care providers office?*
MEDIA LITERACY	
SocMed_TrueFalse *How much do you agree or disagree - I find it hard to tell whether health information on social media is true or false?*	SocMedWatchedVid *In the last 12 months, did you watch a health-related video on a social media site (for example, YouTube)?*[a]

[a] The wording for Media eHealth Use was modified slightly to parallel the wording in the other eHealth use items.

Ultimately, because eHealth use consists of many different activities, each of these variables were selected for their closeness with concepts in the eHealth literacy skill variables. Each variable name was capitalized to distinguish the variable from related concepts. For clarity, each eHealth use variable is described using the first word of the skill domain.

Basic eHealth Use ("SharedHealthDeviceInfo")

To assess Basic eHealth Use, the variable "SharedHealthDeviceInfo" was used - *Have you shared health information from either an electronic monitoring device or smartphone with a health professional within the last 12 months? 1-Yes, 2-No, 3-N/A I do not have a smartphone or electronic monitoring device.* In Aim 1, this was reported in the original categories. In Aim 2, this was recoded as 0 = No (includes "not applicable") and 1 = Yes. The not applicable category reflected an inability to engage in eHealth use in this manner, thus its recoding as "no".

Computer eHealth Use ("UsedHealthWellnessApps2")

To assess Computer eHealth Use, a variable reflecting a more modern conceptualization of a computing device (e.g., a smartphone or tablet) (Donelle et al., 2024) was used: "UsedHealthWellnessApps2" - *In the past 12 months, have you used a health or wellness app on your tablet or smartphone? 1-Yes, 2-No, 3-N/A - I don't have any health apps on my tablet or smartphone.* In Aim 1, this was reported in the original categories. In Aim 2, this was recoded as 0 = No (includes "not applicable" and "I don't have any health apps on my tablet or smartphone") and 1 = Yes. The two categories reflecting non-use were recoded as "no" given that an individual would not be considered a mobile application user if they did not have one on their device and did not engage in activities in this manner (Donelle et al., 2024).

Scientific eHealth Use ("Electronic2_TestResults")

The variable representing Scientific eHealth Use was "Electronic2_TestResults" - *In the past 12 months have you used the Internet to view medical test results? 1-Yes, 2-No.* In Aim 1, the original categories were maintained, and in Aim 2, the item was just recoded to reflect 0 = No and 1= Yes.

Information eHealth Use ("Electronic2_HealthInfo")

To assess Information eHealth Use, the variable "Electronic2_HealthInfo" was used - *In the past 12 months have you used the Internet to look for health or medical information? 1-Yes, 2-No.* In Aim 1, the original categories were maintained, and in Aim 2, the item was just recoded to reflect 0 = No and 1= Yes.

Health-Related eHealth Use ("Electronic2_MessageDoc")

The variable used to assess Health-Related eHealth Use was "Electronic2_MessageDoc" - *In the past 12 months have you used the Internet to send a message to a health care provider or health care providers office? 1-Yes, 2-No.* In Aim 1, the original categories were maintained, and in Aim 2, the item was just recoded to reflect 0 = No and 1= Yes.

Media eHealth Use ("SocMed_WatchedVid")

Finally, the variable used to assess Media eHealth Use was "SocMedWatchedVid" **-** *In the last 12 months, how often did you watch a health-related video on a social media site (for example, YouTube)? 1-Almost every day to 5-Never.* In Aim 1, the original categories were maintained, and in Aim 2, the categories were dichotomized and the question text amended to mirror the language in the other eHealth use variables: *In the last 12 months, did you watch a health-related video on a social media site (for example, YouTube)?* Response breakdowns were

0 = No (includes “never”) and 1 = Yes (includes “almost every day”, “at least once a week”, “a few times a month”, and “less than once a month”).

eHealth Use Composite Score

To assess overall eHealth use, a composite score called “eHealth Use” was constructed and used exclusively in Aim 2 analyses. This item was created by summing the six eHealth use indicators into one domain-specific composite measure to represent a broader pattern of eHealth use, rather than relying on any single one to validate the eHealth literacy skill items (Shwartz et al., 2015). Construction and analytic application of this composite variable are described in Aim 2 results in Chapter 4. Next, details about the relevant sociodemographic variables used in this study are presented.

3.4.4. Covariates - Sociodemographic Variables

Key sociodemographic variables informed by the eHealth Enhanced Chronic Care Model (eCCM) that were available in the H6 dataset were examined to assess their role in influencing or co-occurring with the relationship between eHealth literacy skill and chronic disease self-management behaviors. The seven sociodemographic variables in this study were selected based on previous research that found that eHealth use and eHealth literacy varied by these individual demographics: gender, age, education level, household income, race/ethnicity, health insurance status, and locality (rural, suburban, or urban) (An et al., 2021; Hoogland et al., 2020; Kontos et al., 2014; Levin-Zamir & Bertschi, 2018; Neter & Brainin, 2019; Shaw Jr et al., 2024; Vazquez et al., 2024; Xesfingi & Vozikis, 2016). Consistent with this literature, sociodemographic variables were included in multivariable models to control for their potential confounding influence on the relationships between eHealth literacy skills and CDSM behaviors, rather than to serve as primary predictors of interest. The specific sociodemographic variables included in the analyses are described below.

Sex Assigned at Birth ("BirthGender")

The variable collecting sex/gender information from participants was called "BirthGender" and reflected individuals' sex assigned at birth- *On your original birth certificate, were you listed as male or female? 1-Male, 2-Female***.** Female was selected as reference category in the regression analyses of Aim 4 because women tend to have higher eHealth use and eHealth literacy skills (Jackson et al., 2008; Kontos et al., 2014; Manes et al., 2024).

Age Range ("AgeGrpB")

Following previous HINTS research using age categories instead of numeric age values, age was assessed using five distinct categories captured in the derived variable "AgeGrpB" (Muro et al., 2024; Richtering et al., 2017). The categories were 1) 18 to 34-year-olds, 2) 35-49-year-olds, 3) 50-64-year-olds, 4) 65-74-year-olds, and 5) 75+ years-old. In most analyses, the youngest age group category was selected as the reference group given the rates of internet-based engagement for each age group (National Telecommunications and Information Administration, 2024).

Education Level ("EducA")

Education level is often a strong predictor of eHealth literacy skills where higher education level is associated with greater eHealth literacy; thus, it is an important variable to include in this analysis (e.g., Berkowsky, 2021; Green, 2022; Neter et al., 2021). This variable was measured using a derived variable "EducA" - *What is the highest level of school you completed? 1- Less than high school, 2-High school graduate, 3- Some college, and 4-College graduate or more.* Given the existing linkages between educational attainment and eHealth literacy, the lowest educational attainment category ("less than high school") was selected as the reference group in most analyses to assess the potential protective effects of completing secondary and post-secondary education on health behaviors (Muro et al., 2024).

Annual Household Income ("HHInc")

Like educational attainment, household income is often a significant predictor of eHealth literacy skills, where greater income predicts higher levels of eHealth literacy (e.g., Choi & DiNitto, 2013; Li, 2018), so it is important to assess the role of household income on the relationship of interest (An et al., 2021; Richtering et al., 2017). This variable was assessed using a derived variable "HHInc" - *What is your (combined) annual household income??*<$20,000, $20,000-34,999, $35,000-49,999, $50,000-74,999, and ≥ $75,000). The lowest income bracket (<$20,000) was selected as the reference group to evaluate the potential protective effects of increasing financial resources on chronic disease self-management, specifically identifying the threshold at which incremental income gains begin to yield statistically significant improvements in health behaviors.

Race / Ethnicity ("RaceEthn5")

Important differences in race-based experiences related to eHealth use have been documented, so including this variable offered insights on the role of race in the relationship between eHealth literacy and chronic disease self-management behaviors (Chesser et al., 2016; Nagori et al., 2024). Like other HINTS research, (Baeker Bispo et al., 2023) the derived variable "RaceEthn5" was used - *1-Non-Hispanic White, 2-Non-Hispanic Black or African American, 3-Hispanic, 4-Non-Hispanic Asian, 5-Non-Hispanic Other*. The Non-Hispanic White was selected as the reference category because this was the most commonly endorsed racial/ethnic category in the U.S at the time of the study (U.S. Census Bureau, 2024).

Health Insurance Status ("HealthInsurance2")

Not as much is known about the role of health insurance status on eHealth literacy skills due to a lack of research studying these two phenomena. However, access to eHealth services is most likely influenced by an individual's ability to engage cost-effectively in health care experiences (Chen et al., 2023). Thus, health insurance status is important to measure related to the overall relationships of interest in this study. I used the variable "HealthInsurance2" for these purposes– *Are you covered by any kind of health insurance or health care plan, including employer-sponsored insurance, prepaid plans, or government plans such as Medicare, Medicaid or TRICARE? 1-Yes, 2-No.* These responses were recoded to indicate 0 = Uninsured and 1 = Insured. Most HINTS respondents have health insurance coverage, so insured was the reference category in regression analyses (National Cancer Institute & Westat, 2023, April).

Locality ("RUC2013")

Finally, given the importance of locality when considering digital divides, I assessed locality as a demographic variable that may be influential on our relationships of interest (Chesser et al., 2016; Guo et al., 2024). The USDA Rural/Urban Designation from 2013 was used (National Cancer Institute & Westat, 2023, April) to provide the relevant variable "RUC2013", but metro and non-metro categories were collapsed into three categories given the distribution of participants that skewed heavily towards metro respondents. The items were thusly coded: 1) Metro – counties in metro areas of 1 million population or more, 2) Metro- counties in metro areas of 250,000 to 1 million, and 3) Non-metro which includes populations of <2,500 up to 249,000 (Zahnd et al., 2022). Metro was the reference category given the higher percentages of populations living in metro areas.

3.4.5. Self-Efficacy & Multimorbidity

The last two variables included in the analyses were Self-Efficacy and Multimorbidity (capitalized to distinguish them as standalone variables).

Self-Efficacy ("OwnAbilityTakeCareHealth")

The underlying conceptual framework guiding this research consists of the Information-Motivation-Behavioral Skills model which lists self-efficacy as an important health behavior skill that tends to predict health behaviors (Fisher et al., 2006; Fisher et al., 2009). The Lily model also references self-efficacy as an element associated with eHealth literacy skills (Norman & Skinner, 2006b). In one HINTS study, those living with chronic conditions were not as confident at managing their health as those who reported having no chronic conditions (Rajamani et al., 2022), indicating that self-efficacy likely plays a role in the relationship between eHealth literacy and CDSM behaviors. Therefore, this variable was included in the models in Aim 4 as a potential confounder or covariate of eHealth literacy and CDSM behaviors.

The H6 variable representing Self-Efficacy is commonly used to capture this construct: "OwnAbilityTakeCareHealth" - *Overall, how confident are you about your ability to take good care of your health? 1-Completely confident to 5-Not at all confident.* (Ezeani et al., 2023; Finney Rutten et al., 2016; Lai et al., 2024; Link et al., 2022; Ye et al., 2024). In Aim 1, results were reported according to each original category. In Aim 4, Self-Efficacy was dichotomized into 0 = Lower Self-Efficacy (includes "not confident at all", "a little confident", and "somewhat confident") and 1 = Higher Self-Efficacy (includes "very confident" and "completely confident") (Rising, Gaysynsky, et al., 2021).

Multimorbidity (Multiple Conditions)

As discussed previously in this dissertation, in addition to individual chronic condition indicators, a binary multimorbidity variable was created to capture disease burden among respondents reporting more than one chronic condition. Consistent with prior HINTS-based research, respondents who endorsed two or more of the selected chronic conditions (diabetes, high blood pressure, heart condition, lung disease, or cancer) were classified as having multiple conditions, or multimorbidity (Ajayi et al., 2022; Manning et al., 2023). This variable was coded as 0 = No and 1 = Yes and used as a covariate and in sensitivity analyses to assess whether overall disease burden influenced the relationships between eHealth literacy, eHealth use, and chronic disease self-management behaviors.

Collectively, each of these variables provided a theoretically grounded operationalization of eHealth literacy skills, eHealth use, chronic disease self-management behaviors, and key covariates using H6 data. A full list of all the study variables is in Appendix A. The following section describes the analytic approach used to examine relationships among these variables.

3.5. Analytic Plan

3.5.1. General Analytic Procedures

As mentioned, the H6 dataset was publicly available, cleaned, and de-identified by NCI and its research partners and hosted at https://hints.cancer.gov. Data files and corresponding weight variables were downloaded and loaded into SAS Studio (version 3.8) and RStudio. SAS Studio was the primary data analysis software used for this dissertation study, specifically for most descriptive and regression analyses using PROC SURVEY commands. RStudio packages such as *survey*, *naniar*, and *mice* were used for analyses requiring more flexible handling of complex survey designs, including weighted correlation matrices and missing data diagnostics (Posit Team, 2026; SAS Studio 3.8).

When applicable, analyses incorporated the full-sample survey weights and the 50 jackknife replicate weights provided by NCI to account for the complex sampling design of HINTS. NCI, along with their partners, clean and label the data and add statistical weights to account for differences in participant responses to try to minimize bias related to fewer responses from rural and minority groups. The weighting procedures utilized national-level estimates from the Census Bureau to adjust the representativeness of the sample and allow for researchers to produce population-level point estimates and analytic conclusions (National Cancer Institute & Westat, 2023, April). In the data itself, replicate weights were constructed using a delete-one jackknife (JK1) procedure, in which subsets of the sample were systematically omitted and survey weights recalculated for each replicate. Variance estimation based on these replicate weights produced standard errors that appropriately reflected sampling variability arising from stratification, clustering, unequal probabilities of selection, and post-survey weighting adjustments. Use of jackknife replicate weights was necessary to avoid underestimating standard errors and overstating statistical precision that would result from assuming simple random sampling (National Cancer Institute & Westat, 2023, April).

The analytic sample of internet users with chronic conditions was developed using a domain variable in SAS and filtering coding during each analytic step to ensure that the jackknife replicate weights were incorporated. All analyses utilized this domain variable to examine patterns among the population of interest without impacting the weighting procedures. Relatedly, despite efforts to capture complete data from survey respondents, data were missing for key variables. Thus, the proceeding section outlines how missing data were handled within this dissertation study.

3.5.2. Missing Data Assessment and Handling

Rates of missingness were examined for all variables included in the analytic sample of 2,888 internet-using adults with at least one chronic condition. Missing data diagnostics, including Little's missing completely at random (MCAR) tests and exploratory assessments of missingness patterns, were conducted in R using the *naniar* package (Little, 1988). These procedures were performed without survey weights, as MCAR testing is a diagnostic tool that does not currently accommodate complex survey weighting.

Little's MCAR test results indicated that missingness varied by domain within the analytic sample (see Appendix B). Specifically, missingness in sociodemographic and eHealth use variables was inconsistent with an MCAR mechanism, whereas missingness in chronic disease self-management variables and self-efficacy did not deviate from MCAR. Missingness in eHealth literacy variables was marginally consistent with MCAR and therefore interpreted cautiously. Taken together, these findings suggested that missingness was likely missing at random (MAR), rather than missing not at random (MNAR).

Missingness for most variables fell below 10% and no single variable exhibited extreme levels of missing data. Because variables associated with patterned missingness (e.g., age, income) were included in all adjusted models and overall rates of missingness were low, a complete-case analytic approach was considered appropriate and unlikely to substantially bias estimated associations (Kindratt, 2022). Research on the validity of complete-case analysis indicates that, when missingness is independent of the outcome conditional on measured covariates, complete-case estimates can be unbiased even under MAR conditions (Ross et al., 2020). Multiple imputation was not pursued because missingness in this secondary survey dataset arose in part due to survey structure and skip logic, making imputation models difficult to specify without strong auxiliary variables and risking illogical imputations; given the low rates of missingness and inclusion of covariates related to missingness, a complete-case analytical approach was appropriate for the current study (Jo, 2022).

Analyses proceeded using a complete-case (listwise deletion) approach, consistent with prior recommendations for complex survey data (Kindratt, 2022; McCully et al., 2013). Data were not deleted from the dataset; instead, cases with missing values were excluded automatically within analytic procedures. As a result, analytic sample sizes varied across models due to item-level missingness on select outcome and covariate measures. Sample sizes for each variable were reported when appropriate under each aim in Chapter 4. In the next section, analytic procedures organized by study aim are presented.

3.5.3. Analytic Procedures by Study Aim

Across analyses, statistical significance was defined as a p value < .05 and 95% confidence intervals were used when reporting predicted probabilities (Lohse & Kliethermes, 2025; Pearson, 1900) and data were monitored with consideration for how well the data met statistical assumptions, where appropriate (i.e., scaling, linear relationship, no outliers, and normal or near-to-normal distribution) (Fein, 2021). Descriptive, bivariate, and criterion validity analyses (Aims 1, 2, and 3) used available-case data which excluded missing values automatically. In Aim 4, complete case analysis was utilized for multivariable regression analyses. Additional assumptions were met prior to multivariate regression analyses, such as independence of errors, linearity in the logit for continuous variables, absence of multicollinearity, and lack of strongly influential outliers (Stoltzfus, 2011). After each analytic procedure, the data were reviewed and interpretations were made based on the findings for each model in accordance with existing analytic recommendations.

Aim 1 Analytic Procedures - Descriptive Characterization of the Sample

Aim 1 focused on describing the analytic sample and examining distributions of all study variables to both assess the characteristics of the sample and to determine if data manipulation was needed to ensure accurate and complete analyses could be completed. Each variable outlined in Section 3.4. was cleaned, recoded, and organized as described.

Survey-weighted descriptive statistics were generated using PROCSURVEYFREQ in SAS for the chronic diseases endorsed by respondents, eHealth literacy skill variables, eHealth use variables, chronic disease self-management behaviors, self-efficacy, and sociodemographic characteristics. Frequencies, weighted percentages, and distributions were reported as appropriate.

Design-adjusted (Rao-Scott) chi-square tests were conducted to examine bivariate associations between each eHealth literacy skill variables and each chronic condition, as well as between each eHealth literacy skill variables and each sociodemographic characteristic. Categories for some variables were collapsed when cell sizes were too small (<5 cases), which is discussed in further detail in Chapter 4 (McHugh, 2013; Moses et al., 1984). Bivariate results are presented in tabular format, including F statistics, degrees of freedom, sample sizes, and *p*-values in Chapter 4.

Aim 2 Analytic Procedures - Alignment Between eHealth Literacy Skills and eHealth Use Behaviors

Aim 2 examined the conceptual alignment between each eHealth literacy skill domain and each corresponding eHealth use behavior as a de facto test of concurrent (criterion) validity

(Gorsuch & McFarland, 1972; Song et al., 2023). Both SAS Studio and RStudio were used to conduct Aim 2 analyses.

First, each eHealth use variable was cleaned, dichotomized, and summarized using survey-weighted frequencies to characterize patterns of engagement across behaviors. Then, pairwise relationships among the six eHealth use variables were examined. Unweighted correlation matrices were assessed in SAS Studio as a diagnostic step to evaluate the strength and direction of associations among each eHealth use item. These analyses were followed by survey-weighted pairwise chi-square analyses in RStudio to account for the complex sampling design. Because these analyses were conducted to assess overall patterns and effect sizes rather than to test independent hypotheses, no multiple-comparison correction was applied (Armstrong, 2014; Song et al., 2013).

Variables representing eHealth use were moderately correlated with one another without evidence of redundancy, supporting their aggregation into a composite eHealth Use score through summation (Sherman et al., 2020). Internal consistency of the composite score was evaluated using Cronbach's alpha ($\alpha = 0.65$) (Cronbach, 1951). Given that the composite was designed to capture a broad range of distinct behaviors via meaningful grouping rather than loading onto a single latent construct, internal consistency was considered acceptable and aligned with methodological guidance for composite measures in population health and behavioral research (Shwartz et al., 2015; Song et al., 2013; Tavakol & Dennick, 2011).

Next, each eHealth literacy skill variable was dichotomized. Unweighted collinearity diagnostics were performed with the eHealth use composite score specified as the outcome variable to determine if any interactions for specific combinations of eHealth literacy variables needed to be accounted for within the adjusted models (Kleinbaum et al., 2013; Shiferaw et al., 2020). There were no problematic collinearities (see Appendix D).

After the two sets of variables were examined, survey-weighted linear regression models were run with the eHealth use composite score specified as the outcome variable to further examine the relationship between eHealth literacy skills and overall eHealth engagement. Linear regression was selected for these analyses because the eHealth use composite score represented an ordered outcome with seven possible values (0–6) and exhibited an approximately linear distribution without extreme skewness. Additionally, prior research and HINTS documentation support treating ordinal composite outcomes as continuous in regression analyses within health behavior research (Calo et al., 2014; Marlow et al., 2019; National Cancer Institute & Westat, 2023, April). Separate regression models examined the association between the composite outcome and each eHealth literacy domain individually, followed by models including all six domains simultaneously to assess their independent contributions.

With analyses exploring the validity of the eHealth literacy skill variables completed in Aim 2, analyses between each eHealth literacy skill variable and each chronic disease self-management variable were conducted in Aim 3.

Aim 3 Analytic Procedures - Domain-Specific Associations with Chronic Disease Self-Management

In pursuit of testing Hypothesis 1, Aim 3 examined the conceptual link between each eHealth literacy skill domain and each of the six chronic disease self-management behaviors. Survey-weighted unadjusted logistic regression models were estimated for each pairing of eHealth literacy skill domain and chronic disease self-management behavior. Adjusted multivariable logistic regression models were then estimated for each chronic disease self-management outcome, including all eHealth literacy skill variables simultaneously to assess domain-specific effects while accounting for potential overlap among skills. No imputation was performed due to the exploratory nature of these analyses and relatively low levels of missingness. Results for these analyses were presented in tabular format and in forest plots for odds ratios in Chapter 4 (Lewis & Clarke, 2001; Manning et al., 2023).

Aim 4 Analytic Procedures - Analyzing the Relationship Between eHealth Literacy and CDSM Behaviors

Finally, Aim 4 analyses evaluated whether overall eHealth literacy skill level predicted overall chronic disease self-management behavior while accounting for self-efficacy. The hypothesized relationship between higher eHealth literacy and higher chronic disease self-management behaviors in Aim 4 (Hypothesis 2) was based on existing research highlighting this expected connection (Mitsutake et al., 2024; Mitsutake et al., 2016; Tsukahara et al., 2020). The inclusion of self-efficacy as a possible covariate with eHealth literacy skill level was also informed by previous research linking the two concepts (Choi, 2020; Sögüt et al., 2022).

In this aim, three new variables were developed: the H6 eHealth Literacy Skill Index (HeLSI), the Partial H6 eHealth Literacy Skill Index (P-HeLSI), which excluded Scientific Literacy due to its non-significant relationship with eHealth use in Aim 2, and the CDSM Behavior Score. Each of these composite variables was created through the summation of the binary indicator variables pertaining to each conceptual grouping (Song et al., 2013). Descriptive statistics for the sample of internet-using adults with chronic conditions were conducted as well as specific summaries of the scores along each type of chronic condition. Further results are presented in Chapter 4.

As part of the composite construction process, internal consistency was evaluated for the three composite measures using Cronbach's alpha (Cronbach, 1951). The CDSM Behavior Score, which included six CDSM indicators—Smoking Status, Physical Activity, Calorie Information, Food Discussion, Alcohol Consumption, and Health Perception—demonstrated low internal consistency ($\alpha = 0.29$), which was expected given that these behaviors represented distinct, non-interchangeable aspects of self-management rather than one single latent construct. The 6-item HeLSI also exhibited lower internal consistency ($\alpha = 0.41$), and the reduced 5-item P-HeLSI showed a comparable level of internal consistency ($\alpha = 0.38$). In each case, these composites were treated as indices representing engagement in the underlying constructs across multiple domains, for which high internal consistency was not required nor entirely expected (Mondal et al., 2024; Song et al., 2023). This approach aligned with established recommendations for the use of composite indices in population health and behavioral research (Shwartz et al., 2015; Song et al., 2013; Tavakol & Dennick, 2011) .

Although each composite score had ordinal origins, the number of levels and the approximately normal distribution supported treating it as a quasi-continuous outcome for regression analysis (Edelsbrunner, 2022; McNeish, 2024; Widaman & Revelle, 2023). Published guidance notes that when ordinal outcomes have multiple categories and the intervals between categories are reasonably consistent, parametric regression methods such as linear regression can be appropriate for exploratory association estimation, particularly in large samples (Edelsbrunner, 2022; Miot, 2020).

Once the new composite scores were created, survey-weighted linear regression models were used to examine unadjusted associations between the continuous composite HeLSI and the continuous CDSM Behavior score (Model 1). Hierarchical adjusted survey-weighted linear regression models were then estimated to examine the relationship between the HeLSI and the CDSM Behavior Score while controlling for key demographics in Model 2 and Model 3 (Sullivan et al., 1999; Witte et al., 1994). Finally, the hypothesized relationship between HeLSI and the CDSM Behavior Score outlined in Hypothesis 2 was tested in the final adjusted survey-weighted linear regression that controlled for self-efficacy and all seven sociodemographic covariates. Due to the number of variables in the final model (Model 4), self-efficacy was dichotomized to avoid overparameterization (Zheng & Agresti, 2000). Analyses using the P-HeLSI were estimated with the CDSM Behavior Score as the outcome variable in another set of the same four hierarchical regression models. Results for each of these Aim 4 analyses are presented in Chapter 4.

3.5.4. Sensitivity and Robustness Analyses

For each aim, I utilized sensitivity and robustness analyses to ensure that variables were performing as expected. In Aim 2, prior to combining the eHealth use variables into one composite variable, I analyzed the bivariate relationships between each eHealth use variable and its corresponding eHealth literacy variable as a sensitivity test to understand how creating a composite variable for eHealth use might have impacted the underlying relationship of interest. In Aim 3, two sensitivity analyses were conducted to evaluate whether the Aim 3 findings were sensitive to survey mode (web vs. paper) and chronic disease burden (multimorbidity). In Aim 4, three sensitivity analyses were conducted using the same survey-weighted linear regression framework as in the main analyses to evaluate the robustness of the primary Aim 4 findings. These analyses examined: whether multimorbidity confounded the association between overall eHealth literacy and CDSM behaviors; whether alternative conceptual groupings of eHealth literacy domains altered the association; and whether differential missingness and complete-case analysis meaningfully influenced the results. Characteristics of complete cases were compared with those of excluded participants using survey-weighted descriptive statistics and domain analysis with jackknife replicate weights (Heeringa et al., 2017; Lumley, 2011). Results from each sensitivity analysis are reported under each aim in Chapter 4.

3.6. Limitations

As a secondary analysis of cross-sectional HINTS data, this study was limited in its ability to make causal inferences. Additionally, some constructs of interest were operationalized using available proxy measures due to survey design and skip logic, and all variables relied on self-reported data. These considerations informed the analytic strategy but did not preclude examination of associations within the study aims.

3.7. Human Subjects Protection

The author has previous experience collecting, de-identifying, analyzing, and managing sensitive data for related research and has received CITI training for human subjects research. The National Cancer Institute's Institutional Review Board approved the Health Information National Trends survey (National Cancer Institute & Westat, 2023, April). The study, which contains deidentified data obtained from the public-facing HINTS website, was declared as exempt research by the University of Maryland Institutional Review Board in 2025.

3.8. Summary

In summary, this chapter presented information about the background of the H6 dataset. I provided information about the sampling strategy and study design guiding the methods of this research study. The population of interest was described and key variables explaining how relationships of interest were analyzed were also discussed. Analytic strategies and methodological decisions were reviewed. Details outlining the analytic procedures using SAS

Studio and RStudio were covered, and explanations of how specific confounding or unexpected elements related to the data were discussed. Finally, an indication of how the rights of human subjects related to this study was provided.

Chapter 4. Results

This chapter presents findings from the secondary analysis of data from Cycle 6 of the 2022 Health Information National Trends Survey (H6). The purpose of this study was to generate new knowledge about how skills related to eHealth literacy could be assessed using the HINTS dataset, the relationship between these eHealth literacy skills and key chronic disease self-management (CDSM) behaviors, and the direction and magnitude of the potential relationship between level of eHealth literacy skill and level of self-reported CDSM behavioral engagement, after controlling for self-efficacy. The following chapter presents findings organized by aim. The guiding research question for this dissertation study was: *What is the association between level of eHealth literacy skill with specific chronic disease self-management behaviors among U.S. adults with a chronic disease?*

4.2. Aim 1 Results– Describing Sample Characteristics and Investigating the eHealth Literacy Skills of the Sample

The objective of Aim 1 was to create a profile of the target population—internet-using adults with chronic conditions—and determine their general eHealth literacy skills using the H6 dataset. Using descriptive statistics in SAS Studio, I generated frequencies and percentages for the sample regarding chronic disease prevalence, CDSM behaviors, eHealth literacy skills, and key variables such as eHealth use, sociodemographics, and self-efficacy. All percentages reported are considered weighted percentages unless otherwise indicated.

4.2.1. Study Sample

The total sample in H6 included data from 6,252 total respondents. For this study, the dataset was filtered to examine behaviors and skills among internet users only. There were 5,166 respondents (85.80%) who were considered internet users as they indicated that they had gone online to access the internet or web, or to send and receive e-mail (National Cancer Institute, 2023b). The characteristics of the study sample are presented in Table 3 and organized by those with chronic conditions and those without to highlight similarities and differences in the makeup of the overall population prior to further filtering among those with just chronic conditions.

The sample was almost evenly split across males and females. Most of the general sample of internet users were insured (90.55%), lived in a metro county with a population over one million residents (55.96%), and were Non-Hispanic White (63.40%). Nearly half of the population made $75,000 or more in annual household income (47.88%). The sample was well-educated; most of the sample had some college (40.70%) or a college degree (35.92%). Respondents ranged in age from 18 to 75+ years old, although most respondents were 64 years old and younger (81.75%). There were many similarities in the makeup of respondents, however, there was an expected difference in rates of chronic conditions based on age. The percentage of individuals reporting having had a chronic condition appeared to increase with age as compared to those without chronic conditions, which is reflected with inverse percentages in Table 3 for age ranges across columns.

Table 3

Demographic Characteristics of Internet Users with and without Chronic Conditions in H6 (total possible n = 5,166)

Characteristics	YES - Chronic Condition (n=2,888)		NO - Chronic Condition (n=2,276)		Total % Internet Users (n=5,166)
	n	% (95% CI)	n	% (95% CI)	%
Sex Assigned at Birth (n=4,831)					
Female	1,673	51.64 (49.59 – 53.69)	1,225	49.84 (47.65 – 52.04)	50.71
Male	1,141	48.36 (46.31 – 50.41)	792	50.16 (47.96 – 52.35)	49.29
Age Range (n=4,954)					
18-34-year-olds	185	12.16 (9.21 – 15.12)	629	40.48 (36.76 – 44.20)	26.86
35-49-year-olds	462	23.30 (20.14 – 26.45)	623	29.74 (26.45 – 33.02)	26.64
50-64-year-olds	953	34.18 (31.05 – 37.32)	539	22.74 (19.97 – 25.52)	28.25
65-74-year-olds	809	19.00 (17.54 – 20.45)	228	5.12 (4.09 – 6.16)	11.80
75+-year-olds	454	11.36 (10.23 – 12.49)	72	1.92 (1.32 – 2.51)	6.46
Education Level (n=4,832)					
Less than high school	114	4.56 (2.97 – 6.14)	64	4.73 (2.58 – 6.88)	4.65
High school graduate	414	18.26 (16.01 – 20.50)	284	19.19 (15.86 – 22.52)	18.73
Some college	906	44.89 (41.93 – 47.86)	511	36.73 (33.66 – 39.79)	40.70
College graduate or more	1,381	32.30 (29.99 – 34.61)	1,158	39.35 (36.85 – 41.85)	35.92
Annual Household Income (n= 4,989)					
Less than $20,000	435	13.87 (11.75 – 15.98)	258	12.21 (9.79 – 14.62)	13.01
$20,000 to < $35,000	362	11.36 (9.27 – 13.45)	209	8.05 (6.36 – 9.74)	9.65
$35,000 to < $50,000	420	12.52 (10.57 – 14.46)	256	10.53 (8.44 – 12.61)	11.49
$50,000 to < $75,000	507	17.51 (14.41 – 20.61)	350	18.38 (15.87 – 20.89)	17.96
$75,000 or More	1,161	44.75 (41.62 – 47.87)	1,031	50.84 (47.89 – 53.79)	47.88
Race / Ethnicity (n= 4,701)					
White (Non-Hispanic)	1,664	65.53 (62.64 – 68.43)	1,164	61.44 (58.75 – 64.13)	63.40
Black or African American (Non-Hispanic)	468	12.07 (10.32 – 13.83)	241	9.05 (7.60 – 10.51)	10.50
Hispanic	380	13.05 (10.75 – 15.34)	370	17.34 (15.04 – 19.64)	15.28
Asian (Non-Hispanic)	110	4.53 (2.46 – 6.01)	145	6.43 (5.00 – 7.87)	5.52
Other (Non-Hispanic)	92	4.81 (3.29 – 6.33)	67	6.43 (4.17 – 7.30)	5.29
Health Insurance Status (n= 4,977)					
Uninsured	142	6.39 (4.46 – 8.32)	226	12.30 (10.67 – 13.92)	9.45
Insured	2,732	93.61 (91.68 – 95.65)	1,877	87.70 (86.08 – 89.33)	90.55
Locality (n=4,999)					
Metro - Counties in areas ≥ 1 million	1,686	54.75 (51.43 – 58.07)	1,345	57.08 (53.62 – 60.54)	55.96
Metro - Counties in areas 250,000-1 million	620	23.52 (20.85 – 26.19)	388	21.76 (18.91 – 24.60)	22.61
Nonmetro - Counties in areas <250,000	582	21.73 (19.16 – 24.30)	378	21.17 (17.79 – 24.54)	21.44
TOTAL	**2,888**	**48.17 (45.99 – 50.34)**	**2,111**	**51.83 (49.65 – 54.00)**	

Note. n values are unweighted frequencies, percentages and 95% Confidence Intervals (CI) are weighted. Sample sizes varied by comparison. Missing values represented <10% of cases.

In total, among the 5,166 internet users in the sample, nearly half reported at least one of the chronic conditions of interest. This initial descriptive analysis was essential for identifying any major differences between respondents with and without chronic conditions within the broader sample of internet users. Having established this context and confirmed that no unexpected disparities required immediate adjustment, I then refined the dataset to focus specifically on the target population for the remainder of the analysis—namely, internet users with chronic conditions. The following section provides details regarding the makeup of the final analytic sample.

4.2.2. Chronic Disease Prevalence

The breakdown of types of conditions and percentages of individuals who reported one or more of those conditions is in Table 4. High blood pressure was the most commonly reported condition (72.94%) followed by diabetes (32.61%), lung disease (25.17%), cancer (20.58%), and heart conditions (13.13%). Importantly, disease classifications were not mutually exclusive, so individuals could report having more than one of these conditions. To understand who reported having more than one condition, I created a new variable to assess multimorbidity (i.e., multiple conditions). While nearly half of this group reported having more than one condition, most individuals in the final sample reported only one (55.31%) or two conditions (29.48%), and a very small percentage reported having all five conditions (0.36%) (Table 4).

Table 4

Self-reported Disease Endorsement Summary for Internet Users with Chronic Conditions in H6 (total possible n = 2,888)

Chronic condition (ever diagnosed)	n[b]	%[c]	95% CI[d]
Diabetes	968	32.61	29.99 – 35.22
High BP	2,125	72.94	70.08 – 75.80
Heart condition	441	13.13	11.10 – 15.16
Lung disease	670	25.17	22.83 – 27.51
Cancer	725	20.58	19.45 – 21.70
Multiple conditions (n=1,412)			
1 condition	1,476	55.31	52.10 – 58.52
2 conditions	918	29.48	26.72 – 32.23
3 conditions	373	11.86	9.79 – 13.93
4 conditions	107	3.00	1.97 – 4.03
5 conditions	14	0.36	0.05 – 0.66

Note. Categories are not mutually exclusive; individuals can endorse multiple categories
[b] Unweighted frequency; Sample size varies by condition: diabetes (n=2875, missing=13), high BP (n=2878, missing=10), heart condition (n=2881, missing=7), lung disease (n=2882, missing=6), and cancer (n=2827, missing=61)
[c] These are the weighted percentages
[d] 95% confidence intervals for weighted percentages

This summary of the sample population provided an important baseline understanding of the types of conditions this subset of respondents reported and the presence of multimorbidity that is later examined in Aims 3 and 4. The next section features descriptive details about the CDSM behaviors among this sample.

4.2.3. Summary of Chronic Disease Self-Management Behaviors Among Internet Users with Chronic Conditions

The following descriptive table (Table 5) provides an overview of how internet users with chronic conditions, henceforth referred to as the sample, reported engagement in each CDSM behavior (i.e., each dependent variable). Based on the goal of this study to examine engagement in CDSM behaviors, each dependent variable was re-coded and standardized into dichotomous variables reflecting whether individuals met the target behavior.

As outlined in Chapter 3, meeting the target behavior meant engagement in certain behaviors. Smoking Status reflected frequency and volume of cigarette use and includes individuals who were either current smokers (“Smokes”) or former/non-smokers (“Does not smoke”). Physical Activity reflected whether individuals met weekly physical activity recommendations (≥150 minutes/week) according to self-reported minutes of activity and number of days engaged in moderate intensity activity in a given week. Dietary Awareness was reflected by two separate variables. The first variable, Calorie Information, reflected an individuals' awareness of calorie information on menus in fast food or sit-down restaurants ("Aware" or "Not aware"). The second variable, Food Discussion, reflected levels of comfortability with sharing information pertaining to access to healthy food with healthcare providers for treatment purposes ("Comfortable" or "Uncomfortable"). Alcohol Consumption reflected the average drinks per week calculated based on whether or not that level of consumption fell "below guidelines" or "above guidelines" for males and females, respectively. Finally, Health Perception reflected a key psychological construct related to the mental health aspect of chronic disease self-management via individual perceptions of health ("Good" or "Poor").

Table 5

Frequencies and Percentages of Engagement in Chronic Disease Self-Management (CDSM) behaviors Among Sample Population (total possible n=2,888)

CDSM Variables	Frequency[a]	%[b]	95% CI[c]
Smoking Status (n=2,818)			
Does not smoke	2,508	87.63	85.19 – 90.06
Smokes	310	12.37	9.94 – 14.81
Physical Activity (n=2,809)			
Meets recommendations	1,007	34.80	31.43 – 38.16
Does not meet recommendations	1,802	65.20	61.84 – 68.57
Calorie Information (n=2,844)			
Aware	1,466	51.42	47.93 – 54.91
Not aware	1,378	48.58	45.09 – 52.07
Food Discussion (n=2,787)			
Comfortable	1,691	58.85	55.74 – 61.95
Uncomfortable	1,096	41.15	38.05 – 44.26
Alcohol Consumption (n=2,689)			
Below guidelines	2,418	89.86	88.45 – 91.27
Above guidelines	271	10.14	8.73 – 11.55
Health Perception (n=2,869)			
Good	2,241	77.53	74.51 – 80.55
Poor	628	22.47	19.45 – 25.49

Note. Alcohol consumption was calculated based on recommendations for weekly intake by male/female gender
[a] Unweighted frequencies, <10% missing for each variable
[b] Weighted percentages
[c] 95% confidence interval for weighted percentages

Across the sample (n=2,888), self-reported engagement in each CDSM behavior varied, with the largest difference between the "healthy" and "unhealthy" behavior conditions occurring in Smoking Status and Alcohol Consumption. Nearly 90% of individuals did not smoke and/or consumed alcohol below recommended guidelines. Other noteworthy differences appeared in the Physical Activity variable, where 65.20% of the sample did <u>not</u> meet physical activity recommendations. Finally, people's perceptions of their health – Health Perception – reflected that most people (77.53%) reported having "Good" or better health at the time of the survey.

This descriptive analysis provided an overview of these target behaviors among the sample prior to examining the association of eHealth literacy with these variables, which were explored in Aims 3 and 4. The next section provides an overview of the eHealth literacy skill variables of interest.

4.2.4. Summary of Variables Representing eHealth Literacy Skills

This section presents the frequencies and percentages of the variables chosen to represent the six eHealth literacy skill domains informed by the Norman & Skinner Lily model among the sample. Initial results are presented in Table 6. For Basic Literacy, most respondents across the sample found it "easy" or "very easy" (57.39% and 17.89%, respectively) to generally understand medical statistics. The Computer Literacy levels across the sample represented individuals' use of the internet to make appointments with health care providers, which most individuals had done (61.14%). When reflecting on level of agreement with the statement, "There are so many different recommendations about preventing cancer, it's hard to know which ones to follow", or Scientific Literacy, more disagreement meant higher scientific literacy. Only about one-third of respondents disagreed either somewhat (21.13%) or strongly (9.05%) with the sentiment. When asked about their confidence in finding helpful health resources on the internet, or Information Literacy, individuals mostly reported being somewhat confident (44.11%) or very confident (34.48%). For Health Literacy, individuals shared their confidence levels in filling out medical forms by themselves, which were fairly high (62.43% very confident). For Media Literacy, which assessed the degree to which someone agreed or disagreed with the idea that it is hard to tell whether health information on social media is true or false, most individuals somewhat agreed (30.93%) or strongly agreed (27.64%). Of note, about 12.24% of the sample were not social media users. Details about how this group of respondents is treated are discussed in subsequent sections.

Table 6

Descriptive Summaries of eHealth Literacy Skill Variables in Aim 1 Among Internet Users with Chronic Conditions (total possible n=2,888)

eHealth Literacy Skills	n[a]	%[b]	95% CI[c]
Basic Literacy (n=2,871) - *In general, how easy or hard do you find it to understand medical statistics?*			
Very hard	66	2.05	1.35 – 2.75
Hard	633	22.67	20.07 – 25.27
Easy	1,657	57.39	53.85 – 60.93
Very Easy	515	17.89	15.31 – 20.47
Computer Literacy (n=2,858) - *In the past 12 months have you used the Internet to make an appointment with a health care provider?*			
Low – Has not used internet to make an appointment	1,118	38.86	36.18 – 41.54
High – Has used internet to make an appointment	1,740	61.14	58.46 – 63.81
Scientific Literacy (n=2,809) - *How much do you agree or disagree: There are so many different recommendations about preventing cancer, it's hard to know which ones to follow?*			
Strongly agree	498	19.46	17.01 – 21.90
Somewhat agree	1,401	50.36	47.14 – 53.58
Somewhat disagree	625	21.13	18.76 – 23.51
Strongly disagree	285	9.05	7.25 – 10.84
Information Literacy (n=2,850) - *How confident are you that you can find helpful health resources on the Internet?*			
Not confident at all	61	1.96	1.14 – 2.77
A little confident	225	7.49	5.55 – 9.43
Somewhat confident	1,183	44.11	41.00 – 47.22
Very confident	1,060	34.48	32.26 – 36.69
Completely confident	321	11.97	9.85 – 14.09
Health Literacy (n=2,883) - *How confident are you filling out medical forms by yourself?*			
Not confident at all	96	4.55	2.82 – 6.27
A little confident	218	7.74	6.40 – 9.08
Somewhat confident	689	25.28	22.14 – 28.42
Very confident	1,880	62.43	59.02 – 65.83
Media Literacy (n=2,804) - *How much do you agree or disagree - I find it hard to tell whether health information on social media is true or false?*			
Strongly agree	719	27.64	24.47 – 30.81
Somewhat agree	901	30.93	30.93 – 36.58
Somewhat disagree	419	14.25	11.59 – 16.90
Strongly disagree	347	12.11	9.96 – 14.25
Not applicable	418	12.24	10.08 – 14.41

Note. Response options were reformatted from the HINTS codebook for Health Literacy from "Not at all" to "Not confident at all", and so on. Media literacy had a "Not applicable" = I do not use social media, which will be recoded as "lower" in subsequent analyses. Missingness was <10% for each variable.
[a] Unweighted frequency; sample size varies by literacy domain.
[b] Weighted percentage
[c] 95% confidence interval for weighted percentages

This initial assessment of all six eHealth literacy variables established a foundational profile of how respondents endorsed each skill, providing essential context for interpreting the analytic results presented in Aims 3 and 4. The next section presents descriptive summaries of each covariate.

4.2.5. Summary of Covariates

Sociodemographic Variables

Seven sociodemographic variables provided important context about the sample population and served as covariates in the regression analyses. Within the sample of internet users with chronic conditions, more than half of the individuals were female (51.64%), White (65.53%), insured (93.61%), and living in metro counties with more than 1 million people in the population (54.75%)(see Table 7). Individuals across all age groups 18 years and older were included, with the highest percentage of individuals clustered in the middle age groups. Nearly half of these individuals had "some college" education (44.89%) and made $75,000 or more in annual household income (44.75%).

Table 7

Demographic Characteristics of Internet Users with Chronic Conditions (total possible n = 2,888)

Characteristics	**n[a]**	**%[b]**	**95% CI[c]**
Sex Assigned at Birth (n=2,814)			
Female	1,673	51.64	49.59 – 53.69
Male	1,141	48.36	46.31 – 50.42
Age Range (n=2,863)			
18-34-years-old	185	12.16	9.21 – 15.12
35-49-years-old	462	23.30	20.14 – 26.45
50-64-years-old	953	34.18	31.05 – 37.32
65-74-years-old	809	19.00	17.54 – 20.46
75+-years-old	454	11.36	10.23 – 12.49
Education Level (n=2,815)			
Less than high school	114	4.55	2.97 – 6.14
High school graduate	414	18.26	16.01 – 20.50
Some college	906	44.89	41.93 – 47.86
College graduate or more	1,381	32.30	29.98 – 34.61
Annual Household Income (n=2,885)			
Less than $20,000	435	13.87	11.75 – 15.98
$20,000 to < $35,000	362	11.36	9.27 – 13.45
$35,000 to < $50,000	420	12.52	10.57 – 14.46
$50,000 to < $75,000	507	17.51	14.42 – 20.61
$75,000 or More	1,161	44.75	41.62 – 47.87
Race/Ethnicity (n=2,714)			
White (Non-Hispanic)	1,664	65.53	62.64 – 68.43
Black or African American (Non-Hispanic)	468	12.07	10.32 – 13.83
Hispanic	380	13.05	10.75 – 15.34
Asian (Non-Hispanic)	110	4.53	2.46 – 6.61
Other (Non-Hispanic)	92	4.81	3.29 – 6.33
Health Insurance Status (n=2,874)	95		
Uninsured	142	6.39	4.45 – 8.32
Insured	2,732	93.61	91.68 – 95.56
Locality (n=2,888)			
Metro - Counties in areas ≥ 1 million	1,686	54.75	51.43 – 58.07
Metro - Counties in areas 250,000-1 million	620	23.52	20.85 – 26.19
Nonmetro - Counties in areas <250,000	582	21.73	19.16 – 24.30

Note. Missingness was <10% for each variable.
[a] Unweighted frequency
[b] Weighted percent
[c] 95% confidence interval of weighted percentage

With these descriptive summaries of the sample population established, I then explored the range of eHealth use behaviors, which are important variables related to the validity check in Aim 2.

eHealth Use Descriptive Summaries

Descriptions for the variables representing types of eHealth use present among the sample population are shown in Table 8. For Basic eHealth Use, which aligns with Basic Literacy, most individuals (68.91%) indicated that they had not shared health information from either an electronic monitoring device or smartphone with a healthcare professional in the last 12 months. For Computer eHealth Use, which aligns with Computer Literacy, most people (57.94%) had used a health or wellness app on their tablet or smartphone in the past 12 months. For Scientific eHealth Use, which aligns with Scientific Literacy, most individuals (72.80%) had used the internet to view medical test results in the past 12 months. Most individuals (83.76%) had also used the internet to look for health or medical information, or Information eHealth Use, which aligns with Information Literacy. Most had also sent a message to a health care provider or a health care provider's office (65.71%), which is Health-Related eHealth Use and that aligns with Health Literacy. Finally, most respondents (60.93%) had watched a health-related video on a social media site such as YouTube at least once in the previous month (at the time of the survey), which is Media eHealth Use and is aligned with Media Literacy.

Table 8

Variables Representing Examples Of eHealth Use Among the Sample Population (total possible n=2,888)

Variables	n[a]	% [b]	95% CI [c]
Basic eHealth Use (n=2,863) - *Have you shared health information from either an electronic monitoring device or smartphone with a health professional within the last 12 months?*			
No	1,985	68.91	65.83 – 72.00
Yes	716	25.22	22.13 – 28.31
Not applicable	162	5.86	4.05 – 7.67
Computer eHealth Use (n=2,786) - *In the past 12 months, have you used a health or wellness app on your tablet or smartphone?*			
No	846	28.84	25.31 – 32.36
Yes	1,536	57.94	54.44 – 61.44
Not applicable	95	3.21	1.73 – 4.70
I don't have any health apps on my tablet or smartphone	309	10.01	8.28 – 11.75
Scientific eHealth Use (n=2,845) - *In the past 12 months have you used the Internet to view medical test results?*			
No	790	27.20	24.08 – 30.31
Yes	2,055	72.80	69.69 – 75.92
Information eHealth Use (n=2,858) - *In the past 12 months have you used the Internet to look for health or medical information?*			
No	450	16.25	13.62 – 18.87
Yes	2,408	83.76	81.13 – 86.38
Health-Related eHealth Use (n=2,850) - *In the past 12 months have you used the Internet to send a message to a health care provider or health care providers office?*			
No	973	34.29	30.93 – 37.65
Yes	1,877	65.71	62.35 – 69.07
Media eHealth Use (n=2,870) - *In the last 12 months, how often did you watch a health-related video on a social media site (for example, YouTube)?*			
Never	1,198	39.07	35.72 – 42.41
Less than once a month	902	31.98	29.03 – 34.92
A few times a month	499	18.56	15.76 – 21.36
At least once a month	180	6.40	4.88 – 7.93
Almost every day	91	3.99	1.99 – 6.00

Note. Sample sizes varied by variable and all variables had <10% missing cases.
[a] Unweighted frequency
[b] Weighted percentage
[c] 95% confidence interval of percentage

From here, these items were dichotomized following procedures outlined in Chapter 3 to facilitate validity tests in Aim 2. More details on these results can be found in Section 4.3.

Self-Efficacy Variable

The final covariate examined in Aim 1 is Self-Efficacy (Table 9), which reflects an individual's perception of how confident they are in their ability to take good care of their health.

Most individuals (90.51%) tended to be confident: “somewhat confident” (25.91%), “very confident” (40.72%), or completely confident (23.88%). A binary version of this variable is used in Aim 4 analyses.

Table 9

Self-Reported Self-Efficacy Levels Among Internet Users with Chronic Conditions (total possible n=2,888)

Variable	**n** [a]	**%** [b]	**95% CI** [c]
Not confident at all	41	1.54	0.65 – 2.43
A little confident	144	7.95	4.92 – 10.98
Somewhat confident	738	25.91	23.25 – 28.57
Very confident	1,272	40.72	37.61 – 43.84
Completely confident	686	23.88	21.60 – 26.16

Note. n=2,881; Missingness rate was below 10%.
[a] Unweighted frequencies
[b] Weighted percentages
[c] 95% confidence intervals of weighted percentage

The next section presents findings for the second part of Aim 1 regarding the bivariate relationships examined between eHealth literacy and other key variables.

4.2.6. Aim 1 Bivariate Results

To assess if key variables were independent or statistically associated with one another, I conducted Rao–Scott adjusted chi-square tests (second order) to account for the complex survey design and sampling weights and >2 categories for some variables. To meet minimum cell size requirements for the design-adjusted chi-square tests, I recoded two variables prior to analysis. Specifically, Media Literacy responses indicating “not applicable” were moved into the lower Media Literacy category, and age categories were collapsed by combining adults aged 18–34 and 35–49 years-old for analyses of Information Literacy since this was the only variable for whom no individuals fell into the lowest category. Results are organized by eHealth literacy variable below.

eHealth Literacy and Chronic Conditions

Bivariate analyses (Table 10) showed that Basic Literacy did <u>not</u> differ significantly by

- Diabetes, $F(2.28, 111.95, N=2{,}860) = 1.25, p = .294$
- High blood pressure (BP), $F(2.46, 120.45, N = 2{,}862) = 1.26, p = .290$
- Lung disease, $F(2.86, 140.17, N = 2{,}866) = 1.32, p = .271$, or
- Cancer status, $F(2.90, 141.98, N = 2{,}810) = 0.70, p = .552$.

In contrast, significant differences in Basic Literacy were observed by

- Heart condition, $F(2.71, 132.78, N = 2{,}865) = 3.07, p = .035$, and the
- Presence of multiple chronic conditions, $F(2.73, 133.91, N = 2{,}871) = 3.29, p = .027$.

Bivariate analyses for Computer Literacy showed that Computer Literacy did <u>not</u> differ significantly by any condition status:

- Diabetes, $F(1, 49, N = 2{,}845) = 0.15, p = .704$
- High blood pressure, $F(1, 49, N = 2{,}848) = 0.67, p = .416$
- Heart condition, $F(1, 49, N = 2{,}851) = 0.55, p = .461$
- Lung disease, $F(1, 49, N = 2{,}852) = 0.84, p = .365$
- Cancer, $F(1, 49, N = 2{,}798) = 0.50, p = .483$, or the
- Presence of multiple chronic conditions, $F(1, 49, N = 2{,}858) = 1.86, p = .177$.

Similarly, Scientific Literacy did <u>not</u> differ significantly by any condition status:

- Diabetes, $F(2.68, 131.34, N = 2{,}799) = 1.12, p = .341$
- High blood pressure, $F(2.83, 138.56, N = 2{,}800) = 1.97, p = .125$
- Heart condition, $F(2.79, 136.72, N = 2{,}803) = 0.25, p = .849$
- Lung disease, $F(2.95, 144.61, N = 2{,}804) = 1.39, p = .250$
- Cancer, $F(2.59, 127.03, N = 2{,}804) = 0.66, p = .554$, or the
- Presence of multiple chronic conditions, $F(2.95, 144.35, N = 2{,}809) = 1.81, p = .148$.

When examining Information Literacy, findings also showed that Information Literacy did <u>not</u> differ significantly by any condition status:

- Diabetes, $F(3.63, 177.72, N = 2{,}837) = 0.27, p = .884$
- High blood pressure, $F(3.82, 187.20, N = 2{,}840) = 0.93, p = .444$
- Heart condition, $F(3.54, 173.28, N = 2{,}843) = 1.83, p = .134$
- Lung disease, $F(3.18, 155.76, N = 2{,}844) = 0.78, p = .512$
- Cancer, $F(3.49, 170.95, N = 2{,}790) = 0.92, p = .446$, or the
- Presence of multiple chronic conditions, $F(3.68, 180.45, N = 2{,}850) = 1.32, p = .267$.

Health Literacy did <u>not</u> differ significantly by

- High blood pressure, F(1.95, 95.59, $N = 2{,}874$) = 0.78, $p = .459$
- Heart condition, F(2.59, 126.68, $N = 2{,}877$) = 1.13, $p = .337$
- Lung disease, F(2.34, 114.87, $N = 2{,}878$) = 2.56, $p = .073$ and
- Cancer, F(2.89, 141.58, $N = 2{,}822$) = 1.18, $p = .318$.

In contrast, Health Literacy did significantly differ by

- Diabetes, F(2.06, 101.17, $N = 2871$) = 4.63, $p = .011$, and the
- Presence of multiple chronic conditions, F(2.47, 120.90, $N = 2{,}883$) = 4.36, $p = .010$.

Finally, Media Literacy did not differ significantly by most condition statuses:

- Diabetes, F(1, 49, $N = 2{,}793$) = 1.47, $p = .231$
- High blood pressure, F(1, 49, $N = 2{,}795$) = 2.03, $p = .160$
- Heart condition, F(1, 49, $N = 2{,}798$) = 0.01, $p = .946$
- Cancer, F(1, 49, $N = 2{,}744$) = 0.50, $p = .483$, or the
- Presence of multiple chronic conditions, F(1, 49, $N = 2{,}804$) = 0.02, $p = .887$.

Except for lung disease

- Lung disease, F(1, 49, $N = 2{,}799$) = 4.11, $p = .048$

Table 10

Survey-adjusted Chi-square Associations Between Chronic Disease Status and eHealth Literacy Skill (p-values)[a]

Health literacy domain	Diabetes	High BP	Heart condition	Lung disease	Cancer	Multiple conditions
Basic Literacy	.294	.290	**.035***	.271	.552	**.027***
Computer Literacy	.704	.416	.461	.365	.483	.177
Scientific Literacy	.341	.125	.849	.250	.554	.148
Information Literacy	.884	.444	.134	.512	.446	.267
Health Literacy	**.011****	.459	.337	.073	.318	**.010****
Media Literacy	.231	.160	.946	**.048***	.483	.887

[a] *p*-values are from Rao–Scott design-adjusted Chi-square tests reported as F statistics using jackknife replicate weights.
Significance levels: * $p < .05$, ** $p < .01$, *** $p < .001$.

In summary, most eHealth literacy domains did not differ significantly by disease type. There were a small number of domain-specific differences for Basic Literacy, Health Literacy, and Media Literacy. These findings suggest that, outside of a couple of minor deviations, disease status is not a dominant driver of eHealth literacy skills. However, the presence of multiple conditions seemed to be a possible confounder, so this was explored in Aim 3 and 4 sensitivity analyses. The next section presents findings from similar bivariate analyses among the eHealth literacy variables and the sociodemographic variables of interest.

eHealth Literacy and Sociodemographic Characteristics

Similar analyses were conducted between each eHealth literacy variable and each sociodemographic variable to assess if there were any significant associations that may have an outsized effect on the final relationship of interest (eHealth literacy and CDSM behaviors). Bivariate analyses (Table 11) showed that Basic Literacy <u>did not</u> vary significantly by

- Sex Assigned at Birth, $F(2.75, 134.81, N = 2{,}797) = 0.36, p = .763$
- Age, $F(6.55, 320.81, N = 2{,}846) = 1.13, p = .343$
- Education level, $F(4.98, 244.05, N = 2{,}798) = 1.98, p = .083$
- Race/ethnicity, $F(5.43, 266.12, N = 2{,}699) = 1.64, p = .145$
- Health insurance status, $F(2.39, 116.96, N = 2{,}858) = 0.66, p = .543$, and
- Locality, $F(5.09, 249.46, N = 2{,}871) = 0.81, p = .545$.

However, Basic Literacy <u>did</u> significantly vary by

- Annual household income, $F(6.75, 330.61, N = 2{,}868) = 2.89, p = .007$.

While Computer Literacy <u>did not</u> vary significantly by

- Sex Assigned at Birth, $F(1, 49, N = 2{,}785) = 0.58, p = .449$,
- Health insurance status, $F(1, 49, N = 2{,}845) = 0.07, p = .797$.

Computer Literacy <u>did</u> significantly vary by

- Age, $F(3.27, 160.05, N = 2{,}833) = 7.93, p < .001$
- Education level, $F(2.75, 134.97, N = 2{,}786) = 10.92, p < .001$
- Annual household income, $F(3.32, 162.84, N = 2{,}856) = 7.18, p < .001$
- Race/ethnicity, $F(2.91, 142.36, N = 2{,}689) = 3.16, p = .028$, and
- Locality, $F(1.99, 97.58, N = 2{,}858) = 21.89, p < .001$

Scientific Literacy <u>did not</u> vary significantly by

- Sex Assigned at Birth, $F(2.67, 131.04, N = 2{,}790) = 2.76, p = .051$
- Annual household income, $F(7.84, 384.10, N = 2{,}806) = 0.56, p = .810$
- Race/ethnicity, $F(7.18, 352.04, N = 2{,}697) = 1.36, p = .221$
- Health insurance status, $F(2.64, 129.41, N = 2{,}796) = 0.14, p = .916$, and
- Locality, $F(4.70, 230.40, N = 2{,}809) = 1.95, p = .091$.

However, Scientific Literacy <u>did</u> vary significantly by

- Age, F(7.36, 360.69, N = 2,787) = 2.08, p = .042, and
- Education level, F(5.14, 251.70, N = 2,791) = 2.46, p = .032.

Information Literacy <u>did not</u> vary significantly by

- Sex Assigned at Birth, F(3.50, 171.38, N = 2,777) = 1.10, p = .355
- Annual household income, F(10.66, 522.43, N = 2,847) = 1.00, p = .443
- Race/ethnicity, F(5.39, 264.16, N = 2,681) = 1.54, p = .173
- Health insurance status, F(1.42, 69.76, N = 2,836) = 0.61, p = .494, and
- Locality, F(6.53, 320.11, N = 2,850) = 1.00, p = .431.

However, Information Literacy <u>did</u> vary significantly by

- Age, F(7.80, 382.22, N = 2,826) = 3.06, p = .003, and
- Education level, F(8.97, 439.62, N = 2,778) = 1.95, p = .044.

Health Literacy <u>did not</u> vary significantly by

- Annual household income, F(5.35, 261.93, N = 2,880) = 1.90, p = .089
- Race/ethnicity, F(3.42, 167.68, N = 2,710) = 1.51, p = .207
- Health insurance status, F(1.54, 75.33, N = 2,872) = 0.02, p = .951, and
- Locality, F(3.05, 149.57, N = 2,883) = 0.78, p = .506.

In contrast, Health Literacy <u>did</u> vary significantly by

- Sex Assigned at Birth, F(2.34, 114.48, N = 2,809) = 3.63, p = .024
- Age, F(4.83, 236.88, N = 2,859) = 2.56, p = .030
- Education level, F(4.29, 209.98, N = 2,810) = 3.82, p = .004.

Media Literacy <u>did not</u> vary significantly by most sociodemographic variables

- Sex Assigned at Birth, F(1, 49, N = 2,731) = 0.04, p = .837
- Education level, F(2.54, 124.55, N = 2,733) = 1.95, p = .135
- Annual household income, F(3.34, 163.51, N = 2,802) = 1.55, p = .200
- Health insurance status, F(1, 49, N = 2,793) = 1.31, p = .257, and
- Locality, F(1.79, 87.70, N = 2,804) = 0.72, p = .477.

But Media Literacy did vary significantly by

- Age, F(2.90, 142.32, N = 2,783) = 4.66, p = .004
- Race/ethnicity, F(3.70, 181.20, N = 2,646) = 2.69, p = .037

Table 11

Associations Between Sociodemographics and eHealth Literacy Skills (p-values)[a]

Health literacy domain	Sex	Age	Education Level	Income	Race / Ethnicity	Health Insurance Status	Locality
Basic Literacy	.763	.343	.083	**.007****	.145	.543	.545
Computer Literacy	.449	**<.001*****	**<.001*****	**<.001*****	**.028***	.797	**<.001*****
Scientific Literacy	.051	**.042***	**.032***	.810	.221	.916	.091
Information Literacy	.355	**.003****	**.044***	.443	.173	.494	.431
Health Literacy	**.024***	**.030***	**.004****	.089	.207	.951	.506
Media Literacy	.837	**.004****	.135	.200	.037	.257	.477

[a] p-values from design-adjusted (Rao–Scott) chi-square tests.
Significance levels: $p < .05$, ** $p < .01$, *** $p < .001$.

The bivariate tests results showed that associations between sociodemographic characteristics and eHealth literacy skills varied across literacy domains. Some domains reflected significant differences by age, education level, and income while others showed little variation across sociodemographic groups. Together, these findings provided relevant baseline information for understanding the possible role of these covariates in shaping the posed relationship between eHealth literacy skills and CDSM behaviors and led to the selection of the hierarchical regression models in Aim 4.

4.2.7. Aim 1 Summary

The objective of Aim 1 was to describe the characteristics of the sample of internet users with chronic conditions. Descriptive summaries provided insights into the nuanced backgrounds of the sample population and presented details about eHealth literacy skills, CDSM behaviors, eHealth use, sociodemographics, and other related variables. Bivariate analyses provided foundational knowledge of the existing associations among relevant variables that informed subsequent analyses in later aims. In the next section, results from the Aim 2 analyses are presented.

4.3. Aim 2 Results – Validating eHealth Literacy

As discussed in earlier chapters, variables in HINTS do not directly measure eHealth literacy skills, but they do capture behaviors that approximate these skills as they are defined by the Norman & Skinner Lily model (2006b). The objective in Aim 2 was to establish a relationship among the variables representing the six domains of eHealth literacy skills with related eHealth use variables in the H6 dataset to assess concurrent validity for the eHealth literacy skill variables. Results in this subsection reflect the conceptual role of eHealth use as the mechanism through which eHealth literacy is expected to be associated with chronic disease self-management behaviors. In this section, I first assessed how well the six eHealth use variables aligned with one another to determine the level of conceptual concordance they exhibited. Then, I assessed the relationship between eHealth literacy and eHealth use.

4.3.1. eHealth Use Patterns Among the Sample

In Aim 2, each eHealth use variable was standardized and re-coded into binary variables (Yes/No) according to logic outlined in Chapter 3 (Section 3.4.3). Table 12 reflects the frequencies and percentages of each eHealth use variable after recoding. The resulting distributions were generally well-balanced and aligned with expected patterns of eHealth engagement. Most individuals had used the internet to look for health or medical information in the previous 12 months—Information eHealth Use (83.76%). Similarly, most individuals had used the internet to view medical test results in the previous 12 months—Scientific eHealth Use (72.80%). On the other hand, most individuals (74.78%) had not shared information from a monitoring device or smartphone in the past year, Basic eHealth Use. Engagement in the other eHealth use activities varied more evenly, with many people endorsing the affirmative response option for Computer eHealth Use, Health-Related eHealth Use, and Media eHealth use. All variables demonstrated adequate distributions and low missingness (<10%).

Table 12

eHealth Use Frequencies and Weighted Percentages for Aim 2 Analysis (total possible n=2,888)

eHealth Use Variables	n[a]	% [b]	95% CI [c]
Basic eHealth Use (n=2,863) - *Have you shared health information from either an electronic monitoring device or smartphone with a health professional within the last 12 months?*			
No	2,147	74.78	71.69 – 77.87
Yes	716	25.23	22.13 – 28.31
Computer eHealth Use (n=2,786) - *In the past 12 months, have you used a health or wellness app on your tablet or smartphone?*			
No	1,250	42.06	38.56 – 45.56
Yes	1,536	57.94	54.44 – 61.44
Scientific eHealth Use (n=2,845) - *In the past 12 months have you used the Internet to view medical test results?*			
No	790	27.20	24.08 – 30.31
Yes	2,055	72.80	69.69 – 75.92
Information eHealth Use (n=2,858) - *In the past 12 months have you used the Internet to look for health or medical information?*			
No	450	16.25	13.62 – 18.87
Yes	2,408	83.76	81.13 – 86.38
Health-Related eHealth Use (n=2,850) - *In the past 12 months have you used the Internet to send a message to a health care provider or health care provider's office?*			
No	973	34.29	30.93 – 37.65
Yes	1,877	65.71	62.35 – 69.07
Media eHealth Use (n=2,870) **-** *In the last 12 months, did you watch a health-related video on a social media site (for example, YouTube)?*			
No	1,198	39.07	35.72 – 42.41
Yes	1,672	60.94	57.59 – 62.28

Note. Media eHealth Use was reworded to fit the framing of the other variables. Recoding is discussed in Chapter 3.
[a] Unweighted frequency
[b] Weighted percentage
[c] 95% confidence interval of weighted percentage

Overall, each variable contained enough variation in the frequency breakdown to allow for the next set of tests.

Pairwise Chi-Square Analyses among eHealth Use Variables

To assess whether there was a meaningful grouping among the six binary eHealth use variables reflecting a construct suitable for aggregation, two analyses were conducted. First, an unweighted correlation analysis was conducted in SAS Studio to explore unweighted associations among the variables. Second, R Studio was used to conduct Rao-Scott weighted chi-square tests (i.e., pairwise comparisons) among the 15 pairs of eHealth use variables to assess the relationships among each pair.

The unweighted Pearson correlation analysis showed that each of the six eHealth use variables were statistically significantly associated with one another ($p<.001$ for all six variables)(Table 13). Effect sizes ranged from small (e.g., Basic & Information, r=0.11; Basic & Scientific, r=0.16; Basic & Media, r=0.13) to medium (e.g., Media & Computer, r=0.22; Media & Information, r=0.23; Computer & Basic, r=0.26) to larger (e.g., Scientific & Health, r=0.52) effects.

Table 13

Unweighted Pearson correlation Matrix among 6 eHealth Use Variables (n=2,715)

	Mean (SD)	**Pearson correlation coefficient (r) for each comparison**					
		1	2	3	4	5	6
1. Basic eHealth Use	0.26 (0.44)	-					
2. Computer eHealth Use	0.56 (0.50)	0.26	-				
3. Scientific eHealth Use	0.74 (0.44)	0.16	0.33	-			
4. Information eHealth Use	0.86 (0.35)	0.11	0.25	0.32	-		
5. Health-Related eHealth Use	0.68 (0.47)	0.23	0.31	0.52	0.29	-	
6. Media eHealth Use	0.59 (0.49)	0.13	0.22	0.15	0.23	0.16	-

Note. All p-values were significant at the $p<.001$ level***. r is Pearson correlation coefficient

To account for the complex survey design, Rao–Scott adjusted chi-square tests were conducted in RStudio to examine associations among the six eHealth use variables across 15 unique pairs. The survey-weighted analyses produced design-adjusted F statistics and confirmed the pattern observed in the unweighted correlation analysis. Statistically significant associations were observed for all pairs of eHealth use behaviors ($p < .01$ for all comparisons; Table 14).

Table 14

Weighted Pairwise Comparisons in R Studio for Each Pair of eHealth Use Variables

Variable 1	**Variable 2**	**F**	**p-value***
Basic eHealth Use	Computer eHealth Use	56.4	<.001
Basic eHealth Use	Scientific eHealth Use	30.4	<.001
Basic eHealth Use	Information eHealth Use	9.04	.004
Basic eHealth Use	Health-Related eHealth Use	65.6	<.001
Basic eHealth Use	Media eHealth Use	16.1	<.001
Computer eHealth Use	Scientific eHealth Use	137.0	<.001
Computer eHealth Use	Information eHealth Use	44.1	<.001
Computer eHealth Use	Health-Related eHealth Use	89.3	<.001
Computer eHealth Use	Media eHealth Use	51.4	<.001
Scientific eHealth Use	Information eHealth Use	110.0	<.001
Scientific eHealth Use	Health-Related eHealth Use	192.0	<.001
Scientific eHealth Use	Media eHealth Use	37.6	<.001
Information eHealth Use	Health-Related eHealth Use	112.0	<.001
Information eHealth Use	Media eHealth Use	43.3	<.001
Health-Related eHealth Use	Media eHealth Use	44.1	<.001

Note. Each row represents a pairwise comparison of eHealth use behaviors. Rao–Scott adjusted chi-square tests accounting for complex survey design were conducted in R; reported statistics are design-adjusted F values. All numerator degrees of freedom (df) = 1 and all denominator df = 49. * All p-values were significant at $p < .01$.

In summary, both unweighted correlation analyses and survey-weighted association tests indicated that the six eHealth use variables were statistically associated and conceptually related without being redundant. The unweighted Pearson correlations suggested small-to-moderate relationships among the variables, while the survey-weighted Rao–Scott tests confirmed statistically significant associations across all pairs. Together, these findings support the use of the six indicators as components of a composite measure of eHealth use.

4.3.2. Bivariate Analyses between eHealth Use Variables & Corresponding eHealth Literacy Variable

Prior to creating a composite variable, I wanted to determine if there were existing statistically significant associations between the eHealth use and eHealth literacy variable pairs. Weighted Rao–Scott chi-square tests showed that most of the pairs of use and skill variables were statistically associated to varying degrees, except for Scientific eHealth use and Scientific Literacy (Table 15).

Table 15

Associations Between eHealth Literacy Skill Domains and Corresponding eHealth Use Behaviors

eHealth Literacy Skill Domains	Corresponding eHealth Use Variable	F[a]	Df (Num, Den)[b]	*p*-value
Basic Literacy	Basic eHealth Use	2.92	2.46, 120.31	**.047***
Computer Literacy	Computer eHealth Use	137.84	1, 49	**<.001*****
Scientific Literacy	Scientific eHealth Use	0.81	2.98, 145.79	.489
Information Literacy	Information eHealth Use	7.32	3.17, 155.17	**<.001*****
Health Literacy	Health-Related eHealth Use	7.81	2.15, 105.26	**<.001*****
Media Literacy	Media eHealth Use	6.14	1, 49	**.017***

Note. Unweighted sample sizes varied for each test: Basic Literacy n=2,846, Computer Literacy n=2,761, Scientific Literacy n=2,770, Information Literacy n=2,823, Health Literacy n=2,846, Media Literacy n=2,789.
[a] Values are Rao–Scott adjusted F statistics from survey-weighted chi-square tests using jackknife replicate weights.
[b] Df = Degrees of freedom and reflect design correction.
Significance levels: * $p < .05$, ** $p < .01$, *** $p < .001$.

Although imperfect due to the non-significance of Scientific Literacy with Scientific eHealth Use, these 12 items were mostly well-aligned and conceptually related. Therefore, I continued with the plan to combine these domain-specific eHealth use questions into one composite score called "eHealth Use". The next sections provide details on the development and testing of the eHealth use composite score and each eHealth literacy skill variable.

4.3.3. eHealth Use Composite Score Creation

Prior to creating the composite variable, I conducted an unweighted correlation analysis with the six eHealth use variables (as written and coded in Table 12). The analysis demonstrated moderate, although borderline questionable, internal consistency for the proposed composite measure (Cronbach's $\alpha = 0.65$). Item–total correlations were uniformly positive and of moderate magnitude (0.27–0.49), indicating that each indicator contributed meaningfully to the overall construct. Removal of any individual item did not meaningfully improve the overall alpha (see Appendix C), suggesting that no single variable disproportionately influenced the reliability estimate. Taken together, these results indicate that the six eHealth use variables capture related but nonredundant aspects of eHealth engagement and provide acceptable internal consistency for constructing a composite measure.

Given that the composite was intentionally constructed to capture a broad range of distinct eHealth use behaviors rather than a single latent construct, and that Cronbach's alpha is known to underestimate internal consistency when an index spans multiple related behaviors or domains, this level of internal consistency was considered acceptable for use in the criterion validity analyses that followed.

Thus, I summed the binary eHealth use variables into one variable. Weighted descriptive statistics for this new eHealth Use variable reflected that there were seven possible "scores" for the eHealth Use composite variable, ranging from individuals engaging in 0 behaviors (5.45%) to all 6 behaviors (12.48%)(Table 16). Most respondents (58.44%), however, engaged in 4 or more behaviors.

Table 16

Distribution of eHealth Use Composite Scores among Internet Users with Chronic Conditions (n=2,888)

Number of eHealth use behaviors	Frequency [a]	Percent [b]	95% Confidence Interval [c]
0	167	5.45	3.73 – 7.17
1	251	8.60	6.72 – 10.47
2	340	11.80	9.59 – 13.98
3	501	15.72	13.76 – 17.67
4	647	21.56	18.92 – 24.21
5	644	24.40	21.68 – 27.13
6	337	12.48	10.27 – 14.70

[a] Unweighted frequency
[b] Weighted percentage
[c] 95% confidence interval of weighted percentage

Next, I standardized the eHealth literacy variables into binary variables and assessed how well they aligned together by using collinearity diagnostics. Then, I examined the relationship between each eHealth literacy variable and the composite eHealth Use variable through weighted linear regressions to re-assess the conceptual linkage among these variables.

4.3.4. Dichotomization of eHealth Literacy Variables and Multicollinearity Check

As detailed in Chapter 3, established literature guided the dichotomization of each eHealth literacy skill variable, resulting in a two-level classification distinguishing lower from higher skill levels. Descriptive statistics were produced for these binary variables (Table 17). Distributions across the variables were mixed. Computer Literacy Binary showed 61.14% of individuals reporting higher levels and 38.86% reporting lower levels. In a more extreme example, about 87.71% of individuals reported that they had higher levels of Health Literacy Binary, and 75.28% reported higher Basic Literacy Binary levels. For Scientific, Information, and Media Literacy Binary levels, the majority of respondents indicated lower levels of those literacies (69.82%, 53.55%, and 73.65%, respectively).

Table 17

Frequencies and Percentages of Binary eHealth Literacy Variables (n=2,888)

Variable	n[a]	%[b]	95% Confidence Interval[c]
Basic Literacy (Binary)			
Lower	699	24.72	21.88 – 27.56
Higher	2,172	75.28	72.44 – 78.12
Computer Literacy (Binary)			
Lower	1,118	38.86	36.18 – 41.54
Higher	1,740	61.14	58.46 – 63.81
Scientific Literacy (Binary)			
Lower	1,899	69.82	66.92 – 72.72
Higher	910	30.18	27.28 – 33.08
Information Literacy (Binary)			
Lower	1,469	53.55	50.66 – 56.45
Higher	1,381	46.45	43.55 – 49.34
Health Literacy (Binary)			
Lower	314	12.29	10.18 – 14.39
Higher	2,569	87.71	86.60 – 89.82
Media Literacy (Binary)			
Lower	2,038	73.65	70.36 – 76.93
Higher	766	26.36	23.07 – 29.64

Note. Missingness for each variable was <10%.
[a] Unweighted frequency
[b] Weighted percentage
[c] 95% confidence interval of weighted percentage

After dichotomizing each eHealth literacy variable and before evaluating domain-specific associations with eHealth use, I confirmed that the eHealth literacy domains functioned as statistically distinct predictors rather than overlapping elements of the same construct. Unweighted collinearity diagnostics were conducted among the six binary eHealth literacy domains, with the eHealth use composite score specified as the outcome variable. Collinearity diagnostics indicated excellent tolerance values (0.92–0.97), low variance inflation factors (1.04–1.09), and acceptable condition indices (<30), indicating no evidence of problematic multicollinearity among the predictors (see Appendix D). Although several literacy domains were conceptually related, the diagnostics suggested that no domain was redundant and that each retained sufficient unique variance for inclusion in the model. With this dichotomization complete, I then assessed the relationship between the eHealth Use composite score and each binary eHealth Literacy skill domain variable.

4.3.5. eHealth Use and eHealth Literacy Linear Regression

To understand the strength and direction of eHealth use behavior and each eHealth literacy domain, I conducted survey-weighted linear regression analyses using jackknife replicate weights to capture bivariate and multivariable associations. Each model was designed to assess if higher eHealth literacy skill levels corresponded with higher scores of the eHealth use composite variable. The unadjusted models looked at each eHealth literacy skill variable as an independent predictor of the eHealth Use composite score, and then, in the adjusted, or full, model all six eHealth literacy variables were entered in at the same time as covariates.

Survey-weighted linear regression results indicated that several of the eHealth literacy skill domains were significantly associated with the eHealth Use composite score in unadjusted analyses (Table 18). Computer Literacy demonstrated the strongest association, with adults reporting higher Computer Literacy exhibiting substantially higher eHealth use scores compared with those with lower Computer Literacy ($B = 1.82$, $SE = 0.11$, $p < .001$). This association remained strong after adjustment for the other eHealth literacy skill domains ($B = 1.66$, $SE = 0.12$, $p < .001$).

In unadjusted models, Basic Literacy, Information Literacy, Health Literacy, and Media Literacy were each significantly associated with higher eHealth use. After mutual adjustment, Information Literacy and Health Literacy remained independently associated with higher eHealth use composite scores, whereas associations for Basic Literacy and Media Literacy were attenuated and no longer statistically significant. Scientific Literacy was not significantly associated with eHealth use in either unadjusted or adjusted models.

Table 18

Survey-weighted Linear Regression Analysis Examining eHealth Literacy Skill Variables as Predictors of eHealth Use (n=2,888)

	Unadjusted				**Adjusted**			
Predictor[a]	**B**	**SE**	**t**	***p***	**B**	**SE**	**t**	***p***
Basic Literacy (Binary)								
Lower (ref)	—	—	—	—	—	—	—	—
Higher	**0.52**	0.12	4.34	**<.001*** **	0.22	0.12	1.86	.068
Computer Literacy (Binary)								
Lower (ref)	—	—	—	—	—	—	—	—
Higher	**1.82**	0.11	16.06	**<.001*** **	**1.66**	0.12	14.22	**<.001*** **
Scientific Literacy (Binary)								
Lower (ref)	—	—	—	—	—	—	—	—
Higher	0.13	0.13	1.00	.321	-0.09	0.11	-0.82	.414
Information Literacy (Binary)								
Lower (ref)	—	—	—	—	—	—	—	—
Higher	**0.72**	0.11	6.34	**<.001*** **	**0.33**	0.10	3.21	**<.002***
Health Literacy (Binary)								
Lower (ref)	—	—	—	—	—	—	—	—
Higher	**0.82**	0.20	4.10	**<.001*** **	**0.51**	0.17	2.94	**.005** **
Media Literacy (Binary)								
Lower (ref)	—	—	—	—	—	—	—	—
Higher	**0.22**	0.11	2.03	**.047***	0.04	0.09	0.42	.674

Note. Estimates are survey-weighted using jackknife replicate weights. Reference (ref) categories are shown in parentheses. R^2=0.302. Denominator df=49
[a] Unadjusted sample sizes: Basic (n=2,870), Computer (n=2,858), Scientific (n=2,808), Information (n=2,850), Health (n=2,882), Media (n=2,804); Adjusted sample size: n=2,671
Significance levels: * $p < .05$, ** $p < .01$, *** $p < .001$.
Fit statistics: Basic/eHealthUse R2 = 0.02, Root Mean Square Error (RMSE) = 1.68; Computer/eHealthUse R2 = 0.28, RMSE = 1.44; Scientific/eHealthUse R2 = 0.00, RMSE = 1.69; Information/eHealthUse R2 = 0.04, RMSE = 1.65; Health/eHealthUse R2 = 0.03, RMSE = 1.67; Media/eHealthUse R2 = 0.00, RMSE = 1.69; Full Model R2 = 0.29, RMSE = 1.41.

The fully adjusted model accounted for approximately 30% of the survey-weighted variance in eHealth use (R^2= 0.29), indicating that eHealth literacy skills, like Computer Literacy, Information Literacy, and Health Literacy, contribute meaningfully to eHealth use behaviors.

4.3.6. Aim 2 Summary

In summary, results from Aim 2 analyses indicated that several eHealth literacy skill domains aligned with measures of eHealth use, providing modest convergent construct-validity support for the selected eHealth literacy skill domains. Positive associations were observed between most eHealth literacy skills and the composite eHealth use score, consistent with the theorized linkage between literacy-related skills and engagement in eHealth behaviors. Scientific Literacy was consistently not associated with the six eHealth use indicators or the final eHealth use composite score.

Scientific Literacy was endorsed by a smaller proportion of respondents relative to other literacy domains, and it was not significantly associated with eHealth use behaviors in either unadjusted or adjusted models. This pattern suggests that while Scientific Literacy may be important for evaluating health evidence, it may not be necessary for performing routine eHealth activities such as accessing health information, communicating with providers, or using digital health tools. In contrast, Computer, Information, and Health Literacy demonstrated stronger associations with eHealth use, indicating that functional digital and health communication skills may play a more central role in enabling engagement with digital health resources.

Despite these weak empirical associations in Aim 2, Scientific Literacy, as it was operationalized in this dissertation, remained conceptually related to the other eHealth literacy skills. Accordingly, Scientific Literacy was retained in Aims 3 and 4 to preserve the theoretical integrity of the multidimensional concept of eHealth literacy. Aim 3 subsequently examined relationships among the eHealth literacy skill variables themselves, as well as their associations with chronic disease self-management behaviors.

4.4. Aim 3 Results – Understanding How Individual eHealth Literacy Skills Relate to Individual Chronic Disease Self-Management Behaviors

In Aim 3, I examined the theoretical linkage between each eHealth literacy skill domain and each chronic disease self-management (CDSM) behavior. As informed by relationships outlined in the Information-Motivation-Behavioral Skills model, multivariable regression analyses were conducted to test **Hypothesis 1 (H1)**: **Separate unadjusted and adjusted regression models will each show that variables representing each eHealth literacy skill domain will be significantly associated with each of the five chronic disease self-management variables, respectively**. This section presents the results from logistic regression analyses between the variables of interest.

4.4.2. Logistic Regression Model Results

To address Hypothesis 1, survey-weighted logistic regression models using jackknife replicate weights were conducted to examine the associations between each binary eHealth literacy skill variable (Basic Literacy, Computer Literacy, Scientific Literacy, Information Literacy, Health Literacy, and Media Literacy) and each binary CDSM behavior (Smoking Status, Physical Activity, Calorie Information, Food Discussion, Alcohol Consumption, and Health Perception). First, the main effect of each eHealth literacy skill on each CDSM variable was modeled using bivariate logistic regressions. Then, multivariable logistic regression models were fit to estimate adjusted associations while controlling for the other eHealth literacy skill domains. Models were fit using complete-case analysis; therefore, analytic sample sizes varied across outcomes due to differential missingness in outcome and covariate measures.

Numeric results from these tests are in Tables 19-23 and are organized by CDSM variable. Globally, although the eHealth literacy skill variables showed a trend where higher levels of eHealth literacy skills were associated with higher odds of individuals endorsing the target CDSM behavior (i.e., non-smoking or meeting physical activity recommendations), few of these relationships were statistically significant. In the unadjusted model for Smoking Status (Table 19), individuals with higher Computer Literacy had 58% higher odds of not smoking compared with those with lower Computer Literacy (OR = 1.58, 95% CI [1.03 - 2.42]). This association was attenuated and no longer statistically significant after adjusting for the other literacy domains. Other eHealth literacy skills were not statistically significantly associated as predictors of non-smoking behaviors.

Table 19

Associations between eHealth Literacy Skill Domains and Smoking Status

Variable	Unadjusted Models		Adjusted Model	
	OR	**95% CI**	**aOR**	**95% CI**
Basic Literacy	1.40	0.89 – 2.18	1.46	0.79 – 2.69
Computer Literacy	**1.58***	**1.03 – 2.42**	1.44	0.98 – 2.12
Scientific Literacy	1.25	0.77 – 2.02	1.44	0.93 – 2.22
Information Literacy	1.25	0.83 – 1.90	0.86	0.57 – 1.30
Health Literacy	1.25	0.64 – 2.43	1.05	0.63 – 1.79
Media Literacy	0.75	0.51 – 1.11	0.82	0.46 – 1.46

Note. OR = unadjusted odds ratio; aOR = adjusted odds ratio. Reference category for all literacy variables is low literacy (0). Adjusted models include all six literacy variables. Analyses account for complex survey design using jackknife replicate weights. Unadjusted models and adjusted models were estimated on different analytic samples: Basic Literacy n=2,802, Computer Literacy n=2,788, Scientific Literacy n=2,788 Information Literacy n=2,781, Health Literacy n=2,813, Media Literacy n=2,737. Sample size for adjusted model was n=2,650.
* *reflects significant results*

Results for the Physical Activity outcome were slightly different (Table 20). Higher levels of Computer Literacy (OR = 1.61, 95% CI [1.24, 2.10]) and Health Literacy (OR = 1.70, 95% CI [1.22 - 2.38]) were significantly associated with higher odds of meeting physical activity recommendations. These associations remained statistically significant in the adjusted model, although at slightly lower odds, with higher Computer Literacy (aOR = 1.58, 95% CI [1.19 - 2.10]) and higher Health Literacy (aOR = 1.50, 95% CI [1.02 - 2.21]) independently associated with increased odds of meeting physical activity recommendations. No statistically significant associations were observed for Basic, Scientific, Information, or Media Literacy domains in either unadjusted or adjusted models.

Table 20

Associations between eHealth Literacy Skill Domains and Physical Activity

	Unadjusted Models		Adjusted Model	
Variable	**OR**	**95% CI**	**aOR**	**95% CI**
Basic Literacy	1.32	0.88 – 1.97	1.18	0.76 – 1.83
Computer Literacy	**1.61***	**1.24 – 2.10**	**1.58***	**1.19 – 2.10**
Scientific Literacy	1.08	0.77 – 1.53	1.05	0.73 – 1.49
Information Literacy	1.09	0.81 – 1.48	1.03	0.74 – 1.44
Health Literacy	**1.70***	**1.22 – 2.38**	**1.50***	**1.02 – 2.21**
Media Literacy	0.90	0.66 – 1.23	0.84	0.61 – 1.17

Note. OR = unadjusted odds ratio; aOR = adjusted odds ratio. Reference category for all literacy variables is low literacy (0). Adjusted models include all six literacy variables. Analyses account for complex survey design using jackknife replicate weights. Unadjusted models and adjusted models were estimated on different analytic samples: Basic Literacy n=2,792, Computer Literacy n=2,779, Scientific Literacy n=2,763 Information Literacy n=2,774, Health Literacy n=2,805, Media Literacy n=2,730. Sample size for adjusted model was n=2,629.
* *reflects significant results*.

Whether an individual paid attention to calorie information on menus in fast food or sit-down restaurants (i.e., Calorie Information) was not significantly associated with most eHealth literacy skills in both unadjusted and adjusted models (Table 21). However, individuals reporting higher Basic Literacy did have higher odds of calorie information awareness in both unadjusted (OR = 1.58, 95% CI [1.14 - 2.18]) and adjusted models (aOR = 1.44, 95% CI [1.01 -2.06]).

Table 21

Associations between eHealth Literacy Skill Domains and Calorie Information Behaviors

	Unadjusted models		Adjusted model	
Variable	**OR**	**95% CI**	**aOR**	**95% CI**
Basic Literacy	**1.58***	**1.14 – 2.18**	**1.44***	**1.01 – 2.06**
Computer Literacy	1.30	0.99 – 1.69	1.18	0.88 – 1.58
Scientific Literacy	1.11	0.83 – 1.49	1.01	0.74 – 1.36
Information Literacy	1.24	0.97 – 1.59	1.16	0.88 – 1.53
Health Literacy	1.41	0.95 – 2.09	1.21	0.76 – 1.94
Media Literacy	1.27	0.94 – 1.73	1.16	0.85 – 1.59

Note. OR = unadjusted odds ratio; aOR = adjusted odds ratio. Reference category for all literacy variables is low literacy (0). Adjusted models include all six literacy variables. Analyses account for complex survey design using jackknife replicate weights. Unadjusted models and adjusted models were estimated on different analytic samples: Basic Literacy n=2,829, Computer Literacy n=2,815, Scientific Literacy n=2,793 Information Literacy n=2,808, Health Literacy n=2,839, Media Literacy n=2,763. Sample size for adjusted model was n=2,659.
* *reflects significant results.*

In the next comparison, individuals with higher levels of Basic Literacy had higher odds of being comfortable with sharing information related to accessing healthy food with healthcare providers (i.e., Food Discussion) in both unadjusted (OR = 1.60, 95% CI [1.19 - 2.15]) and adjusted models (aOR = 1.64, 95% CI [1.22 – 2.22])(Table 22). All other eHealth literacy skill domains were not significantly associated with this outcome in both unadjusted and adjusted models.

Table 22.
Associations between eHealth Literacy Skill Domains and Food Discussion Behaviors

Variable	Unadjusted Models		Adjusted Model	
	OR	**95% CI**	**aOR**	**95% CI**
Basic Literacy	**1.60***	**1.19 – 2.15***	**1.64***	**1.22 – 2.22**
Computer Literacy	1.04	0.77 – 1.42	0.95	0.68 – 1.33
Scientific Literacy	1.02	0.74 – 1.42	0.97	0.69 – 1.37
Information Literacy	1.18	0.92 – 1.51	1.14	0.89 – 1.47
Health Literacy	0.99	0.71 – 1.39	0.88	0.62 – 1.27
Media Literacy	0.93	0.66 – 1.33	0.86	0.59 – 1.26

Note. OR = unadjusted odds ratio; aOR = adjusted odds ratio. Reference category for all literacy variables is low literacy (0). Adjusted models include all six literacy variables. Analyses account for complex survey design using jackknife replicate weights. Unadjusted models and adjusted models were estimated on different analytic samples: Basic Literacy n=2,775, Computer Literacy n=2,758, Scientific Literacy n=2,741, Information Literacy n=2,752, Health Literacy n=2,783, Media Literacy n=2,715. Sample size for adjusted model was n=2,615.
* *reflects significant results.*

In both unadjusted and adjusted models, none of the eHealth literacy skill domains were significantly associated with Alcohol Consumption above or below guidelines (Table 23). Most skills reflected higher literacy levels with higher odds of being below guidelines except for Information Literacy and Media Literacy, which reflected lower odds of being below guidelines with higher levels of literacy. However, these results were not significant and should be interpreted with caution.

Table 23

Associations between eHealth Literacy Skill Domains and Alcohol Consumption

	Unadjusted models		Adjusted model	
Variable	**OR**	**95% CI**	**aOR**	**95% CI**
Basic Literacy	1.02	0.57–1.83	1.03	0.54 – 1.96
Computer Literacy	1.05	0.68–1.64	1.13	0.71 – 1.79
Scientific Literacy	1.20	0.76–1.90	1.25	0.79 – 2.00
Information Literacy	0.83	0.51–1.35	0.86	0.52 – 1.40
Health Literacy	1.15	0.64–2.05	1.17	0.61 – 2.23
Media Literacy	0.67	0.41 – 1.09	0.67	0.40 – 1.11

Note. OR = unadjusted odds ratio; aOR = adjusted odds ratio. Reference category for all literacy variables is low literacy (0). Adjusted models include all six literacy variables. Analyses account for complex survey design using jackknife replicate weights. Unadjusted models and adjusted models were estimated on different analytic samples: Basic Literacy n=2,673, Computer Literacy n=2,662, Scientific Literacy n=2,671, Information Literacy n=2,656, Health Literacy n=2,684, Media Literacy n=2,621. Sample size for adjusted model was n=2,548.
* *reflects significant results.*

Finally, higher levels of Basic Literacy (OR = 2.60, 95% CI [1.83 – 3.69]) and Health Literacy (OR = 2.30, 95% CI [1.43 - 3.69]) were both strongly associated with significantly increased odds of individuals reporting "good" levels of perceived health over "poor" health (Table 24). These relationships remained significant but slightly lower in the adjusted model for both Basic (aOR = 2.23, 95% CI [1.49 – 3.36]) and Health Literacy (aOR = 1.85, 95% CI [1.11 – 3.07]). Higher Media Literacy was associated with <u>lower</u> odds of reporting "good" health in both the unadjusted and adjusted models, the latter in which Media Literacy became significant (aOR = 0.63, 95% CI [0.45 – 0.90]). All other literacy skills were not significant in either model.

Table 24

Associations between eHealth Literacy Skill Domains and Health Perception

	Unadjusted models		Adjusted model	
Variable	**OR**	**95% CI**	**aOR**	**95% CI**
Basic Literacy	**2.60***	**1.83–3.69**	**2.23***	**1.49 – 3.36**
Computer Literacy	1.05	0.78–1.43	0.90	0.62 – 1.31
Scientific Literacy	1.24	0.93–1.66	1.22	0.90 – 1.65
Information Literacy	1.36	0.96–1.94	1.30	0.87 – 1.95
Health Literacy	**2.30***	**1.43–3.69**	**1.85***	**1.11 – 3.07**
Media Literacy	0.76	0.53 – 1.40	**0.63***	**0.45 – 0.90**

Note. OR = unadjusted odds ratio; aOR = adjusted odds ratio. Reference category for all literacy variables is low literacy (0). Adjusted models include all six literacy variables. Analyses account for complex survey design using jackknife replicate weights. Unadjusted models and adjusted models were estimated on different analytic samples: Basic Literacy n=2,854, Computer Literacy n=2,839, Scientific Literacy n=2,793, Information Literacy n=2,832, Health Literacy n=2,864, Media Literacy n=2,786. Sample size for adjusted model was n=2,657.
* *reflects significant results*

In conclusion, higher eHealth literacy skills were not uniformly associated with target chronic disease self-management behaviors on their own. Instead, associations varied by literacy domain and outcome. Basic Literacy and Health Literacy emerged as the domains most consistently associated with favorable outcomes, particularly Physical Activity and Health Perception, while Computer, Scientific, Information, and Media Literacy showed limited independent associations after adjustment. Model fit statistics were evaluated using Akaike Information Criterion (AIC) values across domain-specific models and the full model including all eHealth literacy domains (Table 25). Lower AIC values indicate improved model fit while accounting for model complexity.

Table 25

Model Fit Statistics (AIC) for Survey-Weighted Logistic Regression Models Predicting Chronic Disease Self-Management Behaviors

	eHealth literacy variables (Binary versions)						
OUTCOME	**Basic**	**Computer**	**Scientific**	**Information**	**Health**	**Media**	**Full**
Smoking Status	74,482,146	74,001,169	74,462,002	74,341,262	74,284,406	73,322,667	70,906,479
Physical Activity	127,840,207	126,793,280	127,099,968	127,597,365	127,725,854	125,872,797	120,827,244
Calorie Information	138,706,667	139,116,241	138,088,569	138,316,878	139,678,766	136,951,517	131,323,125
Food Discussion	133,069,053	133,886,633	132,699,712	132,764,365	134,438,917	132,144,331	126,774,795
Alcohol Consumption	63,130,096	62,866,709	62,677,658	62,448,396	63,165,970	62,177,492	60,575,333
Health Perception	104,954,224	108,425,254	106,853,141	106,569,405	107,259,337	106,537,060	97,982,115

Note. Models were estimated using survey-weighted logistic regression with jackknife replicate weights to account for the complex HINTS sampling design. Analyses were restricted to respondents who reported Internet use and at least one chronic condition.

Across all six CDSM behaviors, the full model consistently produced the lowest AIC values, indicating better overall model fit relative to models including individual literacy domains alone. This pattern suggests that multiple dimensions of eHealth literacy operate jointly to influence CDSM behaviors rather than any single literacy skill acting independently. To ensure that these findings held based on different disease burden and survey assessment formats, I conducted sensitivity tests prior to Aim 4. The following section provides the results of these procedures.

4.4.4. Sensitivity Analyses – The Role of Form Type and Multimorbidity

I conducted sensitivity analyses to ensure that results were not biased by how the data were collected nor across disease burden. First, HINTS captures how individuals completed the questionnaire – either using the web-based version or the paper-based version. In the subsample of 2,888 individuals, about two-thirds (63.37%) completed the questionnaire using the web-based version, while the rest (36.63%) used the paper version. Survey-weighted logistic regression analysis using the adjusted models for each CDSM outcome variable, all six eHealth literacy variables, and the Form Type variable showed that survey mode (web [reference] vs.

paper) was not significantly associated with Smoking Status (aOR = 1.07, 95% CI [0.70 - 1.64]), Physical Activity (aOR = 0.91, 95% CI [0.67 - 1.24]), Calorie Information (aOR = 1.02, 95% CI [0.78 - 1.36]), Food Discussion (aOR = 1.08, 95% CI [0.83 - 1.42]), Alcohol Consumption (aOR = 1.21, 95% CI [0.76 - 1.91]), and Health Perception (aOR = 0.96, 95% CI [0.68 - 1.36]), and did not materially affect the literacy estimates across all models.

In the second sensitivity test, I examined if disease burden (i.e., multimorbidity) influenced the relationship of interest between the eHealth literacy skills variables and each CDSM variable. In Aim 1 results, eHealth literacy domains did not differ meaningfully by individual chronic disease type in bivariate analyses (see Section 4.2.6) but did differ somewhat by number of chronic conditions someone endorsed (i.e., "multiple conditions"). Therefore, multivariable models were adjusted for chronic disease burden and run in survey-weighted logistic regression analyses again to determine if these multiple conditions had an impact on the relationships of interest. In the sample of 2,888, just under half (44.69%) reported having had more than one chronic condition. Adjusted multivariable models in weighted logistic regressions found that the presence of multiple conditions did not statistically impact the relationships of interest for Smoking Status (aOR = 0.69, 95% CI [0.46 - 1.04]), Calorie Information (aOR = 1.04, 95% CI [0.81 - 1.33]), Food Discussion (aOR = 0.89, 95% CI [0.63 – 1.26]), and Alcohol Consumption (aOR = 1.46, 95% CI [0.93 - 2.27]).

Additionally, the inclusion of multimorbidity in the model did not meaningfully alter the associations between most eHealth literacy domains and meeting physical activity recommendations except for Health Literacy, which became non-significant (aOR 1.36, 95% CI [0.93 – 2.01]), reflecting some attenuation. Multimorbidity was also significantly and inversely associated with individuals meeting physical activity recommendations; individuals with multiple conditions had approximately 49% lower odds of meeting physical activity recommendations compared with those without multiple conditions, after adjusting for other variables in the model (aOR = 0.51, 95% CI [0.36 - 0.72]).

Lastly, for the Health Perception outcome variable, the adjusted model accounting for multimorbidity showed that multimorbidity was associated with lower reported odds of reporting good health (aOR = 0.44, 95% CI [0.29 - 0.68]). The model also showed that Basic Literacy remained strongly associated with better self-rated health (aOR = 2.16, 95% CI [1.40 – 3.33]), whereas Health Literacy was no longer statistically significant in the model (aOR = 1.63, 95% CI [0.97 - 2.77]).

Sensitivity analyses were conducted to evaluate the robustness of the full models by adjusting for survey form type and by including a variable capturing multiple chronic conditions. Model fit statistics were compared using Akaike Information Criterion (AIC) values (Table 26). Adjusting for survey form type produced AIC values that were nearly identical to the primary models, indicating that the results were not sensitive to survey form differences. Models including the number of chronic conditions yielded slightly lower AIC values across outcomes, suggesting modest improvements in model fit. However, these adjustments did not meaningfully alter the substantive findings, supporting the robustness of the primary analytic models.

Table 26

Model Fit Statistics (AIC) for Survey-Weighted Logistic Regression Models Predicting Chronic Disease Self-Management Behaviors – Sensitivity Tests

OUTCOME	Full	Form Type	Multimorbidity
Smoking Status	70,906,479	70,895,387	70,562,991
Physical Activity	120,827,244	120,787,341	118,521,339
Calorie Information	131,323,125	131,320,995	131,315,497
Food Discussion	126,774,795	126,743,514	126,705,857
Alcohol Consumption	60,575,333	60,510,122	60,298,324
Health Perception	97,982,115	97,975,688	95,413,358

Note. Models were estimated using survey-weighted logistic regression with jackknife replicate weights to account for the complex HINTS sampling design. Analyses were restricted to respondents who reported Internet use and at least one chronic condition.

Together, however, these results indicated that an individual's endorsement of multiple conditions was a possible confounder in the relationship between eHealth literacy skills and chronic disease self-management behaviors. Therefore, as I proceeded into Aim 4 analyses, I analyzed multimorbidity as a possible confounder in the subsequent sensitivity analyses.

4.4.5. Aim 3 Summary

Overall, results in Aim 3 showed that that most of the selected variables representing eHealth literacy skills were not statistically significantly associated with variables selected to represent chronic disease self-management behaviors on their own. Instead, these associations were outcome-specific—there were some statistically significant relationships between variables, which partially supports Hypothesis 1. Summarily, findings across Aim 3 were consistent with the underlying theorized relationship between eHealth literacy skill and CDSM, as informed by the Information-Motivation-Behavioral skills model. Despite variability in the significance of the findings, the overall directional pattern of the results support the conceptualization of both the independent and dependent variables as composite variables. The following section presents findings for Aim 4.

4.5. Aim 4 Results– Understanding the Contextualized Relationship between eHealth Literacy and Chronic Disease Self-Management

The final aim sought to determine the direction and magnitude of the expected relationship between overall level of eHealth literacy skill and the overall level of chronic disease self-management (CDSM) behavior engagement. Both eHealth literacy skill and CDSM variable groupings were organized into composite, or index, variables to reflect multiple dimensions of eHealth literacy skills and CDSM behaviors, respectively. Additionally, self-efficacy was introduced and explored as a possible covariate or confounder of the relationship of interest.

For exploratory purposes, each eHealth literacy skill variable was retained in Aim 4 analyses. Although Scientific Literacy did not demonstrate direct criterion alignment with its corresponding eHealth use indicator in Aim 2, it was kept in the composite score due to the conceptualization of eHealth literacy in this dissertation study. However, analyses were conducted with and without Scientific Literacy to determine how its inclusion impacted the relationships of interest.

The following sections describe the process through which the index scores were created followed by the results from regression analyses, including sensitivity checks. This section concludes with a summary of the findings.

4.5.1. H6 eHealth Literacy Skill Index (HeLSI)

The six binary eHealth literacy skill variables were combined through summation into a composite score called the H6 eHealth Literacy Skill Index (HeLSI). The prevalence of higher levels of each type of literacy varied across domains, reflecting the differing complexity of the underlying skills (as shown in Table 17). However, each indicator demonstrated sufficient variability and conceptual relevance, supporting their inclusion in the composite index.

To avoid downward bias due to item nonresponse, composite scores were only computed for respondents with complete data on all component items. Item-level missingness was low (≤7% for all variables)(see Appendix B). Total possible index scores could range from “0”, which meant no endorsement of any of the “higher” literacy domains, to “6”, which meant total endorsement of each of the “higher” literacy domains. Summary statistics in Table 27 show that for this new index variable, scores were spread across all levels, although most individuals fell in the middle with scores of 3 (25.33%), 4 (26.74%), and 5 (13.22%).

Table 27

Frequencies and Percentages of New Composite H6 eHealth Literacy Skill Index (HeLSI) Containing All Six eHealth Literacy Skill Domains

# eHL skills	n	%	95% CI
0	36	1.27	0.62 – 1.92
1	189	7.78	6.47 – 9.08
2	483	20.68	17.52 – 23.83
3	705	25.33	22.04 – 28.63
4	726	26.74	23.49 – 30.00
5	390	13.22	11.41 – 15.04
6	142	4.98	3.50 – 6.46
Total	2,671		*Missing = 217*

Note. Unweighted frequencies, weighted percentages, and weighted 95% confidence intervals (CI). # eHL skills = Number of eHealth literacy skills individuals reported positive (or 1) endorsement.

Following the same summation procedures as above, I created a Partial H6 eHealth Literacy Skill Index (P-HeLSI) that excluded Scientific Literacy. The unweighted frequencies and weighted percentages for this P-HeLSI variable are in Table 28. Values did not differ greatly from the full index but were reduced in most categories except for the category representing three skills.

Table 28

Frequencies and percentages of Partial H6 eHealth Literacy Index (P-HeLSI)

# eHL skills	n	%	95% CI
0	45	1.42	0.77 – 2.08
1	235	9.76	7.74 – 11.77
2	609	23.41	20.60 – 26.23
3	825	29.21	25.47 – 32.95
4	753	26.95	24.01 – 29.90
5	269	9.25	7.48 – 11.01
Total	2,736		*Missing = 152*

Note. Unweighted frequencies, weighted percentages, and weighted 95% confidence intervals (CI). # eHLskills = Number of eHealth literacy skills individuals reported positive (or 1) endorsement.

When examining the trends across indices, the results were similarly grouped (Figure 4). Most individuals endorsed eHealth literacy skills in the middle range.

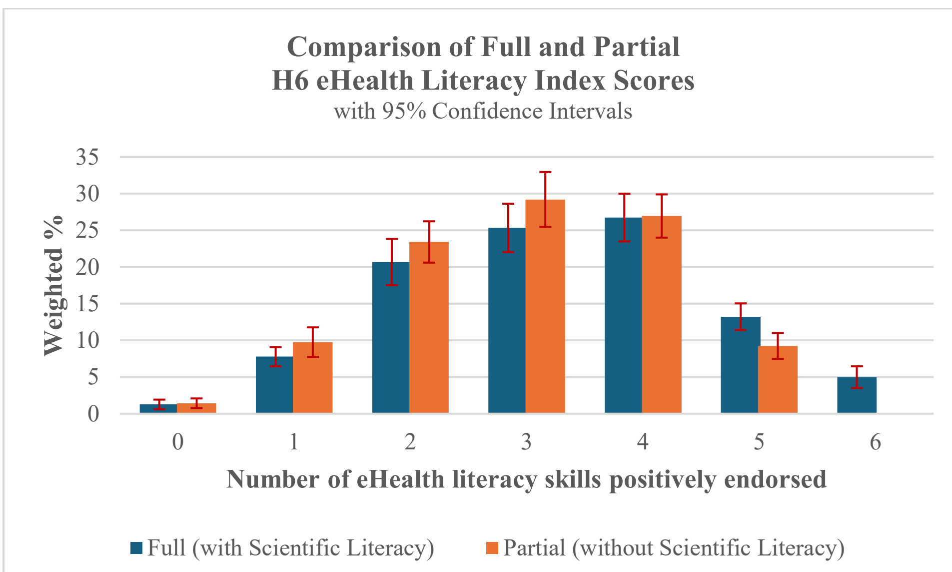

Figure 4. *Bar chart showing the distribution of H6 eHealth Literacy Index Scores with and without Scientific Literacy*

Overall, mean HeLSI scores varied across several sociodemographic characteristics (Table 29). Higher scores were observed among individuals with greater educational attainment and higher household income, while older adults exhibited lower average scores. Differences by sex and insurance status were minimal. Individuals living in a metro area with more than one million residents reflected higher mean scores. Similar patterns emerged for the P-HeLSI.

Table 29

Mean eHealth Literacy Skill Index Scores by Sociodemographic Characteristics among Internet Users with Chronic Conditions (n=2,888)

Characteristic	Full eHealth Literacy Index (HeLSI)		Partial eHealth Literacy Index (Partial HeLSI)	
	Mean	95% CI	Mean	95% CI
H6 eHealth Literacy Skill Index Scores				
HeLSI	**3.42**	**3.35 – 3.49**	**--**	**--**
Partial HeLSI	**--**	**--**	**3.11**	**3.04 – 3.17**
Sex Assigned at Birth				
Male	3.30	3.16–3.43	2.99	2.86–3.13
Female	3.27	3.18–3.37	2.98	2.89–3.07
Age Range				
18–34-years old	3.46	3.09–3.82	3.18	2.89–3.46
35–49-years old	3.51	3.30–3.72	3.22	3.01–3.42
50–64-years old	3.28	3.17–3.40	2.99	2.89–3.10
65–74-years old	3.15	3.02–3.27	2.81	2.69–2.93
75+-years old	2.84	2.59–3.09	2.53	2.32–2.74
Education Level				
Less than High School	3.06	2.55–3.57	2.70	2.34–3.06
High School Graduate	2.84	2.60–3.08	2.59	2.36–2.83
Some College	3.19	3.06–3.32	2.92	2.81–3.03
College Graduate or More	3.68	3.57–3.79	3.33	3.23–3.43
Annual Household Income				
<$20,000	3.03	2.79–3.27	2.73	2.54–2.93
$20,000–34,999	2.97	2.69–3.24	2.64	2.36–2.92
$35,000–49,999	3.22	3.06–3.39	2.92	2.77–3.07
$50,000–74,999	3.38	3.17–3.60	3.12	2.96–3.29
≥$75,000	3.40	3.29–3.52	3.10	3.00–3.20
Race/Ethnicity				
Non-Hispanic White	3.23	3.12–3.35	2.93	2.82–3.04
Non-Hispanic Black	3.68	3.47–3.89	3.34	3.16–3.51
Hispanic	3.21	2.92–3.51	2.96	2.71–3.21
Non-Hispanic Asian	3.11	2.86–3.36	2.93	2.68–3.18
Non-Hispanic Other	3.48	3.16–3.80	3.22	2.97–3.47
Health Insurance Status				
Uninsured	3.25	2.65–3.85	2.93	2.48–3.37
Insured	3.28	3.19–3.37	2.99	2.91–3.07
Locality				
Metro ≥1 million	3.47	3.35–3.58	3.15	3.05–3.24
Metro 250k–1 million	3.13	2.95–3.30	2.85	2.65–3.04
Smaller metro / nonmetro	2.98	2.79–3.17	2.71	2.55–2.86

Note. Values represent survey-weighted mean H6 eHealth Literacy Skill Index scores with 95% confidence intervals estimated using jackknife replicate weights. The full index ranges from 0–6 and the partial index ranges from 0–5.

After creating the eHealth Literacy indices, I did the same for the CDSM variables.

4.5.2. CDSM Behavior Score

The variables for each CDSM behavior were collapsed into one index score called the "CDSM Behavior Score" by summation of complete data from respondents on all component items. Scores ranged from 0-6, where "0" meant they did not engage in any of the target CDSM behaviors (e.g., smokes, does not meet physical activity recommendations, consumes over the recommended alcohol guidelines, etc.) and "6" meant they did engage in all the target CDSM behaviors. The unweighted frequencies and weighted percentages (Table 30) reflected a similar pattern to the HeLSI where most participants endorsed 3-5 target behaviors.

Table 30

Frequencies and percentages of new composite CDSM Behavior Score

# CDSM target behaviors endorsed	n	%	95% CI
0	3	0.03	0.00 – 0.07
1	41	1.66	0.83 – 2.49
2	233	9.14	6.91 – 11.38
3	507	22.36	19.22 – 25.50
4	788	30.00	26.89 - 33.10
5	728	27.34	24.49 – 30.20
6	264	9.47	7.77 – 11.17
Total	2,564		*Missing = 324*

Note. Unweighted frequencies, weighted percentages, and weighted 95% confidence intervals (CI). # CDSM target behaviors endorsed = Number of "target" behaviors individuals reported.

As seen in Figure 5, the distribution of the scores across the CDSM Behavior Score index followed a fairly normal distribution, with a slight left skew.

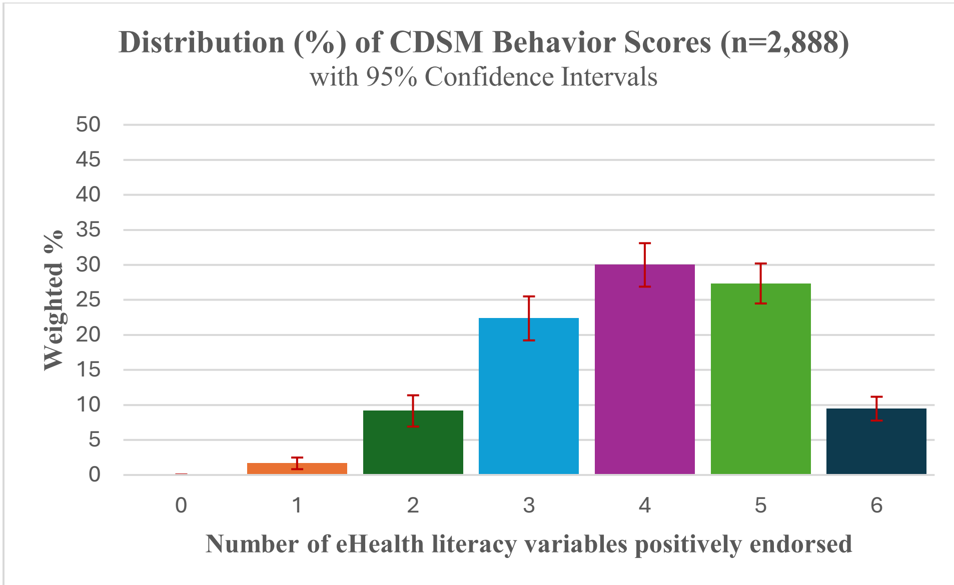

Figure 5. *Bar chart featuring distribution of CDSM variables in index*

Descriptively, mean CDSM scores varied across sociodemographic characteristics (Table 31). Higher mean scores were observed among older adults, respondents with greater educational attainment, and those with higher household incomes. Lower mean scores were observed among younger adults, respondents with lower income, and those living in smaller metro or nonmetro areas. Differences by sex assigned at birth, race/ethnicity, insurance status, and locality appeared more modest.

Table 31

Mean Chronic Disease Self-Management (CDSM) Scores by Sociodemographic Characteristics among Internet Users with Chronic Conditions (n=2,888)

Characteristic	**Mean**	**95% Confidence Interval**
CDSMs	**4.12**	**4.05 - 4.16**
Sex Assigned at Birth		
Male	4.05	3.91 – 4.19
Female	3.96	3.88 – 4.04
Age Range		
18–34-years-old	3.90	3.52 – 4.28
35–49-years-old	3.83	3.67 – 3.99
50–64-years-old	4.01	3.88 – 4.14
65–74-years-old	4.20	4.06 – 4.33
75+-years-old	4.16	3.99 – 4.33
Education Level		
Less than High School	3.36	3.03 – 3.70
High School Graduate	3.85	3.63 – 4.07
Some College	3.94	3.82 – 4.06
College Graduate or More	4.26	4.17 – 4.36
Annual Household Income		
<$20,000	3.38	3.20 – 3.56
$20,000–34,999	3.82	3.59 – 4.05
$35,000–49,999	3.93	3.78 – 4.08
$50,000–74,999	4.14	3.93 – 4.34
≥ $75,000	4.18	4.06 – 4.30
Race/Ethnicity		
Non-Hispanic White	4.07	3.96 – 4.17
Non-Hispanic Black	3.85	3.69 – 4.02
Hispanic	3.86	3.64 – 4.07
Non-Hispanic Asian	4.29	3.69 – 4.89
Non-Hispanic Other	3.62	3.20 – 4.04
Health Insurance Status		
Uninsured	3.81	3.33 – 4.29
Insured	4.02	3.93 – 4.10
Locality		
Metro ≥1 million	4.05	3.95 – 4.15
Metro 250k–1 million	3.97	3.81 – 4.14
Smaller metro / nonmetro	3.93	3.78 – 4.08

Note. Values represent survey-weighted mean chronic disease self-management (CDSM) scores with 95% confidence intervals estimated using jackknife replicate weights.

Finally, Table 32 presents survey-weighted mean scores for the HeLSI, the P-HeLSI, and the CDSM Behavior Score across the six chronic condition categories in the sample. Overall, as reported in previous tables, respondents had a mean HeLSI score of 3.42 (95% CI: 3.35–3.49) and a mean P-HeLSI score of 3.11 (95% CI: 3.04–3.17). The mean CDSM Behavior Score in this sample was 4.11 (95% CI: 4.05–4.16).

Table 32

Survey-Weighted Mean HeLSI, P-HeLSI, and CDSM Behavior Scores by Disease Type among Internet Users with Chronic Conditions (n=2,888)

Characteristic	**HeLSI**		**P-HeLSI**		**CDSM Behavior Score**	
Index Scores	**Mean**	**95% CI**	**Mean**	**95% CI**	**Mean**	**95% CI**
Overall scores	**3.42**	**3.35 – 3.49**	**3.11**	**3.04 - 3.17**	**4.11**	**4.05 - 4.16**
Diabetes	3.16	2.99 - 3.33	2.86	2.69 - 3.03	3.77	3.64 - 3.90
HighBP	3.23	3.13 - 3.32	2.94	2.86 - 3.02	3.99	3.89 - 4.09
Heart Condition	3.17	2.90 - 3.45	2.85	2.62 - 3.09	3.79	3.57 - 4.00
Lung Disease	3.21	3.05 - 3.36	2.94	2.80 - 3.09	3.69	3.51 - 3.87
Cancer	3.36	3.19 - 3.52	3.04	2.91 - 3.18	4.14	4.00 - 4.29
Number of Conditions						
1 condition	3.40	3.27 - 3.52	3.08	2.96 - 3.19	4.17	4.06 - 4.28
2 conditions	3.14	3.00 - 3.27	2.87	2.75 - 2.99	3.88	3.76 - 4.00
3 conditions	3.23	2.97 - 3.49	2.96	2.74 - 3.18	3.64	3.40 - 3.88
4 conditions	2.70	2.03 - 3.38	2.37	1.83 - 2.91	3.63	3.18 - 4.07
5 conditions	3.92	3.59 - 4.26	3.64	3.03 - 4.25	2.85	1.33 - 4.37

Note. Estimates are survey-weighted using jackknife replicate weights to account for the complex HINTS sampling design. Analyses were restricted to internet users with at least one chronic condition. HeLSI = eHealth Literacy Skill Index; P-HeLSI = Partial eHealth Literacy Skill Index; CDSM = Chronic Disease Self-Management.

Mean eHealth literacy and CDSM scores varied across disease groups, but several conditions showed a similar pattern in which lower eHealth literacy scores corresponded with lower mean CDSM behavior scores. For example, respondents with diabetes, heart conditions, and lung disease had lower mean HeLSI and P-HeLSI scores than the overall sample, and these groups also had lower mean CDSM behavior scores. In contrast, respondents with cancer had scores closer to the overall sample mean across all three measures, including the highest CDSM behavior score among the disease groups shown.

A similar descriptive pattern appeared across number of chronic conditions for respondents with one to four conditions, where lower mean HeLSI and P-HeLSI scores generally corresponded with lower CDSM behavior scores as multimorbidity increased. Respondents with one condition had the highest mean CDSM score, whereas those with two, three, or four conditions had progressively lower mean CDSM scores alongside lower eHealth literacy index scores. However, the estimates for respondents with four and especially five conditions should be interpreted cautiously given the wide confidence intervals, which suggest greater uncertainty due to smaller subgroup sizes. Notably, the group with five conditions showed the highest mean eHealth literacy scores but the lowest mean CDSM score, a pattern that may reflect instability in the estimate rather than a substantive departure from the broader trend.

After creating and analyzing the descriptive summaries of each of these scores, I then conducted two sets of regression analyses, one with the HeLSI and one with the P-HeLSI as the predictors. Then, sensitivity tests provided insights into the role of possible other variables at play. Linear regression models were utilized because both eHealth literacy and chronic disease self-management behaviors were operationalized as continuous scale scores.

4.5.3. Examining relationship between eHealth Literacy and CDSM Behaviors

To examine the unadjusted relationship between the HeLSI and the CDSM Behavior Score, I conducted hierarchical survey-weighted linear regression analyses using four separate models. First, I modeled the two main variables of interest (HeLSI and CDSM Behavior Score) against one another (Model 1). In Model 2, I added three key sociodemographic characteristics (education level, annual household income, and age range) that were most frequently associated with the different domains of eHealth literacy skills in Aim 1. Then, in Model 3, I added the remaining sociodemographic characteristics. In Model 4 ("Full model"), I added Self-Efficacy as a covariate based on its theoretical linkage to the main relationship of interest. Prior to including it in the regression analysis, per steps outlined in Chapter 3, Self-Efficacy was dichotomized to prevent overparameterization of the last model. Results from each of these steps are presented in Table 33.

Table 33

Hierarchical Linear Regression Analyses Estimating Relationship Between HeLSI and CDSM Behavior Score, with Relevant Covariates

	Model 1 – eHealth Literacy		Model 2 – Key Covariates		Model 3 – Full Demographic		Model 4 – Full with Self-Efficacy	
Variable	**B (95% CI)**	**p-value**	**B (95% CI)**	**p-value**	**B (95% CI)**	**p-value**	**B (95% CI)**	**p-value**
HeLSI	**0.15** (0.10–0.19)	**<.001*****	**0.13** (0.07–0.18)	**<.001*****	**0.13** (0.08–0.19)	**<.001*****	**0.08** (0.03–0.12)	**.003****
Education Level								
(Ref: Less than HS)								
High school graduate	--	--	**0.46** (0.42–0.87)	**.032***	**0.46** (0.03–0.89)	**.038***	**0.46** (0.02–0.91)	**.043***
Some college	--	--	**0.43** (0.01–0.84)	**.044***	0.44 (-0.00–0.88)	.051	0.45 (-0.00–0.91)	.051
College graduate	--	--	**0.60** (0.20–1.00)	**.004****	**0.60** (0.16–1.04)	**.008****	**0.61** (0.16–1.06)	**.009****
Annual Household Income								
(Ref: <$20k)								
$20k - <$35k	--	--	**0.37** (0.09–0.65)	**.010***	0.37 (0.08–0.66)	**.013***	**0.29** (0.01–0.57)	**.041***
$35k - <$50k	--	--	**0.37** (0.16–0.59)	**<.001*****	0.34 (0.12–0.56)	**.003****	**0.37** (0.15–0.58)	**<.001*****
$50k - <$75K	--	--	**0.59** (0.28–0.90)	**<.001*****	0.55 (0.25–0.86)	**<.001*****	**0.54** (0.23–0.84)	**<.001*****
$75k+	--	--	**0.58** (0.33–0.83)	**<.001*****	0.55 (0.27–0.82)	**<.001*****	**0.49** (0.21–0.76)	**<.001*****
Age Range								
(Ref: 18-34 year olds)								
35 – 49-year-olds	--	--	-0.10 (-0.49–0.29)	.614	-0.08 (-0.43–0.28)	.671	-0.08 (-0.45–0.28)	.643
50 – 64-year-olds	--	--	0.06 (-0.35–0.48)	.757	0.08 (-0.29–0.46)	.650	0.01 (-0.37–0.40)	.941
65 – 74-year-olds	--	--	0.29 (-0.08–0.64)	.118	0.31 (-0.01–0.63)	.059	0.18 (-0.16–0.52)	.289
75+ -year-olds	--	--	0.31 (-0.12–0.73)	.151	0.31 (-.08–0.71)	.120	0.22 (- 0.17–0.61)	.257
Sex Assigned at Birth								
(Ref: Female)								
Male	--	--	--	--	0.05 (-0.11–0.21)	.515	0.09 (-0.06–0.25)	.227
Race / Ethnicity								
(Ref: White)								
Black	--	--	--	--	-0.07 (-0.29–0.15)	.528	-0.06 (-0.27–0.14)	.531
Hispanic	--	--	--	--	-0.04 (-0.29–0.22)	.778	-0.05 (-0.26–0.17)	.665
Non-Hispanic Asian	--	--	--	--	0.32 (-0.32–0.96)	.317	0.43 (-0.35–1.22)	.274
Non-Hispanic Other	--	--	--	--	-0.28 (-0.73–0.18)	.224	-0.15 (-0.59–0.30)	.508
Health Insurance Status								
(Ref: Insured)								
Not insured	--	--	--	--	0.02 (-0.48–0.52)	.934	0.09 (-0.35–0.52)	.693
Locality								
(Ref: Metro, >1mill)								
Metro (250k – 1mill)	--	--	--	--	-0.15 (-0.23–0.20)	.890	-0.04 (-0.25–0.17)	.725
Nonmetro (<250k)	--	--	--	--	0.06 (-0.11–0.23)	.452	0.05 (-0.12–0.22)	.544
Self-Efficacy								
(Ref: Lower self-efficacy)								
Higher self-efficacy	--	--	--	--	--	--	**0.66** (0.49–0.84)	**<.001*****

Note. Sample sizes varied by model due to listwise deletion. Samples were: Model 1 n=2,446, Model 2 n= 2,435, Model 3 n=2,365, and Model 4 n=2,361. Significance levels: * $p < .05$, ** $p < .01$, *** $p < .001$. Fit statistics: Model 1 $R^2 = 0.03$, RMSE = 1.16; Model 2 $R^2 = 0.09$, RMSE = 1.12; Model 3 $R^2 = 0.10$, RMSE = 1.12; Model 4 $R^2 = 0.16$, RMSE = 1.08.

In Model 1, eHealth literacy skill was a statistically significant predictor of level of CDSM behaviors. Each one-unit increase in the HeLSI score was associated with a 0.15-point increase in the CDSM Behavior Score (95% CI [0.10–0.19]). This association remained significant as additional variables were added across models, although the magnitude was attenuated. The biggest drop in the relationship appeared when Self-Efficacy was added to the model (Model 4).

In Model 2, the association between eHealth literacy skill and CDSM behaviors remained significant after adjusting for education, income, and age. Compared with individuals earning less than $20,000 in annual household income, those earning $75,000 or more had, on average, CDSM Behavior Scores that were 0.58 units higher (95% CI [0.33–0.83]), after accounting for the other variables. Similarly for education, individuals who were college graduates had CDSM Behavior Scores that were 0.60 units higher than those with less than a high school degree (95% CI [0.20–1.00]), after adjustment for other variables.

Interestingly, despite individual significance with some of the eHealth literacy predictors in Aim 1, age was not statistically significantly associated with CDSMs in any of the models. However, across age categories, point estimates suggested that higher outcome scores were associated generally with higher age as compared to the lowest age group. Importantly, none of the age group comparisons reached statistical significance, and confidence intervals overlapped substantially, indicating no evidence of an independent age-related association after adjustment.

Model 3 reflected the inclusion of all seven sociodemographic variables originally selected as important conceptually informed covariates. eHealth literacy skills were still independently associated with higher levels of CDSM behaviors after adjusting for each of these variables ($B = 0.13$, 95%CI [0.08–0.19]). The results in this model were similar to those in

Model 2 where higher compared to lower levels of education and income were still significantly associated with higher levels of CDSM behaviors. None of the other sociodemographic variables were statistically significantly associated with higher levels of CDSM behaviors, although most variables reflected positive relationships. Race/ethnicity, on the other hand, reflected mostly a negative relationship suggesting that when compared to White individuals, individuals in Black, Hispanic, and Non-Hispanic Other categories had lower levels of CDSM Behavior scores. However, individuals who were Non-Hispanic Asian had higher CDSM Behavior scores as compared to White individuals in Models 3 and 4, after adjusting for the other variables. These results were not significant and therefore require additional exploration.

Finally, in the full model (isolated in Table 34), the HeLSI was statistically and independently associated with the CDSM Behavior Score after adjusting for Self-Efficacy and relevant sociodemographic characteristics. Specifically, individuals with higher eHealth literacy skills had CDSM Behavior Scores that were, on average, 0.08 units higher (95% CI [0.03–0.12]). This indicates that higher eHealth literacy skills are independently associated with greater engagement in chronic disease self-management behaviors, beyond the effects of age, education, income, and other structural factors. Higher education levels and annual household incomes from the reference category also reflected significant and positive relationships with the CDSM Behavior Score.

Table 34

Hierarchical Regression Results for the Full Model (Model 4) of HeLSI and CDSM Behavior Score, Including Self-Efficacy and Relevant Sociodemographic Characteristics

Predictor	Estimate (*B*)	SE	*t*-value	*p*-value	95% CI
eHealth Literacy					
HeLSI	**0.08**	0.02	3.13	**.003****	0.03–0.12
Sex Assigned at Birth (*ref: Female*)					
Male	0.09	0.08	1.22	.227	−0.06–0.25
Age Range (*ref: 18-34 years old*)					
35 – 49-year-olds	−0.08	0.18	−0.47	.643	−0.45–0.28
50 - 64-year-olds	0.01	0.19	0.07	.941	−0.37–0.40
65 - 74-year-olds	0.18	0.17	1.07	.289	−0.16–0.52
75+-year-olds	0.22	0.19	1.15	.257	−0.17–0.61
Education Level (*ref: Less than high school*)					
High school graduate	**0.46**	0.22	2.08	**.043***	0.02–0.91
Some college	0.45	0.23	2.00	.051	−0.00–0.91
College graduate	**0.61**	0.23	2.70	**.009****	0.16–1.06
Annual Household Income (*ref: <$20,000*)					
$20,000-34,999	**0.29**	0.14	2.09	**.041***	0.01–0.57
$35,000-49,999	**0.37**	0.11	3.46	**.001****	0.15–0.58
$50,000-74,999	**0.54**	0.15	3.50	**.001****	0.23–0.84
≥ $75,000	**0.49**	0.14	3.57	**<.001*****	0.21–0.76
Race / Ethnicity (*ref: White*)					
Black	−0.06	0.10	−0.63	.531	−0.27–0.14
Hispanic	−0.05	0.11	−0.44	.665	−0.26–0.17
Non-Hispanic Asian	0.43	0.39	1.11	.274	−0.35–1.22
Non-Hispanic Other	−0.15	0.22	−0.67	.508	−0.59–0.30
Health Insurance Status (*ref: Insured*)					
Not insured	0.09	0.22	0.40	.693	−0.35–0.52
Locality (*ref: Metro counties with > 1 million people*)					
Counties with 250,000 to 1 million	−0.04	0.10	−0.35	.725	−0.25–0.17
Counties with <250,000 people	0.05	0.09	0.61	.544	−0.12–0.22
Self-Efficacy (*ref: Lower self-efficacy*)					
Higher self-efficacy	**0.66**	0.09	7.55	**<.001*****	0.49–0.84

Note. Significance levels: **p* < .05, ** *p* < .01, *** *p* < .001.

The magnitude of the association between the HeLSI and CDSM Behavior Scores was attenuated after the inclusion of Self-Efficacy, suggesting that Self-Efficacy may partially account for the relationship between eHealth literacy and CDSM behaviors. Consistent with this interpretation, Self-Efficacy emerged as the strongest predictor in the fully adjusted model; each one-unit increase in Self-Efficacy was associated with a 0.66-unit increase in CDSM Behavior Scores (B = 0.66, 95% CI [0.49–0.84]). Although eHealth literacy remained statistically significant, its reduced magnitude following adjustment for Self-Efficacy suggests overlapping explanatory pathways linking eHealth literacy skills and chronic disease self-management behaviors. Model fit statistics further supported the final specification, with the proportion of explained variance increasing from $R^2 = 0.03$ in the unadjusted model to $R^2 = 0.16$ in the fully adjusted model.

In conclusion, Hypothesis 2 was supported across all four models, with higher levels of self-reported eHealth literacy, as measured by the HeLSI, significantly associated with higher levels of chronic disease self-management behaviors, as measured by the CDSM Behavior Score.

4.5.4. Examining Partial eHealth Literacy and CDSM Behaviors

Given the findings in Aim 2 where Scientific Literacy was the one eHealth literacy skill domain variable that was not associated with eHealth use, I wanted to understand how the operationalization of eHealth literacy in Aim 4 was impacted by Scientific Literacy. Thus, I conducted a separate survey-weighted hierarchical linear regression with a modified HeLSI that did not include Scientific Literacy called the P-HeLSI. This partial model was then estimated in each of the previously outlined models. Results from these analyses are in Table 35.

Table 35

Hierarchical Linear Regression Analyses Estimating Relationship Between P-HeLSI and CDSM Behavior Score, with Covariates

	Model 1 – eHealth Literacy		Model 2 – Key covariates		Model 3 – Full demographic		Model 4 – Full with Self-Efficacy	
Variable	**B (95% CI)**	***p*-value**	**B (95% CI)**	***p*-value**	**B (95% CI)**	***p*-value**	**B (95% CI)**	***p*-value**
P-HeLSI	**0.17** (0.11–0.22)	**<.001*** **	**0.15** (0.08–0.21)	**<.001*** **	**0.15** (0.09–0.22)	**<.001*** **	**0.09** (0.04–0.15)	**.002** **
Education Level *(Ref: Less than HS)*								
High school graduate	--	--	**0.45** (0.05–0.85)	**.030***	**0.45** (0.03–0.87)	**.035***	**0.46** (0.03–0.89)	**.037***
Some college	--	--	**0.41** (0.02–0.81)	**.042***	**0.43** (0.01–0.85)	**.047***	**0.45** (0.01–0.89)	**.047***
College graduate	--	--	**0.59** (0.21–0.98)	**.003** **	**0.60** (0.18–1.01)	**.006** **	**0.60** (0.17–1.04)	**.008** **
Annual Household Income *(Ref: <$20k)*								
$20k - <$35k	--	--	**0.38** (0.10–0.65)	**.009** **	**0.37** (0.09–0.66)	**.012***	**0.29** (0.01–0.57)	**.041***
$35k - <$50k	--	--	**0.37** (0.15–0.59)	**.001** **	**0.33** (0.11–0.56)	**.005** **	**0.36** (0.14–0.57)	**.002** **
$50k - <$75K	--	--	**0.57** (0.26–0.88)	**<.001*** **	**0.53** (0.23–0.83)	**<.001*** **	**0.51** (0.21–0.82)	**.001** **
$75k+	--	--	**0.57** (0.32–0.82)	**<.001*** **	**0.54** (0.26–0.81)	**<.001*** **	**0.47** (0.20–0.75)	**.001** **
Age Range *(Ref: 18–34-year-olds)*								
35 – 49-year-olds	--	--	-0.11 (-0.50–0.29)	.585	-0.08 (-0.45–0.28)	.643	-0.09 (-0.45–0.27)	.615
50 – 64-year-olds	--	--	0.06 (-0.35–0.47)	.760	0.08 (-0.28–0.45)	.647	0.02 (-0.37–0.40)	.930
65 – 74-year-olds	--	--	0.30 (-0.07–0.66)	.107	0.32 (-0.00–0.64)	.052	0.19 (-0.15–0.53)	.263
75+ -year-olds	--	--	0.32 (-0.10–0.74)	.137	0.32 (-0.07–0.72)	.108	0.23 (-0.16–0.62)	.236
Sex Assigned at Birth *(Ref: Female)*								
Male	--	--	--	--	0.06 (-0.10–0.22)	.490	0.10 (-0.06–0.25)	.209
Race / Ethnicity *(Ref: White)*								
Black	--	--	--	--	-0.09 (-0.30–0.13)	.421	-0.09 (-0.29–0.12)	.400
Hispanic	--	--	--	--	-0.05 (-0.30–0.21)	.723	-0.05 (-0.27–0.16)	.627
Non-Hispanic Asian	--	--	--	--	0.31 (-0.31–0.93)	.324	0.43 (-0.35–1.21)	.275
Non-Hispanic Other	--	--	--	--	-0.29 (-0.74–0.17)	.212	-0.16 (-0.60–0.29)	.488
Health Insurance Status *(Ref: Insured)*								
Not insured	--	--	--	--	0.03 (-0.48–0.54)	.908	0.09 (-0.34–0.53)	.670
Locality *(Ref: Metro, >1mill)*								
Metro (250k – 1mill)	--	--	--	--	-0.02 (-0.24–0.19)	.840	-0.04 (-0.25–0.16)	.673
Nonmetro (<250k)	--	--	--	--	0.06 (-0.11–0.23)	.460	0.05 (-0.12–0.22)	.536
Self-Efficacy *(Ref: Lower self-efficacy)*								
Higher self-efficacy	--	--	--	--	--	--	**0.66** (0.48–0.84)	**<.001*** **

Note. Model sample sizes varied due to listwise deletion. Sample sizes were: Model 1 n= 2,454, Model 2 n= 2,443, Model 3 n= 2,372, Model 4 n= 2,368. Significance levels: * $p < .05$, ** $p < .01$, *** $p < .001$. Fit Statistics Model 1 $R^2 = 0.03$, RMSE = 1.16; Model 2 $R^2 = 0.09$, RMSE = 1.12; Model 3 $R^2 = 0.10$, RMSE = 1.19; Model 4 $R^2 = 0.17$, RMSE = 1.08.

Across all four models, the P-HeLSI remained a statistically significant predictor of higher CDSM Behavior Scores. Compared with the original analysis, modest improvements in effect size were observed when Scientific Literacy was excluded from the composite. For example, in the unadjusted model (Model 1), a one-unit increase in the P-HeLSI was associated with a 0.17-unit increase in CDSM Behavior Scores, compared with a 0.15-unit increase observed in the corresponding model from the original analysis.

Coefficients and significance levels for sociodemographic characteristics in Models 2 and 3, including education and income, showed minimal changes, and the association between Self-Efficacy and CDSM behaviors in the fully adjusted model remained virtually identical. These findings suggest that excluding Scientific Literacy from the composite index did not materially alter the relationship between eHealth literacy and chronic disease self-management behaviors. Instead, the stability, and slight strengthening, of the association indicates that Scientific Literacy, as operationalized in this study, contributed less to the overall explanatory power of the HeLSI, without meaningfully influencing the relationship of interest either with or without adjustment for Self-Efficacy.

This supplementary analysis supported the robustness of the HeLSI and suggested that the observed associations were not driven by any single literacy domain.

Next, in the final tests in Aim 4, sensitivity analyses were conducted to explore the role of multimorbidity in the relationship of interest, potential variation in the Lily model eHealth literacy groupings, and the potential effects of complete case analysis on the overall results.

4.5.5. Sensitivity Analysis: The Role of Multimorbidity, Analytic and Context-Specific eHealth Literacy, and Missingness due to Complete Case Analysis

Three sensitivity analyses were conducted using the full survey-weighted linear regression models from Section 4.5.3. and 4.5.4. The first analysis explored the role of multimorbidity in the relationship between eHealth literacy and CDSM behaviors. The second analysis was a conceptual exploration of eHealth literacy as two sub-scales representing analytic and context-specific eHealth literacy. The third analysis consisted of a robustness check to determine how missingness impacted the final relationship.

Assessing the possible impact of multimorbidity on the relationship between HeLSI and CDSM Behavior Score

Findings from Aim 3 suggested that multimorbidity functioned as a potential confounder in some domain-specific models. Accordingly, multimorbidity was introduced as a covariate in this Aim 4 additional analysis to evaluate its impact within models examining overall eHealth literacy and composite CDSM behaviors. In the fully adjusted model with Self-Efficacy (Table 36), having multiple chronic conditions was independently associated with <u>lower</u> CDSM behavior scores (B = -0.29, 95% CI [-0.48 to -0.11]). Inclusion of this variable, however, did not meaningfully alter the association between eHealth literacy and self-management behaviors although it attenuated it very slightly (B = 0.07, 95% CI [0.02–0.12)]. The inclusion of multimorbidity slightly improved model fit ($R^2 = 0.18$ vs. $R^2 = 0.16$) but did not meaningfully alter the relationship between eHealth literacy, Self-Efficacy, and CDSM behaviors. This indicates that while disease burden may negatively impact capacity, it does not meaningfully confound the observed relationship between overall eHealth literacy and CDSM.

Table 36

Hierarchical Regression Results for the Full Model (Model 4) of H6 eHealth Literacy Index and CDSM Behavior Score, Including Self-Efficacy, Relevant Sociodemographic Characteristics, and Multimorbidity

Predictor	Estimate (*B*)	SE	*t*-value	*p*-value	95% CI
eHealth Literacy					
H6 eHealth Literacy Index	**0.07**	0.025	2.94	**.005****	0.02–0.12
Sex Assigned at Birth (*ref: Female*)					
Male	0.10	0.08	1.31	.198	-0.05–0.25
Age Range (*ref: 18-34 years old*)					
35 – 49-years-old	-0.06	0.17	-0.35	.725	-0.40–0.28
50 - 64-years-old	0.08	0.18	0.42	.675	-0.29–0.45
65 - 74-years-old	0.28	0.16	1.79	.079	-0.04– 0.60
75+-years-old	0.34	0.18	1.91	.063	-0.02– 0.70
Education Level (*ref: Less than high school*)					
High school graduate	**0.41**	0.20	2.07	**.044***	0.01–0.81
Some college	**0.41**	0.20	2.07	**.044***	0.01–0.81
College graduate	**0.55**	0.20	2.79	**.008****	0.15–0.95
Annual Household Income (*ref: <$20,000*)					
$20,000-34,999	0.23	0.14	1.67	.101	-0.05–0.52
$35,000-49,999	**0.33**	0.10	3.28	**.002****	0.13–0.53
$50,000-74,999	**0.47**	0.14	3.32	**.002****	0.19–0.76
≥ $75,000	**0.41**	0.13	3.12	**.003****	0.15–0.67
Race / Ethnicity (*ref: White*)					
Black	-0.05	0.10	-0.46	.648	-0.25–0.16
Hispanic	-0.03	0.11	-0.32	.749	-0.25–0.18
Non-Hispanic Asian	0.42	0.36	1.17	.246	-0.30–1.15
Non-Hispanic Other	-0.12	0.22	-0.53	.599	-0.57–0.33
Health Insurance Status (*ref: Insured*)					
Not insured	0.03	0.23	0.14	.889	-0.42–0.49
Locality (*ref: Metro counties with > 1 million)*					
Counties with 250,000 to 1 million	-0.05	0.11	-0.46	.650	-0.26–0.16
Counties with <250,000 people	0.06	0.08	0.72	.473	-0.11–0.23
Self-Efficacy (*ref: Lower self-efficacy*)					
Higher self-efficacy	**0.64**	0.09	7.19	**<.001*****	0.46–0.81
Multiple Conditions *(ref: No)*					
Yes	**-0.29**	0.09	-3.16	**.003****	-0.48 to -0.11

Note. Multiple conditions is the variable representing multimorbidity. Significance levels: * $p < .05$, ** $p < .01$, *** $p < .001$. Sample n=2,361. R^2 =0.18, RMSE = 1.07.

Exploring the impact of alternative eHealth literacy groupings on the relationship between eHealth literacy and CDSM behaviors

Conceptually, Norman & Skinner have previously grouped the six domains of eHealth literacy into two clusters in the Lily model: analytic eHealth literacy and context-specific eHealth literacy. Analytic eHealth literacy variables include Basic, Information, and Media literacies. Context-specific eHealth literacy variables include Computer, Scientific, and Health literacies. Findings from Aim 2 and 3 suggested that there were some differences between eHealth literacy domains and across CDSM behaviors. This sensitivity test was designed to assess if a stronger model of the association between aspects of eHealth literacy and CDSM behaviors would result if they were separated. Each set of variables were summed into a score 0-3 for the Context-Specific eHealth Literacy and Analytic eHealth Literacy variables. These were then run in a direct model with the composite CDSM Behavior Score followed by similar subsequent models as the original index. Results are in Table 37 and Table 38.

Table 37

Hierarchical regression results examining the relationship between Context-specific eHealth literacy Index and CDSM Behavior Score, with covariates

	Model 1 – eHealth Literacy		**Model 2 – Key covariates**		**Model 3 – Full demographic**		**Model 4 – Context-Specific eHL & Self-Efficacy**	
Variable	**B (95% CI)**	**p-value**	**B (95% CI)**	**p-value**	**B (95% CI)**	**p-value**	**B (95% CI)**	**p-value**
Context-specific eHealth Literacy index (Computer, Scientific, & Health Literacies)	**0.21** (0.11 – 0.30)	**<.001*** **	**0.16** (0.06–0.26)	**.003** **	**0.16** (0.06 – 0.26)	**.002** **	0.09 (-0.01 – 0.18)	.071
Education *(Ref: Less than HS)*								
High school graduate	--	--	**0.45** (0.01 – 0.89)	**.045***	0.45 (-0.02–0.92)	.059	0.46 (-0.00–0.92)	.052
Some college	--	--	0.41 (-0.02 – 0.83)	.064	0.42 (-0.06–0.89)	.082	0.44 (-0.04–0.92)	.069
College graduate	--	--	**0.62** (0.20 – 1.05)	**.005** **	**0.62** (0.15–1.08)	**.010***	**0.61** (0.14–1.08)	**.012***
Annual Household Income *(Ref: <$20k)*								
$20k - <$35k	--	--	**0.37** (0.08–0.66)	**.013***	**0.37** (0.05–0.69)	**.025***	0.30 (-0.01–0.60)	.054
$35k - <$50k	--	--	**0.38** (0.17–0.59)	**.001** **	**0.35** (0.13–0.57)	**.003** **	**0.37** (0.16–0.58)	**.001** **
$50k - <$75K	--	--	**0.61** (0.31–0.91)	**.001** **	**0.59** (0.29–0.90)	**.001** **	**0.56** (0.26–0.87)	**.001** **
$75k+	--	--	**0.60** (0.34–0.86)	**<.001*** **	**0.57** (0.28–0.85)	**.001** **	**0.50** (0.22–0.78)	**.001** **
Age Range *(Ref: 18-34 year olds)*								
35–49-year-olds	--	--	-0.08 (-0.46–0.31)	.692	-0.06 (-0.42–0.29)	.713	-0.08 (-0.43–0.28)	.667
50–64 -year-olds	--	--	0.06 (-0.34–0.47)	.756	0.07 (-0.29–0.44)	.687	0.01 (-0.38–0.39)	.974
65–74 -year-olds	--	--	0.28 (-0.08–0.63)	.122	0.28 (-0.04–0.60)	.088	0.16 (-0.18–0.49)	.345
75+ year-olds	--	--	0.23 (-0.16–0.63)	.245	0.25 (-0.13–0.63)	.189	0.18 (-0.20–0.56)	.333
Sex Assigned at Birth *(Ref: Female)*								
Male	--	--	--	--	0.05 (-0.11–0.22)	.537	0.09 (-0.06–0.25)	.234
Race / Ethnicity *(Ref: White)*								
Black	--	--	--	--	-0.07 (-0.29–0.14)	.500	-0.07 (-0.28–0.13)	.475
Hispanic	--	--	--	--	-0.06 (-0.33–0.20)	.621	-0.07 (-0.28–0.15)	.538
Non-Hispanic Asian	--	--	--	--	0.24 (-0.34–0.83)	.406	0.40 (-0.36–1.16)	.300
Non-Hispanic Other	--	--	--	--	-0.24 (-0.65–0.17)	.248	-0.12 (-0.54–0.30)	.563
Health Insurance Status *(Ref: Insured)*								
Not insured	--	--	--	--	-0.01 (-0.54–0.51)	.960	0.07 (-0.36–0.51)	.746
Locality *(Ref: Metro, >1million)*								
Metro (250k – 1mill)	--	--	--	--	-0.02 (-0.23–0.19)	.839	-0.04 (-0.24–0.16)	.688
Nonmetro (<250k)	--	--	--	--	0.02 (-0.15–0.18)	.857	0.02 (-0.15–0.19)	.821
Self-Efficacy *(Ref: Lower self-efficacy)*								
Higher self-efficacy	--	--	--	--	--	--	**0.70** (0.53–0.87)	**<.001*** **

Note. $p < .05$, ** $p < .01$, *** $p < .001$. Sample sizes varied by model due to listwise deletion. Model fit statistics for Model 1: N=2,525, $R^2 = 0.02$, RMSE = 1.17, Model F = 18.82, p<.001; Model 2: N=2,512, $R^2 = 0.09$, RMSE = 1.13, Model F = 14.13, p<.001; Model 3: N=2,433, $R^2 = 0.09$, RMSE = 1.13, Model F = 9.26, p<.001; Model 4: N=2,428, $R^2 = 0.17$, RMSE = 1.08, Model F = 15.89, p<.001. eHL = eHealth Literacy.

Results in Table 37 show that when Computer, Scientific, and Health Literacies are combined into a composite score—Context-Specific eHealth Literacy Index—and estimated as the independent variable in the full model, this score is statistically significantly associated with CDSM behaviors. For each one unit increase in this Context-Specific eHealth Literacy Index, CDSM Behavior Scores increase from 0.21 units in the unadjusted model to 0.16 units in the full demographic model, reflecting a drop (Model 3). However, once Self-Efficacy is entered into the last model (Model 4), it reduces the Context-Specific eHealth Literacy Index coefficient by half, and it is no longer significantly associated with CDSM Behavior Scores on its own. The coefficient in Model 4 for Context-Specific eHealth Literacy is somewhat higher than that in Table 34 with the full HeLSI index (0.09 compared to 0.08), although it falls out of significance in this version.

Like in other analyses (Table 33 & 35), for the most part, increasing income and education levels remained positively, significantly, and independently associated with CDSMs in these models, after controlling for the other variables in each model. All other variables reflected similar patterns to the full HeLSI models, with some changes to the number of negatively associated categories with the relationship of interest.

Results for the Analytic eHealth Literacy Index followed a similar pattern, although these results indicate a more stable relationship across the models than the Context-Specific index (Table 38). Analytic eHealth Literacy (Basic, Information, and Media Literacies) is a significant independent predictor of CDSM Behavior Scores across all four models, although it is largely attenuated in Model 4 once Self-Efficacy is added. For each one unit increase in the Analytic eHealth Literacy Index, CDSM Behavior Scores increase from 0.09 to 0.17 units, based on the different models. Unsurprisingly, patterns of significant and positive independent relationships across the education levels and income levels remained significant in this analysis as they did in the main, full HeLSI analysis and Context-Specific index, reinforcing the importance of these individual factors on CDSMs, generally. Furthermore, Self-Efficacy remained an important and even stronger predictor of CDSM Behavior Score levels than the Analytic eHealth Literacy Index, which aligns with earlier findings ($B = 0.67$, 95% CI [0.49–0.85]).

These two separate analyses reflecting a conceptual subgrouping aligned with the underlying components of the eHealth Literacy Lily model showed that as subscales, these two subgroupings were moderately successful predictors of CDSM behaviors. While the Context-Specific eHealth Literacy Index was stronger in the first model than the Analytic eHealth Literacy Index, the second Index managed to remain more significant as more covariates were added. This suggests that the variables making up the Analytic Index might be contributing more to the full HeLSI than the variables making up the Context-Specific Index. The differences across models between the Analytic Index and the full H6 Index are slight, suggesting that the full HeLSI, as a comprehensive, multidimensional index, is still a strong predictor of CDSM behaviors and can be retained to capture even more dimensions of eHealth literacy successfully.

Table 38

Hierarchical regression results examining the relationship between Analytic eHealth literacy Index and CDSM Behavior Score, with covariates

	Model 1 – eHealth Literacy		**Model 2 – Key covariates**		**Model 3 – Full demographic**		**Model 4 – Analytic eHL & Self-Efficacy**	
Variable	**B (95% CI)**	**p-value**	**B (95% CI)**	**p-value**	**B (95% CI)**	**p-value**	**B (95% CI)**	**p-value**
Analytic eHealth Literacy index (Basic, Information, & Media Literacies)	**0.17** (0.09–0.25)	**<.001*****	**0.15** (0.07–0.24)	**.001****	**0.16** (0.08–0.25)	**.001****	**0.09** (0.02–0.16)	**.019***
Education Level *(Ref: Less than HS)*								
High school graduate	--	--	**0.42** (0.03–0.82)	**.037***	**0.43** (0.02–0.85)	**.042***	**0.45** (0.03–0.87)	**.037***
Some college	--	--	**0.42** (0.03–0.81)	**.034***	**0.44** (0.02–0.85)	**.039***	**0.45** (0.02–0.88)	**.039***
College graduate	--	--	**0.62** (0.24–0.99)	**.002****	**0.62** (0.21–1.02)	**.004****	**0.62** (0.20–1.04)	**.004****
Annual Household Income *(Ref: <$20k)*								
$20k - <$35k	--	--	**0.38** (0.12–0.64)	**.006****	**0.38** (0.10–0.65)	**.008****	**0.29** (0.02–0.56)	**.034***
$35k - <$50k	--	--	**0.40** (0.19–0.62)	**.001****	**0.37** (0.14–0.59)	**.002****	**0.38** (0.17–0.59)	**.001****
$50k - <$75K	--	--	**0.60** (0.29–0.90)	**.001****	**0.56** (0.26–0.86)	**.001****	**0.53** (0.23–0.83)	**.001****
$75k+	--	--	**0.60** (0.36–0.85)	**<.001*****	**0.57** (0.31–0.83)	**<.001*****	**0.49** (0.23–0.76)	**.001****
Age Ranges *(Ref: 18–34-year-olds)*								
35–49-year-olds	--	--	-0.12 (-0.53–0.28)	.536	-0.10 (-0.47–0.27)	.597	-0.10 (-0.47–0.27)	.591
50–64 -year-olds	--	--	0.05 (-0.37–0.47)	.819	0.08 (-0.30–0.45)	.687	0.01 (-0.38–0.40)	.961
65–74 -year-olds	--	--	0.25 (-0.11–0.62)	.173	0.28 (-0.04–0.61)	.087	0.17 (-0.17–0.51)	.333
75+ year-olds	--	--	0.28 (-0.15–0.72)	.201	0.30 (-0.11–0.70)	.147	0.21 (-0.19–0.60)	.296
Sex Assigned at Birth *(Ref: Female)*								
Male	--	--	--	--	0.05 (-0.11–0.21)	.527	0.10 (-0.06–0.25)	.215
Race / Ethnicity *(Ref: White)*								
Black	--	--	--	--	-0.06 (-0.27–0.15)	.572	-0.07 (-0.27–0.14)	.508
Hispanic	--	--	--	--	-0.04 (-0.29–0.21)	.749	-0.05 (-0.27–0.17)	.643
Non-Hispanic Asian	--	--	--	--	0.32 (-0.33–0.98)	.327	0.44 (-0.36–1.23)	.276
Non-Hispanic Other	--	--	--	--	-0.27 (-0.75–0.20)	.258	-0.14 (-0.60–0.32)	.539
Health Insurance Status *(Ref: Insured)*								
Not insured	--	--	--	--	0.03 (-0.48–0.54)	.891	0.10 (-0.34–0.54)	.665
Locality *(Ref: Metro, >1million)*								
Metro (250k – 1mill)	--	--	--	--	-0.04 (-0.26–0.17)	.676	-0.06 (-0.26–0.15)	.570
Nonmetro (<250k)	--	--	--	--	0.04 (-0.13–0.21)	.661	0.04 (-0.13–0.21)	.674
Self-Efficacy *(Ref: Lower self-efficacy)*								
Higher self-efficacy	--	--	--	--	--	--	**0.67** (0.49–0.85)	**<.001*****

Note. $p < .05$, ** $p < .01$, *** $p < .001$. Sample sizes varied by model due to listwise deletion. Model fit statistics for Model 1: N=2,470, $R^2 = 0.02$, RMSE = 1.17, Model F = 19.62, p<.001; Model 2: N=2,458, $R^2 = 0.08$, RMSE = 1.13, Model F = 11.41, p<.001 ; Model 3: N=2,387, $R^2 = 0.09$, RMSE = 1.12, Model F = 7.07, p<.001; Model 4: N=2,383, $R^2 = 0.16$, RMSE = 1.08, Model F = 13.18, p<.001. eHL = eHealth literacy.

Sensitivity analysis assessing the impact of complete-case analysis on relationships of interest

As a final sensitivity analysis and to ensure the findings in Aim 4 were not biased by higher rates of missing data in some categories of select variables due to listwise deletion, I conducted a robustness analysis. Missing data analyses showed that while missingness within categories varied between 0 – 15% for most variables, some categories were disproportionately missing data at rates closer to 30% (Table 39). This meant that individuals in these categories had missing data for one or more of the ten variables in the model.

Table 39

Complete Case Analysis Robustness Check Assessing Rates of Missingness Across Relevant Aim 4 Variables

Variable (Categories)	**Complete Cases (%)**	**Missing Cases (%)**	**Total in Category (%)**	**Within Category % Missing**
CDSM Scores				
0 behaviors	0.10	0.00	0.10	0.00%
1 behaviors	1.60	0.10	1.70	5.88%
2 behaviors	8.20	0.90	9.10	9.89%
3 behaviors	21.40	1.10	22.50	4.89%
4 behaviors	28.70	1.30	30.00	4.33%
5 behaviors	25.30	2.00	27.30	7.33%
6 behaviors	8.90	0.60	9.50	6.32%
HeLSI Scores				
0 skills	1.20	0.10	1.30	7.69%
1 skills	7.00	0.80	7.80	10.26%
2 skills	18.80	1.90	20.70	9.18%
3 skills	23.10	2.20	25.30	8.70%
4 skills	23.90	2.90	26.80	10.82%
5 skills	12.00	1.30	13.30	9.77%
6 skills	4.50	0.50	5.00	10.00%
Sex Assigned at Birth				
Male	43.34	5.02	48.36	10.38%
Female	43.50	8.14	51.64	15.75%
Age Range				
18 – 34-year-olds	11.50	0.66	12.16	5.43%
35 - 49-year-olds	20.41	2.89	23.30	12.41%
50 - 64-year-olds	29.88	4.30	34.18	12.59%
65 - 74-year-olds	15.64	3.36	19.00	17.70%
75+-year-olds	7.93	3.42	11.36	30.13%
Race / Ethnicity				
White	59.77	5.76	65.53	8.79%
Black	10.01	2.07	12.07	17.11%
Hispanic	10.90	2.15	13.05	16.45%
Non-Hispanic Asian	4.27	0.27	4.53	5.88%
Non-Hispanic Other	4.28	0.53	4.81	10.98%
Education Level				
Less than HS	3.92	0.64	4.56	13.95%
HS graduate	15.65	2.61	18.26	14.28%
Some college	38.59	6.30	44.89	14.03%
College graduate	28.59	3.70	32.30	11.47%
Income				
<$20,000	9.87	3.99	13.87	28.80%
$20,000-34,999	9.20	2.16	11.36	19.00%
$35,000-49,999	9.73	2.79	12.52	22.27%
$50,000-74,999	15.58	1.94	17.51	11.06%
≥ $75,000	40.36	4.38	44.75	9.80%
Locality				
Metro - 1million+	46.25	8.50	54.75	15.52%
Metro - 250,000-1mill	20.04	3.48	23.52	14.78%
Nonmetro- < 250,000	18.37	3.37	21.73	15.49%
Health Insurance Status				
Not insured	5.47	0.92	6.39	14.41%
Insured	79.50	14.11	93.61	15.07%
Self-Efficacy (Binary)				
Lower	31.02	4.37	35.40	12.36%
Higher	53.75	10.86	64.60	16.81%

Note. Percentages are weighted using survey sampling weights and estimated using domain analysis with jackknife replicate weights. Complete cases were defined as respondents with non-missing values for all variables included in the fully adjusted Aim 4 model. Analyses were restricted to internet-using adults with chronic conditions. 1mill: 1 million population

Respondents who fell into the 75+ years-old category and the earning <$20,000 in annual income category reflected missing data with missingness at rates of 30.13% and 28.80%, respectively. I therefore re-ran the survey-weighted linear regression model (Model 4) after excluding respondents in the 75+ age category and the <$20,000 income category, restricting the analysis to 1,755 individuals with complete data, to assess whether the primary associations observed in Model 4 were sensitive to this differential missingness.

Despite the exclusion of categories with high missingness and the adjustment of reference categories for analytic purposes, the predictors of CDSM behaviors remained materially unchanged (Table 40). eHealth Literacy maintained a stable, positive association with self-management behaviors (B = 0.07, 95% CI [0.02–0.13]), while Self-Efficacy was once again the strongest predictor (B = -0.63, 95% CI [-0.82 to -0.44]). Because the reference category for Self-Efficacy was reversed in this sensitivity analysis, the negative coefficient reflects lower self-efficacy being associated with fewer self-management behaviors, holding other variables constant. Estimates for income and education were no longer significant for the most part; the negative coefficients reflect the switch in reference categories. However, the lowest education was substantially associated with lower levels of CDSMs behaviors (B = -0.76, 95% CI [-1.33 to -0.20]), which aligns with findings in previous models. The loss of significance in some variables is likely due to a loss of power due to the restricted sample size.

In conclusion, the consistency of results across the primary and restricted-sample models substantially mitigates concerns regarding bias due to differential nonresponse. Together, these findings suggest that the observed association between eHealth literacy and chronic disease self-management behaviors is robust and is unlikely to be driven by patterns of missing data.

Table 40

Hierarchical regression sensitivity analysis results examining main relationship of interest while controlling for high rates of missingness in select Income and Age variable categories (n=1,755).

Predictor	Estimate (*B*)	SE	*t*-value	*p*-value	95% CI
eHealth Literacy					
HeLSI	**0.07**	0.03	2.65	**.011****	0.02–0.13
Education Level					
Less than HS	**-0.76**	0.28	-2.74	**.009****	-1.33 to -0.20
High school graduate	-0.12	0.16	-0.76	.448	-0.44–0.20
Some college	-0.13	0.09	-1.52	.134	-0.31–0.04
College graduate (ref)					
Income					
<$20,000 removed	xxx	xxx	xxx	xxx	xxx
$20,000-34,999	-0.22	0.14	-1.62	.112	-0.50–0.05
$35,000-49,999	-0.14	0.12	-1.19	.238	-0.38–0.10
$50,000-74,999	0.06	0.15	0.36	.718	-0.25–0.36
≥ $75,000 (ref)	-	-	-	-	-
Age Range					
18-34	-0.03	0.20	-0.13	.895	-0.43–0.38
35 - 49	-0.03	0.10	-0.25	.802	-0.22–0.17
50 – 64 (ref)	-	-	-	-	-
65 - 74	**0.21**	0.10	2.05	**.045***	0.01–0.41
75+ removed	xxx	xxx	xxx	xxx	xxx
Sex Assigned at Birth					
Male (ref)[a]					
Female	-0.12	0.08	-1.50	.139	-0.28–0.04
Race / Ethnicity					
White (ref)	-	-	-	-	-
Black	-0.06	0.12	-0.48	.636	-0.29–0.18
Hispanic	-0.12	0.14	-0.89	.379	-0.39–0.15
Non-Hispanic Asian	0.49	0.40	1.23	.224	-0.31–1.30
Non-Hispanic Other	-0.38	0.23	-1.63	.110	-0.84–0.09
Health Insurance Status					
Insured (ref)	-	-	-	-	-
Not insured	0.02	0.23	0.06	.949	-0.46–0.49
Locality					
Metro counties with > 1 million (ref)	-	-	-	-	-
Counties with 250,000 to 1 million	-0.06	0.12	-0.53	.599	-0.31–0.18
Counties with <250,000 people	0.02	0.10	0.22	.823	-0.17–0.22
Self-Efficacy					
Lower self-efficacy	**-0.63**	0.10	-6.59	**<.001*****	-0.82 to -0.44
Higher self-efficacy (ref)	-	-	-	-	-

Note. $p < .05$, ** $p < .01$, *** $p < .001$. Analysis was restricted to the sensitivity domain ($n = 1{,}755$) excluding categories with missingness rates > 25% (Age 75+ and Income <$20,000). To ensure model stability within this restricted subsample, reference categories for certain demographic variables were adjusted to the most frequent or stable category (e.g., Higher Self-Efficacy, College Graduate, and Income ≥ $75,000). While these adjustments invert the direction of certain coefficients compared to Table 27, the magnitude, significance, and relative relationships between variables remain materially unchanged. Model fit statistics: N=1,755, $R^2 = 0.14$, RMSE = 1.08, Model F = 9.37, p<.001
[a] Due to analytic shifting, male became the reference category.

4.5.6. Aim 4 Summary

Aim 4 analyses yielded several important and nuanced findings regarding the relationship between eHealth literacy, Self-Efficacy, and chronic disease self-management behaviors. Consistent with Hypothesis 2, higher levels of self-reported eHealth literacy were significantly associated with higher levels of self-management behaviors in multivariable models. Higher HeLSI scores reflected increases in CDSM Behavior Scores. Although the inclusion of Self-Efficacy attenuated this association, eHealth literacy remained a significant predictor in fully adjusted models. Together, these results suggest that eHealth literacy and Self-Efficacy are independently and positively associated with chronic disease self-management behaviors.

When eHealth literacy was modeled as a composite index, its association with chronic disease self-management behaviors was stronger and more consistent than when individual eHealth literacy domains were entered separately. In the models in Aim 3 in which individual eHealth literacy domains were entered simultaneously, results showed that most individual domains were not independently associated with individual self-management behaviors. In contrast, the composite HeLSI in Aim 4 demonstrated a robust association across chronic disease self-management outcomes, particularly when examining both eHealth Literacy and CDSM behaviors as multidimensional constructs.

Sensitivity tests in Aim 4 contributed to a deeper understanding of the contextualized relationship between eHealth literacy and CDSM behaviors. In the first test, inclusion of multimorbidity as a covariate in the full regression model (modeling the role of self-efficacy on the relationship of interest) confirmed that greater disease burden was independently associated with lower chronic disease self-management behavior scores; however, adjustment for multimorbidity did not materially alter the association between overall eHealth literacy and self-management behaviors, indicating that this relationship was robust to variation in chronic condition burden.

In the second sensitivity test, conceptually-grouped eHealth literacy indices demonstrated that both Context-Specific and Analytic eHealth Literacy were associated with chronic disease self-management behaviors, though their stability differed across models. The Analytic eHealth Literacy Index remained significantly associated with self-management behaviors after adjustment for Self-Efficacy, whereas the Context-Specific index was substantially attenuated and no longer independently associated once Self-Efficacy was included. These findings support retention of the full HeLSI as a stable, multidimensional predictor of self-management behaviors.

Finally, although systematic missingness was observed among older and lower-income respondents, sensitivity analyses using domain-based models indicated that the primary associations between eHealth literacy, self-efficacy, and self-management behaviors were not substantially different. These findings suggest that the observed relationships were stable across analytic specifications and were not driven by demographic patterns of nonresponse.

4.6. Chapter 4 Summary

This chapter presented the results from analyses addressing each of the four study aims examining the general patterns of eHealth literacy skills, eHealth use, and chronic disease self-management behaviors, as well as the patterns across sociodemographic groups among adult internet users with chronic conditions in the U.S. Analyses across aims demonstrated consistent patterns in the presence of eHealth literacy in the target population, the significant association with criterion variables, and the significant and multidimensional relationship with the outcomes of interest.

Multivariable regression analyses indicated that eHealth literacy was significantly associated with chronic disease self-management behaviors, with effect estimates remaining stable after adjustment for sociodemographic covariates and self-efficacy. Self-Efficacy was also independently associated with self-management outcomes. Inclusion of Self-Efficacy attenuated, but did not eliminate, the association between eHealth literacy and self-management behaviors. Findings across aims further showed that selected sociodemographic characteristics were associated with variation in both eHealth literacy and self-management behaviors, while patterns of missingness and sensitivity analyses did not significantly change the primary results.

Collectively, these results provide an empirical foundation for interpreting the relationships among eHealth literacy, Self-Efficacy, and chronic disease self-management using H6 data. Chapter 5 situates these findings within the existing literature, discusses their implications for public health practice and research, and considers study limitations and directions for future work.

Chapter 5. Discussion

Individuals who live with some of the most common and debilitating chronic conditions typically need to engage in regular self-management activities throughout a given day. In an increasingly eHealth-centric healthcare environment, individuals are often required to employ different technologies to manage their chronic conditions and interact with their healthcare teams. Increasingly, those living with chronic conditions need to develop and utilize eHealth literacy skills to successfully navigate an information-rich, dynamic, and complex eHealth environment. In light of advances made in the provision of eHealth tools for disease management during and following the COVID-19 pandemic, there is a need to understand how eHealth literacy skills relate to specific chronic disease self-management (CDSM) behaviors of individuals living with chronic conditions in the U.S. to better design patient-focused education and services.

This dissertation used nationally representative data to examine patterns of behaviors approximating eHealth literacy skills among U.S. adults living with five common chronic conditions, and to evaluate how these skills related to CDSM behaviors. This dissertation employed a systematic approach to identifying variables approximating the six domains of the Norman & Skinner eHealth Literacy Lily model, evaluating their validity and cohesiveness, and examining their associations with common CDSM behaviors, thereby addressing the study's aims and hypotheses. In doing so, this study answered the main research question: *What is the association between level of eHealth literacy skill with specific chronic disease self-management behaviors among U.S. adults with a chronic disease?* The findings also address a gap in the literature concerning how multidimensional eHealth literacy-related skills are associated with real-world self-management behaviors in a population-based sample.

Chapter 5 interprets the findings from this research study in the context of existing theory and empirical literature, discusses implications for eHealth literacy measurement and chronic disease self-management, and identifies strengths and limitations of this work and directions for future research.

5.1. Study Findings by Aim

In this dissertation research study, I sought to explore if the multidimensional concept of eHealth literacy could be measured using the HINTS Cycle 6 (H6) data. Additionally, I sought to determine if these skills were significantly associated with some of the most commonly recommended CDSM behaviors that were also measured using the H6 data. In this study, eHealth literacy was defined as: *A multidimensional set of skills that can be measured at different levels and that represent successful engagement in eHealth behaviors associated with basic literacy, computer literacy, scientific literacy, information literacy, health literacy, and media literacy.*

Results across the four aims of this dissertation study showed that eHealth literacy is a multidimensional concept that is mostly captured using variables present in H6. Some of these eHealth literacy skills were individually associated with some CDSM behaviors while others were not. Collectively, based on how these concepts were operationalized, a significant positive relationship existed between the level of eHealth literacy skills and the level of engaging in recommended CDSM behaviors when these items were modeled together. This relationship persisted in the presence of a stronger predictor of CDSM behaviors, self-efficacy. Even using imperfect measures, eHealth literacy skills appeared to be meaningfully associated with eHealth use and CDSM behaviors.

The following sections provide in-depth descriptions of the findings across aims and includes a discussion on implications, significance, and recommendations for each key finding. Later sections discuss theoretical and scientific implications of this research, limitations of this study, and conclusions for future research for the field of public health.

5.1.1. Aim 1 Findings

Sociodemographic characteristics of sample population

Among the 5,166 internet users in H6, just under half of the respondents (n=2,888) reported having one of the five chronic conditions of interest. This proportion was slightly lower than national averages placing individuals with chronic conditions at over 50% of the adult population; however, only data reflecting five of the most common and impactful conditions were included rather than every chronic condition captured in H6 (Watson et al., 2025). Among these 2,888 internet users with chronic conditions, results reflected the self-reported prevalence of each chronic condition. High blood pressure represented the majority of cases followed by diabetes, lung disease, cancer, and heart conditions, respectively, which aligns with national prevalence rates of these conditions among adult populations in the U.S. (Chobufo et al., 2020; Goorani et al., 2024). As expected, multimorbidity was common. About 45% of respondents had more than one chronic condition, which is slightly lower than national estimates of 51% adults with multiple chronic conditions (Watson et al., 2025). This difference could be due in part to the specific conditions chosen for this analysis, as national estimates often include other conditions such as obesity, depression, asthma, arthritis, kidney disease, and related diseases.

The descriptive findings for the sociodemographic variables were largely supported by the literature, although with minor differences. For instance, more females than males reported having had a chronic condition, whereas for each of these conditions, males tend to have higher incidence rates (Connelly et al., 2022; Freedman et al., 2026; Gwira et al., 2024; H. I. Kim et al., 2018; Silveyra et al., 2021). Age distributions in the proportion of the sample reporting at least one chronic condition mirrored related national statistics, where most of those with chronic conditions were midlife adults (aged 35–64 years old) and the proportion of the sample who had chronic conditions across each age category increased as age increased (Watson et al., 2025). This was expected given the nature of chronic conditions that tend to occur due to the accumulation of disease exposures as one ages (Haapanen et al., 2025).

When looking at race and ethnicity alone, there were minimal racial differences in the prevalence of chronic conditions across the sample of internet users. However, more Black or African Americans (Non-Hispanic) reported having a chronic condition than not, which aligns with literature reflecting known racial differences in disease prevalence among these racial and ethnic groups when compared to White or Asian individuals (Elman et al., 2025).

Educational trends were more surprising. Among the general H6 population, 36.1% of adults had some college experience and 30.3% had a college degree or more (National Cancer Institute, 2023b). In contrast, among U.S. adults with chronic conditions who used the internet in the sample, 44.9% reported some college experience and 32.3% reported a college degree or higher. These weighted estimates suggest that the analytic sample represented a more highly educated segment of adults with chronic conditions than expected, because higher rates of chronic conditions tend to appear in adults with lower levels of educational attainment (Choi et al., 2024; Oates et al., 2017). This, however, could be due to how education was analyzed in this study at a sample level rather than within specific groups of the sample; research shows there may be important racial or ethnic effects on the incidence of chronic conditions that dampen the effect of higher educational levels and would be worth exploring in follow-up research (Assari & Zare, 2025).

Regarding income, those with chronic conditions had higher percentages of lower income than those without a chronic condition in the sample of internet users; however, for those in the $75,000+ category, a higher percentage of individuals reported not having a chronic condition than having one. This study examined annual household income, which could include income from more than one individual. National estimates show that median household income is closer to $84,000/year (U.S. Census Bureau et al., 2025), so the $75,000 a year category in the data still falls below average estimates. Without further details regarding how much over $75,000 a year individuals made in annual household income, it is hard to determine how much income plays a role in disease incidence among this sample.

Most individuals in the sample had insurance coverage, although a higher percentage of those without health insurance than their counterparts reported no chronic conditions. While not all uninsured individuals have health problems, this gap could be due in part to the reality that many uninsured individuals often forgo care and may not know they have a condition (Kommera et al., 2025; Tolbert et al., 2024).

Lastly, most individuals with and without chronic conditions lived in metro counties with more than 1 million in population. A visual inspection of the distribution showed that as the sample became more rural, the percentage of individuals reporting having had one of the chronic conditions increased. This aligns with known disparities in geography and chronic disease rates in the U.S. where individuals in rural areas tend to have higher rates of chronic illness than those in more metropolitan areas (Coughlin et al., 2019).

Overall, the sociodemographic profile of the sample largely mirrored established national estimates for adults living with these five chronic conditions. While certain subgroups, such as midlife adults and those with higher levels of educational attainment, were represented at slightly higher-than-average levels, these distributions remain consistent with the known epidemiology of chronic disease in the U.S. Consequently, the sample provides a reasonably representative foundation for interpreting the eHealth literacy trends among adults with key chronic conditions in this study.

Chronic disease self-management patterns among the sample population

Regarding engagement in the six chronic disease self-management target behaviors (smoking status, physical activity, calorie information, food discussion, alcohol consumption, and health perception), survey respondents in the sample of internet users with chronic conditions were largely adherent to target behaviors, aligning with national trends for the most part. For smoking status, the percentage of individuals in the sample who reported that they were never or former smokers was around 88%. Despite well-established health guidance linking better health outcomes with smoking cessation, 12% of the sample reported current smoking behaviors. These findings align with current national evidence that found that midlife and older adult populations with lung disease and heart disease continue smoking even in the presence of one or more chronic conditions (Loretan et al., 2022) and with the overall smoking behavior in the H6 sample (National Cancer Institute, 2023b). As discussed, maintaining a non-smoking status is associated with improved health outcomes for individuals living with chronic conditions because it can help limit exacerbations related to diabetes, lung disease, heart disease, cancer, and hypertension (Rigotti et al., 2022). Thus, there remain opportunities for future interventions to continue to address smoking status as a specific health-promoting behavior among this population despite the relatively high rates of non-smoking.

For the second behavior, about one-third of individuals met recommended physical activity guidelines, a finding that mirrors existing research that found insufficient physical activity levels in populations of adults with chronic conditions (Cascino et al., 2019; Xu et al., 2023). This phenomenon of lower physical activity and lower health literacy has been studied before in previous research that showed how barriers to engaging in adequate physical activity could result from fundamental gaps in knowledge, environmental impacts on motivation, and self-regulation skills for implementing behaviors within the context of disease management (Zhang et al., 2025). Determining additional details about why these individuals do not engage in physical activity at the recommended rates is a necessary next step to better understanding how the eHealth literacy skills of this population may further interact with setting and meeting physical activity goals.

Individuals with chronic conditions are often instructed to monitor their diet and calorie intake as part of their disease management. Awareness of calorie information is one way to monitor dietary intake (Gorski & Roberto, 2015; Post et al., 2010), as well as collaborating with healthcare providers (L. Zhang et al., 2025). Results from this dissertation study showed that most individuals in the sample were aware of calorie information on menus in fast food or related restaurants (51%), which is higher than the general H6 population, of which 47% reported noticing calorie information. This level of awareness among the dissertation sample is in line with estimates for the general population that 40-50% of adults notice this information, despite federal guidelines from the Food and Drug Administration requiring most fast food and related restaurants to feature calorie information on their menus (Restrepo, 2024; Rising et al., 2021; U.S. Food and Drug Administration, 2023). Additionally, less than half of participants were comfortable discussing food access issues with their healthcare providers. In fact, nearly 60% of individuals were uncomfortable with discussing food issues with their providers, which is higher than in previous studies and in the overall H6 dataset (Benyahia et al., 2025; National Cancer Institute, 2023b). These results highlight the complexity of capturing and communicating dietary behaviors for those with chronic conditions. They also may reflect a need to further explore if there are any important gaps in how people perceive the role of food access in their disease management (Silva et al., 2023). Monitoring daily dietary intake and related behaviors is a key aspect of chronic disease self-management, and this sample struggled to engage in these behaviors at target rates. While there are other ways to measure dietary awareness, these items in H6 identify two key areas where future interventional or cross-sectional research could address gaps in dietary awareness and explore how studying the presence of eHealth literacy skills may help identify new ways to fill those gaps.

When accounting for gender-based differences in alcohol consumption recommendations, most of the study sample (nearly 90%) reported that they drank below recommended guidelines, which is lower than national estimates for related behaviors such as binge drinking and heavy alcohol use (National Institute on Alcohol Abuse and Alcoholism, 2025). However, there were more missing data for this outcome compared to the others which may have impacted findings because individuals who were uncomfortable discussing their alcohol consumption may have elected to skip those questions (Davis et al., 2010). These findings show that measuring alcohol consumption among this population of adults with chronic conditions is imperfect and likely challenging given the nature of the topic. New items in HINTS that measure general behaviors as well as cognitions about alcohol consumption could potentially lead to a better capture of alcohol consumption and better insights into how eHealth literacy skills might influence those behaviors.

Finally, the last behavior, an individual's perception of their health, reflected an important theoretically-driven cognitive aspect of daily chronic disease self-management which requires attunement with one's own health status. In this sample, about three-quarters of the participants indicated that they had at least a good perception of their general health. This finding aligned with general results from the H6 data (National Cancer Institute, 2023b) and previous H6 research among adults with diabetes who reported 44.1% good, 19.5% very good, or 3.7% excellent general health (Hu et al., 2025). These findings indicate that most of these adults with chronic conditions do not report poor perceptions of health, despite the presence of a disease. This offers promising insights into how individuals may perceive their condition(s) and how that perception may shape their other health behaviors, which could inform future efforts to improve health outcomes through an enhanced sense of self and well-being among this population.

General trends across eHealth Literacy skill domains

Overall, descriptive findings from Aim 1 suggested that eHealth literacy skills among internet-using adults with chronic conditions in H6 generally aligned with established patterns observed in prior studies. Across domains, respondents demonstrated relatively stronger confidence in foundational and functional skills—such as Basic (also referred to as Traditional) Literacy, Computer Literacy, Information Literacy, and Health Literacy—while showing comparatively weaker endorsement of more evaluative or critical domains, including Scientific Literacy and Media Literacy. This distribution is consistent with prior research indicating that many adults feel comfortable accessing and using health information but face greater challenges when interpreting conflicting recommendations or assessing credibility in complex digital information environments (Levin-Zamir & Bertschi, 2018; Snow et al., 2016; Sudbury-Riley et al., 2017). In the context of this sample, these findings suggest that while adults with common chronic conditions possess foundational health literacy skills, they may face significant gaps in the specialized, context-specific skills required for evaluating higher-level concepts or medical recommendations. This has critical implications for disease management, as individuals must navigate high-stakes decisions and complex health environments daily (Thorne et al., 2003). Success in these disease management areas likely depends on the very critical and scientifically-oriented eHealth literacy skills, of which this sample reported lower levels. To better understand the differences across eHealth literacy skill domain, the following sections review the specific descriptive results within each domain, beginning with foundational skills and concluding with the more critically evaluative context-based skills.

To begin, Basic Literacy levels were relatively high in this sample, with over three-quarters of respondents reporting that medical statistics were "easy" or "very easy" to understand. Given that this analytic sample was restricted to internet users with chronic conditions, this finding is not unexpected; individuals who routinely engage with health systems and digital platforms may develop greater familiarity with numerical and health-related information over time (Andreadis et al., 2025). For Computer Literacy, 61% of the sample had used the internet to make appointments, which was higher than in previous HINTS research among the full HINTS population, where closer to 50-55% had done this (National Cancer Institute, 2023; Rajamani et al., 2021). Little is known about the role between Computer Literacy and chronic disease self-management, but available evidence suggests that lower digital health care literacy is associated with lower use of health applications, patient portals, and video telehealth (Nelson et al., 2022). Accordingly, it is plausible that greater disease burden, as evident in our sample, is associated with higher Computer Literacy to the extent that ongoing care increasingly requires interaction with digital tools (e.g., portals, apps, telehealth); however, this relationship warrants direct empirical testing.

Like Basic and Computer Literacies, Health Literacy also appeared moderately strong, with more than 60% of respondents reporting being “very confident” filling out medical forms independently, which is slightly higher than the 57% level of the general H6 population (National Cancer Institute, 2023). While higher Health Literacy is generally associated with higher overall engagement in health-promoting behaviors, like building disease knowledge or adhering to medication, studies show mixed results when it comes to meeting diet and exercise goals (Cabezas et al., 2025; Noblin & Rutherford, 2017). However, nearly 40% of the sample reported lower levels of confidence in filling out medical forms, a skill gap that has been linked to decreased comfort navigating healthcare environments (Kaphingst et al., 2014). In the context of chronic disease self-management, these findings suggest that a substantial portion of adults may encounter administrative barriers that preclude them from feeling fully informed or effectively partnered with their care teams. Ultimately, ensuring that all patients feel confident in basic healthcare navigation is a critical first step toward fostering the high-level patient agency required to manage chronic conditions effectively over the long term.

Information Literacy demonstrated moderate levels of self-reported confidence, with nearly half of respondents (47%) indicating they were “very” or “completely” confident in finding helpful health resources online. About 44% of respondents were “somewhat confident”. These findings aligned almost identically with the greater H6 sample, suggesting that these levels of confidence were not unique to the study sample (National Cancer Institute, 2023b). More generally, these results align with literature suggesting that information-seeking behaviors are common among individuals managing chronic conditions, who often rely on the internet to supplement clinical care, monitor symptoms, and support decision-making (Dean et al., 2017; Jacobs et al., 2017). These findings imply that individuals living with these chronic conditions are only moderately confident in finding helpful health resources on the internet. This may open them up to being more reliant on information they encounter from others, which may lack credibility (Manganello et al., 2017). Ultimately, identifying areas where those with chronic conditions struggle with finding credible information is a prerequisite for developing targeted interventions that move patients from being passive recipients of peer-shared content to more active, discerning navigators of relevant and accurate disease information.

Importantly, the first four domains reflect skills that are closely tied to direct interaction with health systems and digital tools, which may help explain their stronger performance in later analytic models. In contrast, Scientific Literacy showed a markedly different pattern. More than two-thirds of respondents agreed either strongly or somewhat that there are "so many different recommendations about preventing cancer" that it is hard to know which ones to follow. This widespread endorsement suggested persistent difficulty translating scientific guidance into actionable knowledge, even among digitally connected adults. Rather than indicating complete disengagement, this pattern likely reflects ongoing confusion in an increasingly crowded and inconsistent health information landscape, especially when it comes to identifying mis- and disinformation. Similar findings have been documented in prior HINTS cycles and broader public health surveillance, highlighting the challenges posed by evolving guidelines, conflicting expert opinions, and mixed media messaging (Hesse et al., 2017). These findings emphasize the need for a renewed focus on assessing and addressing Scientific Literacy levels in populations such as these who may rely more on technical and jargon-filled health education and health promotional materials.

Finally, Media Literacy followed a similar pattern of relative weakness. Over half of respondents agreed that it is hard to tell whether health information on social media is true or false, and an additional proportion reported not using social media at all. These findings suggest that individuals with chronic conditions are likely heterogenous in their use of social media as well as their ability to critically appraise health information in social media environments, which aligns with previous HINTS research that found differences in social media use among those with chronic conditions (Alhusseini et al., 2021). Ultimately, higher levels of media literacy are associated with higher levels of overall health literacy because these critical appraisal skills can help support informed decision making (Mutlu et al., 2025). Thus, these findings show that adults with these common chronic conditions likely need greater support in building these media literacy skills to support their daily decision-making processes related to their disease management.

Additional analyses in Aim 1 explored if eHealth literacy skill domains varied by disease type. Bivariate analyses found that for the most part, eHealth literacy skill domains were not significantly associated with specific types of chronic conditions. However, there was some evidence that different skill domains might be impacted by the presence of multiple chronic conditions. These findings align with results from similar studies where multimorbidity was associated with lower health literacy (Chauhan et al., 2024; Wieczorek et al., 2023), and it extends previous research examining digital health literacy among adults with different chronic conditions to highlight the potential homogeneity in eHealth literacy skills based on disease type (Zaghloul et al., 2025). Multimorbidity was further explored in subsequent aims.

5.1.2. Aim 2 Findings

In Aim 2, the Uses and Gratifications Theory (UGT) guided the selection of six variables to represent distinct eHealth use behaviors that reflected possible interpretations of eHealth literacy skills in action. eHealth use itself was conceptualized as a set of purposive, goal-directed behaviors that reflected active engagement with eHealth technologies to meet personal health-related needs. The six eHealth use behaviors included in the composite score—sharing device data with providers, using health or wellness apps, viewing medical test results, searching for health information online, messaging healthcare providers, and watching health-related videos on social media—each represented different pathways through which individuals actively used eHealth tools to gratify health-related needs. These needs included informational gratification (e.g., seeking health information or test results), instrumental gratification (e.g., managing appointments, monitoring health, or communicating with providers), and experiential gratification (e.g., learning through video-based content).

There were several interesting findings regarding the eHealth use of the study population. First, respondents in the sample generally engaged in most of these eHealth use activities, reflecting new patterns in greater eHealth use among HINTS respondents than in previous research (Kontos et al., 2014; Shaw Jr et al., 2024; Sherman et al., 2020). This could be due in large part to the increase in eHealth use during the COVID-19 pandemic, an insight that warrants further follow-up to see if these behaviors persist or increase years after the pandemic concluded (Deshpande et al., 2023). Second, results showed that most of these adults did not share health information from electronic monitoring devices or smartphones with health professionals. Despite reported benefits of using these types of digital interventions in care management (Al Mahmud et al., 2026), only about one-quarter of the study population engaged in this behavior.

This seems to align with current estimates of remote patient monitoring (RPM) trends among adults with chronic diseases in the U.S., but it also highlights a potential disparity that emerged despite COVID-19 investments in these services if individuals are not engaging at expected levels (Joo et al., 2025; Mahashabde et al., 2025; Paul et al., 2025). On a related note, more than half of the study population reported using health and wellness applications on their tablets or smartphones. This finding aligns with research studying previous HINTS respondents with chronic conditions who reported similar levels of engagement (H. Wang et al., 2021) while also emphasizing an opportunity to consider how literacy skills related to that mHealth might lead to greater outcomes.

Results from the bivariate analyses in Aim 2 showed that the two sets of variables were fairly well-aligned with one another (internal validity) and with the other set (concurrent validity). In particular, Computer Literacy and Computer eHealth use were the most closely aligned, which was consistent with expectations given their shared operationalization around the use of specific technologies to accomplish defined health-related tasks (Durmuş, 2024). On the other hand, Scientific Literacy and Scientific eHealth Use were not significantly associated with one another. This could reflect a conceptual mismatch or a misspecification of Scientific Literacy and the HINTS variable used in this analysis that impacted its relationship to the eHealth use variable. This is not unexpected because Scientific Literacy is often captured by knowledge of scientific processes and topics, but strong measures of this type of literacy are lacking (Briones, 2015; Kelp et al., 2023; Rosenthal, 2020). Consequently, these findings underscore the need for more robust, validated scales that can more accurately bridge the gap between scientific knowledge and its practical application in eHealth contexts.

When the relationship between eHealth literacy and eHealth use was examined in regression analyses, results showed that these variables were justifiably related to one another. Due to the limited number of HINTS items capturing these constructs, there was some conceptual overlap between the eHealth use variables and the eHealth literacy variables, which was expected (Lee & Tak, 2022). Overall, the eHealth use composite score demonstrated its strongest and most consistent associations with Computer Literacy, Information Literacy, and Health Literacy. These associations remained significant in the full model that adjusted for all six eHealth literacy skill domains, whereas associations with other domains were attenuated.

Consistent with the purpose of Aim 2, these results established a defensible empirical foundation for evaluating domain-specific associations between eHealth literacy skills and chronic disease self-management behaviors in subsequent aims. Ultimately, despite mixed findings in Aim 2, Aim 3 analyses continued as planned due to the importance of understanding how a combined set of eHealth literacy skills might be related to the chronic disease self-management variables of interest.

5.1.3. Aim 3 Findings

Results in Aim 3 were mixed. The binary versions of Basic Literacy and Health Literacy remained mostly significant predictors of each CDSM behavior across all models. These findings were not entirely unexpected given that the items making up Basic and Health Literacy are used in HINTS analyses and related research to reflect aspects of *health literacy*, which suggests that these items were valid measures of their underlying constructs (Blake et al., 2024; Chew et al., 2004; Manganello & Clayman, 2011; Stagliano & Wallace, 2013).

Basic and Health Literacies were significantly and strongly associated with higher odds of better reported health status (health perception). Good health perception reflects, in part, success with the emotional side of chronic disease self-management, and higher health literacy skills have been linked to this emotional side of CDSM in previous research (Hakimzadeh & Adib-Hajbaghery, 2021; Mathaka et al., 2023). Basic Literacy was associated mostly with dietary awareness behaviors, calorie information and food discussion, but it was also associated with health perception. Conceptually, having a better perceived ability to understand medical statistics and a greater awareness of calorie information at restaurants reflects a level of numeracy that individuals may have, which has been shown to be important in disease management especially in older individuals (Miller et al., 2017). This could also potentially translate to a greater comfort with food access discussions with healthcare providers (food discussion) due to higher food and nutrition numeracy skills (Hashemzadeh et al., 2024).

Computer Literacy and Health Literacy were significantly associated with physical activity in both unadjusted and adjusted models. Computer Literacy reflects ease with which an individual uses technology for basic healthcare-related purposes while Health Literacy reflects confidence in filling out medical forms, in this study. Even though most individuals in the sample were not meeting physical activity recommendations, these significant relationships reflected that these particular literacy domains showed potential as possible influences on physical activity behaviors. These findings are supported by previous research that showed that higher levels of digital health literacy, as measured by the eHealth Literacy Questionnaire (Kayser et al., 2018), were associated with higher odds of meeting physical activity recommendations and getting adequate physical activity (Zangger et al., 2024).

Furthermore, while multimorbidity emerged as a potential influencing factor on eHealth literacy skills in the earlier bivariate analyses, sensitivity tests in Aim 3 confirmed that multimorbidity was showing up as a dampener on the relationship between some of the eHealth literacy skills for some of the CDSM behaviors. This result presented further evidence that controlling for multimorbidity in the final analyses was necessary to avoid potential confounding.

In sum, unadjusted and adjusted models did not show that each eHealth literacy skill variable was significantly associated with each CDSM behavior, as expected in Hypothesis 1. However, most of the relationships between the skill variables and the outcome variables reflected positive relationships, if nonsignificant. Because some of the variables were strong predictors and others were not, this suggested that either the variables representing the non-significant eHealth literacy domains were not well aligned with the underlying constructs after all, or that these items were not strong predictors of specific behaviors on their own. These implications are further reflected upon in Section 5.5. Aim 4 analyses explored how the development of index variables representing the core concepts of interest—eHealth literacy and CDSM behaviors—yielded different results.

5.1.4. Aim 4 Findings

Primary Association Between eHealth Literacy and CDSM Behaviors

Analyses in Aim 4 examined the association between overall eHealth literacy skills and CDSM behaviors among U.S. internet-using adults with chronic conditions, while accounting for self-efficacy, sociodemographic characteristics, and potential sources of bias related to multimorbidity and missing data (i.e., covariates). Across multiple model specifications and sensitivity analyses, results consistently showed that higher levels of eHealth literacy skills were associated with greater engagement in CDSM behaviors, which supported Hypothesis 2.

In unadjusted and partially adjusted models, scores in the H6 eHealth Literacy Skill Index (HeLSI) were positively and significantly associated with composite CDSM Behavior scores, indicating that individuals reporting higher levels of eHealth literacy skills engaged in a greater average number of recommended self-management behaviors. This association remained statistically significant after adjustment for key sociodemographic factors, including age, gender, education, income, race/ethnicity, insurance status, and locality. Similar results appeared for the Partial HeLSI (P-HeLSI), which excluded Scientific Literacy; although, results in the full model reflected that higher P-HeLSI scores were associated with a 0.09 increase in CDSM Behavior Scores, which was 0.01 unit higher than the results using the HeLSI. This reflected that the removal of Scientific Literacy from the index resulted in a slightly more powerful scale predictor, although this difference was not large enough to warrant the dismissal of the HeLSI outright.

The Role of Self-Efficacy

When self-efficacy was introduced into the fully adjusted models, it emerged as the strongest and most consistent predictor of CDSM behaviors. Individuals with higher self-efficacy engaged in substantially more self-management behaviors compared with those reporting lower self-efficacy, independent of eHealth literacy and sociodemographic factors. This finding was ultimately unsurprising given the well-known importance of self-efficacy on health-related behaviors (Bandura, 1997; Clark & Dodge, 1999; Fisher et al., 2009). Furthermore, the inclusion of self-efficacy attenuated the association between eHealth literacy and CDSM behaviors. This pattern suggests that while eHealth literacy independently contributes to self-management activities, part of its influence may operate through mechanisms related to confidence, perceived capability, or readiness to act.

Multimorbidity as a Potential Confounder

Multimorbidity was examined as a potential confounder in Aim 4 models. In adjusted analyses, the presence of multiple chronic conditions was independently associated with lower CDSM behavior scores, suggesting that greater disease burden constrains individuals' ability to engage in recommended self-management behaviors. However, inclusion of multimorbidity in the models did not meaningfully alter the association between eHealth literacy and CDSM behaviors. The eHealth literacy coefficient was slightly attenuated but remained statistically significant, indicating that disease burden does not account for the observed relationship. These findings suggested that while multimorbidity negatively affected self-management capacity overall, eHealth literacy remained relevant across levels of disease burden.

Sensitivity Analyses: Alternative eHealth Literacy Indices & Complete-Case Analysis

To assess the robustness of the primary findings, additional sensitivity analyses explored alternative conceptualizations of eHealth literacy based on the Lily model's proposed subgroupings: analytic eHealth literacy (Basic, Information, and Media Literacies) and context-specific eHealth literacy (Computer, Scientific, and Health Literacies). Both alternative indices were positively associated with CDSM behaviors in unadjusted and adjusted models. The Analytic eHealth Literacy Index demonstrated a more stable association across models, remaining statistically significant even after inclusion of sociodemographic covariates. In contrast, the Context-Specific eHealth Literacy Index showed stronger associations in earlier models but was more substantially attenuated after self-efficacy was added, suggesting greater conceptual overlap between context-specific skills and confidence in managing health behaviors. Despite these differences, the magnitude and direction of effects across the alternative indices were comparable to those observed for the full HeLSI or the P-HeLSI. This suggested that, while these groupings could be potentially useful for examining specific elements within eHealth literacy, the full index remained a more comprehensive measure of eHealth literacy skills relevant to chronic disease self-management.

Finally, robustness checks were conducted to assess whether differential missingness influenced the primary findings. Although missing data were more common in certain sociodemographic categories, sensitivity analyses restricting the sample to respondents without high-missingness categories produced substantively comparable results. Across restricted and full-sample models, eHealth literacy remained positively associated with CDSM behaviors, and self-efficacy continued to be the strongest predictor. The stability of coefficients across these analyses suggested that the observed relationships were unlikely to be driven by patterns of missing data or listwise deletion.

5.2. Overall Takeaways, Implications, and Recommendations

5.2.1. Chronic Disease Self-Management Behaviors & eHealth Literacy in the Sample

This sample of 2,888 adults with diabetes, hypertension, heart disease, lung disease, and/or cancer engaged in the six target CDSM behaviors at varied levels. For example, individuals engaged in an average of 4 out of 6 behaviors as measured by the CDSM Behavior Score ($\bar{x} = 4.12$), and target behavior engagement ranged from 35% (physical activity) to 90% (alcohol consumption) across the sample. For some of the target behaviors—such as drinking alcohol below recommended guidelines and non-smoking—individuals in the sample largely adhered to these behaviors; however, far fewer individuals 1) met physical activity recommendations, 2) paid attention to calorie information in restaurants, and/or 3) felt comfortable discussing food access issues with their healthcare providers. Related to eHealth literacy skills, Aim 3 results showed that higher Basic, Computer, and Health Literacy levels were each associated with higher odds of engaging in these three behaviors.

These results show that there were observable patterns between levels of specific eHealth literacy domains and higher odds of engaging in dietary- and activity-related behaviors. This suggests that elements of numeracy (Basic Literacy - understanding medical statistics), technological knowhow (Computer Literacy - using the internet to engage with healthcare providers), and navigating clinical components (Health Literacy - filling out medical forms), play an important role in how successfully individuals with chronic conditions implement nutritional changes into their routines and engage in adequate physical activity (Silva et al., 2026; Zoellner et al., 2009).

As an overall health goal, individuals in the target sample would ideally report higher levels of engagement in each of these self-management behaviors in subsequent research. Researchers and clinicians should explore how health-promoting approaches, that consider how specific eHealth literacy skill domains impact engagement in these behaviors, could lead to these health behavior improvements. For example, given the importance and relevance of meeting physical activity and dietary goals when managing a chronic condition, future research should explore how and why higher levels of basic, computer, and health literacies seem to influence higher engagement in these behaviors. Providing individuals with applications or tools to track calorie intake and access to food may benefit from an additional focus on increasing an individual's ability to understand the statistics they encounter, fill out the fields within the calorie tracker, and navigate clinical interactions designed to support their dietary goals. Similarly, encouraging individuals to get adequate physical activity at moderate- to vigorous rates may require individuals to wear heartrate monitors or other wearable technology that tracks distance or exertion. Coupling interventions such as these with a focus on basic, computer, and health literacy skill building might lead to better rates of engagement and overall health outcomes.

5.2.2. eHealth Use and Its Role in Validating eHealth Literacy Skills

As discussed previously, the operationalization and examination of the relationship between eHealth literacy and eHealth use was guided by the Uses and Gratifications Theory and previous eHealth literacy, eHealth use, and HINTS research. Results from Aims 1 and 2 showed that most individuals in the sample engaged in most of these eHealth use behaviors at relatively high levels. Bivariate comparisons showed that the six eHealth use variables were conceptually related with one another, reflecting small to medium size effects. For the most part, aside from Scientific eHealth use and Scientific Literacy, most use and literacy pairs were statistically significantly aligned.

When combined, the eHealth use items reflected modest internal consistency (Cronbach's $\alpha = 0.65$), and individuals in the sample mostly engaged in a high number of eHealth behaviors (four or higher out of six). Five out of six eHealth literacy skills were also individually associated with higher eHealth use composite scores, although only three—Computer, Information, and Health Literacies—were significantly associated in the full model. Taken together, these results showed an important connection between higher eHealth literacy and higher eHealth use, which extends current research that explored the inverse relationship (lower eHealth literacy and lower eHealth use) (Deshpande et al., 2023).

The lack of a significant association for Scientific Literacy, however, was an important finding that deviated from the rest of the results in Aim 2. The fact that Scientific Literacy did not demonstrate criterion alignment with the selected eHealth use indicator was most likely due to how the variable was operationalized and general scientific literacy trends. First, the variable

“TooManyRecommendations” that was used to assess this skill is flawed. Prior analyses of HINTS data demonstrate that endorsement of the “strongly agree” category, which reflects greater confusion and is reverse-coded, has increased over time (Hesse et al., 2017). As a result, this item may capture perceived confusion or information fatigue more than the applied skills necessary to engage in eHealth use behaviors, contributing to its weaker association with the eHealth use composite score.

Secondly, Scientific Literacy is notoriously difficult to capture and map. Due to increased availability of competing scientific and health-related information online, the ability to assess an individual’s capacity to discern accurate scientific information is constantly diminishing (Snow et al., 2016). This reflects an overall limitation of this domain and highlights an opportunity for future research to consider what Scientific Literacy should look like in an information environment where the scientific method is contested as the gold standard for producing evidence and established and shared truths are difficult to determine.

Overall, there were important differences in the relationship between eHealth literacy and eHealth use based on eHealth literacy skill domain. When looked at individually against a variety of eHealth use behaviors, not every skill domain was relevant. This could suggest that, in certain cases, some domains of eHealth literacy skills may not be as relevant for some eHealth use behaviors. While previous research that looked at eHealth literacy among Black/African American adults with chronic conditions using the one-factor eHEALS found relatively higher rates of eHealth literacy in this sample, they also identified some variation and multiple factor loadings using the eHEALS items (Paige et al., 2017). The presence of conceptually-related yet distinct ideas within the eHEALS framework could explain the slight variability in the performance of these measures among this sample. Individuals with chronic conditions may differ in specific applications of their eHealth literacy skills when encountering different eHealth use tools. These findings warrant further research: if certain eHealth literacy skills are only relevant for certain eHealth use behaviors, then the question arises if all six domains are needed to link skills with behaviors or if more parsimonious measurements of eHealth literacy are sufficient.

This dissertation study is among the first studies to explore the connection between variables representing eHealth literacy and eHealth use, where the presence of eHealth use is intended to reflect the presence of eHealth literacy skills. Related research introduced a new 14-item German instrument called the eHealth Literacy and Use Scale (eHLUS) to explore aspects of eHealth literacy, as measured by the eHEALS scale, and use of mHealth-based medical applications, but they only explored mHealth-related eHealth use (Stephan et al., 2025). Results from this dissertation study show that there is an important linkage between these two concepts that could potentially influence the relationship between eHealth literacy skills and health behaviors that warrants further exploration.

This dissertation also produced a new, theoretically-based approach to measuring both eHealth literacy skills and eHealth use, where eHealth use is more broadly operationalized than in previous research. Furthermore, the HINTS items selected to represent a range of eHealth use activities performed fairly well in the correlation and regression models; therefore, these items can be used in future research to measure eHealth use as a multidimensional concept. Together, these findings suggest that eHealth use and eHealth literacy have important conceptual overlaps and can and should be measured together to provide more contextualized and behaviorally-based insights into eHealth literacy, eHealth use, and health behaviors.

5.2.3. Measuring eHealth Literacy Skills Using HINTS Items

Results across aims yielded new insights into the utility of using HINTS items to measure eHealth literacy skills and their influence on CDSM behaviors. Aim 1 findings indicated that while this sample exhibited relatively strong confidence in accessing and using health information, more complex evaluative skills such as those that involve scientific interpretation and media credibility assessments were less developed. Aim 2 findings showed that items measuring eHealth literacy skill domains were largely associated with related eHealth use, except for Scientific Literacy. Aim 3 findings showed that some eHealth literacy skill domains were better associated with individual CDSM behaviors than others. Aim 4 showed that, despite these differences, each of the six items representing the six eHealth literacy skills domains performed sufficiently well as a composite index score. Additional results showed that Scientific Literacy, as operationalized in this study, might not be as relevant for estimating the relationship between eHealth literacy skills and CDSM behaviors.

The variation in these patterns of endorsement of each eHealth literacy skill domain, especially for Scientific and Media Literacies, suggested that these items likely captured multiple dimensions of related concepts. These findings extend existing eHealth literacy literature by showing that eHealth literacy skill was not a monolithic concept within this population (Zaghloul et al., 2025), but rather a complex and multidimensional composite idea. Although the Lily model presents these domains as more or less conceptually equal components of eHealth literacy (Milanti et al., 2025; Norman & Skinner, 2006b), the present findings suggest that the empirical influence of each domain may be uneven, with some domains showing stronger and more consistent behavioral relevance than others.

The findings from Aim 3 and Aim 4 suggest that while individual eHealth literacy skill domains were generally weak or inconsistent predictors of specific chronic disease self-management behaviors, the composite measure of eHealth literacy demonstrated a small but statistically significant association with overall self-management engagement. This pattern likely reflects the fact that composite indices capture shared variance across related literacy skills, representing a broader underlying capability rather than the influence of any single domain. In other words, eHealth literacy may function less as a set of discrete skills tied to particular behaviors and more as a general enabling capacity that supports engagement in health management activities. Although the magnitude of the association observed in this study was modest, the consistency of the relationship across models suggests that the composite eHealth literacy construct captures a meaningful, if limited, dimension of individuals' ability to engage in chronic disease self-management. These findings therefore support the interpretation that eHealth literacy operates as a holistic behavioral skill within the IMB framework, while also highlighting that improvements in any single literacy domain alone may be insufficient to meaningfully influence specific self-management behaviors.

Given the breadth of eHealth use behaviors, the scope of eHealth literacy skills, and the implications for the behaviors and skills on health outcomes, it is clear that capturing the dynamic interplay among these variables is complicated. The availability of multiple types of tools measuring eHealth literacy reflects this complexity (Paige et al., 2017; Refahi et al., 2022; Zaghloul et al., 2025). In fact, existing research explores the concept of eHealth literacy using factor analysis where eHealth literacy may be represented by a few key factors rather than all six domains (Hyde et al., 2018; Morales & Eguia, 2025; Paige et al., 2019; Sudbury-Riley et al., 2017). These findings highlight the need for future research to use more sophisticated methods to examine these domains to determine if the presence of these skills uniformly impact behavior or if there are different situations where only some of these eHealth literacy skills play a role in health behaviors.

The Health Information National Trends Survey is designed to capture health information-related behaviors among adults in the U.S. and analyze them using weighting techniques to create a nationally representative profile of these activities. With the widespread adoption of eHealth tools and the importance of understanding eHealth literacy skills that accompany the use of those tools, the National Cancer Institute (NCI), HINTS' sponsoring organization, has an opportunity to refine and capture eHealth literacy using HINTS items. This dissertation study provides preliminary evidence to conduct this type of examination. The analysis of eHealth literacy skills alongside eHealth use behaviors as part of the theory of change related to health behaviors (i.e., CDSM behaviors) in this study provide a new foundation from which future iterations and analyses of HINTS can build. Many of the items explored in this analysis already appear in other cycles of HINTS, which will allow for partial reproduction of these findings. By revisiting the measurement of eHealth in HINTS, NCI could contribute a reliable instrument for measuring eHealth literacy skills over time.

5.2.4. The Interplay of eHealth Literacy, Self-Efficacy, and CDSMs

Across each aim, this study sought to better understand the relationship between eHealth literacy skills, chronic disease self-management behaviors, self-efficacy, and related sociodemographic variables. Key sociodemographic factors were selected to characterize the broader contextual conditions in which individual eHealth engagement and self-management occurred (Gee et al., 2015; Hesse et al., 2017). Results in Aim 1 showed that eHealth literacy skill levels were linked with key demographic characteristics such as age, education level, and income, a fact that is well-documented in the literature (Gero et al., 2025; Großschädl et al., 2025; Hua et al., 2025). Inclusion of these variables in the final analytic models was essential to capture the broader contextual influence on the relationship between eHealth literacy skills and CDSM behaviors.

Demographic characteristics like higher education levels and higher income were associated with higher levels of engaging in CDSM behaviors than higher eHealth literacy skills were. These findings partially align with research from the *All of Us* dataset that showed that social determinants of health like age, income, and health insurance status were more associated with chronic disease outcomes than health literacy (Kunnath et al., 2024). Self-efficacy was also strongly associated with higher levels of CDSM behaviors, even more so than key demographic characteristics. These findings also align with previous research that examined the role of self-efficacy and sociodemographic characteristics on disease self-management and found that while key demographic characteristics were influential on disease behaviors, self-efficacy was also an important, mediating factor (Xie et al., 2020).

Findings in Aim 4 showed that the magnitude of the associations between HeLSI and the CDSM Behavior Score and P-HeLSI and the CDSM Behavior Score were modest but consistent, suggesting that eHealth literacy contributes meaningfully, but not exclusively, to chronic disease self-management. The direct, unadjusted relationship between HeLSI and CDSM behaviors captured via the CDSM Behavior Score ($B = 0.15$, $p<.001$) corresponds with the lower end of the range observed by Kim and colleagues in their meta-analysis where similar values of eHealth literacy—measured using the actual eHEALS instrument—and health behaviors were analyzed (Kim et al., 2023). This finding also mirrors previous research showing that eHEALS scores were a valid and reliable measure of self-reported eHealth literacy among internet-using adults with chronic disease (Paige et al., 2017), while also extending that literature by suggesting that a broader, multidimensional operationalization of eHealth literacy may have stronger utility for understanding how digital health skills translate into enacted self-management behaviors.

These results underscore the importance of considering eHealth literacy as part of the broader constellation of skills and beliefs that support effective chronic disease self-management. In the conceptual model guiding this dissertation research, the Information-Motivation-Behavioral Skills (IMB) model described eHealth Literacy and self-efficacy as co-occurring behavioral skills that influenced CDSMs in a broader context. Results across aims showed this to be the case. Furthermore, findings reflected a complementary relationship between the two constructs because of how the HeLSI score performed in the fourth model when self-efficacy was added. Self-efficacy may be an important complementary element required to effectively translate motivation and information into behavioral skills and actual health behaviors. This conceptualization of the relationship between self-efficacy and eHealth literacy in the context of health management and the magnitude of the relationship aligns clearly with similar findings among adults with Type 2 diabetes (K. A. Kim et al., 2018). Together, these findings offer an opportunity to further contextualize the makeup of behavioral skills within the IMB model.

These findings may also be interpreted through the lens of patient activation (Hibbard et al., 2004). Hibbard's conceptualization of activation emphasizes that successful self-management depends on knowledge, skill, and confidence to manage one's health (2017). Within that context, eHealth literacy and self-efficacy may represent complementary capacities that support more activated engagement in chronic disease self-management, particularly in a digital health environment. However, given that these relationships reflect only a subset of the IMB model, future research could also examine the role of motivations and knowledge on eHealth literacy and self-efficacy and determine how each construct interacts to influence health behaviors.

Results regarding the relationship between eHealth literacy skills, chronic disease self-management, sociodemographic characteristics, and self-efficacy showed that self-efficacy was the strongest predictor of higher CDSM behavioral engagement even though eHealth literacy skills and sociodemographic characteristics were important influencers. Thus, public health interventions seeking to improve chronic disease self-management behaviors should consider how building fundamental self-efficacy and skills can aid individuals in reaching their health goals. Teaching an individual with a chronic condition how to fill out medical forms (skill) will be less effective if they do not believe they can successfully manage their condition (efficacy) in an eHealth environment. Funding should prioritize "mastery experiences" where patients can practice digital tasks in low-stakes environments to build the confidence necessary for reaching CDSM behavioral targets.

5.3. Theoretical and Scientific Implications

5.3.1. Theoretical Implications

Findings from this dissertation research study have important implications for the conceptualization of eHealth Literacy and related health behavior theory. First, this dissertation study found that skills approximating the six eHealth literacy skill domains outlined in the Norman & Skinner Lily model were captured in the H6 dataset. The items from the H6 questionnaire were chosen based on their relative similar wording to the items in the eHEALS scale, which was founded based on descriptions of key eHealth literacy behaviors in the Lily model. By operationalizing and testing six distinct eHealth literacy domains, this study provided empirical support for treating eHealth literacy as a multidimensional construct, rather than a single latent trait.

While the HeLSI score created in Aim 4 was shown to be an independent and consistent predictor of specific CDSM behaviors, the differential performance of domains found in Aim 3 suggest that some skills might be more proximally tied to specific CDSM behaviors than others. Although the HeLSI was an approximation of eHealth literacy skills and may benefit from the inclusion of stronger performing variables, this finding in the context of this study suggests that each skill domain might relate to the others in different ways than previously expected. This is supported by the newer eHealth Literacy 3.0 imagery developed by Milanti, Norman, Chan, So, and Skinner which reflects traditional/basic literacy as fundamental to all other literacy and health and scientific literacies as foundational skills to the remaining three literacies—information, computer, and media (2025). However, for the Lily model to be an effective theoretical framework that guides research examining each distinct domain, further examination is needed to determine the degree to which each domain coalesces and varies from each other and if these relationships change based on the context of its use. There is now an opportunity to more formally test potential differences among these eHealth literacy skills using an eHealth literacy framework to guide psychometric testing of the HeLSI index score. Future research isolating and testing the latent properties of each of these items with one another could extend findings from this dissertation study regarding how these literacies most strongly align with one another.

Another theoretical implication of this research is that the results in this study reinforce the theoretically informed relationship between eHealth literacy and health behaviors outlined in the Information-Motivation-Behavioral (IMB) Skills model. However, findings link self-efficacy closely with eHealth literacy, suggesting that these are potentially complementary or overlapping constructs in this model. This is not entirely unexpected, because both the Lily Model and the IMB draw on fundamental self-efficacy ideas initially introduced in the Social Cognitive Theory (Bandura, 2001; Fisher & Fisher, 1992; Norman & Skinner, 2006). These findings reinforce previous research that linked eHealth literacy skills with self-efficacy and with key health behaviors among adults with Type 2 diabetes (Yang et al., 2026). However, given the cross-sectional nature of the relationship, the ability to determine a causal relationship was not possible, but these findings provide direction for future research to examine the potential causal and potentially mediated pathway between eHealth literacy, self-efficacy, and chronic disease self-management behaviors.

5.3.2. Scientific Contributions

This dissertation makes several meaningful scientific contributions to the fields of eHealth, eHealth literacy, and chronic disease self-management. First, this study demonstrates a replicable, theory-driven approach to operationalizing eHealth literacy using population-based survey data. By systematically mapping existing HINTS items to the six domains of the eHealth Literacy Lily model and empirically evaluating their alignment with eHealth use behaviors, this work advances methods for studying complex constructs such as eHealth literacy in a secondary dataset. Additionally, the inclusion of a social media component via the media literacy variable offers an opportunity to fill a gap in the literature highlighting a lack of Web 2.0 measures in eHEALS (J. Lee et al., 2021). Importantly, this dissertation showed that formative indices with modest internal consistency can be analytically appropriate when the goal is to summarize engagement across distinct domains rather than measure a single latent trait. This contributes to ongoing methodological discussions around the value of composite measures in population health research (Hyder et al., 2012; Lines et al., 2023).

Second, there are several types of health behaviors captured in the HINTS dataset; however, this dissertation study is among the first to link these commonly-recommended key health behaviors into a composite measure built by referencing existing measures of self-care in chronic illness. This score, despite its low reliability (Cronbach's $\alpha = 0.29$), offers researchers an opportunity to track engagement in these key health behaviors across HINTS iterations, leading to new insights into trends in behaviors and associations between aspects of eHealth literacy and these relevant CDSM behaviors.

Next, this study extends empirical literature by examining domain-specific eHealth literacy skills in relation to multiple chronic disease self-management behaviors, rather than focusing on single outcomes. As the Middle Range Theory of Chronic Illness highlights, chronic disease self-management is multidimensional and process-oriented (Riegel et al., 2019; Riegel et al., 2012; Riegel et al., 2026). While interpretations of the findings in this study are limited due to the cross-sectional nature of the data, the use of a composite score to measure key CDSM behaviors represents an opportunity for future research to more comprehensively explore co-occurring, everyday self-management practices that collectively characterize how individuals live with chronic illness. Furthermore, the fact that disease type was not associated with eHealth literacy indicators suggests that this observed relationship may reflect the impact of eHealth literacy on foundational self-management behaviors relevant across chronic diseases.

Finally, through an effort to validate the items used to measure eHealth literacy, this dissertation offers evidence supporting a skill-use-behavior pathway in which eHealth literacy skills enacted through eHealth use behaviors impact self-management behaviors. While preliminary, this potential conceptual pathway offers an opportunity to potentially merge the Uses and Gratification Theory with relevant eHealth literacy frameworks.

5.4. Study Strengths & Limitations

5.4.1. Strengths

In addition to the theoretical and scientific contributions outlined above, this dissertation research also boasts a few strengths. This dissertation research study is one of the first studies of its kind to explore the six dimensions of eHealth literacy as outlined by the eHealth literacy Lily model using a nationally representative dataset. The use of validated and widely used items in HINTS provided an evidence-based foundation for this research. Further, the ability to use weighted estimates to provide nationally representative results advances eHealth literacy research that is typically plagued by small sample sizes or underpowered analyses (Barbati et al., 2025; Wang et al., 2021).

Many eHealth literacy research studies examine the multiple dimensions of the Lily model using eHEALS which reflects just one score (El Benny et al., 2021). This dissertation study provide a comprehensive analysis of eHealth literacy at both individual domain levels and at a composite level. This study offers an evidence-based operationalization of key eHealth literacy domains, specifically media literacy and scientific literacy, that are often difficult to map in national datasets (Levin-Zamir & Bertschi, 2018).

Despite mixed results regarding these domains, the findings from this dissertation study extend what is known about population-level estimates of a multidimensional conceptualization of eHealth literacy among adults with chronic conditions. Furthermore, this study's exploration of multiple dimensions of eHealth literacy skills among a sample of adult internet users with chronic conditions is novel.

The findings in this study, related to how eHealth literacy skills are independently associated with CDSM behaviors despite the influence of the potentially mediating role of self-efficacy, provide new clarity to the theoretical linkages between individual characteristics like eHealth literacy and individual behaviors, like the specific CDSM behaviors explored here.

5.4.2. *Limitations*

This dissertation has several important limitations that should be considered when interpreting the findings. These limitations primarily relate to the operationalization of eHealth literacy using variables from an existing dataset, the cross-sectional nature of the study and its implications for causal inference, analytic decisions related to variable construction, the use of composite indices, and the impact of complete case analysis on missing data. While these constraints shape the interpretation of results, they do not undermine the overall contribution of the study and instead highlight important directions for future research.

As discussed, the HINTS 6 questionnaire did not include variables that directly aligned with each of the six domains in the eHealth literacy Lily model; therefore, eHealth literacy skills were estimated using available data. Guided by the theoretical foundation of the eHEALS framework (Norman & Skinner, 2006a), I identified and operationalized variables that approximated each domain by reflecting applied skills and perceptions rather than comprehensive domain-specific measures. However, this operationalization was imperfect. Because eHEALS does not distinctly tie each specific item within the scale to a specific eHealth literacy skill domain, I had to deduce which item in eHEALS most likely corresponded with each eHealth literacy domain and apply it to the relevant HINTS item. Given the nature of this type of survey, the number of questions provided that aligned with each skill domain was limited to only one or two per domain. This led to imperfect overlaps between the underlying concepts and the actual variables used in analyses, and, as a result, captured only partial and data-specific representations of each construct rather than each fundamental item.

This limitation was particularly salient for domains such as Scientific Literacy and Media Literacy, where available HINTS items reflected perceptions of information overload or difficulty discerning credibility rather than direct assessments of scientific reasoning or evaluative skill. These variables performed less reliably than the other measures selected for this study. Although there are known issues with measuring these two literacies (Norman, 2011), future research is needed to explore the validity of these items independently and within the context of the overall index to encourage more confidence in their use in follow-up HINTS studies.

Furthermore, while the eHEALS scale was used as a guide when selecting the HINTS variables to measure eHealth literacy, this dissertation study deviated from the original conceptualization of eHEALS as a unidimensional measure. Instead, the selected variables in this study reflected more of an index score with related but not well-correlated domains. As a result, the reliability and internal validity of this H6 eHealth Literacy index need further examination to determine if they can be used successfully in follow-up studies. The findings that some of the items are weaker fits with the overall H6 eHealth Literacy Index is mitigated by results from previous research that indicated that some of the eight items within eHEALS also perform poorly in certain populations (Stellefson et al., 2017).

Finally, the selection of eHealth use variables for Aim 2 required balancing conceptual alignment with survey design constraints, including skip logic and item availability across respondents. Although the selected eHealth use variables aligned reasonably well with core elements of each literacy domain, these associations were inherently imperfect. Importantly, eHealth literacy is not synonymous with eHealth use, and the criterion validity assessed in Aim 2 should be interpreted as supportive rather than definitive. These findings underscore the need for future research that more intentionally links digital skills, use behaviors, and health outcomes using instruments designed for that purpose.

Additionally, the cross-sectional nature of the HINTS data limits the ability to draw causal inferences or to fully characterize dynamic relationships among eHealth literacy, self-efficacy, and chronic disease self-management behaviors. While the analyses in this study identified robust associations between these constructs, the temporal ordering of effects cannot be established (Finney Rutten et al., 2020; Wang & Cheng, 2020). In particular, the observed attenuation of eHealth literacy effects after accounting for self-efficacy raises important theoretical questions about whether eHealth literacy functions as a component of behavioral skills, a precursor to self-efficacy, or both. These relationships likely operate bidirectionally and evolve over time, especially as individuals gain experience managing chronic conditions and interacting with digital health tools.

Longitudinal and experimental studies are needed to disentangle these pathways and to clarify how eHealth literacy and self-efficacy jointly contribute to sustained self-management. Additionally, although sensitivity analyses suggested that relationships did not differ substantially by individual chronic disease type, chronic conditions are heterogeneous in their management demands. Future research should examine whether the role of eHealth literacy varies across specific disease contexts, treatment regimens, or stages of illness.

Several analytic decisions also warrant discussion. To facilitate interpretability and consistency across models, I dichotomized several variables. These procedures led to standardized values which reduced variability, an issue that has been brought up in previous eHealth literacy research (Paige et al., 2017). While dichotomization can improve model stability and clarity, particularly in large survey datasets, it also entails a loss of information and may obscure meaningful gradients in skill or behavior (Altman & Royston, 2006; MacCallum et al., 2002; Prince Nelson et al., 2017). Although data remained relatively stable across aims despite this standardization, future studies should explore alternative modeling approaches using ordinal or continuous versions of these variables where feasible.

Similarly, the composite indices used to summarize eHealth literacy skills and chronic disease self-management behaviors demonstrated relatively low internal consistency, with Cronbach's alpha values in the 0.30–0.40 range. These values reflect the fact that the composites were intentionally constructed as formative indices representing engagement across distinct domains rather than reflective scales measuring a single latent construct (Taber, 2018). As noted in prior methodological work, low internal consistency does not invalidate such indices but does highlight their limitations for capturing cohesion among heterogeneous behaviors. Future research could explore alternative weighting schemes, latent variable models, or domain-specific composites to improve measurement precision (McKenna & Heaney, 2020).

Finally, missing data also presented an important limitation. As is common in HINTS analyses, missingness was not completely random and was disproportionately concentrated in certain sociodemographic categories, particularly older adults and those with lower income. While a complete case analysis was used due to the conceptual nature of this dissertation study, the sufficient sample size of internet users with chronic conditions, the fact that missingness was considered MAR for the most part, and many of the analytic models were controlling for the other variables, sensitivity analyses were required to demonstrate that primary associations remained stable when categories with high missingness were excluded (Ross et al., 2020).

Because variables associated with missingness were included as covariates in multivariable models, the primary findings appeared robust; however, some limitations to generalizability remain. More advanced missing data techniques, such as multiple imputation, may be appropriate in future studies designed specifically to address these issues.

Chronic conditions, while similar in many ways, are not uniform and may generate different management requirements and health behaviors. Different behaviors may have a different impact on the management of each disease condition. The target CDSM behaviors in this study were selected as fundamental behaviors that help reduce the impact and incidence of chronic conditions. However, there are likely differences in the engagement in each of these behaviors based on disease type, which was outside the scope of this study. Although sensitivity tests suggested that most of the behaviors were not very different based on disease type, future research should explore the extent to which the relationship between eHealth literacy and CDSM behaviors might differ based on disease type.

Additional limitations include reliance on self-reported measures, which may be subject to recall and social desirability bias, and the broader context of data collection during the COVID-19 pandemic, which affected response rates and health behaviors nationwide (Harper et al., 2020; Kormos & Gifford, 2014). These issues are not unique to this study but should be acknowledged when interpreting the findings. Despite these limitations, the consistency of findings across multiple analytic approaches and sensitivity analyses supports the overall robustness of the results and provides a strong empirical foundation for future longitudinal and intervention-based research on eHealth literacy and chronic disease self-management.

5.5. Future Research

While there are several directions this dissertation research could take, there are three key areas that could guide future research. First, since this dissertation research began, the National Cancer Institute released a new dataset, HINTS 7 (H7). In this updated, entirely post-pandemic sample, they asked additional questions about eHealth use and general eHealth behaviors. Most of the variables from the current study appear in H7, so future research could explore the trends in behaviors among the variables selected to represent eHealth literacy and chronic disease self-management among a new sample of internet users with chronic conditions to determine if patterns hold. Furthermore, some variables may be a better fit with some of the eHealth literacy skills operationalized in this study, and analyses using these variables may yield more relevant associations with CDSM behaviors. There is now an opportunity for future research to use the findings from this research study to identify appropriate eHealth literacy skill variables and validate these items into a scale or index in future HINTS datasets. Presently, there is no annual database capturing eHealth literacy insights, thus having an annual source of nationally representative data reflecting eHealth literacy trends among the American population could be very valuable for policymakers, researchers, and public health practitioners.

Next, this study used existing theory, previous research, and validated conceptual models to identify items to reflect eHealth literacy skill and eHealth use. Results from this study showed that eHealth literacy could be approximated using specific HINTS items; however, the conceptual fit was imperfect because the content of the items reflected overlapping constructs. For instance, the findings that specific literacies, as operationalized in this study, might play a more powerful role in self-management behaviors than others suggests that the domains may overlap with one another in uneven ways. This may be due, in part, to how these HINTS items were worded as self-reported perceptions, actions, or skills. This is not too dissimilar from the widely-used eHEALS scale that similarly lacks distinctiveness and mixes knowledge, confidence, and skills. While the authors of the Lily model recently introduced the Lily Model 3.0 (Milanti et al., 2025) to reimagine eHealth literacy as related but different component parts, the lack of empirical data using this model limits its interpretability.

This dissertation study provides new evidence showing that there are key differences in the eHealth literacy skill domains when associated with eHealth use and CDSM behaviors, and future research is needed to determine how each of these related, yet separate items interact. The specific context- or task-based items used to measure each domain in this dissertation study hold promise for leading the revision and update of an eHEALS model, and the linkage between eHealth literacy skill and eHealth use suggests that eHealth literacy might reflect a combination of capabilities and behaviors. A structural equation modeling approach that looks at all these variables in relation to one another and to CDSM behaviors could yield important insights into how the skills perform together. Additionally, exploratory factor analysis using these items could also lead to a better understanding of how these skill domains may group together. This nuanced understanding of how these skill domains are truly interrelated and interdependent will help guide analytic approaches that seek to understand the impact of addressing overall eHealth literacy via the presence of specific skills.

Lastly, this study found that there were opportunities to improve engagement in target CDSM behaviors among the sample population and that higher self-efficacy is associated with higher levels of CDSM behavior. These findings, in conjunction with the findings of the small but significant relevance of eHealth literacy skills in CDSM behaviors, offer insights that can shape health interventions. Future research should test the practical implications of this research through health behavior interventional studies. Interventions using eHealth tools to manage aspects of daily chronic care—such as dietary monitoring or physical activity engagement—that focus on improving self-efficacy alongside eHealth literacy skills are likely to be successful based on the theoretical implications of this dissertation research. This study also found that individuals with chronic conditions have higher levels of specific eHealth literacy skill domains like Basic, Computer, and Health Literacies than those in the general population. More research is needed to better understand the degree to which self-efficacy drives CDSM behaviors within an eHealth context and how the presence of strong eHealth literacy skills impacts this relationship. This type of longitudinal research could explore more temporal elements of these relationships to determine if eHealth literacy skills and self-efficacy co-occur along the pathway to disease management or if they are ordered in some way (i.e., as a mediating effect). Since multimorbidity was an influential factor in this relationship, effect modification could also be explored in a longitudinal analysis to understand if approaches to those with multiple conditions should differ than those without. Additionally, given an individual's experience managing a chronic condition over time and developing the necessary skills to navigate their health amid an evolving health context, phenomenological or narrative inquiry qualitative research could yield contextualized insights about the process of building self-efficacy and digital skills that would complement findings from quantitative studies. Together, these approaches would generate robust and patient-centered reflections that could help shape ongoing and future health promotion interventions.

5.6. Conclusion

For individuals living with diabetes, high blood pressure, heart conditions, lung disease, or cancer in this post-pandemic eHealth-use centric environment, engaging in daily self-management behaviors is still a challenge. Understanding what enables or constrains these behaviors is therefore important for improving long-term health outcomes. Findings from this dissertation suggest that eHealth literacy skills play a small but meaningful role in supporting chronic disease self-management at the population level. Higher levels of eHealth literacy were associated with greater engagement in several health-promoting behaviors, indicating that individuals with stronger digital health skills may be better equipped to locate, interpret, and apply health information in their daily care.

These skills did not operate in isolation. eHealth literacy co-occurred with self-efficacy, and together these constructs were associated with stronger engagement in chronic disease self-management behaviors. This pattern suggests that digital health skills and confidence in one's ability to manage health are related capacities that may work together to support disease management. At the same time, the findings showed that eHealth literacy was not uniformly distributed across domains. Some areas appeared stronger than others, reinforcing the importance of viewing eHealth literacy as a multidimensional construct rather than a single, evenly developed skill set.

These findings have practical implications for healthcare systems that increasingly rely on digital tools and online health information. Even among internet users with chronic conditions, high levels of multidimensional eHealth literacy were not the norm, suggesting an ongoing gap between the demands of the eHealth environment and the skills needed to navigate it effectively. Designing digital resources that are accessible to individuals with varying literacy profiles, while also supporting self-efficacy, may help strengthen chronic disease self-management over time. By operationalizing these skills using nationally representative data, this dissertation also provides a scalable approach for studying digital health competencies in population health research.

In conclusion, as the eHealth landscape evolves, so too must our understanding of the role eHealth literacy skills play for people navigating this landscape. While this study updates key theories and provides a scalable approach for population-level research, it also serves as a challenge to the field to develop more sophisticated, multidimensional measures that reflect the dynamic nature of digital health. By modernizing theories and identifying paths for future research, this dissertation provides a practical roadmap for navigating a complex eHealth landscape. By grounding theoretical advances in real-world solutions, we can ensure that eHealth literacy and self-efficacy work in tandem to empower individuals, moving from a world where eHealth tools simply exist to one where they are truly accessible, effective, and life-changing.

Appendix

Appendix A – List of Variables

Internet Users (n=1)

OLD NAME	NEW NAME
UseInternet	InternetUsers

Sociodemographics (n=7)

OLD NAMES	NEW NAMES
RUC2013	Locality
HealthInsurance2	Insured
RaceEthn5	RaceEthnicity
IncomeRanges_IMP	Income
EducA	EducationLevel
AgeGrpB	AgeRange
BirthGender	Sex

Covariate (n=1)

OLD NAME	NEW NAME
OwnAbilityTakeCareHealth	Aim1SelfEfficacy

CDSM Variables (n=6)

OLD NAMES	NEW NAMES
WeeklyMinutesModerateExercise	PhysicalActivity
smokeStat	SmokingStatus
NoticeCalorieInfoOnMenu	CalorieInfo
HCPShare_FoodIssues	FoodDiscussion
AvgDrinksPerWeek x Sex	Alcohol Consumption
GeneralHealth	HealthPerception

eHealth Use (n=6)

OLD NAMES	NEW NAMES
SharedHealthDeviceInfo	Basic_eHealthUse
UsedHealthWellnessApps2	Computer_eHealthUse
Electronic2_TestResults	Scientific_eHealthUse
Electronic2_HealthInfo	Information_eHealthUse
Electronic2_MessageDoc	HealthRelated_eHealthUse
SocMed_WatchedVid	Media_eHealthUse

eHealth Literacy (n=6)

OLD NAMES	NEW NAMES
UndMedicalStats	BasicLiteracy
Electronic2_MadeAppts	ComputerLiteracy
TooManyRecommendations	ScientificLiteracy
ConfidentInternetHealth	InformationLiteracy
ConfidentMedForms	HealthLiteracy
SocMed_TrueFalse	MediaLiteracy

Chronic Conditions (n=8)

OLD NAMES	NEW NAMES
MedConditions_Diabetes	Diabetes
MedConditions_HighBP	HighBP
MedConditions_HeartCondition	HeartCondition
MedConditions_LungDisease	LungDisease
EverHadCancer	Cancer
	AnyChronicCondition
	NumChronicConditions
	MultipleConditions

Appendix B - Little's MCAR / MAR Analysis Procedures

Little's MCAR Test Results (n=2888)

Grouped by type of variable. Dataset: hints6_sub_df
1) **Sociodemographic Variables** (n=7; Locality, Insured, RaceEthnicity, Income, EducationLevel, AgeRange, Sex)

- **Result** = Little's MCAR test indicated that missingness for sociodemographic variables was <u>not</u> completely at random ($\chi^2(109) = 222$, $p < .001$).

2) CDSM Variables & Self-Efficacy (n=7; PhysicalActivity, SmokingStatus, CalorieInfo, FoodDiscussion, AlcoholConsumption, HealthPerception, Aim1SelfEfficacy)

- **Result** = Little's MCAR test for the CDSM variables grouped with Self-Efficacy did not provide evidence to reject the null hypothesis that missing data in this set of related variables was missing completely at random ($\chi^2(129) = 141$, $p = .23$).

3) eHealth Use Variables (n=6; Basic_eHealthUse, Computer_eHealthUse, Scientific_eHealthUse, HealthLit_eHealthUse, Information_eHealthUse, Media_eHealthUse)

- **Result** = Little's MCAR test for the eHealth use variables indicated that missingness in eHealth use variables was <u>not</u> completely at random ($\chi^2(73) = 465$, $p < .001$).

4) eHealth Literacy Variables (n=6; BasicLiteracy, ComputerLiteracy, ScientificLiteracy, InformationLiteracy, HealthLiteracy, MediaLiteracy)

- **Result** = For eHealth literacy variables, Little's MCAR test did not provide evidence to reject the null hypothesis that missing data in this set of related variables was missing completely at random ($\chi^2(78) = 99.2$, $p = .053$), although the result was marginal and therefore interpreted cautiously.

Missing data mechanisms were assessed within the analytic sample of internet users with at least one chronic condition using Little's MCAR test across five domains. Missingness in sociodemographic variables ($\chi^2(109) = 222$, $p < .001$), eHealth use variables ($\chi^2(73) = 465$, $p < .001$), eHealth literacy variables ($\chi^2(81) = 158$, $p < .001$), and chronic condition indicators ($\chi^2(23) = 36.2$, $p = .039$) was inconsistent with a missing completely at random (MCAR) mechanism. In contrast, missingness in chronic disease self-management variables did not deviate from MCAR ($\chi^2(129) = 141$, $p = .225$). Overall, these findings indicate that missingness varied by domain within the analytic sample, supporting the use of analytic approaches appropriate under a missing-at-random assumption for subsequent analyses.

Appendix B – Supplemental Table 1
Rates of missing by variable in Aim 4 (n=2,888)

Variable	Missing (n[a])	% Missing
CDSM Variables		
Smoking Status	70	2.42%
Physical Activity	79	2.73%
Calorie Information	44	1.52%
Food Discussion	101	3.50%
Alcohol Consumption	199	6.89%
Health Perception	19	0.66%
eHealth Literacy Skill Variables		
Basic Literacy	17	0.59%
Computer Literacy	30	1.04%
Scientific Literacy	79	2.73%
Information Literacy	38	1.32%
Health Literacy	5	0.17%
Media Literacy	84	2.91%
Sociodemographic Variables		
Sex Assigned at Birth	74	2.56%
Age Range	25	0.87%
Education Level	73	2.53%
Income	3	0.10%
Race/Ethnicity	174	6.03%
Insurance Status	14	0.48%
Locality	0	0.00%
Covariates		
Self-Efficacy	7	0.24%
Multiple Conditions	0	0.00%

[a] Unweighted frequency (n=2,888)

Appendix C – Cronbach's Alpha of eHealth Use Composite

Supplemental Table 3. eHealth Use Variable Cronbach Coefficient Alpha (n=2,715)		
	Item–total correlation	**Alpha if item deleted**
	0.282	0.647
	0.438	0.591
	0.382	0.617
	0.479	0.577
	0.485	0.573
	0.267	0.658
	0.654	

The CORR Procedure

6 Variables:	Basic_eHealthUse_A2 Computer_eHealthUse_A2 Scientific_eHealthUse_A2 Information_eHealthUse_A2 HealthLit_eHealthUse_A2 Media_eHealthUse_A2

Simple Statistics

Variable	N	Mean	Std Dev	Sum	Minimum	Maximum
Basic_eHealthUse_A2	2715	0.25635	0.43670	696.00000	0	1.00000
Computer_eHealthUse_A2	2715	0.55875	0.49663	1517	0	1.00000
Scientific_eHealthUse_A2	2715	0.73775	0.43994	2003	0	1.00000
Information_eHealthUse_A2	2715	0.85599	0.35117	2324	0	1.00000
HealthLit_eHealthUse_A2	2715	0.67477	0.46855	1832	0	1.00000
Media_eHealthUse_A2	2715	0.59374	0.49122	1612	0	1.00000

Cronbach Coefficient Alpha

Variables	Alpha
Raw	0.654436
Standardized	0.658472

Cronbach Coefficient Alpha with Deleted Variable

Deleted Variable	Raw Variables		Standardized Variables	
	Correlation with Total	Alpha	Correlation with Total	Alpha
Basic_eHealthUse_A2	0.282001	0.646876	0.275600	0.655264
Computer_eHealthUse_A2	0.438044	0.590800	0.437836	0.597919
Scientific_eHealthUse_A2	0.478998	0.577370	0.481777	0.581512
Information_eHealthUse_A2	0.381727	0.616929	0.380657	0.618703
HealthLit_eHealthUse_A2	0.484566	0.572781	0.490379	0.578255
Media_eHealthUse_A2	0.267523	0.657564	0.271161	0.656763

Pearson Correlation Coefficients, N = 2715
Prob > |r| under H0: Rho=0

	Basic_eHealthUse_A2	Computer_eHealthUse_A2	Scientific_eHealthUse_A2	Information_eHealthUse_A2	HealthLit_eHealthUse_A2	Media_eHealthUse_A2
Basic_eHealthUse_A2	1.00000	0.25673 <.0001	0.16210 <.0001	0.11349 <.0001	0.22754 <.0001	0.13356 <.0001
Computer_eHealthUse_A2	0.25673 <.0001	1.00000	0.32856 <.0001	0.24607 <.0001	0.30620 <.0001	0.21794 <.0001
Scientific_eHealthUse_A2	0.16210 <.0001	0.32856 <.0001	1.00000	0.32069 <.0001	0.51558 <.0001	0.14619 <.0001

Information_eHealthUse_A2	0.11349 <.0001	0.24607 <.0001	0.32069 <.0001	1.00000	0.29074 <.0001	0.22674 <.0001
HealthLit_eHealthUse_A2	0.22754 <.0001	0.30620 <.0001	0.51558 <.0001	0.29074 <.0001	1.00000	0.15572 <.0001
Media_eHealthUse_A2	0.13356 <.0001	0.21794 <.0001	0.14619 <.0001	0.22674 <.0001	0.15572 <.0001	1.00000

Appendix D - Collinearity Diagnostics for Binary eHealth Literacy Variables

Parameter Estimates							
Variable	**DF**	**Parameter Estimate**	**Standard Error**	**t Value**	**Pr > |t|**	**Tolerance**	**Variance Inflation**
Intercept	1	1.89109	0.10548	17.93	<.0001	.	0
BasicLitBinary	1	0.05443	0.06711	0.81	0.4174	0.92672	1.07907
ComputerLitBinary	1	1.53946	0.05789	26.59	<.0001	0.95910	1.04265
ScientificLitBinary	1	0.09626	0.05983	1.61	0.1077	0.96443	1.03688
InformationLitBinary	1	0.46532	0.05733	8.12	<.0001	0.92594	1.07998
HealthLitBinary	1	0.30359	0.09214	3.29	0.0010	0.95428	1.04791
MediaLitBinary	1	0.36078	0.05676	6.36	<.0001	0.96833	1.03271

Collinearity Diagnostics									
#	**Eigenvalue**	**Condition Index**	**Proportion of Variation**						
			Intercept	**BasicLitBinary**	**ComputerLitBinary**	**ScientificLitBinary**	**InformationLitBinary**	**HealthLitBinary**	**MediaLitBinary**
1	4.99694	1.00000	0.00255	0.00729	0.01052	0.01109	0.01164	0.00357	0.00979
2	0.66708	2.73692	0.00107	0.00011314	0.00309	0.72484	0.00365	0.00089584	0.13858
3	0.50256	3.15324	0.00097289	0.00050964	0.02583	0.15840	0.52095	0.00064250	0.22476
4	0.33736	3.84859	0.00006480	0.00002509	0.68626	0.01312	0.33177	0.00029512	0.15324
5	0.30246	4.06459	0.00809	0.27460	0.20336	0.08031	0.12786	0.03458	0.26873
6	0.14634	5.84341	0.05328	0.68978	0.04444	0.00645	0.00013986	0.25573	0.10591
7	0.04725	10.28382	0.93397	0.02769	0.02650	0.00579	0.00399	0.70428	0.09899

Glossary

The following section provides definitions or explanations for key terms used in this dissertation.

eHealth – eHealth consists of web-based and software programs, mHealth (smartphone or tablet apps, text messaging, wearable devices, etc.), health information technology, telehealth/telemedicine, electronic medical records, and advanced computing sciences related to big data, genomics and artificial intelligence (Taylor et al., 2022).

eHealth tools – eHealth tools are comprised of the multimodal health information technologies available for engaging in healthcare virtually. Common eHealth tools are smartphone applications, electronic health records, online medical records, e-prescribing, telehealth/telemedicine, remote monitoring devices (like home blood pressure cuffs, Bluetooth or Wi-Fi enabled scales, smartwatches, etc.), and online health communities (Chan, 2021; Schulte et al., 2021; Shaw et al., 2017)

eHealth literacy– eHealth literacy is often described as a noun, or something than an individual has or exhibits, an ability or a capacity (Centers for Disease Control and Prevention, 2024, June; Norman & Skinner, 2006b). These interchangeable definitions can add to the confusion surrounding how to define and measure eHealth literacy. In this study, I define eHealth literacy as a multidimensional set of skills that can be measured in different levels and that represent successful engagement in eHealth activities associated with basic (traditional) literacy, computer literacy, scientific literacy, information literacy, health literacy, and media literacy (see Chapter 2 for more details on this definition).

Chronic conditions (preventable chronic diseases or non-communicable diseases) – These chronic conditions tend to be diseases that are caused by and "deeply affected by shifts and changes in lifestyle related to diet, smoking, physical activity, and alcohol use" (Hacker, 2024, p. 117).

Chronic disease self-management (CDSM) behaviors – Chronic disease self-management (CDSM) behaviors reflect specific individual-level activities that contribute positively or negatively to health outcomes related to specific chronic conditions (Lorig et al., 2001). These behaviors often include symptom management and general health monitoring, medication management, maintaining appropriate levels of nutrition and exercise, and engaging in regular interactions with healthcare providers (Grady & Gough, 2014; Hacker, 2024). This study focuses specifically on six key indicators of CDSM behaviors: alcohol consumption, smoking status, physical activity levels, calorie information awareness, comfortability discussing food issues, and self-reported perception of health.

Health behavior skills and health behaviors (via IMB) – Fisher and colleagues describe "health behavior skills" in the IMB as individual objective abilities coupled with individual senses of self-efficacy. (Fisher et al., 2006; Fisher et al., 2009) The behavioral skills represent someone's underlying skills to engage in specific behaviors as well as their perceived ability to engage in those specific behaviors. This two-dimensional description of behavioral skills fits well with chronic disease self-management studies because of the long-term, deeply rooted practice of managing a chronic disease on a daily basis. Health behaviors, according to the IMB model, refer to health promotion activities that either include initiating or maintaining health promotion practices or reducing risky health behaviors.

Health Information National Trends Survey (HINTS) – HINTS is a nationally representative data fielded regularly by the National Cancer Institute to track changes in the field of health communication and information technology. HINTS is comprised of a questionnaire that is either completed via paper or online. There have been many cycles of HINTS since its inception in 2003. We are using HINTS, cycle 6 (H6). (National Cancer Institute, n.d.–a)

Digital divide – The digital divide is a term used to describe how access to technology is often a social determinant of health that can worsen or improve health disparities (Alkureishi et al., 2021). Adoption of eHealth is not even across the population, so it is important to reflect on the digital divide that remains within specific demographic groups when analyzing nationally representative data (Veinot et al., 2018).

Multimorbidity – Multimorbidity is a term to describe the presence of multiple conditions in one individual. It is often considered just the presence of two or more conditions in an individual, and in the case of this dissertation, that would reflect two or more chronic conditions. However, multimorbidity sometimes is confused with comorbidity, which is the co-occurrence of a condition with one primary condition being the key disease (Skou et al., 2022). Multimorbidity does not refer to an order of the diseases, rather, it simply reflects that an individual has multiple conditions.

Telemedicine vs. telehealth – Although sometimes used interchangeably, telehealth and telemedicine are different terms. Telehealth represents a broader term that encompasses all healthcare services delivered remotely using technology, including administrative tasks and provider training (Federal Communications Commission (FCC), n.d.). Telemedicine is a subset of telehealth and refers to the remote delivery of clinical services like diagnosis, treatment, and patient monitoring.

References

Abbott, S., Parretti, H. M., Hazlehurst, J., & Tahrani, A. A. (2021). Socio-demographic predictors of uptake of a virtual group weight management program during the COVID-19 pandemic. *Journal of Human Nutrition and Dietetics*, *34*(3), 480–484. https://doi.org/https://doi.org/10.1111/jhn.12850

Adams, S. G., Smith, P. K., Allan, P. F., Anzueto, A., Pugh, J. A., & Cornell, J. E. (2007). Systematic review of the chronic care model in chronic obstructive pulmonary disease prevention and management. *Arch Intern Med*, *167*(6), 551–561. https://doi.org/10.1001/archinte.167.6.551

Adetunji, C. O., Olaniyan, O. T., Adeyomoye, O., Dare, A., Adeniyi, M. J., Alex, E., Rebezov, M., Garipova, L., & Shariati, M. A. (2022). eHealth, mHealth, and Telemedicine for COVID-19 Pandemic. In S. K. Pani, S. Dash, W. P. dos Santos, S. A. Chan Bukhari, & F. Flammini (Eds.), *Assessing COVID-19 and Other Pandemics and Epidemics using Computational Modelling and Data Analysis* (pp. 157–168). Springer International Publishing. https://doi.org/10.1007/978-3-030-79753-9_10

Adibi, S. (2015). Introduction. In S. Adibi (Ed.), *Mobile Health: A Technology Road Map* (pp. 1–7). Springer International Publishing. https://doi.org/10.1007/978-3-319-12817-7_1

Adler-Milstein, J., & Jha, A. K. (2017). HITECH Act Drove Large Gains In Hospital Electronic Health Record Adoption. *Health Affairs*, *36*(8), 1416–1422. https://doi.org/10.1377/hlthaff.2016.1651

Agency for Healthcare Research. (2021). *2021 National Healthcare Quality and Disparities Report*. https://www.ncbi.nlm.nih.gov/books/NBK578537/

Agnihothri, S., Cui, L., Delasay, M., & Rajan, B. (2020). The value of mHealth for managing chronic conditions. *Health Care Management Science*, *23*(2), 185–202. https://doi.org/10.1007/s10729-018-9458-2

Airola, E. (2021). Learning and Use of eHealth Among Older Adults Living at Home in Rural and Nonrural Settings: Systematic Review. *J Med Internet Res*, *23*(12), e23804. https://doi.org/10.2196/23804

Ajayi, K. V., Wachira, E., Onyeaka, H. K., Montour, T., Olowolaju, S., & Garney, W. (2022). The Use of Digital Health Tools for Health Promotion Among Women With and Without Chronic Diseases: Insights From the 2017-2020 Health Information National Trends Survey. *JMIR Mhealth Uhealth*, *10*(8), e39520. https://doi.org/10.2196/39520

Al Mahmud, A., Joachim, S., Jayaraman, P. P., Learmonth, C., Tyagi, S., Forkan, A. R. M., Shuakat, M., Wickramasinghe, N., Wheeler, J., Best, S., & Trainer, A. (2026). Digital Health Interventions to Support Chronic Disease Management: Systematic Scoping Review. *JMIR Mhealth Uhealth*, *14*, e63742. https://doi.org/10.2196/63742

Alexander, G. C., Tajanlangit, M., Heyward, J., Mansour, O., Qato, D. M., & Stafford, R. S. (2020). Use and Content of Primary Care Office-Based vs Telemedicine Care Visits During the COVID-19 Pandemic in the US. *JAMA Network Open*, *3*(10), e2021476–e2021476. https://doi.org/10.1001/jamanetworkopen.2020.21476

Alhammad, N., Alajlani, M., Abd-alrazaq, A., Epiphaniou, G., & Arvanitis, T. (2024). Patients' Perspectives on the Data Confidentiality, Privacy, and Security of mHealth Apps: Systematic Review [Review]. *J Med Internet Res*, *26*, e50715. https://doi.org/10.2196/50715

Alhusseini, N., Banta, J. E., Oh, J., & Montgomery, S. B. (2021). Social Media Use for Health Purposes by Chronic Disease Patients in the United States. *Saudi J Med Med Sci*, *9*(1), 51–58. https://doi.org/10.4103/sjmms.sjmms_262_20

Alkureishi, M. A., Choo, Z. Y., Rahman, A., Ho, K., Benning-Shorb, J., Lenti, G., Velázquez Sánchez, I., Zhu, M., Shah, S. D., & Lee, W. W. (2021). Digitally Disconnected: Qualitative Study of Patient Perspectives on the Digital Divide and Potential Solutions. *JMIR Hum Factors*, *8*(4), e33364. https://doi.org/10.2196/33364

Allegrante, J. P., Wells, M. T., & Peterson, J. C. (2019). Interventions to Support Behavioral Self-Management of Chronic Diseases. *Annu Rev Public Health*, *40*, 127–146. https://doi.org/10.1146/annurev-publhealth-040218-044008

Allory, E., Scheer, J., De Andrade, V., Garlantézec, R., & Gagnayre, R. (2024). Characteristics of self-management education and support programmes for people with chronic diseases delivered by primary care teams: a rapid review. *BMC Primary Care*, *25*(1), 46. https://doi.org/10.1186/s12875-024-02262-2

Altman, D. G., & Royston, P. (2006). The cost of dichotomising continuous variables. *Bmj*, *332*(7549), 1080. https://doi.org/10.1136/bmj.332.7549.1080

Alzarea, A. I., Khan, Y. H., Alzarea, S. I., Alanazi, A. S., Alsaidan, O. A., Alrowily, M. J., Al-Shammari, M., Almalki, Z. S., Algarni, M. A., & Mallhi, T. H. (2024). Assessment of Health-Related Quality of Life Among Patients with Chronic Diseases and Its Relationship with Multimorbidity: A Cross-Sectional Study from Saudi Arabia. *Patient Prefer Adherence*, *18*, 1077–1094. https://doi.org/10.2147/ppa.S448915

An, L., Bacon, E., Hawley, S., Yang, P., Russell, D., Huffman, S., & Resnicow, K. (2021). Relationship Between Coronavirus-Related eHealth Literacy and COVID-19 Knowledge, Attitudes, and Practices among US Adults: Web-Based Survey Study [Original Paper]. *J Med Internet Res*, *23*(3), e25042. https://doi.org/10.2196/25042

Andersen, R. M. (2008). National Health Surveys and the Behavioral Model of Health Services Use. *Medical Care*, *46*(7), 647–653.

Anderson, E., & Durstine, J. L. (2019). Physical activity, exercise, and chronic diseases: A brief review. *Sports Med Health Sci*, *1*(1), 3–10. https://doi.org/10.1016/j.smhs.2019.08.006

Andreadis, K., Buderer, N., & Langford, A. T. (2025). Patients' Understanding of Health Information in Online Medical Records and Patient Portals: Analysis of the 2022 Health Information National Trends Survey. *J Med Internet Res*, *27*, e62696. https://doi.org/10.2196/62696

Ansah, J. P., & Chiu, C. T. (2022). Projecting the chronic disease burden among the adult population in the United States using a multi-state population model. *Front Public Health*, *10*, 1082183. https://doi.org/10.3389/fpubh.2022.1082183

Anthony, D., Campos-Castillo, C., & Nishii, A. (2024). Patient-centered communication, disparities, and patient portals in the US, 2017-2022. *Am J Manag Care*, *30*(1), 19–25. https://doi.org/10.37765/ajmc.2024.89483

Apolinário-Hagen, J., Menzel, M., Hennemann, S., & Salewski, C. (2018). Acceptance of Mobile Health Apps for Disease Management Among People With Multiple Sclerosis: Web-Based Survey Study. *JMIR Form Res*, *2*(2), e11977. https://doi.org/10.2196/11977

Aponte, J., & Nokes, K. M. (2017). Validating an electronic health literacy scale in an older hispanic population. *J Clin Nurs*, *26*(17-18), 2703–2711. https://doi.org/10.1111/jocn.13763

Araújo-Soares, V., Hankonen, N., Presseau, J., Rodrigues, A., & Sniehotta, F. F. (2019). Developing Behavior Change Interventions for Self-Management in Chronic Illness: An Integrative Overview. *Eur Psychol*, *24*(1), 7–25. https://doi.org/10.1027/1016-9040/a000330

Ardissone, A., Leonowicz-Bukała, I., & Struck-Peregończyk, M. (2024). "Can Anyone Tell Me…". Online Health Communities in Diabetes Self-Management in Poland and Italy. *Health Commun*, 1–8. https://doi.org/10.1080/10410236.2024.2348842

Arias López, M. D. P., Ong, B. A., Borrat Frigola, X., Fernández, A. L., Hicklent, R. S., Obeles, A. J. T., Rocimo, A. M., & Celi, L. A. (2023). Digital literacy as a new determinant of health: A scoping review. *PLOS Digit Health*, *2*(10), e0000279. https://doi.org/10.1371/journal.pdig.0000279

Armstrong, R. A. (2014). When to use the Bonferroni correction. *Ophthalmic Physiol Opt*, *34*(5), 502–508. https://doi.org/10.1111/opo.12131

Arora, N. K., Hesse, B. W., Rimer, B. K., Viswanath, K., Clayman, M. L., & Croyle, R. T. (2008). Frustrated and confused: the American public rates its cancer-related information-seeking experiences. *J Gen Intern Med*, *23*(3), 223–228. https://doi.org/10.1007/s11606-007-0406-y

Asan, O., Crotty, B., Nagavally, S., & Egede, L. E. (2019). Patient Centered Communication and E-Health Information Exchange Patterns: Findings From a National Cross-Sectional Survey. *IEEE Journal of Translational Engineering in Health and Medicine*, *7*, 1–7. https://doi.org/10.1109/JTEHM.2018.2884925

Assari, S., & Zare, H. (2025). Weaker Effects of Educational Attainment on Chronic Medical Conditions in American Indian Alaska Native, Black, and Latino Adults: National Health Interview Survey 2023. *Open J Med Sci*, *5*(1). https://doi.org/10.31586/ojms.2025.1150

Ashman, J. J., Loredana, S., & Okeyode, T. (2023). *Characteristics of Office-based Physician Visits by Age, 2019* [Report]. https://stacks.cdc.gov/view/cdc/125462

Audulv, Å. (2013). The over time development of chronic illness self-management patterns: a longitudinal qualitative study. *BMC Public Health*, *13*(1), 452. https://doi.org/10.1186/1471-2458-13-452

Aung, H., Tan, R., Flynn, C., Divall, P., Wright, A., Murphy, A., Shaw, D., Ward, T. J. C., & Greening, N. J. (2024). Digital remote maintenance inhaler adherence interventions in COPD: a systematic review and meta-analysis. *Eur Respir Rev*, *33*(174). https://doi.org/10.1183/16000617.0136-2024

Ausili, D., Barbaranelli, C., Rossi, E., Rebora, P., Fabrizi, D., Coghi, C., Luciani, M., Vellone, E., Di Mauro, S., & Riegel, B. (2017). Development and psychometric testing of a theory-based tool to measure self-care in diabetes patients: the Self-Care of Diabetes Inventory. *BMC Endocr Disord*, *17*(1), 66. https://doi.org/10.1186/s12902-017-0218-y

Austin, E. W., Austin, B. W., Borah, P., Domgaard, S., & McPherson, S. M. (2023). How Media Literacy, Trust of Experts and Flu Vaccine Behaviors Associated with COVID-19 Vaccine Intentions. *Am J Health Promot*, *37*(4), 464–470. https://doi.org/10.1177/08901171221132750

Baeker Bispo, J., Douyon, A., Ashad-Bishop, K., Balise, R., & Kobetz, E. (2023). How Trust in Cancer Information Has Changed in the Era of COVID-19: Patterns by Race and Ethnicity. *J Health Commun*, *28*(3), 131–143. https://doi.org/10.1080/10810730.2022.2117439

Bailey, R. L. (2021). Overview of dietary assessment methods for measuring intakes of foods, beverages, and dietary supplements in research studies. *Curr Opin Biotechnol*, *70*, 91–96. https://doi.org/10.1016/j.copbio.2021.02.007

Ban, S., Kim, Y., & Seomun, G. (2024). Digital health literacy: A concept analysis. *Digit Health*, *10*, 20552076241287894. https://doi.org/10.1177/20552076241287894

Bandura, A. (1977). Self-efficacy: Toward a unifying theory of behavioral change. *Psychological Review*, *84*(2), 191–215. https://doi.org/10.1037/0033-295X.84.2.191

Bandura, A. (1997). *Self-efficacy: The exercise of control*. W H Freeman/Times Books/ Henry Holt & Co.

Bandura, A. (2001). Social cognitive theory: an agentic perspective. *Annu Rev Psychol*, *52*, 1–26. https://doi.org/10.1146/annurev.psych.52.1.1

Banerjee, S., Alabaster, A., Kipnis, P., & Adams, A. S. (2021). Factors associated with persistent high health care utilization in managed Medicaid. *Am J Manag Care*, *27*(8), 340–344. https://doi.org/10.37765/ajmc.2021.88725

Barbati, C., Maranesi, E., Giammarchi, C., Lenge, M., Bonciani, M., Barbi, E., Vigezzi, G. P., Dragoni, M., Bailoni, T., Odone, A., & Bevilacqua, R. (2025). Effectiveness of eHealth literacy interventions: a systematic review and meta-analysis of experimental studies. *BMC Public Health*, *25*(1), 288. https://doi.org/10.1186/s12889-025-21354-x

Barbería-Latasa, M., Gea, A., & Martínez-González, M. A. (2022). Alcohol, Drinking Pattern, and Chronic Disease. *Nutrients*, *14*(9). https://doi.org/10.3390/nu14091954

Barker, W., Chang, W., Everson, J., Gabriel, M., Patel, V., Richwine, C., & Strawley, C. (2024). The Evolution of Health Information Technology for Enhanced Patient-Centric Care in the United States: Data-Driven Descriptive Study [Original Paper]. *J Med Internet Res*, *26*, e59791. https://doi.org/10.2196/59791

Barlow, J., Wright, C., Sheasby, J., Turner, A., & Hainsworth, J. (2002). Self-management approaches for people with chronic conditions: a review. *Patient Education and Counseling*, *48*(2), 177–187. https://doi.org/https://doi.org/10.1016/S0738-3991(02)00032-0

Barr, V. J., Robinson, S., Marin-Link, B., Underhill, L., Dotts, A., Ravensdale, D., & Salivaras, S. (2003). The expanded Chronic Care Model: an integration of concepts and strategies from population health promotion and the Chronic Care Model. *Hosp Q*, *7*(1), 73–82. https://doi.org/10.12927/hcq.2003.16763

Bauer, U. E., Briss, P. A., Goodman, R. A., & Bowman, B. A. (2014). Prevention of chronic disease in the 21st century: elimination of the leading preventable causes of premature death and disability in the USA. *The Lancet*, *384*(9937), 45–52. https://doi.org/10.1016/S0140-6736(14)60648-6

Beaglehole, R., Ebrahim, S., Reddy, S., Voûte, J., & Leeder, S. (2007). Prevention of chronic diseases: a call to action. *The Lancet*, *370*(9605), 2152–2157. https://doi.org/10.1016/S0140-6736(07)61700-0

Benavidez, G. A., Zahnd, W. E., Hung, P., & Eberth, J. M. (2024). Chronic Disease Prevalence in the US: Sociodemographic and Geographic Variations by Zip Code Tabulation Area. *Preventing Chronic Disease*, *21*, E14. https://doi.org/10.5888/pcd21.230267

Bensken, W. P., Dong, W., Gullett, H., Etz, R. S., & Stange, K. C. (2021). Changing Reasons for Visiting Primary Care Over a 35-Year Period. *The Journal of the American Board of Family Medicine*, *34*(2), 442–448. https://doi.org/10.3122/jabfm.2021.02.200145

Benyahia, S. A., Torikashvili, J., Paturu, T., Mikhael, M., Nguyen, O. T., Islam, J. Y., Tabriz, A. A., Hong, Y. R., & Turner, K. L. (2025). Comfort With Sharing Food Insecurity Risk for Clinical Care Among Individuals With and Without a Cancer History: Findings From a National Survey. *AJPM Focus*, *4*(5), 100395. https://doi.org/10.1016/j.focus.2025.100395

Berkman, N. D., Sheridan, S. L., Donahue, K. E., Halpern, D. J., Viera, A., Crotty, K., Holland, A., Brasure, M., Lohr, K. N., Harden, E., Tant, E., Wallace, I., & Viswanathan, M. (2011). Health literacy interventions and outcomes: an updated systematic review. *Evid Rep Technol Assess (Full Rep)*(199), 1–941.

Berkowsky, R. W. (2021). Exploring Predictors of eHealth Literacy Among Older Adults: Findings From the 2020 CALSPEAKS Survey. *Gerontol Geriatr Med*, *7*, 23337214211064227. https://doi.org/10.1177/23337214211064227

Bernell, S., & Howard, S. W. (2016). Use Your Words Carefully: What Is a Chronic Disease? *Front Public Health*, *4*, 159. https://doi.org/10.3389/fpubh.2016.00159

Bhatla, A., Ding, J., Mhaimeed, O., Spaulding, E. M., Commodore-Mensah, Y., Plante, T. B., Shan, R., Marvel, F. A., & Martin, S. S. (2024). Patterns of Telehealth Visits After the COVID-19 Pandemic Among Individuals With or at Risk for Cardiovascular Disease in the United States. *J Am Heart Assoc*, *13*(17), e036475. https://doi.org/10.1161/jaha.124.036475

Biancuzzi, H., Dal Mas, F., Bidoli, C., Pegoraro, V., Zantedeschi, M., Negro, P. A., Campostrini, S., & Cobianchi, L. (2023). Economic and Performance Evaluation of E-Health before and after the Pandemic Era: A Literature Review and Future Perspectives. *International Journal of Environmental Research and Public Health*, *20*(5), 4038. https://doi.org/10.3390/ijerph20054038

Bitar, H., & Alismail, S. (2021). The role of eHealth, telehealth, and telemedicine for chronic disease patients during COVID-19 pandemic: A rapid systematic review. *Digit Health*, *7*, 20552076211009396. https://doi.org/10.1177/20552076211009396

Blake, K. D., Moser, R. P., D'Angelo, H., Gaysynsky, A., & Vanderpool, R. C. (2024). The Evolution of NCI's Health Information National Trends Survey: Methods, Data, and Future Directions. *JNCI: Journal of the National Cancer Institute*. https://doi.org/10.1093/jnci/djae317

Bodenheimer, T., Lorig, K., Holman, H., & Grumbach, K. (2002). Patient Self-management of Chronic Disease in Primary Care. *JAMA*, *288*(19), 2469–2475. https://doi.org/10.1001/jama.288.19.2469

Bodie, G. D., & Dutta, M. J. (2008). Understanding health literacy for strategic health marketing: eHealth literacy, health disparities, and the digital divide. *Health Mark Q*, *25*(1-2), 175–203. https://doi.org/10.1080/07359680802126301

Bokolo, A. J. (2021). Application of telemedicine and eHealth technology for clinical services in response to COVID-19 pandemic. *Health and Technology*, *11*(2), 359–366. https://doi.org/10.1007/s12553-020-00516-4

Bol, N., Helberger, N., & Weert, J. C. M. (2018). Differences in mobile health app use: A source of new digital inequalities? *The Information Society*, *34*(3), 183–193. https://doi.org/10.1080/01972243.2018.1438550

Boogerd, E. A., Arts, T., Engelen, L. J., & van de Belt, T. H. (2015). "What Is eHealth": Time for An Update? [Letter to the Editor]. *JMIR Res Protoc*, *4*(1), e29. https://doi.org/10.2196/resprot.4065

Brady, T. J., Sacks, J. J., Terrillion, A. J., & Colligan, E. M. (2018). Operationalizing Surveillance of Chronic Disease Self-Management and Self-Management Support. *Prev Chronic Dis*, *15*, E39. https://doi.org/10.5888/pcd15.170475

Brandtweiner, R., Donat, E., & Kerschbaum, J. (2010). How to become a sophisticated user: a two-dimensional approach to e-literacy. *New Media & Society*, *12*(5), 813–833. https://doi.org/10.1177/1461444809349577

Briones, R. (2015). Harnessing the Web: How E-Health and E-Health Literacy Impact Young Adults' Perceptions of Online Health Information. *Med 2 0*, *4*(2), e5. https://doi.org/10.2196/med20.4327

Bronfenbrenner, U. (1977). Toward an experimental ecology of human development. *American psychologist*, *32*(7), 513.

Brørs, G., Larsen, M. H., Hølvold, L. B., & Wahl, A. K. (2023). eHealth literacy among hospital health care providers: a systematic review. *BMC Health Serv Res*, *23*(1), 1144. https://doi.org/10.1186/s12913-023-10103-8

Brørs, G., Norman, C. D., & Norekvål, T. M. (2020). Accelerated importance of eHealth literacy in the COVID-19 outbreak and beyond. *European Journal of Cardiovascular Nursing*, *19*(6), 458–461. https://doi.org/10.1177/1474515120941307

Brown, K. A., Timotijevic, L., Barnett, J., Shepherd, R., Lähteenmäki, L., & Raats, M. M. (2011). A review of consumer awareness, understanding and use of food-based dietary guidelines. *British Journal of Nutrition*, *106*(1), 15–26. https://doi.org/10.1017/S0007114511000250

Brownson, R. C., & Bright, F. S. (2004). Chronic Disease Control in Public Health Practice: Looking Back and Moving Forward. *Public Health Reports (1974-)*, *119*(3), 230–238. https://doi.org/10.1016/j.phr.2004.04.001

Buttorff, C., Ruder, T., & Bauman, M. (2017). *Multiple Chronic Conditions in the United States*. https://www.rand.org/content/dam/rand/pubs/tools/TL200/TL221/RAND_TL221.pdf

Cabezas, M. F., Nazar, G., Ranchor, A. V., & Annema, C. (2025). The Effect of Health Literacy Interventions on Self-management in Chronic Diseases: A Systematic Review. *Ann Behav Med*, *59*(1). https://doi.org/10.1093/abm/kaaf073

Cascino, T. M., McLaughlin, V. V., Richardson, C. R., Behbahani-Nejad, N., Moles, V. M., Visovatti, S. H., & Jackson, E. A. (2019). Barriers to physical activity in patients with pulmonary hypertension. *Pulmonary Circulation*, *9*(2), 2045894019847895. https://doi.org/https://doi.org/10.1177/2045894019847895

Calo, W. A., Ortiz, A. P., Colon-Lopez, V., Krasny, S., & Tortolero-Luna, G. (2014). Factors associated with perceived patient-provider communication quality among Puerto Ricans. *J Health Care Poor Underserved*, *25*(2), 491–502. https://doi.org/10.1353/hpu.2014.0074

Cantril, H., & Allport, G. W. (1935). The psychology of radio. *Harper*. https://psycnet.apa.org/record/1936-00491-000.

Catapan, S. d. C., Nair, U., Gray, L., Cristina Marino Calvo, M., Bird, D., Janda, M., Fatehi, F., Menon, A., & Russell, A. (2021). Same goals, different challenges: A systematic review of perspectives of people with diabetes and healthcare professionals on Type 2 diabetes care. *Diabetic Medicine*, *38*(9), e14625. https://doi.org/https://doi.org/10.1111/dme.14625

Centers for Disease Control and Prevention. (2024). *Preventing Chronic Diseases: What You Can Do Now*. https://www.cdc.gov/chronic-disease/prevention/index.html

Centers for Disease Control and Prevention. (2024, July). *Fast Facts: Health and Economic Costs of Chronic Conditions*. https://www.cdc.gov/chronic-disease/data-research/facts-stats/index.html

Centers for Disease Control and Prevention. (2024, June). *eHealth Literacy*. https://www.cdc.gov/health-literacy/php/research-summaries/ehealth.html

Centers for Disease Control and Prevention. (2024, May). *National Diabetes Statistics Report*. https://www.cdc.gov/diabetes/php/data-research/index.html

Centers for Disease Control and Prevention. (2024, October). *About Chronic Diseases*. https://www.cdc.gov/chronic-disease/about/index.html

Centers for Disease Control and Prevention. (2025). *About Moderate Alcohol Use*. https://www.cdc.gov/alcohol/about-alcohol-use/moderate-alcohol-use.html

Centers for Disease Control and Prevention, & National Center for Health Statistics. (2024, Sept.). *Surveys and Data Collection Systems*. https://www.cdc.gov/nchs/surveys/index.html

Centers for Medicare & Medicaid Services. (2024). *2024 National Impact Assessment of the Centers for Medicare & Medicaid Services (CMS) Quality Measures Report*. https://www.cms.gov/files/document/2024-national-impact-assessment-report.pdf

Champlin, S., & Mackert, M. (2016). Creating a Screening Measure of Health Literacy for the Health Information National Trends Survey. *Am J Health Promot*, *30*(4), 291–293. https://doi.org/10.1177/0890117116639557

Chan, J. (2021). Exploring digital health care: eHealth, mHealth, and librarian opportunities. *J Med Libr Assoc*, *109*(3), 376–381. https://doi.org/10.5195/jmla.2021.1180

Chang, S. J., Choi, S., Kim, S.-A., & Song, M. (2014). Intervention Strategies Based on Information-Motivation-Behavioral Skills Model for Health Behavior Change: A Systematic Review. *Asian Nursing Research*, *8*(3), 172–181. https://doi.org/https://doi.org/10.1016/j.anr.2014.08.002

Chang, S. J., Lee, K.-e., Yang, E., & Ryu, H. (2022). Evaluating a theory-based intervention for improving eHealth literacy in older adults: a single group, pretest–posttest design. *BMC Geriatrics*, *22*(1), 918. https://doi.org/10.1186/s12877-022-03545-y

Chauhan, A., Linares-Jimenez, F. G., Dash, G. C., de Zeeuw, J., Kumawat, A., Mahapatra, P., de Winter, A. F., Mohan, S., van den Akker, M., & Pati, S. (2024). Unravelling the role of health literacy among individuals with multimorbidity: a systematic review and meta-analysis. *BMJ Open*, *14*(12), e073181. https://doi.org/10.1136/bmjopen-2023-073181

Chen, S., Li, M., Chen, Y., Zhang, Y., Li, Y., Tai, X., & Zhang, X. (2024). Exploring the evolution of eHealth in disease management: A bibliometric analysis from 1999 to 2023. *Digit Health*, *10*, 20552076241288647. https://doi.org/10.1177/20552076241288647

Chen, X., Hay, J. L., Waters, E. A., Kiviniemi, M. T., Biddle, C., Schofield, E., Li, Y., Kaphingst, K., & Orom, H. (2018). Health Literacy and Use and Trust in Health Information. *J Health Commun*, *23*(8), 724–734. https://doi.org/10.1080/10810730.2018.1511658

Chen, X., Luo, G., Li, M., & Kreps, G. (2023). Examining the Relationship between Health Literacy and Preventive Care Use. *Health behavior research*, *6*(4). https://doi.org/10.4148/2572-1836.1206

Chesser, A., Burke, A., Reyes, J., & Rohrberg, T. (2016). Navigating the digital divide: A systematic review of eHealth literacy in underserved populations in the United States. *Informatics for Health and Social Care*, *41*(1), 1–19. https://doi.org/10.3109/17538157.2014.948171

Chew, L. D., Bradley, K. A., & Boyko, E. J. (2004). Brief questions to identify patients with inadequate health literacy. *Fam Med*, *36*(8), 588–594.

Chew, L. D., Griffin, J. M., Partin, M. R., Noorbaloochi, S., Grill, J. P., Snyder, A., Bradley, K. A., Nugent, S. M., Baines, A. D., & Vanryn, M. (2008). Validation of screening questions for limited health literacy in a large VA outpatient population. *J Gen Intern Med*, *23*(5), 561–566. https://doi.org/10.1007/s11606-008-0520-5

Chiva-Blanch, G., & Badimon, L. (2019). Benefits and Risks of Moderate Alcohol Consumption on Cardiovascular Disease: Current Findings and Controversies. *Nutrients*, *12*(1). https://doi.org/10.3390/nu12010108

Chobufo, M. D., Gayam, V., Soluny, J., Rahman, E. U., Enoru, S., Foryoung, J. B., Agbor, V. N., Dufresne, A., & Nfor, T. (2020). Prevalence and control rates of hypertension in the USA: 2017-2018. *Int J Cardiol Hypertens*, *6*, 100044. https://doi.org/10.1016/j.ijchy.2020.100044

Chodosh, J., Morton, S. C., Mojica, W., Maglione, M., Suttorp, M. J., Hilton, L., Rhodes, S., & Shekelle, P. (2005). Meta-Analysis: Chronic Disease Self-Management Programs for Older Adults. *Annals of Internal Medicine*, *143*(6), 427–438. https://doi.org/10.7326/0003-4819-143-6-200509200-00007

Choi, J. Y., Choi, D., Mehta, N. K., Ali, M. K., & Patel, S. A. (2024). Diabetes Disparities in the United States: Trends by Educational Attainment from 2001 to 2020. *American Journal of Preventive Medicine*, *67*(3), 319–327. https://doi.org/10.1016/j.amepre.2024.04.006

Choi, M. (2020). Association of eHealth Use, Literacy, Informational Social Support, and Health-Promoting Behaviors: Mediation of Health Self-Efficacy. *International Journal of Environmental Research and Public Health*, *17*(21), 7890. https://doi.org/10.3390/ijerph17217890

Choi, N. G., & DiNitto, D. M. (2013). The Digital Divide Among Low-Income Homebound Older Adults: Internet Use Patterns, eHealth Literacy, and Attitudes Toward Computer/Internet Use [Original Paper]. *J Med Internet Res*, *15*(5), e93. https://doi.org/10.2196/jmir.2645

Chow, E., Virani, A., Pinkney, S., Abdulhussein, F. S., van Rooij, T., Görges, M., Wasserman, W., Bone, J., Longstaff, H., & Amed, S. (2024). Caregiver and Youth Characteristics That Influence Trust in Digital Health Platforms in Pediatric Care: Mixed Methods Study [Original Paper]. *J Med Internet Res*, *26*, e53657. https://doi.org/10.2196/53657

Chu, J. N., Sarkar, U., Rivadeneira, N. A., Hiatt, R. A., & Khoong, E. C. (2022). Impact of language preference and health literacy on health information-seeking experiences among a low-income, multilingual cohort. *Patient Educ Couns*, *105*(5), 1268–1275. https://doi.org/10.1016/j.pec.2021.08.028

Chung, S. Y., & Nahm, E. S. (2015). Testing reliability and validity of the eHealth Literacy Scale (eHEALS) for older adults recruited online. *Comput Inform Nurs*, *33*(4), 150–156. https://doi.org/10.1097/cin.0000000000000146

Citoni, B., Figliuzzi, I., Presta, V., Volpe, M., & Tocci, G. (2022). Home Blood Pressure and Telemedicine: A Modern Approach for Managing Hypertension During and After COVID-19 Pandemic. *High Blood Press Cardiovasc Prev*, *29*(1), 1–14. https://doi.org/10.1007/s40292-021-00492-4

Clark, N. M., & Dodge, J. A. (1999). Exploring Self-Efficacy as a Predictor of Disease Management. *Health Education & Behavior*, *26*(1), 72–89. https://doi.org/10.1177/109019819902600107

Coleman, K., Austin, B. T., Brach, C., & Wagner, E. H. (2009). Evidence on the Chronic Care Model in the new millennium. *Health Aff (Millwood)*, *28*(1), 75–85. https://doi.org/10.1377/hlthaff.28.1.75

Connelly, P. J., Currie, G., & Delles, C. (2022). Sex Differences in the Prevalence, Outcomes and Management of Hypertension. *Curr Hypertens Rep*, *24*(6), 185–192. https://doi.org/10.1007/s11906-022-01183-8

Connolly, G., Costa-Font, J., & Srivastava, D. (2025). Did COVID-19 reduce the digital divide? A systematic review. *Health Policy and Technology*, 100979. https://doi.org/https://doi.org/10.1016/j.hlpt.2025.100979

Corbin, J., & Strauss, A. (1985). Managing chronic illness at home: Three lines of work. *Qualitative Sociology*, *8*(3), 224–247. https://doi.org/10.1007/BF00989485

Corbin, J. M., & Strauss, A. (1988). *Unending work and care: Managing chronic illness at home*. Jossey-Bass.

Coughlin, S. S., Clary, C., Johnson, J. A., Berman, A., Heboyan, V., Benevides, T., Moore, J., & George, V. (2019). Continuing Challenges in Rural Health in the United States. *J Environ Health Sci*, *5*(2), 90–92.

Creer, T. L., Renne, C. M., & Christian, W. P. (1976). Behavioral contributions to rehabilitation and childhood asthma. *Rehabil Lit*, *37*(8), 226–232,247.

Crocker, B., Feng, O., & Duncan, L. R. (2023). Performance-Based Measurement of eHealth Literacy: Systematic Scoping Review. *J Med Internet Res*, *25*, e44602. https://doi.org/10.2196/44602

Cronbach, L. J. (1951). Coefficient Alpha and the Internal Structure of Tests. *Psychometrika*, *16*(3), 297–334. https://doi.org/10.1007/BF02310555

da Fonseca, M. H., Kovaleski, F., Picinin, C. T., Pedroso, B., & Rubbo, P. (2021). E-Health Practices and Technologies: A Systematic Review from 2014 to 2019. *Healthcare (Basel)*, *9*(9). https://doi.org/10.3390/healthcare9091192

da Silva Lopes, A. M., Colomer-Lahiguera, S., Darnac, C., Giacomini, S., Bugeia, S., Gutknecht, G., Spurrier-Bernard, G., Aedo-Lopez, V., Mederos, N., Latifyan, S., Addedo, A., Michielin, O., & Eicher, M. (2023). Development of an eHealth-enhanced model of care for the monitoring and management of immune-related adverse events in patients treated with immune checkpoint inhibitors. *Supportive Care in Cancer*, *31*(8), 484. https://doi.org/10.1007/s00520-023-07934-w

Datta, P., Eiland, L., Samson, K., Donovan, A., Anzalone, A. J., & McAdam-Marx, C. (2022). Telemedicine and health access inequalities during the COVID-19 pandemic. *J Glob Health*, *12*, 05051. https://doi.org/10.7189/jogh.12.05051

Davis-Ajami, M. L., Lu, Z. K., & Wu, J. (2019). Multiple chronic conditions and associated health care expenses in US adults with cancer: a 2010–2015 Medical Expenditure Panel Survey study. *BMC Health Services Research*, *19*(1), 981. https://doi.org/10.1186/s12913-019-4827-1

Davis, C. G., Thake, J., & Vilhena, N. (2010). Social desirability biases in self-reported alcohol consumption and harms. *Addict Behav*, *35*(4), 302–311. https://doi.org/10.1016/j.addbeh.2009.11.001

Davis, J., Fischl, A. H., Beck, J., Browning, L., Carter, A., Condon, J. E., Dennison, M., Francis, T., Hughes, P. J., Jaime, S., Lau, K. H. K., McArthur, T., McAvoy, K., Magee, M., Newby, O., Ponder, S. W., Quraishi, U., Rawlings, K., Socke, J.,…Villalobos, S. (2022).

2022 National Standards for Diabetes Self-Management Education and Support. *Diabetes Care*, *45*(2), 484–494. https://doi.org/10.2337/dc21-2396

Dawson, D. A. (2003). Methodological issues in measuring alcohol use. *Alcohol Res Health*, *27*(1), 18–29.

de Oliveira Collet, G., de Morais Ferreira, F., Ceron, D. F., de Lourdes Calvo Fracasso, M., & Santin, G. C. (2024). Influence of digital health literacy on online health-related behaviors influenced by internet advertising. *BMC Public Health*, *24*(1), 1949. https://doi.org/10.1186/s12889-024-19506-6

Dean, C. A., Geneus, C. J., Rice, S., Johns, M., Quasie-Woode, D., Broom, K., & Elder, K. (2017). Assessing the significance of health information seeking in chronic condition management. *Patient Education and Counseling*, *100*(8), 1519–1526. https://doi.org/https://doi.org/10.1016/j.pec.2017.03.012

Demeyer, H., Hermans, F., & Troosters, T. (n.d.). *Physical activity recommendations for patients with Chronic Obstructive Pulmonary Disease*. https://www.thoracic.org/members/assemblies/assemblies/pr/quarterly-bite/physical-activity-recommendations-for-patients-with-chronic-obstructive-pulmonary-disease.php

Deshpande, N., Arora, V. M., Vollbrecht, H., Meltzer, D. O., & Press, V. (2023). eHealth Literacy and Patient Portal Use and Attitudes: Cross-sectional Observational Study. *JMIR Hum Factors*, *10*, e40105. https://doi.org/10.2196/40105

Dickson, V. V., Iovino, P., De Maria, M., Vellone, E., Alvaro, R., Di Matteo, R., Dal Molin, A., Lusignani, M., Bassola, B., Maconi, A., Bolgeo, T., & Riegel, B. (2022). Psychometric Testing of the Self-Care of Coronary Heart Disease Inventory Version 3.0. *J Cardiovasc Nurs*. https://doi.org/10.1097/jcn.0000000000000952

Ding, Y., Li, F., Fan, Z., Zhang, J., Gu, J., Li, X., Wei, L., Zhang, Y., Xu, H., & Cui, Y. (2023). Factors influencing self-management behavior during the "Blanking Period" in patients with atrial fibrillation: A cross-sectional study based on the information-motivation-behavioral skills model. *Heart Lung*, *58*, 62–68. https://doi.org/10.1016/j.hrtlng.2022.11.006

Doak, C. C., Doak, L. G., & Root, J. H. (1996). Teaching Patients with Low Literacy Skills. *AJN The American Journal of Nursing*, *96*(12).

Dominick, G. M., Friedman, D. B., & Hoffman-Goetz, L. (2009). Do we need to understand the technology to get to the science? A systematic review of the concept of computer literacy in preventive health programs. *Health Education Journal*, *68*(4), 296–313. https://doi.org/10.1177/0017896909349289

Donelle, L., Hiebert, B., & Hall, J. (2024). An investigation of mHealth and digital health literacy among new parents during COVID-19 [Original Research]. *Frontiers in Digital Health*, *Volume 5 - 2023*. https://doi.org/10.3389/fdgth.2023.1212694

Doraiswamy, S., Jithesh, A., Mamtani, R., Abraham, A., & Cheema, S. (2021). Telehealth Use in Geriatrics Care during the COVID-19 Pandemic-A Scoping Review and Evidence Synthesis. *Int J Environ Res Public Health*, *18*(4). https://doi.org/10.3390/ijerph18041755

Doyle-Lindrud, S. (2020). State of eHealth in Cancer Care: Review of the Benefits and Limitations of eHealth Tools. *Clin J Oncol Nurs*, *24*(3), 10–15. https://doi.org/10.1188/20.Cjon.S1.10-15

Dresden, S. M., McCarthy, D. M., Engel, K. G., & Courtney, D. M. (2019). Perceptions and expectations of health-related quality of life among geriatric patients seeking emergency

care: a qualitative study. *BMC Geriatrics*, *19*(1), 209. https://doi.org/10.1186/s12877-019-1228-6
Duffy, E., Chilazi, M., Cainzos-Achirica, M., & Michos, E. D. (2021). Cardiovascular Disease Prevention During the COVID-19 Pandemic: Lessons Learned and Future Opportunities. *Methodist Debakey Cardiovasc J*, *17*(4), 68–78. https://doi.org/10.14797/mdcvj.210
DuGoff, E. H., Canudas-Romo, V., Buttorff, C., Leff, B., & Anderson, G. F. (2014). Multiple chronic conditions and life expectancy: a life table analysis. *Med Care*, *52*(8), 688–694. https://doi.org/10.1097/mlr.0000000000000166
Durmuş, A. (2024). The influence of digital literacy on mHealth app usability: The mediating role of patient expertise. *Digit Health*, *10*, 20552076241299061. https://doi.org/10.1177/20552076241299061
Durstine, J. L., Gordon, B., Wang, Z., & Luo, X. (2013). Chronic disease and the link to physical activity. *Journal of Sport and Health Science*, *2*(1), 3–11. https://doi.org/https://doi.org/10.1016/j.jshs.2012.07.009
Edelsbrunner, P. A. (2022). A model and its fit lie in the eye of the beholder: Long live the sum score. *Front Psychol*, *13*, 986767. https://doi.org/10.3389/fpsyg.2022.986767
El Benny, M., Kabakian-Khasholian, T., El-Jardali, F., & Bardus, M. (2021). Application of the eHealth Literacy Model in Digital Health Interventions: Scoping Review [Review]. *J Med Internet Res*, *23*(6), e23473. https://doi.org/10.2196/23473
Elgamal, R. (2024). Meta-analysis: eHealth literacy and attitudes towards internet/computer technology. *Patient Education and Counseling*, *123*, 108196. https://doi.org/https://doi.org/10.1016/j.pec.2024.108196
Elman, M. R., Quiñones, A. R., McAvay, G. J., Wyk, B. V., Nagel, C. L., & Allore, H. G. (2025). Contribution of chronic conditions to mortality: Differences by race and ethnicity. *Aging and Health Research*, *5*(2), 100231. https://doi.org/https://doi.org/10.1016/j.ahr.2025.100231
Ernsting, C., Stühmann, L. M., Dombrowski, S. U., Voigt-Antons, J. N., Kuhlmey, A., & Gellert, P. (2019). Associations of Health App Use and Perceived Effectiveness in People With Cardiovascular Diseases and Diabetes: Population-Based Survey. *JMIR Mhealth Uhealth*, *7*(3), e12179. https://doi.org/10.2196/12179
Eysenbach, G. (2001). What is e-health? *J Med Internet Res*, *3*(2), E20. https://doi.org/10.2196/jmir.3.2.e20
Ezeani, A., Boggan, B., Hopper, L. N., Herren, O. M., & Agurs-Collins, T. (2023). Associations Between Cancer Risk Perceptions, Self-Efficacy, and Health Behaviors by BMI Category and Race and Ethnicity. *International Journal of Behavioral Medicine*. https://doi.org/10.1007/s12529-023-10225-7
Fabrizi, D., Rebora, P., Luciani, M., Di Mauro, S., Valsecchi, M. G., & Ausili, D. (2020). How do self-care maintenance, self-care monitoring, and self-care management affect glycated haemoglobin in adults with type 2 diabetes? A multicentre observational study. *Endocrine*, *69*(3), 542–552. https://doi.org/10.1007/s12020-020-02354-w
Fagherazzi, G., Goetzinger, C., Rashid, M. A., Aguayo, G. A., & Huiart, L. (2020). Digital Health Strategies to Fight COVID-19 Worldwide: Challenges, Recommendations, and a Call for Papers [Viewpoint]. *J Med Internet Res*, *22*(6), e19284. https://doi.org/10.2196/19284

Fan, K., & Zhao, Y. (2022). Mobile health technology: a novel tool in chronic disease management. *Intelligent Medicine*, *2*(1), 41–47. https://doi.org/https://doi.org/10.1016/j.imed.2021.06.003
Faux-Nightingale, A., Philp, F., Chadwick, D., Singh, B., & Pandyan, A. (2022). Available tools to evaluate digital health literacy and engagement with eHealth resources: A scoping review. *Heliyon*, *8*(8). https://doi.org/10.1016/j.heliyon.2022.e10380
Fava, V. M. D., & Lapão, L. V. (2024). Provision of Digital Primary Health Care Services: Overview of Reviews [Review]. *J Med Internet Res*, *26*, e53594. https://doi.org/10.2196/53594
Federal Communications Commission (FCC). (n.d.). *Telehealth, Telemedicine, and Telecare: What's What?* https://www.fcc.gov/general/telehealth-telemedicine-and-telecare-whats-what
Fein, E. C., Gilmour, J., Machin, T., & Hendry, L. . (2021). Statistics for research students: An open access resource with self-tests and illustrative examples [Open access edition]. In. University of Southern Queensland.
Ferrer, R. A., & Klein, W. M. P. (2015). Risk perceptions and health behavior. *Current opinion in psychology*, *5*, 85–89. https://doi.org/https://doi.org/10.1016/j.copsyc.2015.03.012
Filabadi, Z. R., Estebsari, F., Milani, A. S., Feizi, S., & Nasiri, M. (2020). Relationship between electronic health literacy, quality of life, and self-efficacy in Tehran, Iran: A community-based study. *Journal of Education and Health Promotion*, *9*(1), 175. https://doi.org/10.4103/jehp.jehp_63_20
Finney Rutten, L. J., Blake, K. D., Skolnick, V. G., Davis, T., Moser, R. P., & Hesse, B. W. (2020). Data Resource Profile: The National Cancer Institute's Health Information National Trends Survey (HINTS). *Int J Epidemiol*, *49*(1), 17–17j. https://doi.org/10.1093/ije/dyz083
Finney Rutten, L. J., Davis, T., Beckjord, E. B., Blake, K., Moser, R. P., & Hesse, B. W. (2012). Picking up the pace: changes in method and frame for the health information national trends survey (2011-2014). *J Health Commun*, *17*(8), 979–989. https://doi.org/10.1080/10810730.2012.700998
Finney Rutten, L. J., Hesse, B. W., St Sauver, J. L., Wilson, P., Chawla, N., Hartigan, D. B., Moser, R. P., Taplin, S., Glasgow, R., & Arora, N. K. (2016). Health Self-Efficacy Among Populations with Multiple Chronic Conditions: the Value of Patient-Centered Communication. *Adv Ther*, *33*(8), 1440–1451. https://doi.org/10.1007/s12325-016-0369-7
Fisher, J. D., & Fisher, W. A. (1992). Changing AIDS-risk behavior. *Psychol Bull*, *111*(3), 455–474. https://doi.org/10.1037/0033-2909.111.3.455
Fisher, J. D., Fisher, W. A., Amico, K. R., & Harman, J. J. (2006). An information-motivation-behavioral skills model of adherence to antiretroviral therapy. *Health Psychol*, *25*(4), 462–473. https://doi.org/10.1037/0278-6133.25.4.462
Fisher, W., Fisher, J., & Harman, J. (2009). The Information-Motivation-Behavioral Skills Model: A General Social Psychological Approach to Understanding and Promoting Health Behavior. In (pp. 82–106). https://doi.org/10.1002/9780470753552.ch4
Fisher, W. A., Fisher, J. D., & Harman, J. (2003). The information-motivation-behavioraI skills model: A general social psychological approach to understanding and promoting health behavior. In *Social psychological foundations of health and illness.* (pp. 82–106). Blackwell Publishing. https://doi.org/10.1002/9780470753552.ch4

Foote, D., Giger, J. T., Murray, T. D., Engelhardt, E., & Flaherty, C. (2023). Validation of the eHEALTH Literacy Scale (Eheals) With Military Service Members. *Military Medicine*, *188*(11-12), e3621–e3627. https://doi.org/10.1093/milmed/usad315

Freedman, A. A., Colangelo, L. A., Ning, H., Borrowman, J. D., Lewis, C. E., Schreiner, P. J., Khan, S. S., & Lloyd-Jones, D. M. (2026). Sex Differences in Age of Onset of Premature Cardiovascular Disease and Subtypes: The Coronary Artery Risk Development in Young Adults Study. *Journal of the American Heart Association*, *15*(3), e044922. https://doi.org/doi:10.1161/JAHA.125.044922

Frostholm, L., Oernboel, E., Christensen, K. S., Toft, T., Olesen, F., Weinman, J., & Fink, P. (2007). Do illness perceptions predict health outcomes in primary care patients? A 2-year follow-up study. *Journal of Psychosomatic Research*, *62*(2), 129–138. https://doi.org/https://doi.org/10.1016/j.jpsychores.2006.09.003

Fryar, C. D., Kit, B., Carroll, M. D., & Afful, J. (2024). *Hypertension prevalence, awareness, treatment, and control among adults age 18 and older: United States, August 2021–August 2023.* [NCHS Data Brief no 511]. https://dx.doi.org/10.15620/cdc/164016

Garcia, M. C., Rossen, L. M., Bastian, B., Faul, M., Dowling, N. F., Thomas, C. C., Schieb, L., Hong, Y., Yoon, P. W., & Iademarco, M. F. (2019). Potentially Excess Deaths from the Five Leading Causes of Death in Metropolitan and Nonmetropolitan Counties - United States, 2010-2017. *MMWR Surveill Summ*, *68*(10), 1–11. https://doi.org/10.15585/mmwr.ss6810a1

García, M. C., Rossen, L. M., Matthews, K., Guy, G., Trivers, K. F., Thomas, C. C., Schieb, L., & Iademarco, M. F. (2024). Preventable Premature Deaths from the Five Leading Causes of Death in Nonmetropolitan and Metropolitan Counties, United States, 2010–2022. *Morbidity and Mortality Weekly Surveillance Summary*, *73*(No. SS-2), 1–11. https://doi.org/http://dx.doi.org/10.15585/mmwr.ss7302a1

Gaziano, T. A., Galea, G., & Reddy, K. S. (2007). Scaling up interventions for chronic disease prevention: the evidence. *The Lancet*, *370*(9603), 1939–1946. https://doi.org/10.1016/S0140-6736(07)61697-3

Gee, P. M., Greenwood, D. A., Paterniti, D. A., Ward, D., & Miller, L. M. (2015). The eHealth Enhanced Chronic Care Model: a theory derivation approach. *J Med Internet Res*, *17*(4), e86. https://doi.org/10.2196/jmir.4067

Gero, K., Backhaus-Hoven, I., Höhmann, A., Dragano, N., & Hoven, H. (2025). Low income and health literacy: a systematic scoping review. *Arch Public Health*, *83*(1), 291. https://doi.org/10.1186/s13690-025-01781-3

Gertz, A. H., Pollack, C. C., Schultheiss, M. D., & Brownstein, J. S. (2022). Delayed medical care and underlying health in the United States during the COVID-19 pandemic: A cross-sectional study. *Prev Med Rep*, *28*, 101882. https://doi.org/10.1016/j.pmedr.2022.101882

Ghani, M., Adler, C., & Yeung, H. (2021). Patient Factors Associated with Interest in Teledermatology: Cross-sectional Survey [Original Paper]. *JMIR Dermatol*, *4*(1), e21555. https://doi.org/10.2196/21555

Ghotbi, T., Salami, J., Kalteh, E. A., & Ghelichi-Ghojogh, M. (2021). Self-management of patients with chronic diseases during COVID19: a narrative review. *J Prev Med Hyg*, *62*(4), E814–e821. https://doi.org/10.15167/2421-4248/jpmh2021.62.4.2132

Giacalone, A., Marin, L., Febbi, M., Franchi, T., & Tovani-Palone, M. R. (2022). eHealth, telehealth, and telemedicine in the management of the COVID-19 pandemic and beyond:

Lessons learned and future perspectives. *World J Clin Cases*, *10*(8), 2363–2368. https://doi.org/10.12998/wjcc.v10.i8.2363
Giansanti, D. (2022). The Digital Health: From the Experience of the COVID-19 Pandemic Onwards. *Life (Basel)*, *12*(1). https://doi.org/10.3390/life12010078
Gille, S., Griese, L., & Schaeffer, D. (2021). Preferences and Experiences of People with Chronic Illness in Using Different Sources of Health Information: Results of a Mixed-Methods Study. *Int J Environ Res Public Health*, *18*(24). https://doi.org/10.3390/ijerph182413185
Glanz, K., Rimer, B. K., & Viswanath, K. V. (2015). *Health behavior: Theory, research, and practice, 5th ed*. Jossey-Bass/Wiley.
Goh, L. H., Siah, C. J. R., Tam, W. W. S., Tai, E. S., & Young, D. Y. L. (2022). Effectiveness of the chronic care model for adults with type 2 diabetes in primary care: a systematic review and meta-analysis. *Systematic Reviews*, *11*(1), 273. https://doi.org/10.1186/s13643-022-02117-w
Golinelli, D., Boetto, E., Carullo, G., Nuzzolese, A. G., Landini, M. P., & Fantini, M. P. (2020). Adoption of Digital Technologies in Health Care During the COVID-19 Pandemic: Systematic Review of Early Scientific Literature. *J Med Internet Res*, *22*(11), e22280. https://doi.org/10.2196/22280
Goodman, R. A., Posner, S. F., Huang, E. S., Parekh, A. K., & Koh, H. K. (2013). Defining and measuring chronic conditions: imperatives for research, policy, program, and practice. *Prev Chronic Dis*, *10*, E66. https://doi.org/10.5888/pcd10.120239
Goorani, S., Zangene, S., & Imig, J. D. (2024). Hypertension: A Continuing Public Healthcare Issue. *Int J Mol Sci*, *26*(1). https://doi.org/10.3390/ijms26010123
Gorski, M. T., & Roberto, C. A. (2015). Public health policies to encourage healthy eating habits: recent perspectives. *J Healthc Leadersh*, *7*, 81–90. https://doi.org/10.2147/jhl.S69188
Gorsuch, R. L., & McFarland, S. G. (1972). Single vs. Multiple-Item Scales for Measuring Religious Values. *Journal for the Scientific Study of Religion*, *11*(1), 53–64. https://doi.org/10.2307/1384298
Grady, P. A., & Gough, L. L. (2014). Self-management: a comprehensive approach to management of chronic conditions. *Am J Public Health*, *104*(8), e25–31. https://doi.org/10.2105/ajph.2014.302041
Green, B. B., Cook, A. J., Ralston, J. D., Fishman, P. A., Catz, S. L., Carlson, J., Carrell, D., Tyll, L., Larson, E. B., & Thompson, R. S. (2008). Effectiveness of Home Blood Pressure Monitoring, Web Communication, and Pharmacist Care on Hypertension Control: A Randomized Controlled Trial. *JAMA*, *299*(24), 2857–2867. https://doi.org/10.1001/jama.299.24.2857
Green, G. (2022). Seniors' eHealth literacy, health and education status and personal health knowledge. *DIGITAL HEALTH*, *8*, 20552076221089803. https://doi.org/10.1177/20552076221089803
Green, J. E., Brown, A. G., & Ohri-Vachaspati, P. (2015). Sociodemographic Disparities among Fast-Food Restaurant Customers Who Notice and Use Calorie Menu Labels. *Journal of the Academy of Nutrition and Dietetics*, *115*(7), 1093–1101. https://doi.org/10.1016/j.jand.2014.12.004
Greiwe, J. (2022). Telemedicine Lessons Learned During the COVID-19 Pandemic. *Curr Allergy Asthma Rep*, *22*(1), 1–5. https://doi.org/10.1007/s11882-022-01026-1

Griebel, L., Enwald, H., Gilstad, H., Pohl, A. L., Moreland, J., & Sedlmayr, M. (2018). eHealth literacy research-Quo vadis? *Inform Health Soc Care*, *43*(4), 427–442. https://doi.org/10.1080/17538157.2017.1364247

Griffin, A. C., & Chung, A. E. (2019). Health Tracking and Information Sharing in the Patient-Centered Era: A Health Information National Trends Survey (HINTS) Study. *AMIA Annu Symp Proc*, *2019*, 1041–1050.

Gritz, E. R., Vidrine, D. J., & Cororve Fingeret, M. (2007). Smoking Cessation: A Critical Component of Medical Management in Chronic Disease Populations. *American Journal of Preventive Medicine*, *33*(6, Supplement), S414–S422. https://doi.org/https://doi.org/10.1016/j.amepre.2007.09.013

Gropper, S. S. (2023). The Role of Nutrition in Chronic Disease. *Nutrients*, *15*(3). https://doi.org/10.3390/nu15030664

Großschädl, F., Marston, H. R., Ivan, L., Prabhu, V., & Earle, S. (2025). Age as an important predictor for digital health literacy: Cross-sectional evidence of internet users from an international multisite study in North America and EU countries. *Educational Gerontology*, 1–14. https://doi.org/10.1080/03601277.2025.2505568

Grover, A., & Joshi, A. (2014). An overview of chronic disease models: a systematic literature review. *Glob J Health Sci*, *7*(2), 210–227. https://doi.org/10.5539/gjhs.v7n2p210

Guo, X., Gu, X., Jiang, J., Li, H., Duan, R., Zhang, Y., Sun, L., Bao, Z., Shen, J., & Chen, F. (2019). A Hospital-Community-Family–Based Telehealth Program for Patients With Chronic Heart Failure: Single-Arm, Prospective Feasibility Study [Original Paper]. *JMIR Mhealth Uhealth*, *7*(12), e13229. https://doi.org/10.2196/13229

Guo, Y., Hong, Z., Cao, C., Cao, W., Chen, R., Yan, J., Hu, Z., & Bai, Z. (2024). Urban-Rural Differences in the Association of eHealth Literacy With Medication Adherence Among Older People With Frailty and Prefrailty: Cross-Sectional Study. *JMIR Public Health Surveill*, *10*, e54467. https://doi.org/10.2196/54467

Gwira, J. A., Fryar, C. D., & Gu, Q. (2024). Prevalence of Total, Diagnosed, and Undiagnosed Diabetes in Adults: United States, August 2021-August 2023. *NCHS Data Brief*(516). https://doi.org/10.15620/cdc/165794

Haapanen, M. J., Niku, J., Mikkola, T. M., Vetrano, D. L., Calderón-Larrañaga, A., Dekhtyar, S., Kajantie, E., von Bonsdorff, M. B., & Eriksson, J. G. (2025). Observed and hidden factors underlying the accumulation of chronic diseases across eight major organ systems: a longitudinal birth cohort study. *The Lancet Healthy Longevity*, *6*(5). https://doi.org/10.1016/j.lanhl.2025.100710

Hacker, K. (2024). The Burden of Chronic Disease. *Mayo Clinic Proceedings: Innovations, Quality & Outcomes*, *8*(1), 112–119. https://doi.org/https://doi.org/10.1016/j.mayocpiqo.2023.08.005

Hahn, E. A., Magasi, S. R., Carlozzi, N. E., Tulsky, D. S., Wong, A., Garcia, S. F., Lai, J. S., Hammel, J., Miskovic, A., Jerousek, S., Goldsmith, A., Nitsch, K., & Heinemann, A. W. (2017). Health and Functional Literacy in Physical Rehabilitation Patients. *Health Lit Res Pract*, *1*(2), e71–e85. https://doi.org/10.3928/24748307-20170427-02

Hakimzadeh, Z., & Adib-Hajbaghery, M. (2021). The Effects of a Health Literacy Training Intervention on Self-Care Behaviors and Treatment Adherence in Patients with Ischemic Heart Diseases. *EJMO*, *5*(4). https://doi.org/10.14744/ejmo.2021.61673

Haluza, D., & Wernhart, A. (2019). Does gender matter? Exploring perceptions regarding health technologies among employees and students at a medical university. *International*

Journal of Medical Informatics, *130*, 103948. https://doi.org/https://doi.org/10.1016/j.ijmedinf.2019.08.008

Hanebutt, R., & Mohyuddin, H. (2023). The Digital Domain: A "Super" Social Determinant of Health. *Prim Care*, *50*(4), 657–670. https://doi.org/10.1016/j.pop.2023.04.002

Harper, L., Kalfa, N., Beckers, G. M. A., Kaefer, M., Nieuwhof-Leppink, A. J., Fossum, M., Herbst, K. W., & Bagli, D. (2020). The impact of COVID-19 on research. *J Pediatr Urol*, *16*(5), 715–716. https://doi.org/10.1016/j.jpurol.2020.07.002

Harris, L., Ginzburg, S., Brach, C., Block, L., & Parnell, T. A. (2019). A Model Collaboration to Develop a Health Literate Care Curriculum: Preparing the Next Generation of Physicians to Deliver Excellent Patient Outcomes and Experiences. *NAM Perspect*, *2019*. https://doi.org/10.31478/201910a

Hartman, J. E., Boezen, H. M., Zuidema, M. J., de Greef, M. H. G., & ten Hacken, N. H. T. (2014). Physical Activity Recommendations in Patients with Chronic Obstructive Pulmonary Disease. *Respiration*, *88*(2), 92–100. https://doi.org/10.1159/000360298

Hasannejadasl, H., Roumen, C., Smit, Y., Dekker, A., & Fijten, R. (2022). Health Literacy and eHealth: Challenges and Strategies. *JCO Clinical Cancer Informatics*(6), e2200005. https://doi.org/10.1200/CCI.22.00005

Hashemzadeh, M., Akhlaghi, M., Akbarzadeh, M., Nabizadeh, K., Miri, H. H., & Kazemi, A. (2024). Nutrition literacy and eating habits in children from food-secure versus food-insecure households: A cross-sectional study. *Medicine (Baltimore)*, *103*(39), e39812. https://doi.org/10.1097/md.0000000000039812

Hayes-Watson, C., Nuss, H., Tseng, T. S., Parada, N., Yu, Q., Celestin, M., Guillory, D., Winn, K., & Moody-Thomas, S. (2017). Self-management practices of smokers with asthma and/or chronic obstructive pulmonary disease: a cross-sectional survey. *COPD Research and Practice*, *3*(1), 3. https://doi.org/10.1186/s40749-017-0022-0

Health Resources Service Administration (HRSA). (2023, December). *Telehealth policy changes after the COVID-19 public health emergency*. https://telehealth.hhs.gov/providers/telehealth-policy/policy-changes-after-the-covid-19-public-health-emergency

Heeringa, S. G., West, B. T., Heeringa, S. G., & Berglund, P. A. (2017). *Applied survey data analysis*. chapman and hall/CRC.

Heiss, R., Nanz, A., & Matthes, J. (2023). Social media information literacy: Conceptualization and associations with information overload, news avoidance and conspiracy mentality. *Computers in Human Behavior*, *148*, 107908. https://doi.org/https://doi.org/10.1016/j.chb.2023.107908

Hesse, B. W., Greenberg, A. J., Peterson, E. B., & Chou, W. S. (2017). The Health Information National Trends Survey (HINTS): A Resource for Consumer Engagement and Health Communication Research. *Stud Health Technol Inform*, *240*, 330–346.

Hesse, B. W., Moser, R. P., Rutten, L. J., & Kreps, G. L. (2006). The health information national trends survey: research from the baseline. *J Health Commun*, *11 Suppl 1*, vii–xvi. https://doi.org/10.1080/10810730600692553

Hibbard, J. H. (2017). Patient activation and the use of information to support informed health decisions. *Patient Education and Counseling*, *100*(1), 5–7. https://doi.org/https://doi.org/10.1016/j.pec.2016.07.006

Hibbard, J. H., Stockard, J., Mahoney, E. R., & Tusler, M. (2004). Development of the Patient Activation Measure (PAM): conceptualizing and measuring activation in patients and consumers. *Health Serv Res*, *39*(4 Pt 1), 1005–1026. https://doi.org/10.1111/j.1475-6773.2004.00269.x

Hinrichs, S. H., & Zarcone, P. (2013). The Affordable Care Act, meaningful use, and their impact on public health laboratories. *Public Health Rep*, *128 Suppl 2*(Suppl 2), 7–9. https://doi.org/10.1177/00333549131280s202

Hocking, A., Laurence, C., & Lorimer, M. (2013). Patients' knowledge of their chronic disease - the influence of socio-demographic characteristics. *Aust Fam Physician*, *42*(6), 411–416.

Hoffman, D. L., Novak, T. P., & Schlosser, A. (2000). The Evolution of the Digital Divide: How Gaps in Internet Access May Impact Electronic Commerce. *Journal of Computer-Mediated Communication*, *5*(3). https://doi.org/10.1111/j.1083-6101.2000.tb00341.x

Holman, H. R. (2020). The Relation of the Chronic Disease Epidemic to the Health Care Crisis. *ACR Open Rheumatol*, *2*(3), 167–173. https://doi.org/10.1002/acr2.11114

Holt, K. A., Karnoe, A., Overgaard, D., Nielsen, S. E., Kayser, L., Røder, M. E., & From, G. (2019). Differences in the Level of Electronic Health Literacy Between Users and Nonusers of Digital Health Services: An Exploratory Survey of a Group of Medical Outpatients. *Interact J Med Res*, *8*(2), e8423. https://doi.org/10.2196/ijmr.8423

Hong, Y. A., Jiang, S., & Liu, P. L. (2020). Use of Patient Portals of Electronic Health Records Remains Low From 2014 to 2018: Results From a National Survey and Policy Implications. *Am J Health Promot*, *34*(6), 677–680. https://doi.org/10.1177/0890117119900591

Hoogland, A. I., Mansfield, J., Lafranchise, E. A., Bulls, H. W., Johnstone, P. A., & Jim, H. S. L. (2020). eHealth literacy in older adults with cancer. *Journal of Geriatric Oncology*, *11*(6), 1020–1022. https://doi.org/https://doi.org/10.1016/j.jgo.2019.12.015

Hsu, W., Chiang, C., & Yang, S. (2014). The Effect of Individual Factors on Health Behaviors Among College Students: The Mediating Effects of eHealth Literacy [Original Paper]. *J Med Internet Res*, *16*(12), e287. https://doi.org/10.2196/jmir.3542

Hu, J., Hong, Y. R., Rivero-Mendoza, D., Donahoo, W. T., Ospina, N. S., Staras, S. A., Shenkman, E., & Mkuu, R. S. (2025). Cancer beliefs, risk perceptions, and health protective behaviors among people living with diabetes in the United States: Results from the Health Information National Trends Survey. *Prev Med Rep*, *57*, 103206. https://doi.org/10.1016/j.pmedr.2025.103206

Hua, Z., Yuqing, S., Qianwen, L., & Hong, C. (2025). Factors Influencing eHealth Literacy Worldwide: Systematic Review and Meta-Analysis [Review]. *J Med Internet Res*, *27*, e50313. https://doi.org/10.2196/50313

Huang, J., Chan, S. C., Ko, S., Tong, E., Cheung, C. S. K., Wong, W. N., Cheung, N. T., & Wong, M. C. S. (2023). Associations between adoption of eHealth management module and optimal control of HbA1c in diabetes patients. *npj Digital Medicine*, *6*(1), 67. https://doi.org/10.1038/s41746-023-00807-w

Huang, X., & Fan, J. (2023). Understand the Impact of Technology Feature in Online Health Communities: Why the Representation of Information Matters. *International Journal of Human–Computer Interaction*, *39*(4), 691–706. https://doi.org/10.1080/10447318.2022.2046922

Huhta, A. M., Hirvonen, N., & Huotari, M. L. (2018). Health Literacy in Web-Based Health Information Environments: Systematic Review of Concepts, Definitions, and Operationalization for Measurement. *J Med Internet Res*, *20*(12), e10273. https://doi.org/10.2196/10273

Hunt, X., Hameed, S., Tetali, S., Ngoc, L. A., Ganle, J., Huq, L., Shakespeare, T., Smythe, T., Ilkkursun, Z., Kuper, H., Acarturk, C., Kannuri, N. K., Mai, V. Q., Khan, R. S., & Banks, L. M. (2023). Impacts of the COVID-19 pandemic on access to healthcare among people with disabilities: evidence from six low- and middle-income countries. *Int J Equity Health*, *22*(1), 172. https://doi.org/10.1186/s12939-023-01989-1

Huygens, M. W. J., Vermeulen, J., Swinkels, I. C. S., Friele, R. D., van Schayck, O. C. P., & de Witte, L. P. (2016). Expectations and needs of patients with a chronic disease toward self-management and eHealth for self-management purposes. *BMC Health Services Research*, *16*(1), 232. https://doi.org/10.1186/s12913-016-1484-5

Hyde, L. L., Boyes, A. W., Evans, T. J., Mackenzie, L. J., & Sanson-Fisher, R. (2018). Three-Factor Structure of the eHealth Literacy Scale Among Magnetic Resonance Imaging and Computed Tomography Outpatients: A Confirmatory Factor Analysis. *JMIR Hum Factors*, *5*(1), e6. https://doi.org/10.2196/humanfactors.9039

Hyder, A. A., Puvanachandra, P., & Morrow, R. H. (2012). Measuring the health of populations: explaining composite indicators. *J Public Health Res*, *1*(3), 222–228. https://doi.org/10.4081/jphr.2012.e35

Ibecheozor, C., Morales, J., Ross, J., Ezeofor, A., McKie, C., Scott, V. F., Kibreab, A., Howell, C., Aduli, F., Brim, H., Ashktorab, H., Oyawusi, M., McDonald-Pinkett, S., & Laiyemo, A. O. (2024). Nutritional Calorie Labeling and Menu Ordering Practices Among US Adults With Chronic Illnesses. *Cureus*, *16*(4), e58484. https://doi.org/10.7759/cureus.58484

Idler, E. L., & Kasl, S. (1991). Health Perceptions and Survival: Do Global Evaluations of Health Status Really Predict Mortality? *Journal of Gerontology*, *46*(2), S55–S65. https://doi.org/10.1093/geronj/46.2.S55

Institute of Medicine Committee on Health, L. (2004). In L. Nielsen-Bohlman, A. M. Panzer, & D. A. Kindig (Eds.), *Health Literacy: A Prescription to End Confusion*. National Academies Press (US). https://doi.org/10.17226/10883

Institute of Medicine Roundtable on Health, L. (2009). The National Academies Collection: Reports funded by National Institutes of Health. In *Health Literacy, eHealth, and Communication: Putting the Consumer First: Workshop Summary*. National Academies Press (US). https://doi.org/10.17226/12474

Istepanian, R. S. H., Jovanov, E., & Zhang, Y. T. (2004). Guest Editorial Introduction to the Special Section on M-Health: Beyond Seamless Mobility and Global Wireless Health-Care Connectivity. *IEEE Transactions on Information Technology in Biomedicine*, *8*(4), 405–414. https://doi.org/10.1109/TITB.2004.840019

Ivanitskaya, L., Laus, R., & Casey, A. M. (2004). Research Readiness Self-Assessment. *Journal of Library Administration*, *41*(1-2), 167–183. https://doi.org/10.1300/J111v41n01_13

Jaarsma, T., Hill, L., Bayes-Genis, A., La Rocca, H. B., Castiello, T., Čelutkienė, J., Marques-Sule, E., Plymen, C. M., Piper, S. E., Riegel, B., Rutten, F. H., Ben Gal, T., Bauersachs, J., Coats, A. J. S., Chioncel, O., Lopatin, Y., Lund, L. H., Lainscak, M., Moura, B.,…Strömberg, A. (2021). Self-care of heart failure patients: practical management recommendations from the Heart Failure Association of the European Society of Cardiology. *Eur J Heart Fail*, *23*(1), 157–174. https://doi.org/10.1002/ejhf.2008

Jackson, D. N., Trivedi, N., & Baur, C. (2021). Re-Prioritizing Digital Health and Health Literacy in Healthy People 2030 to Affect Health Equity. *Health Commun*, *36*(10), 1155–1162. https://doi.org/10.1080/10410236.2020.1748828

Jackson, L. A., Zhao, Y., Kolenic, A., Fitzgerald, H. E., Harold, R., & Von Eye, A. (2008). Race, Gender, and Information Technology Use: The New Digital Divide. *CyberPsychology & Behavior*, *11*(4), 437–442. https://doi.org/10.1089/cpb.2007.0157

Jacobs, R. J., Lou, J. Q., Ownby, R. L., & Caballero, J. (2016). A systematic review of eHealth interventions to improve health literacy. *Health Informatics Journal*, *22*(2), 81–98. https://doi.org/10.1177/1460458214534092

Jacobs, W., Amuta, A. O., & Jeon, K. C. (2017). Health information seeking in the digital age: An analysis of health information seeking behavior among US adults. *Cogent Social Sciences*, *3*(1), 1302785. https://doi.org/10.1080/23311886.2017.1302785

James, D. C., & Harville, C., 2nd. (2016). eHealth Literacy, Online Help-Seeking Behavior, and Willingness to Participate in mHealth Chronic Disease Research Among African Americans, Florida, 2014-2015. *Prev Chronic Dis*, *13*, E156. https://doi.org/10.5888/pcd13.160210

Jang, M. (2023). Why Do People Use Telemedicine Apps in the Post-COVID-19 Era? Expanded TAM with E-Health Literacy and Social Influence. *Informatics*, *10*(4), 85.

Jang, S. H., & Je, N. (2022). The relationship between digital literacy, loneliness, quality of life, and health-promoting behaviors among the elderly in the age of COVID-19. *International Journal of Advanced and Applied Sciences*, *9*(4), 71–79.

Jansen, D. L., Heijmans, M. J. W. M., Rijken, M., Spreeuwenberg, P., Grootendorst, D. C., Dekker, F. W., Boeschoten, E. W., Kaptein, A. A., & Groenewegen, P. P. (2013). Illness perceptions and treatment perceptions of patients with chronic kidney disease: Different phases, different perceptions? *British Journal of Health Psychology*, *18*(2), 244–262. https://doi.org/https://doi.org/10.1111/bjhp.12002

Jia, J., Van Horn, L., Linder, J. A., Ackermann, R. T., Kandula, N. R., & O'Brien, M. J. (2023). Menu Calorie Label Use and Diet Quality: a Cross-Sectional Study. *Am J Prev Med*, *65*(6), 1069–1077. https://doi.org/10.1016/j.amepre.2023.07.003

Jiang, S., & Beaudoin, C. E. (2016). Health literacy and the internet: An exploratory study on the 2013 HINTS survey. *Computers in Human Behavior*, *58*, 240–248. https://doi.org/https://doi.org/10.1016/j.chb.2016.01.007

Jiang, S., & Hong, Y. A. (2018). Mobile-based patient-provider communication in cancer survivors: The roles of health literacy and patient activation. *Psychooncology*, *27*(3), 886–891. https://doi.org/10.1002/pon.4598

Jiao, W., Chang, A., Ho, M., Lu, Q., Liu, M. T., & Schulz, P. J. (2023). Predicting and Empowering Health for Generation Z by Comparing Health Information Seeking and Digital Health Literacy: Cross-Sectional Questionnaire Study. *J Med Internet Res*, *25*, e47595. https://doi.org/10.2196/47595

Jo, S. (2022). The Use of Multiple Imputation to Handle Missing Data in Secondary Datasets: Suggested Approaches when Missing Data Results from the Survey Structure. *Inquiry*, *59*, 469580221088627. https://doi.org/10.1177/00469580221088627

Jokinen, A., Stolt, M., & Suhonen, R. (2021). Ethical issues related to eHealth: An integrative review. *Nursing Ethics*, *28*(2), 253–271. https://doi.org/10.1177/0969733020945765

Joo, J. H., Lieu, N., Tang, Y., Browne, D. S., Agusala, B., & Liao, J. M. (2025). Trends in utilization of remote monitoring in the United States. *Health Aff Sch*, *3*(6), qxaf115. https://doi.org/10.1093/haschl/qxaf115

Kaphingst, K. A., Weaver, N. L., Wray, R. J., Brown, M. L., Buskirk, T., & Kreuter, M. W.

(2014). Effects of patient health literacy, patient engagement and a system-level health literacy attribute on patient-reported outcomes: a representative statewide survey. *BMC Health Serv Res*, *14*, 475. https://doi.org/10.1186/1472-6963-14-475

Kaplan, G. A., & Camacho, T. (1983). Perceived health and mortality: a nine-year follow-up of the human population laboratory cohort. *Am J Epidemiol*, *117*(3), 292–304. https://doi.org/10.1093/oxfordjournals.aje.a113541

Karatas, M., Eriskin, L., Deveci, M., Pamucar, D., & Garg, H. (2022). Big Data for Healthcare Industry 4.0: Applications, challenges and future perspectives. *Expert Systems with Applications*, *200*, 116912. https://doi.org/https://doi.org/10.1016/j.eswa.2022.116912

Karnoe, A., Furstrand, D., Christensen, K. B., Norgaard, O., & Kayser, L. (2018). Assessing Competencies Needed to Engage With Digital Health Services: Development of the eHealth Literacy Assessment Toolkit [Original Paper]. *J Med Internet Res*, *20*(5), e178. https://doi.org/10.2196/jmir.8347

Katsaliaki, K. (2024). Factors influencing use of eHealth services during and after the COVID-19 pandemic. *Health Serv Manage Res*, 9514848241275777. https://doi.org/10.1177/09514848241275777

Kayser, L., Karnoe, A., Furstrand, D., Batterham, R., Christensen, K. B., Elsworth, G., & Osborne, R. H. (2018). A Multidimensional Tool Based on the eHealth Literacy Framework: Development and Initial Validity Testing of the eHealth Literacy Questionnaire (eHLQ) [Original Paper]. *J Med Internet Res*, *20*(2), e36. https://doi.org/10.2196/jmir.8371

Keesara, S., Jonas, A., & Schulman, K. (2020). Covid-19 and Health Care's Digital Revolution. *New England Journal of Medicine*, *382*(23), e82. https://doi.org/doi:10.1056/NEJMp2005835

Kelly, J. T., Caffery, L. J., Thomas, E. E., de Camargo Catapan, S., Smith, A. C., Isbel, N., Mayr, H., Webb, L., Campbell, K. L., Macdonald, G. A., Coombes, J. S., Keating, S. E., & Hickman, I. J. (2025). Determining the digital health literacy and potential solutions to support people with complex chronic conditions to engage with digital models of care. *Patient Education and Counseling*, *140*, 109278. https://doi.org/https://doi.org/10.1016/j.pec.2025.109278

Kelp, N. C., McCartney, M., Sarvary, M. A., Shaffer, J. F., & Wolyniak, M. J. (2023). Developing Science Literacy in Students and Society: Theory, Research, and Practice. *J Microbiol Biol Educ*, *24*(2). https://doi.org/10.1128/jmbe.00058-23

Keshta, I., & Odeh, A. (2021). Security and privacy of electronic health records: Concerns and challenges. *Egyptian Informatics Journal*, *22*(2), 177–183. https://doi.org/https://doi.org/10.1016/j.eij.2020.07.003

Keuper, J., van Tuyl, L. H. D., de Geit, E., Rijpkema, C., Vis, E., Batenburg, R., & Verheij, R. (2024). The impact of eHealth use on general practice workload in the pre-COVID-19 era: a systematic review. *BMC Health Serv Res*, *24*(1), 1099. https://doi.org/10.1186/s12913-024-11524-9

Kim, H., & Xie, B. (2017). Health literacy in the eHealth era: A systematic review of the literature. *Patient Education and Counseling*, *100*(6), 1073–1082. https://doi.org/https://doi.org/10.1016/j.pec.2017.01.015

Kim, H. I., Lim, H., & Moon, A. (2018). Sex Differences in Cancer: Epidemiology, Genetics and Therapy. *Biomol Ther (Seoul)*, *26*(4), 335–342. https://doi.org/10.4062/biomolther.2018.103

Kim, H. K., & Tandoc, E. C., Jr. (2022). Consequences of Online Misinformation on COVID-19: Two Potential Pathways and Disparity by eHealth Literacy. *Front Psychol*, *13*, 783909. https://doi.org/10.3389/fpsyg.2022.783909

Kim, J., Youm, H., Kim, S., Choi, H., Kim, D., Shin, S., & Chung, J. (2024). Exploring the Influence of YouTube on Digital Health Literacy and Health Exercise Intentions: The Role of Parasocial Relationships. *Behav Sci (Basel)*, *14*(4). https://doi.org/10.3390/bs14040282

Kim, K., Shin, S., Kim, S., & Lee, E. (2023). The Relation Between eHealth Literacy and Health-Related Behaviors: Systematic Review and Meta-analysis. *J Med Internet Res*, *25*, e40778. https://doi.org/10.2196/40778

Kim, K. A., Kim, Y. J., & Choi, M. (2018). Association of Electronic Health Literacy With Health-Promoting Behaviors in Patients With Type 2 Diabetes: A Cross-sectional Study. *CIN: Computers, Informatics, Nursing*, *36*(9), 438–447. https://doi.org/10.1097/cin.0000000000000438

Kindratt, T. B. (2022). *Big Data for Epidemiology: Applied Data Analysis Using National Health Surveys*. Mavs Open Press.

Kleinbaum, D. G., Kupper, L. L., Nizam, A., & Rosenberg, E. S. (2013). *Applied regression analysis and other multivariable methods* (Fifth edition. ed.). Cengage Learning.

Knowles, H., Swoboda, T. K., Sandlin, D., Huggins, C., Takami, T., Johnson, G., & Wang, H. (2023). The association between electronic health information usage and patient-centered communication: a cross sectional analysis from the Health Information National Trends Survey (HINTS). *BMC Health Services Research*, *23*(1), 1398. https://doi.org/10.1186/s12913-023-10426-6

Koh, H. K., Brach, C., Harris, L. M., & Parchman, M. L. (2013). A proposed 'health literate care model' would constitute a systems approach to improving patients' engagement in care. *Health Aff (Millwood)*, *32*(2), 357–367. https://doi.org/10.1377/hlthaff.2012.1205

Kokkinakis, D. (2022). eHealth Literacy and Capability in the Context of the Pandemic Crisis. In H. Falk Erhag, U. Lagerlöf Nilsson, T. Rydberg Sterner, & I. Skoog (Eds.), *A Multidisciplinary Approach to Capability in Age and Ageing* (pp. 109–129). Springer International Publishing. https://doi.org/10.1007/978-3-030-78063-0_9

Kominski, G. F., Nonzee, N. J., & Sorensen, A. (2017). The Affordable Care Act's Impacts on Access to Insurance and Health Care for Low-Income Populations. *Annu Rev Public Health*, *38*, 489–505. https://doi.org/10.1146/annurev-publhealth-031816-044555

Kommera, K., Cabrero Castro, J. E., & Downer, B. (2025). The association between becoming uninsured and forgoing medical care among middle-aged and older adults in Mexico with chronic health conditions. *Innov Aging*, *9*(8), igaf078. https://doi.org/10.1093/geroni/igaf078

Kontos, E., Blake, K. D., Chou, W.-Y. S., & Prestin, A. (2014). Predictors of eHealth Usage: Insights on The Digital Divide From the Health Information National Trends Survey 2012 [Original Paper]. *J Med Internet Res*, *16*(7), e172. https://doi.org/10.2196/jmir.3117

Kormos, C., & Gifford, R. (2014). The validity of self-report measures of proenvironmental behavior: A meta-analytic review. *Journal of Environmental Psychology*, *40*, 359–371. https://doi.org/https://doi.org/10.1016/j.jenvp.2014.09.003

Kruse, C. S., Argueta, D. A., Lopez, L., & Nair, A. (2015). Patient and Provider Attitudes Toward the Use of Patient Portals for the Management of Chronic Disease: A Systematic Review [Review]. *J Med Internet Res*, *17*(2), e40. https://doi.org/10.2196/jmir.3703

Kunnath, A. J., Sack, D. E., & Wilkins, C. H. (2024). Relative predictive value of sociodemographic factors for chronic diseases among All of Us participants: a descriptive analysis. *BMC Public Health*, *24*(1), 405. https://doi.org/10.1186/s12889-024-17834-1

Kyaw, M. Y., Aung, M. N., Koyanagi, Y., Moolphate, S., Aung, T. N. N., Ma, H. K. C., Lee, H., Nam, H.-K., Nam, E. W., & Yuasa, M. (2024). Sociodigital Determinants of eHealth Literacy and Related Impact on Health Outcomes and eHealth Use in Korean Older Adults: Community-Based Cross-Sectional Survey. *JMIR Aging*, *7*, e56061. https://doi.org/10.2196/56061

Laddu, D. R., Biggs, E., Kaar, J., Khadanga, S., Alman, R., & Arena, R. (2023). The impact of the COVID-19 pandemic on cardiovascular health behaviors and risk factors: A new troubling normal that may be here to stay. *Progress in Cardiovascular Diseases*, *76*, 38–43. https://doi.org/https://doi.org/10.1016/j.pcad.2022.11.017

Lai, Y. K., Ye, J. F., Ran, Q., & Ao, H. S. (2024). Internet-based eHealth technology for emotional well-being among the older adults with a family cancer history: full mediation effects of health information self-efficacy and cancer fatalism. *BMC Psychol*, *12*(1), 232. https://doi.org/10.1186/s40359-024-01701-0

Lane, S., Fitzsimmons, E., Zelefksy, A., Klein, J., Kaur, S., Viswanathan, S., Garg, M., Feldman, J. M., & Jariwala, S. P. (2023). Assessing Electronic Health Literacy at an Urban Academic Hospital. *Appl Clin Inform*, *14*(2), 365–373. https://doi.org/10.1055/a-2041-4500

Langford, A., Orellana, K., Kalinowski, J., Aird, C., & Buderer, N. (2020). Use of Tablets and Smartphones to Support Medical Decision Making in US Adults: Cross-Sectional Study. *JMIR Mhealth Uhealth*, *8*(8), e19531. https://doi.org/10.2196/19531

Latulippe, K., Hamel, C., & Giroux, D. (2017). Social Health Inequalities and eHealth: A Literature Review With Qualitative Synthesis of Theoretical and Empirical Studies [Original Paper]. *J Med Internet Res*, *19*(4), e136. https://doi.org/10.2196/jmir.6731

Lee, A. (2020). Philosophy of Primary Health Care. In B. Y. F. Fong, V. T. S. Law, & A. Lee (Eds.), *Primary Care Revisited : Interdisciplinary Perspectives for a New Era* (pp. 23–38). Springer Singapore. https://doi.org/10.1007/978-981-15-2521-6_2

Lee, H. E., & Cho, J. (2017). What Motivates Users to Continue Using Diet and Fitness Apps? Application of the Uses and Gratifications Approach. *Health Communication*, *32*(12), 1445–1453. https://doi.org/10.1080/10410236.2016.1167998

Lee, H. Y., Kim, S., Neese, J., & Lee, M. H. (2021). Does health literacy affect the uptake of annual physical check-ups?: Results from the 2017 US health information national trends survey. *Arch Public Health*, *79*(1), 38. https://doi.org/10.1186/s13690-021-00556-w

Lee, J., Lee, E.-H., & Chae, D. (2021). eHealth Literacy Instruments: Systematic Review of Measurement Properties [Review]. *J Med Internet Res*, *23*(11), e30644. https://doi.org/10.2196/30644

Lee, J., Lee, E. H., & Chae, D. (2021). eHealth Literacy Instruments: Systematic Review of Measurement Properties. *J Med Internet Res*, *23*(11), e30644. https://doi.org/10.2196/30644

Lee, J., & Tak, S. H. (2022). Factors associated with eHealth literacy focusing on digital literacy components: A cross-sectional study of middle-aged adults in South Korea. *Digit Health*, *8*, 20552076221102765. https://doi.org/10.1177/20552076221102765

Lee, K. S., Feltner, F. J., Bailey, A. L., Lennie, T. A., Chung, M. L., Smalls, B. L., Schuman, D. L., & Moser, D. K. (2019). The relationship between psychological states and health perception in individuals at risk for cardiovascular disease. *Psychol Res Behav Manag*, *12*, 317–324. https://doi.org/10.2147/prbm.S198280

Lee, W. L., Lim, Z. J., Tang, L. Y., Yahya, N. A., Varathan, K. D., & Ludin, S. M. (2022). Patients' Technology Readiness and eHealth Literacy: Implications for Adoption and Deployment of eHealth in the COVID-19 Era and Beyond. *CIN: Computers, Informatics, Nursing*, *40*(4).

Levin-Zamir, D., & Bertschi, I. (2018). Media Health Literacy, eHealth Literacy, and the Role of the Social Environment in Context. *International Journal of Environmental Research and Public Health*, *15*(8), 1643.

Lewis, J., Ray, P., & Liaw, S. T. (2016). Recent Worldwide Developments in eHealth and mHealth to more Effectively Manage Cancer and other Chronic Diseases – A Systematic Review. *Yearb Med Inform*, *25*(01), 93–108. https://doi.org/10.15265/IY-2016-020

Lewis, J. E., Arheart, K. L., LeBlanc, W. G., Fleming, L. E., Lee, D. J., Davila, E. P., Cabán-Martinez, A. J., Dietz, N. A., McCollister, K. E., Bandiera, F. C., & Clark, J. D. (2009). Food label use and awareness of nutritional information and recommendations among persons with chronic disease12. *The American Journal of Clinical Nutrition*, *90*(5), 1351–1357. https://doi.org/https://doi.org/10.3945/ajcn.2009.27684

Lewis, S., & Clarke, M. (2001). Forest plots: trying to see the wood and the trees. *Bmj*, *322*(7300), 1479–1480. https://doi.org/10.1136/bmj.322.7300.1479

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

Li, S., Cui, G., Yin, Y., & Xu, H. (2023). Associations between health literacy, digital skill, and eHealth literacy among older Chinese adults: A cross-sectional study. *Digit Health*, *9*, 20552076231178431. https://doi.org/10.1177/20552076231178431

Li, X. (2018). Understanding eHealth Literacy From a Privacy Perspective: eHealth Literacy and Digital Privacy Skills in American Disadvantaged Communities. *American Behavioral Scientist*, *62*(10), 1431–1449. https://doi.org/10.1177/0002764218787019

Li, X., & Liu, Q. (2020). Social Media Use, eHealth Literacy, Disease Knowledge, and Preventive Behaviors in the COVID-19 Pandemic: Cross-Sectional Study on Chinese Netizens [Original Paper]. *J Med Internet Res*, *22*(10), e19684. https://doi.org/10.2196/19684

Li, Y., & Guo, M. (2021). Scientific Literacy in Communicating Science and Socio-Scientific Issues: Prospects and Challenges [Systematic Review]. *Frontiers in Psychology*, *12*. https://doi.org/10.3389/fpsyg.2021.758000

Li, Z., Lu, F., Wu, J., Bao, R., Rao, Y., Yang, Y., & Wang, H. (2024). Usability and Effectiveness of eHealth and mHealth Interventions That Support Self-Management and Health Care Transition in Adolescents and Young Adults With Chronic Disease: Systematic Review. *J Med Internet Res*, *26*, e56556. https://doi.org/10.2196/56556

Liao, Y., King, A. J., Lyons, B. A., & Kaphingst, K. A. (2025). Limited Awareness of Alcohol-Related Cancer Risk Factors among Spanish-Preferring Adults in a National US Survey. *Cancer Epidemiology, Biomarkers & Prevention*, *34*(5), 754–761. https://doi.org/10.1158/1055-9965.Epi-24-1354

Lin, A. W., Baik, S. H., Aaby, D., Tello, L., Linville, T., Alshurafa, N., & Spring, B. (2020). eHealth Practices in Cancer Survivors With BMI in Overweight or Obese Categories: Latent Class Analysis Study. *JMIR Cancer*, *6*(2), e24137. https://doi.org/10.2196/24137

Lin, C. Y., Ganji, M., Griffiths, M. D., Bravell, M. E., Broström, A., & Pakpour, A. H. (2020). Mediated effects of insomnia, psychological distress and medication adherence in the association of eHealth literacy and cardiac events among Iranian older patients with heart failure: a longitudinal study. *Eur J Cardiovasc Nurs*, *19*(2), 155–164. https://doi.org/10.1177/1474515119873648

Lines, L. M., Long, M. C., Zangeneh, S., DePriest, K., Piontak, J., Humphrey, J., & Subramanian, S. (2023). Composite Indices of Social Determinants of Health: Overview, Measurement Gaps, and Research Priorities for Health Equity. *Population Health Management*, *26*(5), 332–340. https://doi.org/10.1089/pop.2023.0106

Link, E., Baumann, E., Kreps, G. L., Czerwinski, F., Rosset, M., & Suhr, R. (2022). Expanding the Health Information National Trends Survey Research Program Internationally to Examine Global Health Communication Trends: Comparing Health Information Seeking Behaviors in the U.S. and Germany. *Journal of Health Communication*, *27*(8), 545–554. https://doi.org/10.1080/10810730.2022.2134522

Little, R. J. A. (1988). A Test of Missing Completely at Random for Multivariate Data with Missing Values. *Journal of the American Statistical Association*, *83*(404), 1198–1202. https://doi.org/10.1080/01621459.1988.10478722

Lohse, K. R., & Kliethermes, S. (2025). Approaching Significance: Statistical Guidance for Authors and Reviewers. *J Neurol Phys Ther*, *49*(4), 240–247. https://doi.org/10.1097/npt.0000000000000526

Lopez, J. Z., Lee, M., Park, S. K., Zolezzi, M. E., Mitchell-Bennett, L. A., Yeh, P. G., Perez, L., Heredia, N. I., McPherson, D. D., McCormick, J. B., & Reininger, B. M. (2024). An expanded chronic care management approach to multiple chronic conditions in Hispanics using community health workers as community extenders in the Rio Grande Valley of Texas. *Preventive Medicine*, *184*, 107975. https://doi.org/https://doi.org/10.1016/j.ypmed.2024.107975

Loprinzi, P. D., Addoh, O., & Joyner, C. (2016). Multimorbidity, mortality, and physical activity. *Chronic Illness*, *12*(4), 272–280. https://doi.org/10.1177/1742395316644306

Loretan, C. G., Cornelius, M. E., Jamal, A., Cheng, Y. J., & Homa, D. M. (2022). Cigarette Smoking Among US Adults With Selected Chronic Diseases Associated With Smoking, 2010-2019. *Preventing Chronic Disease*, *19*, E62. https://doi.org/10.5888/pcd19.220086

Lorig, K., Chastain, R. L., Ung, E., Shoor, S., & Holman, H. R. (1989). Development and evaluation of a scale to measure perceived self-efficacy in people with arthritis. *Arthritis Rheum*, *32*(1), 37–44. https://doi.org/10.1002/anr.1780320107

Lorig, K. R., & Holman, H. (2003). Self-management education: history, definition, outcomes, and mechanisms. *Ann Behav Med*, *26*(1), 1–7. https://doi.org/10.1207/s15324796abm2601_01

Lorig, K. R., Ritter, P., Stewart, A. L., Sobel, D. S., Brown, B. W., Jr., Bandura, A., Gonzalez, V. M., Laurent, D. D., & Holman, H. R. (2001). Chronic disease self-management program: 2-year health status and health care utilization outcomes. *Med Care*, *39*(11), 1217–1223. https://doi.org/10.1097/00005650-200111000-00008

Lotto, M., Maschio, K. F., Silva, K. K., Ayala Aguirre, P. E., Cruvinel, A., & Cruvinel, T. (2023). eHEALS as a predictive factor of digital health information seeking behavior among Brazilian undergraduate students. *Health Promot Int*, *38*(4). https://doi.org/10.1093/heapro/daab182

Luciani, M., De Maria, M., Page, S. D., Barbaranelli, C., Ausili, D., & Riegel, B. (2022). Measuring self-care in the general adult population: development and psychometric testing of the Self-Care Inventory. *BMC Public Health*, *22*(1), 598. https://doi.org/10.1186/s12889-022-12913-7

Lumley, T. (2011). *Complex surveys: a guide to analysis using R*. John Wiley & Sons.

Luo, J., Collier, W., Magno-Padron, D., Tieman, J., Pires, G., Moss, W., Rosales, M., Kim, J., Agarwal, J. P., & Kwok, A. C. (2022). Characteristics of Nonelderly Adult Health Care Persistent Super Utilizers in Utah. *Population Health Management*, *25*(4), 472–479. https://doi.org/10.1089/pop.2021.0275

Lushniak, B. D., Samet, J. M., Pechacek, T. F., Norman, L. A., & Taylor, P. A. (2014). The Health consequences of smoking—50 years of progress : a report of the Surgeon General [Report].

Lv, N., Xiao, L., Simmons, M. L., Rosas, L. G., Chan, A., & Entwistle, M. (2017). Personalized Hypertension Management Using Patient-Generated Health Data Integrated With Electronic Health Records (EMPOWER-H): Six-Month Pre-Post Study [Original Paper]. *J Med Internet Res*, *19*(9), e311. https://doi.org/10.2196/jmir.7831

Ma, D., Zhou, J., & Zuo, M. (2024). Information Seeking and Receiving of Older Adults with Diabetes in the Online Health Community: An Information Need Contextualization Perspective. *Health Commun*, 1–12. https://doi.org/10.1080/10410236.2024.2349314

Ma, Y., Cheng, H. Y., Cheng, L., & Sit, J. W. H. (2019). The effectiveness of electronic health interventions on blood pressure control, self-care behavioural outcomes and psychosocial well-being in patients with hypertension: A systematic review and meta-analysis. *International Journal of Nursing Studies*, *92*, 27–46. https://doi.org/https://doi.org/10.1016/j.ijnurstu.2018.11.007

MacCallum, R. C., Zhang, S., Preacher, K. J., & Rucker, D. D. (2002). On the practice of dichotomization of quantitative variables. *Psychol Methods*, *7*(1), 19–40. https://doi.org/10.1037/1082-989x.7.1.19

Mackey, L. M., Doody, C., Werner, E. L., & Fullen, B. (2016). Self-Management Skills in Chronic Disease Management:What Role Does Health Literacy Have? *Medical Decision Making*, *36*(6), 741–759. https://doi.org/10.1177/0272989x16638330

Madrigal, L., & Escoffery, C. (2019). Electronic Health Behaviors Among US Adults With Chronic Disease: Cross-Sectional Survey. *J Med Internet Res*, *21*(3), e11240. https://doi.org/10.2196/11240

Magnani, J. W., Mujahid, M. S., Aronow, H. D., Cené, C. W., Dickson, V. V., Havranek, E., Morgenstern, L. B., Paasche-Orlow, M. K., Pollak, A., & Willey, J. Z. (2018). Health Literacy and Cardiovascular Disease: Fundamental Relevance to Primary and Secondary Prevention: A Scientific Statement From the American Heart Association. *Circulation*, *138*(2), e48–e74. https://doi.org/10.1161/cir.0000000000000579

Mahashabde, R., Pandit, A. A., Acharya, M., Ali, M. M., Bogulski, C. A., Eswaran, H., & Hayes, C. J. (2025). Trends in Remote Patient Monitoring Before and After the COVID-19 Public Health Emergency Declaration in the United States: A Comparison Between Rural/Urban and Racial/Ethnic Group. *Telemedicine and e-Health*, *31*(11), 1359–1368. https://doi.org/10.1089/tmj.2025.0071

Maita, K. C., Maniaci, M. J., Haider, C. R., Avila, F. R., Torres-Guzman, R. A., Borna, S., Lunde, J. J., Coffey, J. D., Demaerschalk, B. M., & Forte, A. J. (2024). The Impact of Digital

Health Solutions on Bridging the Health Care Gap in Rural Areas: A Scoping Review. *Perm J*, *28*(3), 130–143. https://doi.org/10.7812/tpp/23.134

Manes, M., Mannarini, A., Pavan, D., Aschieri, D., Khoury, G., Scardovi, B., Bruno, N., Cocozza, S., Gabrielli, D., & Colivicchi, F. (2024). eHealth Literacy and Gender Disparities: Insights from an Internal Survey. *Journal of Cardiology and Cardiovascular Medicine*, *9*(3), 164–171.

Manganello, J., Gerstner, G., Pergolino, K., Graham, Y., Falisi, A., & Strogatz, D. (2017). The Relationship of Health Literacy With Use of Digital Technology for Health Information: Implications for Public Health Practice. *J Public Health Manag Pract*, *23*(4), 380–387. https://doi.org/10.1097/phh.0000000000000366

Manganello, J. A., & Clayman, M. L. (2011). The Association of Understanding of Medical Statistics with Health Information Seeking and Health Provider Interaction in a National Sample of Young Adults. *Journal of Health Communication*, *16*(sup3), 163–176. https://doi.org/10.1080/10810730.2011.604704

Manganello Jennifer, A., Colvin Kimberly, F., Hadley, M., & O'Brien, K. (2024). Get Health‘e’: A Pilot Test of a Digital Health Literacy Intervention for Young Adults. *HLRP: Health Literacy Research and Practice*, *8*(4), e224–e235. https://doi.org/10.3928/24748307-20240723-01

Manning, S. E., Wang, H., Dwibedi, N., Shen, C., Wiener, R. C., Findley, P. A., Mitra, S., & Sambamoorthi, U. (2023). Association of multimorbidity with the use of health information technology. *Digit Health*, *9*, 20552076231163797. https://doi.org/10.1177/20552076231163797

Mantwill, S., Monestel-Umaña, S., & Schulz, P. J. (2015). The Relationship between Health Literacy and Health Disparities: A Systematic Review. *PLoS One*, *10*(12), e0145455. https://doi.org/10.1371/journal.pone.0145455

Marklund, S., Tistad, M., Lundell, S., Östrand, L., Sörlin, A., Boström, C., Wadell, K., & Nyberg, A. (2021). Experiences and Factors Affecting Usage of an eHealth Tool for Self-Management Among People With Chronic Obstructive Pulmonary Disease: Qualitative Study. *J Med Internet Res*, *23*(4), e25672. https://doi.org/10.2196/25672

Marlow, N. M., Samuels, S. K., Jo, A., & Mainous, A. G. (2019). Patient-provider communication quality for persons with disabilities: A cross-sectional analysis of the Health Information National Trends Survey. *Disability and Health Journal*, *12*(4), 732–737. https://doi.org/https://doi.org/10.1016/j.dhjo.2019.03.010

Masterson Creber, R., Allison, P. D., & Riegel, B. (2013). Overall perceived health predicts risk of hospitalizations and death in adults with heart failure: a prospective longitudinal study. *Int J Nurs Stud*, *50*(5), 671–677. https://doi.org/10.1016/j.ijnurstu.2012.10.001

Matarese, M., Clari, M., De Marinis, M. G., Barbaranelli, C., Ivziku, D., Piredda, M., & Riegel, B. (2020). The Self-Care in Chronic Obstructive Pulmonary Disease Inventory: Development and Psychometric Evaluation. *Eval Health Prof*, *43*(1), 50–62. https://doi.org/10.1177/0163278719856660

Mathaka, S., Decha, T., Sivaporn, A., & Thanee, K. (2023). Effects of Enhance Health Literacy through Transformative Learning Program on Self-Management and Hemoglobin A1C Level Among Adults with Uncontrolled Type 2 Diabetes: A Randomized Controlled Trial. *Pacific Rim International Journal of Nursing Research*, *27*(2), 317–333. https://doi.org/10.60099/prijnr.2023.262041

McCully, S. N., Don, B. P., & Updegraff, J. A. (2013). Using the Internet to Help With Diet, Weight, and Physical Activity: Results From the Health Information National Trends Survey (HINTS) [Original Paper]. *J Med Internet Res*, *15*(8), e148. https://doi.org/10.2196/jmir.2612

McHugh, M. L. (2013). The chi-square test of independence. *Biochem Med (Zagreb)*, *23*(2), 143–149. https://doi.org/10.11613/bm.2013.018

McKenna, S. P., & Heaney, A. (2020). Composite outcome measurement in clinical research: the triumph of illusion over reality? *J Med Econ*, *23*(10), 1196–1204. https://doi.org/10.1080/13696998.2020.1797755

McNeish, D. (2024). Practical Implications of Sum Scores Being Psychometrics' Greatest Accomplishment. *Psychometrika*, *89*(4), 1148–1169. https://doi.org/10.1007/s11336-024-09988-z

Mede, N. G., Howell, E. L., Schäfer, M. S., Metag, J., Beets, B., & Brossard, D. (2026). Measuring Science Literacy in a Digital World: Development and Validation of a Multi-Dimensional Survey Scale. *Science Communication*, *48*(1), 93–127. https://doi.org/10.1177/10755470251317379

Megari, K. (2013). Quality of Life in Chronic Disease Patients. *Health Psychol Res*, *1*(3), e27. https://doi.org/10.4081/hpr.2013.e27

Milani, R. V., Bober, R. M., & Lavie, C. J. (2016). The Role of Technology in Chronic Disease Care. *Progress in Cardiovascular Diseases*, *58*(6), 579–583. https://doi.org/https://doi.org/10.1016/j.pcad.2016.01.001

Milanti, A., Norman, C., Chan, D. N. S., So, W. K. W., & Skinner, H. (2025). eHealth Literacy 3.0: Updating the Norman and Skinner 2006 Model. *J Med Internet Res*, *27*, e70112. https://doi.org/10.2196/70112

Miller, L. M. S., Applegate, E., Beckett, L. A., Wilson, M. D., & Gibson, T. N. (2017). Age differences in the use of serving size information on food labels: numeracy or attention? *Public Health Nutrition*, *20*(5), 786–796. https://doi.org/10.1017/S1368980016003219

Miller, W. R., Lasiter, S., Bartlett Ellis, R., & Buelow, J. M. (2015). Chronic disease self-management: a hybrid concept analysis. *Nurs Outlook*, *63*(2), 154–161. https://doi.org/10.1016/j.outlook.2014.07.005

Miot, H. A. (2020). Analysis of ordinal data in clinical and experimental studies. *J Vasc Bras*, *19*, e20200185. https://doi.org/10.1590/1677-5449.200185

Mitsutake, S., Oka, K., Okan, O., Dadaczynski, K., Ishizaki, T., Nakayama, T., & Takahashi, Y. (2024). eHealth Literacy and Web-Based Health Information–Seeking Behaviors on COVID-19 in Japan: Internet-Based Mixed Methods Study [Original Paper]. *J Med Internet Res*, *26*, e57842. https://doi.org/10.2196/57842

Mitsutake, S., Shibata, A., Ishii, K., & Oka, K. (2016). Associations of eHealth Literacy With Health Behavior Among Adult Internet Users [Original Paper]. *J Med Internet Res*, *18*(7), e192. https://doi.org/10.2196/jmir.5413

Mondal, H., Tiu, D. N., Juhi, A., & Mondal, S. (2024). Early Identification of Low Scorers: The Role of Formative Assessments and Summative Assessments. *Cureus*, *16*(12), e76118. https://doi.org/10.7759/cureus.76118

Monkman, H., Kushniruk, A. W., Barnett, J., Borycki, E. M., Greiner, L. E., & Sheets, D. (2017). Are Health Literacy and eHealth Literacy the Same or Different? *Stud Health Technol Inform*, *245*, 178–182.

Morales, J., & Eguia, C. A. (2025). Assessment of eHealth Literacy in Healthcare Service Users: Construction and Validation of a Measurement Instrument. *Clin Pract Epidemiol Ment Health*, *21*, e17450179393541. https://doi.org/10.2174/0117450179393541250722062947

Moses, L. E., Emerson, J. D., & Hosseini, H. (1984). Analyzing data from ordered categories. *N Engl J Med*, *311*(7), 442–448. https://doi.org/10.1056/nejm198408163110705

Mudd, J., Larkins, S., & Watt, K. (2020). The effect of alcohol consumption on clinical outcomes in regional patients with chronic disease: a retrospective chart audit. *Australian and New Zealand Journal of Public Health*, *44*(6), 451–456. https://doi.org/https://doi.org/10.1111/1753-6405.13017

Müller, C. P., Schumann, G., Rehm, J., Kornhuber, J., & Lenz, B. (2023). Self-management with alcohol over lifespan: psychological mechanisms, neurobiological underpinnings, and risk assessment. *Molecular Psychiatry*, *28*(7), 2683–2696. https://doi.org/10.1038/s41380-023-02074-3

Mutlu, H., Bozkurt, G., Öngel, G., & Gümüşboğa, Y. (2025). Access to healthy ınformatıon: the ınteractıon of medıa lıteracy and health lıteracy. *BMC Public Health*, *25*(1), 2800. https://doi.org/10.1186/s12889-025-24022-2

Muro, A., Czajkowski, S., Hall, K. L., Neta, G., Weaver, S. J., & D'Angelo, H. (2024). Climate Change Harm Perception Among U.S. Adults in the NCI Health Information National Trends Survey, 2022. *American Journal of Health Promotion*, *38*(5), 625–632. https://doi.org/10.1177/08901171241228339

Myers, J., Kokkinos, P., Arena, R., & LaMonte, M. J. (2021). The impact of moving more, physical activity, and cardiorespiratory fitness: Why we should strive to measure and improve fitness. *Prog Cardiovasc Dis*, *64*, 77–82. https://doi.org/10.1016/j.pcad.2020.11.003

Nagori, A., Keshvani, N., Patel, L., Dhruve, R., & Sumarsono, A. (2024). Electronic health Literacy gaps among adults with diabetes in the United States: Role of socioeconomic and demographic factors. *Preventive Medicine Reports*, *47*, 102895. https://doi.org/https://doi.org/10.1016/j.pmedr.2024.102895

National Cancer Institute. (2023a). *Health Information National Trends Survey - Cycle 6* (

National Cancer Institute. (2023b). *HINTS 6 Public Codebook*. Bethesda, MD Retrieved from https://hints.cancer.gov/data/Default.aspx

National Cancer Institute. (n.d.–a). *"About HINTS"*. https://hints.cancer.gov/about-hints/learn-more-about-hints.aspx.

National Cancer Institute. (n.d.–b). *HINTS Instrument Development and Validation Procedures*. https://hints.cancer.gov/about-hints/instrument-development.aspx

National Cancer Institute, & Westat. (2023, April). *Health Information National Trends Survey 6 (HINTS 6): HINTS 6 Methodology Report*. https://hints.cancer.gov/docs/methodologyreports/HINTS_6_MethodologyReport.pdf

National Center for Health Statistics. (2025). *National Health Interview Survey, Summary Health Statistics for Adults 2019-2023*. https://nchsdata.cdc.gov/DQS/#nchs-home_coronary-heart-disease/-/total/all-time-periods/1.

National Institute on Alcohol Abuse and Alcoholism. (2024, Dec.). *Drinking levels and patterns defined*. https://www.niaaa.nih.gov/alcohol-health/overview-alcohol-consumption/moderate-binge-drinking

National Institute on Alcohol Abuse and Alcoholism. (2025). *Alcohol use in the United States: Age groups and demographic characteristics*. U.S. Department of Health and Human Services. https://www.niaaa.nih.gov/alcohols-effects-health/alcohol-topics-z/alcohol-facts-and-statistics/alcohol-use-united-states-age-groups-and-demographic-characteristics

National Telecommunications and Information Administration. (2024). *New NTIA Data Show 13 Million More Internet Users in the U.S. in 2023 than 2021* (R. Goldberg, Ed.)

Neiman, P. U., Tsai, T. C., Bergmark, R. W., Ibrahim, A., Nathan, H., & Scott, J. W. (2021). The Affordable Care Act at 10 Years: Evaluating the Evidence and Navigating an Uncertain Future. *J Surg Res*, *263*, 102–109. https://doi.org/10.1016/j.jss.2020.12.056

Nelson, D. E., Kreps, G. L., Hesse, B. W., Croyle, R. T., Willis, G., Arora, N. K., Rimer, B. K., Viswanath, K. V., Weinstein, N., & Alden, S. (2004). The Health Information National Trends Survey (HINTS): development, design, and dissemination. *J Health Commun*, *9*(5), 443–460; discussion 481–444. https://doi.org/10.1080/10810730490504233

Nelson, L. A., Pennings, J. S., Sommer, E. C., Popescu, F., & Barkin, S. L. (2022). A 3-Item Measure of Digital Health Care Literacy: Development and Validation Study. *JMIR Form Res*, *6*(4), e36043. https://doi.org/10.2196/36043

Nelson, L. A., Wallston, K. A., Kripalani, S., LeStourgeon, L. M., Williamson, S. E., & Mayberry, L. S. (2018). Assessing barriers to diabetes medication adherence using the Information-Motivation-Behavioral skills model. *Diabetes Res Clin Pract*, *142*, 374–384. https://doi.org/10.1016/j.diabres.2018.05.046

Neter, E., & Brainin, E. (2012). eHealth Literacy: Extending the Digital Divide to the Realm of Health Information [Original Paper]. *J Med Internet Res*, *14*(1), e19. https://doi.org/10.2196/jmir.1619

Neter, E., & Brainin, E. (2019). Association Between Health Literacy, eHealth Literacy, and Health Outcomes Among Patients With Long-Term Conditions. *European Psychologist*, *24*(1), 68–81. https://doi.org/10.1027/1016-9040/a000350

Neter, E., Brainin, E., & Baron-Epel, O. (2021). Group differences in health literacy are ameliorated in ehealth literacy. *Health Psychology and Behavioral Medicine*, *9*(1), 480–497. https://doi.org/10.1080/21642850.2021.1926256

Newsom, J. T., Huguet, N., McCarthy, M. J., Ramage-Morin, P., Kaplan, M. S., Bernier, J., McFarland, B. H., & Oderkirk, J. (2012). Health behavior change following chronic illness in middle and later life. *J Gerontol B Psychol Sci Soc Sci*, *67*(3), 279–288. https://doi.org/10.1093/geronb/gbr103

Nguyen, J., & Gilbert, L. (2019). Health Literacy among Individuals with Disabilities: A Health Information National Trends Survey Analysis. *Perm J*, *23*. https://doi.org/10.7812/tpp/19.034

Nguyen, M. H., Pham, T. T. M., Nguyen, K. T., Nguyen, Y. H., Tran, T. V., Do, B. N., Dao, H. K., Nguyen, H. C., Do, N. T., Ha, T. H., Phan, D. T., Pham, K. M., Pham, L. V., Nguyen, P. B., Nguyen, H. T. T., Do, T. V., Ha, D. T., Nguyen, H. Q., Ngo, H. T. M.,…Duong, T. V. (2021). Negative Impact of Fear of COVID-19 on Health-Related Quality of Life Was Modified by Health Literacy, eHealth Literacy, and Digital Healthy Diet Literacy: A Multi-Hospital Survey. *Int J Environ Res Public Health*, *18*(9). https://doi.org/10.3390/ijerph18094929

Nittas, V., Zecca, C., Kamm, C. P., Kuhle, J., Chan, A., & von Wyl, V. (2023). Digital health for chronic disease management: An exploratory method to investigating technology adoption potential. *PLoS One*, *18*(4), e0284477. https://doi.org/10.1371/journal.pone.0284477

Noblin, A. M., & Rutherford, A. (2017). Impact of Health Literacy on Senior Citizen Engagement in Health Care IT Usage. *Gerontol Geriatr Med*, *3*, 2333721417706300. https://doi.org/10.1177/2333721417706300

Norgaard, O., Furstrand, D., Klokker, L., Karnoe Knudsen, A., Batterham, R., Kayser, L., & Osborne, R. (2015). The e-health literacy framework: A conceptual framework for characterizing e-health users and their interaction with e-health systems. *Knowledge Management and E-Learning*, *7*, 522–540.

Norman, C. D. (2011). eHealth Literacy 2.0: Problems and Opportunities With an Evolving Concept [Guest Editorial]. *J Med Internet Res*, *13*(4), e125. https://doi.org/10.2196/jmir.2035

Norman, C. D., & Skinner, H. A. (2006a). eHEALS: The eHealth Literacy Scale. *J Med Internet Res*, *8*(4), e27. https://doi.org/10.2196/jmir.8.4.e27

Norman, C. D., & Skinner, H. A. (2006b). eHealth Literacy: Essential Skills for Consumer Health in a Networked World [Viewpoint]. *J Med Internet Res*, *8*(2), e9. https://doi.org/10.2196/jmir.8.2.e9

Nour, T. Y., & Altintaş, K. H. (2023). Effect of the COVID-19 pandemic on obesity and it is risk factors: a systematic review. *BMC Public Health*, *23*(1), 1018. https://doi.org/10.1186/s12889-023-15833-2

Oates, G. R., Jackson, B. E., Partridge, E. E., Singh, K. P., Fouad, M. N., & Bae, S. (2017). Sociodemographic Patterns of Chronic Disease: How the Mid-South Region Compares to the Rest of the Country. *Am J Prev Med*, *52*(1s1), S31–s39. https://doi.org/10.1016/j.amepre.2016.09.004

Office of Disease Prevention and Health Promotion. (2000). *Healthy People 2010: Understanding and Improving Health*. Washington, DC: Office of Disease Prevention and Health Promotion (ODPHP) U.S. Department of Health and Human Services Retrieved from https://eric.ed.gov/?id=ED443794

Oh, H., Rizo, C., Enkin, M., & Jadad, A. (2005). What is eHealth (3): a systematic review of published definitions. *J Med Internet Res*, *7*(1), e1. https://doi.org/10.2196/jmir.7.1.e1

Ojinnaka, C. O., & Adepoju, O. E. (2021). Racial and Ethnic Disparities in Health Information Technology Use and Associated Trends among Individuals Living with Chronic Diseases. *Popul Health Manag*, *24*(6), 675–680. https://doi.org/10.1089/pop.2021.0055

Olvera, R. G., Swoboda, C. M., Joseph, J. J., Bose-Brill, S., McAlearney, A. S., & Walker, D. M. (2025). Individuals' Desire for Social Needs Sharing Among Healthcare Providers: Findings from the 2022 Health Information National Trends Survey. *Journal of General Internal Medicine*. https://doi.org/10.1007/s11606-024-09339-9

Ong-Artborirak, P., Seangpraw, K., Boonyathee, S., Auttama, N., & Winaiprasert, P. (2023). Health literacy, self-efficacy, self-care behaviors, and glycemic control among older adults with type 2 diabetes mellitus: a cross-sectional study in Thai communities. *BMC Geriatrics*, *23*(1), 297. https://doi.org/10.1186/s12877-023-04010-0

Osborn, C. Y., & Egede, L. E. (2010). Validation of an Information-Motivation-Behavioral Skills model of diabetes self-care (IMB-DSC). *Patient Educ Couns*, *79*(1), 49–54. https://doi.org/10.1016/j.pec.2009.07.016

Paasche-Orlow, M. K., & Wolf, M. S. (2007). The causal pathways linking health literacy to health outcomes. *Am J Health Behav*, *31 Suppl 1*, S19–26. https://doi.org/10.5555/ajhb.2007.31.supp.S19

Pagliari, C., Sloan, D., Gregor, P., Sullivan, F., Detmer, D., Kahan, J. P., Oortwijn, W., & MacGillivray, S. (2005). What is eHealth (4): a scoping exercise to map the field. *J Med Internet Res*, *7*(1), e9. https://doi.org/10.2196/jmir.7.1.e9

Paige, S. R., Bunnell, B. E., & Bylund, C. L. (2021). Disparities in Patient-Centered Communication via Telemedicine. *Telemedicine and e-Health*, *28*(2), 212–218. https://doi.org/10.1089/tmj.2021.0001

Paige, S. R., Flood-Grady, E., Krieger, J. L., Stellefson, M., & Miller, M. D. (2021a). Measuring health information seeking challenges in chronic disease: A psychometric analysis of a brief scale. *Chronic Illn*, *17*(2), 151–156. https://doi.org/10.1177/1742395319836476

Paige, S. R., Flood-Grady, E., Krieger, J. L., Stellefson, M., & Miller, M. D. (2021b). Measuring health information seeking challenges in chronic disease: A psychometric analysis of a brief scale. *Chronic Illness*, *17*(2), 151–156. https://doi.org/10.1177/1742395319836476

Paige, S. R., Krieger, J. L., Stellefson, M., & Alber, J. M. (2017). eHealth literacy in chronic disease patients: An item response theory analysis of the eHealth literacy scale (eHEALS). *Patient Educ Couns*, *100*(2), 320–326. https://doi.org/10.1016/j.pec.2016.09.008

Paige, S. R., Stellefson, M., Krieger, J. L., Miller, M. D., Cheong, J., & Anderson-Lewis, C. (2019). Transactional eHealth Literacy: Developing and Testing a Multi-Dimensional Instrument. *J Health Commun*, *24*(10), 737–748. https://doi.org/10.1080/10810730.2019.1666940

Park, C. (2024). Electronic Health Literacy as a Source of Self-Efficacy Among Community-Dwelling Older Adults. *Clin Gerontol*, 1–10. https://doi.org/10.1080/07317115.2024.2373894

Park, H., Moon, M., & Baeg, J. H. (2014). Association of eHealth Literacy With Cancer Information Seeking and Prior Experience With Cancer Screening. *CIN: Computers, Informatics, Nursing*, *32*(9).

Paul, M. M., Khera, N., Elugunti, P. R., Ruff, K. C., Hommos, M. S., Thomas, L. F., Nagaraja, V., Garrett, A. L., Pantoja-Smith, M., Delafield, N. L., Lizaola-Mayo, B. C., Kresin, M. M., Seetharam, M., Nagarakanti, S. R., & Kaur, M. (2025). The State of Remote Patient Monitoring for Chronic Disease Management in the United States. *J Med Internet Res*, *27*, e70422. https://doi.org/10.2196/70422

Pearson, K. (1900). X. On the criterion that a given system of deviations from the probable in the case of a correlated system of variables is such that it can be reasonably supposed to have arisen from random sampling. *The London, Edinburgh, and Dublin Philosophical Magazine and Journal of Science*, *50*(302), 157–175.

Penedo, F. J., Oswald, L. B., Kronenfeld, J. P., Garcia, S. F., Cella, D., & Yanez, B. (2020). The increasing value of eHealth in the delivery of patient-centred cancer care. *Lancet Oncology*, *21*(5), e240–e251. https://doi.org/https://doi.org/10.1016/S1470-2045(20)30021-8

Persoskie, A., Hennessy, E., & Nelson, W. L. (2017). US Consumers' Understanding of Nutrition Labels in 2013: The Importance of Health Literacy. *Prev Chronic Dis*, *14*, E86. https://doi.org/10.5888/pcd14.170066

Petimar, J., Zhang, F., Rimm, E. B., Simon, D., Cleveland, L. P., Gortmaker, S. L., Bleich, S. N., Polacsek, M., Roberto, C. A., & Block, J. P. (2021). Changes in the calorie and nutrient content of purchased fast food meals after calorie menu labeling: A natural experiment. *PLoS Med*, *18*(7), e1003714. https://doi.org/10.1371/journal.pmed.1003714

Piercy, K. L., Troiano, R. P., Ballard, R. M., Carlson, S. A., Fulton, J. E., Galuska, D. A., George, S. M., & Olson, R. D. (2018). The Physical Activity Guidelines for Americans. *JAMA*, *320*(19), 2020–2028. https://doi.org/10.1001/jama.2018.14854

Plante, C., Missiuna, S., & Neudorf, C. (2024). The Validity and Reliability of Dichotomized Self-rated Health Under Different Cutpoints. *medRxiv*, 2024.2004.2018.24306035. https://doi.org/10.1101/2024.04.18.24306035

Polanco-Levicán, K., & Salvo-Garrido, S. (2022). Understanding Social Media Literacy: A Systematic Review of the Concept and Its Competences. *Int J Environ Res Public Health*, *19*(14). https://doi.org/10.3390/ijerph19148807

Posit Team. (2026). *RStudio*. In (Version 2025.09.2 (Build 418)) Posit Software, PBC. https://posit.co/products/open-source/rstudio/

Post, R. E., Mainous, A. G., III, Diaz, V. A., Matheson, E. M., & Everett, C. J. (2010). Use of the Nutrition Facts Label in Chronic Disease Management: Results from the National Health and Nutrition Examination Survey. *Journal of the American Dietetic Association*, *110*(4), 628–632. https://doi.org/10.1016/j.jada.2009.12.015

Price, J. C., & Simpson, D. C. (2022). Telemedicine and Health Disparities. *Clin Liver Dis (Hoboken)*, *19*(4), 144–147. https://doi.org/10.1002/cld.1171

Prince Nelson, S. L., Ramakrishnan, V., Nietert, P. J., Kamen, D. L., Ramos, P. S., & Wolf, B. J. (2017). An evaluation of common methods for dichotomization of continuous variables to discriminate disease status. *Commun Stat Theory Methods*, *46*(21), 10823–10834. https://doi.org/10.1080/03610926.2016.1248783

Prochaska, J. O., DiClemente, C. C., Velicer, W. F., Ginpil, S., & Norcross, J. C. (1985). Predicting change in smoking status for self-changers. *Addictive Behaviors*, *10*(4), 395–406. https://doi.org/https://doi.org/10.1016/0306-4603(85)90036-X

Qian, A. S., Schiaffino, M. K., Nalawade, V., Aziz, L., Pacheco, F. V., Nguyen, B., Vu, P., Patel, S. P., Martinez, M. E., & Murphy, J. D. (2022). Disparities in telemedicine during COVID-19. *Cancer Med*, *11*(4), 1192–1201. https://doi.org/10.1002/cam4.4518

Rahelić, V., Perković, T., Romić, L., Perković, P., Klobučar, S., Pavić, E., & Rahelić, D. (2024). The Role of Behavioral Factors on Chronic Diseases-Practice and Knowledge Gaps. *Healthcare (Basel)*, *12*(24). https://doi.org/10.3390/healthcare12242520

Raj, M., Iott, B., Anthony, D., & Platt, J. (2022). Family Caregivers' Experiences With Telehealth During COVID-19: Insights From Michigan. *Ann Fam Med*, *20*(1), 69–71. https://doi.org/10.1370/afm.2760

Rajamani, G., Kurina, L., & Rosas, L. G. (2021). Investigating Health Information Technology Usage by Sociodemographic Subpopulations to Increase Community Engagement in Healthcare: An Analysis of the Health Information National Trends Survey. *AMIA Annu Symp Proc*, *2021*, 1029–1038.

Rajamani, G., Lindemann, E., Evans, M. D., Pillai, R., Badlani, S., & Melton, G. B. (2022). Health Information Technology Use among Chronic Disease Patients: An Analysis of the United States Health Information National Trends Survey. *Appl Clin Inform*, *13*(3), 752–766. https://doi.org/10.1055/s-0042-1751305

Ramachandran, M., Brinton, C., Wiljer, D., Upshur, R., & Gray, C. S. (2023). The impact of eHealth on relationships and trust in primary care: a review of reviews. *BMC Primary Care*, *24*(1), 228. https://doi.org/10.1186/s12875-023-02176-5

Ramos-Vera, C., Serpa Barrientos, A., Calizaya-Milla, Y. E., Carvajal Guillen, C., & Saintila, J. (2022). Consumption of Alcoholic Beverages Associated With Physical Health Status in Adults: Secondary Analysis of the Health Information National Trends Survey Data. *Journal of Primary Care & Community Health*, *13*, 21501319211066205. https://doi.org/10.1177/21501319211066205

Rañó-Santamaría, O., Fernandez-Merino, C., Castaño-Carou, A. I., Lado-Baleato, Ó., Fernández-Domínguez, M. J., Sanchez-Castro, J. J., & Gude, F. (2022). Health self-perception is associated with life-styles and comorbidities and its effect on mortality is confounded by age. A population based study [Original Research]. *Frontiers in Medicine*, *9*. https://doi.org/10.3389/fmed.2022.1015195

Reedy, J., Krebs-Smith, S. M., Miller, P. E., Liese, A. D., Kahle, L. L., Park, Y., & Subar, A. F. (2014). Higher Diet Quality Is Associated with Decreased Risk of All-Cause, Cardiovascular Disease, and Cancer Mortality among Older Adults. *The Journal of Nutrition*, *144*(6), 881–889. https://doi.org/https://doi.org/10.3945/jn.113.189407

Refahi, H., Klein, M., & Feigerlova, E. (2022). e-Health Literacy Skills in People with Chronic Diseases and What Do the Measurements Tell Us: A Scoping Review. *Telemedicine and e-Health*, *29*(2), 198–208. https://doi.org/10.1089/tmj.2022.0115

Reiners, F., Sturm, J., Bouw, L. J. W., & Wouters, E. J. M. (2019). Sociodemographic Factors Influencing the Use of eHealth in People with Chronic Diseases. *International Journal of Environmental Research and Public Health*, *16*(4), 645.

Reinwarth, A. C., Wicke, F. S., Hettich, N., Ernst, M., Otten, D., Brähler, E., Wild, P. S., Münzel, T., König, J., Lackner, K. J., Pfeiffer, N., & Beutel, M. E. (2023). Self-rated physical health predicts mortality in aging persons beyond objective health risks. *Scientific Reports*, *13*(1), 19531. https://doi.org/10.1038/s41598-023-46882-7

Renzi, E., Baccolini, V., Migliara, G., De Vito, C., Gasperini, G., Cianciulli, A., Marzuillo, C., Villari, P., & Massimi, A. (2022). The Impact of eHealth Interventions on the Improvement of Self-Care in Chronic Patients: An Overview of Systematic Reviews. *Life*, *12*(8), 1253.

Restrepo, B. J. (2024). Adults Noticing Calorie Counts on Restaurant Menus: Evidence From Nationally Representative Data, 2022. *Am J Prev Med*, *66*(6), 1043–1048. https://doi.org/10.1016/j.amepre.2024.01.006

Richtering, S. S., Hyun, K., Neubeck, L., Coorey, G., Chalmers, J., Usherwood, T., Peiris, D., Chow, C. K., & Redfern, J. (2017). eHealth Literacy: Predictors in a Population With Moderate-to-High Cardiovascular Risk [Original Paper]. *JMIR Hum Factors*, *4*(1), e4. https://doi.org/10.2196/humanfactors.6217

Riegel, B., Barbaranelli, C., Sethares, K. A., Daus, M., Moser, D. K., Miller, J. L., Haedtke, C. A., Feinberg, J. L., Lee, S., Stromberg, A., & Jaarsma, T. (2018). Development and initial testing of the self-care of chronic illness inventory. *Journal of Advanced Nursing*, *74*(10), 2465–2476. https://doi.org/https://doi.org/10.1111/jan.13775

Riegel, B., Carlson, B., Moser, D. K., Sebern, M., Hicks, F. D., & Roland, V. (2004). Psychometric testing of the self-care of heart failure index. *Journal of Cardiac Failure*, *10*(4), 350–360. https://doi.org/10.1016/j.cardfail.2003.12.001

Riegel, B., De Maria, M., Barbaranelli, C., Luciani, M., Ausili, D., Dickson, V. V., Jaarsma, T., Matarese, M., Stromberg, A., & Vellone, E. (2025). Measuring Self-Care: A Description of the Family of Disease-Specific and Generic Instruments Based on the Theory of Self-Care of Chronic Illness. *Journal of Cardiovascular Nursing*, *40*(2).

Riegel, B., Jaarsma, T., Lee, C. S., & Strömberg, A. (2019). Integrating Symptoms Into the Middle-Range Theory of Self-Care of Chronic Illness. *Advances in Nursing Science*, *42*(3), 206–215. https://doi.org/10.1097/ans.0000000000000237

Riegel, B., Jaarsma, T., & Strömberg, A. (2012). A middle-range theory of self-care of chronic illness. *ANS Adv Nurs Sci*, *35*(3), 194–204. https://doi.org/10.1097/ANS.0b013e318261b1ba

Riegel, B., Jaarsma, T., & Strömberg, A. (2026). An Update to the Middle-Range Theory of Self-Care of Chronic Illness. *Advances in Nursing Science*, *49*(1), 14–25. https://doi.org/10.1097/ans.0000000000000594

Riegel, B., Lee, C. S., Dickson, V. V., & Carlson, B. (2009). An update on the self-care of heart failure index. *J Cardiovasc Nurs*, *24*(6), 485–497. https://doi.org/10.1097/JCN.0b013e3181b4baa0

Riegel, B., Moser, D. K., Buck, H. G., Dickson, V. V., Dunbar, S. B., Lee, C. S., Lennie, T. A., Lindenfeld, J., Mitchell, J. E., Treat-Jacobson, D. J., Webber, D. E., on behalf of the American Heart Association Council on, C., Stroke, N., Council on Peripheral Vascular, D., Council on Quality of, C., & Outcomes, R. (2017). Self-Care for the Prevention and Management of Cardiovascular Disease and Stroke. *Journal of the American Heart Association*, *6*(9), e006997. https://doi.org/10.1161/JAHA.117.006997

Rigotti, N. A., Kruse, G. R., Livingstone-Banks, J., & Hartmann-Boyce, J. (2022). Treatment of Tobacco Smoking: A Review. *JAMA*, *327*(6), 566–577. https://doi.org/10.1001/jama.2022.0395

Rising, C. J., Gaysynsky, A., Blake, K. D., Jensen, R. E., & Oh, A. (2021). Willingness to Share Data From Wearable Health and Activity Trackers: Analysis of the 2019 Health Information National Trends Survey Data [Original Paper]. *JMIR Mhealth Uhealth*, *9*(12), e29190. https://doi.org/10.2196/29190

Rising, C. J., McKinnon, R. A., Lin, C.-T. J., Jones-Dominic, O. E., Parker, C. C., Wolpert, B., Maroto, M. E., & Oh, A. (2021). U.S. adults noticing and using menu calorie information: Analysis of the National Cancer Institute's Health Information National Trends Survey Data. *Preventive Medicine*, *153*, 106824. https://doi.org/https://doi.org/10.1016/j.ypmed.2021.106824

Ritter, P. L., & Lorig, K. (2014). The English and Spanish Self-Efficacy to Manage Chronic Disease Scale measures were validated using multiple studies. *J Clin Epidemiol*, *67*(11), 1265–1273. https://doi.org/10.1016/j.jclinepi.2014.06.009

Rock, C. L., Thomson, C., Gansler, T., Gapstur, S. M., McCullough, M. L., Patel, A. V., Andrews, K. S., Bandera, E. V., Spees, C. K., Robien, K., Hartman, S., Sullivan, K., Grant, B. L., Hamilton, K. K., Kushi, L. H., Caan, B. J., Kibbe, D., Black, J. D., Wiedt, T. L.,…Doyle, C. (2020). American Cancer Society guideline for diet and physical activity for cancer prevention. *CA: A Cancer Journal for Clinicians*, *70*(4), 245–271. https://doi.org/https://doi.org/10.3322/caac.21591

Rockwell, M. S., Funk, A. J., Huffstetler, A. N., Villalobos, G., Britz, J. B., Webel, B., Richards, A., Epling, J. W., Sabo, R. T., & Krist, A. H. (2024). Screening for Unhealthy Alcohol

Use Among Patients With Multiple Chronic Conditions in Primary Care. *AJPM Focus*, *3*(4), 100233. https://doi.org/https://doi.org/10.1016/j.focus.2024.100233
Rosenthal, S. (2020). Media Literacy, Scientific Literacy, and Science Videos on the Internet [Mini Review]. *Frontiers in Communication*, *5*. https://doi.org/10.3389/fcomm.2020.581585
Ross, R. K., Breskin, A., & Westreich, D. (2020). When Is a Complete-Case Approach to Missing Data Valid? The Importance of Effect-Measure Modification. *Am J Epidemiol*, *189*(12), 1583–1589. https://doi.org/10.1093/aje/kwaa124
Rossmann, C., Karnowski, V., Metag, J., Raupp, J., Reifegerste, D., Riesmeyer, C., Sawalha, N., Lux, A., Esser, A.-L., Kammerer, R., Singh, F., Rödel, N., Brill, J., Gerling, E., & Wiedicke, A. (2026). The Role of Digital Media in Chronic Disease Self-Management: Protocol for a Multimethod Study of the DISELMA Research Consortium. *JMIR Res Protoc*, *15*, e77811. https://doi.org/10.2196/77811
Rubin, A. M. (1994). Media uses and effects: A uses-and-gratifications perspective. In *Media effects: Advances in theory and research.* (pp. 417–436). Lawrence Erlbaum Associates, Inc.
Rudd, R. E. (2015). The evolving concept of Health literacy: New directions for health literacy studies. *Journal of Communication in Healthcare*, *8*(1), 7–9. https://doi.org/10.1179/1753806815Z.000000000105
Rudd, R. E., Rosenfeld, L., & Simonds, V. W. (2012). Health Literacy: A New Area of Research With Links to Communication. *Atlantic Journal of Communication*, *20*(1), 16–30. https://doi.org/10.1080/15456870.2012.637025
Ruggiero, T. E. (2000). Uses and Gratifications Theory in the 21st Century. *Mass Communication and Society*, *3*(1), 3–37. https://doi.org/10.1207/S15327825MCS0301_02
Rummo, P. E., Mijanovich, T., Wu, E., Heng, L., Hafeez, E., Bragg, M. A., Jones, S. A., Weitzman, B. C., & Elbel, B. (2023). Menu Labeling and Calories Purchased in Restaurants in a US National Fast Food Chain. *JAMA Network Open*, *6*(12), e2346851–e2346851. https://doi.org/10.1001/jamanetworkopen.2023.46851
Ryan, P., & Sawin, K. J. (2009). The Individual and Family Self-Management Theory: Background and perspectives on context, process, and outcomes. *Nursing Outlook*, *57*(4), 217–225.e216. https://doi.org/10.1016/j.outlook.2008.10.004
Salvia, M. G., Mattie, H., & Tran, A. (2024). Noticing and Responding to Calorie Labels on Restaurant Menus: Patterns in Sexual-Minority Men. *Am J Prev Med*, *66*(2), 269–278. https://doi.org/10.1016/j.amepre.2023.10.003
SAS Studio 3.8. *on SAS 9.4* SAS Institute.
Scheerder, A., van Deursen, A., & van Dijk, J. (2017). Determinants of Internet skills, uses and outcomes. A systematic review of the second- and third-level digital divide. *Telematics and Informatics*, *34*(8), 1607–1624. https://doi.org/https://doi.org/10.1016/j.tele.2017.07.007
Scherer, L. D., & Pennycook, G. (2020). Who Is Susceptible to Online Health Misinformation? *American Journal of Public Health*, *110*(S3), S276–S277. https://doi.org/10.2105/ajph.2020.305908
Schiltz, N. K. (2022). Prevalence of multimorbidity combinations and their association with medical costs and poor health: A population-based study of U.S. adults. *Front Public Health*, *10*, 953886. https://doi.org/10.3389/fpubh.2022.953886

Schmitt, A., Gahr, A., Hermanns, N., Kulzer, B., Huber, J., & Haak, T. (2013). The Diabetes Self-Management Questionnaire (DSMQ): development and evaluation of an instrument to assess diabetes self-care activities associated with glycaemic control. *Health and Quality of Life Outcomes*, *11*(1), 138. https://doi.org/10.1186/1477-7525-11-138

Schuler, B. R. (2015). Health Perceptions and Quality of Life among Low-Income Adults. *Health Soc Work*, *40*(3), 225–232. https://doi.org/10.1093/hsw/hlv045

Schulman-Green, D., Jaser, S., Martin, F., Alonzo, A., Grey, M., McCorkle, R., Redeker, N. S., Reynolds, N., & Whittemore, R. (2012). Processes of Self-Management in Chronic Illness. *Journal of Nursing Scholarship*, *44*(2), 136–144. https://doi.org/https://doi.org/10.1111/j.1547-5069.2012.01444.x

Schulman-Green, D., Jaser, S. S., Park, C., & Whittemore, R. (2016). A metasynthesis of factors affecting self-management of chronic illness. *Journal of Advanced Nursing*, *72*(7), 1469–1489. https://doi.org/https://doi.org/10.1111/jan.12902

Schulte, M. H. J., Aardoom, J. J., Loheide-Niesmann, L., Verstraete, L. L. L., Ossebaard, H. C., & Riper, H. (2021). Effectiveness of eHealth Interventions in Improving Medication Adherence for Patients With Chronic Obstructive Pulmonary Disease or Asthma: Systematic Review [Review]. *J Med Internet Res*, *23*(7), e29475. https://doi.org/10.2196/29475

Schwarzer, R. (1995). Generalized self-efficacy scale. *Measures in health psychology: A user's portfolio. Causal and control beliefs/Nfer-Nelson*.

Seçkin, G., Yeatts, D., Hughes, S., Hudson, C., & Bell, V. (2016). Being an Informed Consumer of Health Information and Assessment of Electronic Health Literacy in a National Sample of Internet Users: Validity and Reliability of the e-HLS Instrument [Original Paper]. *J Med Internet Res*, *18*(7), e161. https://doi.org/10.2196/jmir.5496

Shahab, L., Brown, J., Gardner, B., & Smith, S. G. (2014). Seeking Health Information and Support Online: Does It Differ as a Function of Engagement in Risky Health Behaviors? Evidence From the Health Information National Trends Survey [Original Paper]. *J Med Internet Res*, *16*(11), e253. https://doi.org/10.2196/jmir.3368

Shahid, I., Zakaria, F., Chang, R., Javed, U., Amin, Z. M., Al-Kindi, S., Nasir, K., & Javed, Z. (2025). Obesity and Atherosclerotic Cardiovascular Disease: A Review of Social and Biobehavioral Pathways. *Methodist Debakey Cardiovasc J*, *21*(2), 23–34. https://doi.org/10.14797/mdcvj.1528

Shaver, J. (2022). The State of Telehealth Before and After the COVID-19 Pandemic. *Prim Care*, *49*(4), 517–530. https://doi.org/10.1016/j.pop.2022.04.002

Shaw Jr, G., Castro, B. A., Gunn, L. H., Norris, K., & Thorpe Jr, R. J. (2024). The Association of eHealth Literacy Skills and mHealth Application Use Among US Adults With Obesity: Analysis of Health Information National Trends Survey Data [Original Paper]. *JMIR Mhealth Uhealth*, *12*, e46656. https://doi.org/10.2196/46656

Shaw, T., McGregor, D., Brunner, M., Keep, M., Janssen, A., & Barnet, S. (2017). What is eHealth (6)? Development of a Conceptual Model for eHealth: Qualitative Study with Key Informants [Original Paper]. *J Med Internet Res*, *19*(10), e324. https://doi.org/10.2196/jmir.8106

Sherman, L. D., Patterson, M. S., Tomar, A., & Wigfall, L. T. (2020). Use of Digital Health Information for Health Information Seeking Among Men Living With Chronic Disease: Data From the Health Information National Trends Survey. *American Journal of Men's Health*, *14*(1), 1557988320901377. https://doi.org/10.1177/1557988320901377

Shield, K. D., Parry, C., & Rehm, J. (2013). Chronic diseases and conditions related to alcohol use. *Alcohol Res*, *35*(2), 155–173.

Shiferaw, K. B., Tilahun, B. C., Endehabtu, B. F., Gullslett, M. K., & Mengiste, S. A. (2020). E-health literacy and associated factors among chronic patients in a low-income country: a cross-sectional survey. *BMC Med Inform Decis Mak*, *20*(1), 181. https://doi.org/10.1186/s12911-020-01202-1

Shiu, L.-S., Liu, C.-Y., Lin, C.-J., & Chen, Y.-C. (2023). What are the roles of eHealth literacy and empowerment in self-management in an eHealth care context? A cross-sectional study. *Journal of Clinical Nursing*, *32*(23-24), 8043–8053. https://doi.org/https://doi.org/10.1111/jocn.16876

Short, M. E., Goetzel, R. Z., Pei, X., Tabrizi, M. J., Ozminkowski, R. J., Gibson, T. B., Dejoy, D. M., & Wilson, M. G. (2009). How accurate are self-reports? Analysis of self-reported health care utilization and absence when compared with administrative data. *J Occup Environ Med*, *51*(7), 786–796. https://doi.org/10.1097/JOM.0b013e3181a86671

Short, S. E., & Mollborn, S. (2015). Social Determinants and Health Behaviors: Conceptual Frames and Empirical Advances. *Current opinion in psychology*, *5*, 78–84. https://doi.org/10.1016/j.copsyc.2015.05.002

Shwartz, M., Restuccia, J. D., & Rosen, A. K. (2015). Composite Measures of Health Care Provider Performance: A Description of Approaches. *Milbank Q*, *93*(4), 788–825. https://doi.org/10.1111/1468-0009.12165

Sieck, C. J., Sheon, A., Ancker, J. S., Castek, J., Callahan, B., & Siefer, A. (2021). Digital inclusion as a social determinant of health. *npj Digital Medicine*, *4*(1), 52. https://doi.org/10.1038/s41746-021-00413-8

Silva, I. T. S. d., Dantas, A. C., Borges, B. E. C., Carvalho, L. M. d., Silva, C. L. B. d., Nascimento, H. R. d. C., Fernandes, M. I. d. C. D., & Vitor, A. F. (2026). Concept Analysis of Digital Health Literacy in Individuals With Chronic Conditions Based on a Scoping Review. *Nursing Forum*, *2026*(1), 5153797. https://doi.org/https://doi.org/10.1155/nuf/5153797

Silva, P., Araújo, R., Lopes, F., & Ray, S. (2023). Nutrition and Food Literacy: Framing the Challenges to Health Communication. *Nutrients*, *15*(22). https://doi.org/10.3390/nu15224708

Silveyra, P., Fuentes, N., & Rodriguez Bauza, D. E. (2021). Sex and Gender Differences in Lung Disease. *Adv Exp Med Biol*, *1304*, 227–258. https://doi.org/10.1007/978-3-030-68748-9_14

Simmons, R. A., Cosgrove, S. C., Romney, M. C., Plumb, J. D., Brawer, R. O., Gonzalez, E. T., Fleisher, L. G., & Moore, B. S. (2017). Health Literacy: Cancer Prevention Strategies for Early Adults. *American Journal of Preventive Medicine*, *53*(3), S73–S77. https://doi.org/10.1016/j.amepre.2017.03.016

Singh, R., & Dixit, S. (2010). Health-Related Quality of Life and Health Management. *Journal of Health Management*, *12*(2), 153–172. https://doi.org/10.1177/097206341001200204

Skiba, M. B., Jacobs, E. T., Crane, T. E., Kopp, L. M., & Thomson, C. A. (2022). Relationship Between Individual Health Beliefs and Fruit and Vegetable Intake and Physical Activity Among Cancer Survivors: Results from the Health Information National Trends Survey. *J Adolesc Young Adult Oncol*, *11*(3), 259–267. https://doi.org/10.1089/jayao.2021.0078

Skou, S. T., Mair, F. S., Fortin, M., Guthrie, B., Nunes, B. P., Miranda, J. J., Boyd, C. M., Pati, S., Mtenga, S., & Smith, S. M. (2022). Multimorbidity. *Nat Rev Dis Primers*, *8*(1), 48. https://doi.org/10.1038/s41572-022-00376-4

Smith, B., & Magnani, J. W. (2019). New technologies, new disparities: The intersection of electronic health and digital health literacy. *International journal of cardiology*, *292*, 280–282. https://doi.org/10.1016/j.ijcard.2019.05.066

Snow, C. E., Dibner, K. A., Committee on Science, L., & Public Perception of, S. (2016). *Science literacy : concepts, contexts, and consequences : a report of the National Academies of Sciences, Engineering, Medicine* (1st ed.). The National Academies Press.

Sögüt, S., Cangöl, E., & Dolu, İ. (2022). The Relationship Between eHealth Literacy and Self-Efficacy Levels in Midwifery Students Receiving Distance Education During the COVID-19 Pandemic. *J Nurs Res*, *30*(2), e203. https://doi.org/10.1097/jnr.0000000000000474

Sohi, I., Franklin, A., Chrystoja, B., Wettlaufer, A., Rehm, J., & Shield, K. (2021). The Global Impact of Alcohol Consumption on Premature Mortality and Health in 2016. *Nutrients*, *13*(9). https://doi.org/10.3390/nu13093145

Song, J., Howe, E., Oltmanns, J. R., & Fisher, A. J. (2023). Examining the Concurrent and Predictive Validity of Single Items in Ecological Momentary Assessments. *Assessment*, *30*(5), 1662–1671. https://doi.org/10.1177/10731911221113563

Song, M. K., Lin, F. C., Ward, S. E., & Fine, J. P. (2013). Composite variables: when and how. *Nurs Res*, *62*(1), 45–49. https://doi.org/10.1097/NNR.0b013e3182741948

Sørensen, K., Van den Broucke, S., Fullam, J., Doyle, G., Pelikan, J., Slonska, Z., Brand, H., & Consortium Health Literacy Project, E. (2012). Health literacy and public health: A systematic review and integration of definitions and models. *BMC Public Health*, *12*(1), 80. https://doi.org/10.1186/1471-2458-12-80

Stagliano, V., & Wallace, L. S. (2013). Brief health literacy screening items predict newest vital sign scores. *J Am Board Fam Med*, *26*(5), 558–565. https://doi.org/10.3122/jabfm.2013.05.130096

Stellefson, M., Chaney, B., Barry, A. E., Chavarria, E., Tennant, B., Walsh-Childers, K., Sriram, P. S., & Zagora, J. (2013). Web 2.0 chronic disease self-management for older adults: a systematic review. *J Med Internet Res*, *15*(2), e35. https://doi.org/10.2196/jmir.2439

Stellefson, M., Dipnarine, K., & Stopka, C. (2013). The Chronic Care Model and Diabetes Management in US Primary Care Settings: A Systematic Review. *Preventing Chronic Disease*, *10*, E26. https://doi.org/10.5888/pcd10.120180

Stellefson, M., Hanik, B., Chaney, B., Chaney, D., Tennant, B., & Chavarria, E. A. (2011). eHealth Literacy Among College Students: A Systematic Review With Implications for eHealth Education [Review]. *J Med Internet Res*, *13*(4), e102. https://doi.org/10.2196/jmir.1703

Stellefson, M., Paige, S. R., Tennant, B., Alber, J. M., Chaney, B. H., Chaney, D., & Grossman, S. (2017). Reliability and Validity of the Telephone-Based eHealth Literacy Scale Among Older Adults: Cross-Sectional Survey [Original Paper]. *J Med Internet Res*, *19*(10), e362. https://doi.org/10.2196/jmir.8481

Stellefson, M. L., Shuster, J. J., Chaney, B. H., Paige, S. R., Alber, J. M., Chaney, J. D., & Sriram, P. S. (2018). Web-based Health Information Seeking and eHealth Literacy among Patients Living with Chronic Obstructive Pulmonary Disease (COPD). *Health Communication*, *33*(12), 1410–1424. https://doi.org/10.1080/10410236.2017.1353868

Stephan, J., Gehrmann, J., Dehner, J. C., Stullich, A., & Richter, M. (2025). Development and validation of the eHealth Literacy and Use Scale (eHLUS) to measure medical app literacy. *Public Health*, *240*, 27–32. https://doi.org/https://doi.org/10.1016/j.puhe.2024.12.057

Sterling, S. A., Palzes, V. A., Lu, Y., Kline-Simon, A. H., Parthasarathy, S., Ross, T., Elson, J., Weisner, C., Maxim, C., & Chi, F. W. (2020). Associations Between Medical Conditions and Alcohol Consumption Levels in an Adult Primary Care Population. *JAMA Network Open*, *3*(5), e204687–e204687. https://doi.org/10.1001/jamanetworkopen.2020.4687

Stimpson, J. P., & Ortega, A. N. (2023). Social media users' perceptions about health mis- and disinformation on social media. *Health Aff Sch*, *1*(4). https://doi.org/10.1093/haschl/qxad050

Stoltzfus, J. C. (2011). Logistic regression: a brief primer. *Acad Emerg Med*, *18*(10), 1099–1104. https://doi.org/10.1111/j.1553-2712.2011.01185.x

Sudbury-Riley, L., FitzPatrick, M., & Schulz, P. J. (2017). Exploring the Measurement Properties of the eHealth Literacy Scale (eHEALS) Among Baby Boomers: A Multinational Test of Measurement Invariance [Original Paper]. *J Med Internet Res*, *19*(2), e53. https://doi.org/10.2196/jmir.5998

Sullivan, L. M., Dukes, K. A., & Losina, E. (1999). Tutorial in biostatistics. An introduction to hierarchical linear modelling. *Stat Med*, *18*(7), 855–888. https://doi.org/10.1002/(sici)1097-0258(19990415)18:7<855::aid-sim117>3.0.co;2-7

Sülz, S., van Elten, H. J., Askari, M., Weggelaar-Jansen, A. M., & Huijsman, R. (2021). eHealth Applications to Support Independent Living of Older Persons: Scoping Review of Costs and Benefits Identified in Economic Evaluations. *J Med Internet Res*, *23*(3), e24363. https://doi.org/10.2196/24363

Sun, M., & Jiang, L. C. (2021). Interpersonal influences on self-management in the eHealth era: Predicting the uses of eHealth tools for self-care in America. *Health & Social Care in the Community*, *29*(2), 464–475. https://doi.org/https://doi.org/10.1111/hsc.13107

Taber, K. S. (2018). The Use of Cronbach's Alpha When Developing and Reporting Research Instruments in Science Education. *Research in Science Education*, *48*(6), 1273–1296. https://doi.org/10.1007/s11165-016-9602-2

Taksler, G. B., Pfoh, E. R., Martinez, K. A., Sheehan, M. M., Gupta, N. M., & Rothberg, M. B. (2022). Comparison of National Data Sources to Assess Preventive Care in the US Population. *Journal of General Internal Medicine*, *37*(2), 318–326. https://doi.org/10.1007/s11606-021-06707-7

Tamminen, A., Virtanen, L., Clemens, T., Nadav, J., Saukkonen, P., Kainiemi, E., Heponiemi, T., & Kaihlanen, A. M. (2023). Perceptions of Finns with chronic diseases about factors affecting their eHealth literacy: A qualitative interview study. *Digit Health*, *9*, 20552076231216395. https://doi.org/10.1177/20552076231216395

Tanaka, J., Kuroda, H., Igawa, N., Sakurai, T., & Ohnishi, M. (2020). Perceived eHealth Literacy and Learning Experiences Among Japanese Undergraduate Nursing Students: A Cross-sectional Study. *CIN: Computers, Informatics, Nursing*, *38*(4).

Tang, P. C., Overhage, J. M., Chan, A. S., Brown, N. L., Aghighi, B., Entwistle, M. P., Hui, S. L., Hyde, S. M., Klieman, L. H., Mitchell, C. J., Perkins, A. J., Qureshi, L. S., Waltimyer, T. A., Winters, L. J., & Young, C. Y. (2013). Online disease management of diabetes: engaging and motivating patients online with enhanced resources-diabetes (EMPOWER-

D), a randomized controlled trial. *Journal of the American Medical Informatics Association : JAMIA*, *20*(3), 526–534. https://doi.org/10.1136/amiajnl-2012-001263

Tariq, A., Khan, S. R., & Basharat, A. (2020). Internet Use, eHealth Literacy, and Dietary Supplement Use Among Young Adults in Pakistan: Cross-Sectional Study. *J Med Internet Res*, *22*(6), e17014. https://doi.org/10.2196/17014

Tavakol, M., & Dennick, R. (2011). Making sense of Cronbach's alpha. *Int J Med Educ*, *2*, 53–55. https://doi.org/10.5116/ijme.4dfb.8dfd

Taylor, M. L., Thomas, E. E., Vitangcol, K., Marx, W., Campbell, K. L., Caffery, L. J., Haydon, H. M., Smith, A. C., & Kelly, J. T. (2022). Digital health experiences reported in chronic disease management: An umbrella review of qualitative studies. *Journal of Telemedicine and Telecare*, *28*(10), 705–717. https://doi.org/10.1177/1357633x221119620

Tebeje, T. H., & Klein, J. (2021). Applications of e-Health to Support Person-Centered Health Care at the Time of COVID-19 Pandemic. *Telemedicine and e-Health*, *27*(2), 150–158. https://doi.org/10.1089/tmj.2020.0201

Tennant, B., Stellefson, M., Dodd, V., Chaney, B., Chaney, D., Paige, S., & Alber, J. (2015). eHealth Literacy and Web 2.0 Health Information Seeking Behaviors Among Baby Boomers and Older Adults [Original Paper]. *J Med Internet Res*, *17*(3), e70. https://doi.org/10.2196/jmir.3992

Thakkar, J., Kurup, R., Laba, T. L., Santo, K., Thiagalingam, A., Rodgers, A., Woodward, M., Redfern, J., & Chow, C. K. (2016). Mobile Telephone Text Messaging for Medication Adherence in Chronic Disease: A Meta-analysis. *JAMA Intern Med*, *176*(3), 340–349. https://doi.org/10.1001/jamainternmed.2015.7667

The Lancet. (2024). The burden of diseases, injuries, and risk factors by state in the USA, 1990–2021: a systematic analysis for the Global Burden of Disease Study 2021. *The Lancet*, *404*(10469), 2314–2340. https://doi.org/10.1016/S0140-6736(24)01446-6

Thornberry, T., & Krohn, M. (2002). Comparison of Self-Report and Official Data for Measuring Crime. *Proceedings of The National Academy of Sciences - PNAS*.

Thorne, S., Paterson, B., & Russell, C. (2003). The Structure of Everyday Self-Care Decision Making in Chronic Illness. *Qualitative Health Research*, *13*(10), 1337–1352. https://doi.org/10.1177/1049732303258039

Tolbert, J., Cervantes, S., Bell, C., & Damico, A. (2024). Key Facts about the Uninsured Population. Retrieved February 2, 2026, from https://www.kff.org/uninsured/key-facts-about-the-uninsured-population/

Triantafyllidis, A., Kondylakis, H., Votis, K., Tzovaras, D., Maglaveras, N., & Rahimi, K. (2019). Features, outcomes, and challenges in mobile health interventions for patients living with chronic diseases: A review of systematic reviews. *Int J Med Inform*, *132*, 103984. https://doi.org/10.1016/j.ijmedinf.2019.103984

Tsukahara, S., Yamaguchi, S., Igarashi, F., Uruma, R., Ikuina, N., Iwakura, K., Koizumi, K., & Sato, Y. (2020). Association of eHealth Literacy With Lifestyle Behaviors in University Students: Questionnaire-Based Cross-Sectional Study [Original Paper]. *J Med Internet Res*, *22*(6), e18155. https://doi.org/10.2196/18155

U.S. Census Bureau. (2024). *QuickFacts: United States*. https://www.census.gov/quickfacts/fact/table/US/PST045224

U.S. Census Bureau, Kollar, M., & Scherer, Z. (2025). *Income in the United States: 2024*. (P60-286). Retrieved from http://census.gov/library/publications/2025/demo/p60-286.html

U.S. Department of Health and Human Services. (2018). *Physical Activity Guidelines for Americans, 2nd edition.* Washington, DC. Retrieved from https://odphp.health.gov/sites/default/files/2019-09/Physical_Activity_Guidelines_2nd_edition.pdf

U.S. Department of Health and Human Services. (2023, May). *HHS Fact Sheet: Telehealth Flexibilities and Resources and the COVID-19 Public Health Emergency*. https://www.hhs.gov/about/news/2023/05/10/hhs-fact-sheet-telehealth-flexibilities-resources-covid-19-public-health-emergency.html

U.S. Department of Health and Human Services. (2025). *Telehealth for rural areas*. Retrieved March 1, 2026 from https://telehealth.hhs.gov/providers/best-practice-guides/telehealth-for-rural-areas/access-to-internet-and-other-telehealth-resources

U.S. Food and Drug Administration. (2023). *Menu Labeling Requirements*. Retrieved April 15, 2026 from https://www.fda.gov/food/nutrition-food-labeling-and-critical-foods/menu-labeling-requirements

United States Department of Agriculture, & U.S. Department of Health and Human Services. (2024). *2020-2025 Dietary Guidelines for Americans*. Retrieved from https://www.dietaryguidelines.gov/sites/default/files/2021-03/Dietary_Guidelines_for_Americans-2020-2025.pdf

United States Public Health Service Office of the Surgeon, G., National Center for Chronic Disease, P., Health Promotion Office on, S., & Health. (2020). Publications and Reports of the Surgeon General. In *Smoking Cessation: A Report of the Surgeon General*. US Department of Health and Human Services.

van der Vaart, R., & Drossaert, C. (2017). Development of the Digital Health Literacy Instrument: Measuring a Broad Spectrum of Health 1.0 and Health 2.0 Skills. *J Med Internet Res*, *19*(1), e27. https://doi.org/10.2196/jmir.6709

van der Vaart, R., van Deursen, A. J., Drossaert, C. H., Taal, E., van Dijk, J. A., & van de Laar, M. A. (2011). Does the eHealth Literacy Scale (eHEALS) Measure What it Intends to Measure? Validation of a Dutch Version of the eHEALS in Two Adult Populations [Original Paper]. *J Med Internet Res*, *13*(4), e86. https://doi.org/10.2196/jmir.1840

van Kessel, R., Wong, B. L. H., Clemens, T., & Brand, H. (2022). Digital health literacy as a super determinant of health: More than simply the sum of its parts. *Internet Interv*, *27*, 100500. https://doi.org/10.1016/j.invent.2022.100500

van Olmen, J. (2022). The Promise of Digital Self-Management: A Reflection about the Effects of Patient-Targeted e-Health Tools on Self-Management and Wellbeing. *International Journal of Environmental Research and Public Health*, *19*(3), 1360.

Vazquez, C. E., Mauldin, R. L., Mitchell, D. N., & Ohri, F. (2024). Sociodemographic Factors Associated With Using eHealth for Information Seeking in the United States: Cross-Sectional Population-Based Study With 3 Time Points Using Health Information National Trends Survey Data [Original Paper]. *J Med Internet Res*, *26*, e54745. https://doi.org/10.2196/54745

Veinot, T. C., Mitchell, H., & Ancker, J. S. (2018). Good intentions are not enough: how informatics interventions can worsen inequality. *Journal of the American Medical Informatics Association : JAMIA*, *25*(8), 1080–1088. https://doi.org/10.1093/jamia/ocy052

Verweel, L., Newman, A., Michaelchuk, W., Packham, T., Goldstein, R., & Brooks, D. (2023). The effect of digital interventions on related health literacy and skills for individuals living with chronic diseases: A systematic review and meta-analysis. *Int J Med Inform*, *177*, 105114. https://doi.org/10.1016/j.ijmedinf.2023.105114

Wagner, E. H. (2019). Organizing Care for Patients With Chronic Illness Revisited. *The Milbank Quarterly*, *97*(3), 659–664. https://doi.org/https://doi.org/10.1111/1468-0009.12416

Wagner, E. H., Austin, B. T., & Von Korff, M. (1996). Organizing care for patients with chronic illness. *Milbank Q*, *74*(4), 511–544.

Wagner, E. H., Austin, Brian T., Von Korff, Michael. (1996). Organizing Care for Patients with Chronic Illness. *The Milbank Quarterly*, *74*(4), 511–544. https://doi.org/10.2307/3350391

Wallace, L. S., Rogers, E. S., Roskos, S. E., Holiday, D. B., & Weiss, B. D. (2006). Brief report: screening items to identify patients with limited health literacy skills. *J Gen Intern Med*, *21*(8), 874–877. https://doi.org/10.1111/j.1525-1497.2006.00532.x

Wang, C., O'Neill, S. M., Rothrock, N., Gramling, R., Sen, A., Acheson, L. S., Rubinstein, W. S., Nease, D. E., Jr., & Ruffin, M. T. t. (2009). Comparison of risk perceptions and beliefs across common chronic diseases. *Prev Med*, *48*(2), 197–202. https://doi.org/10.1016/j.ypmed.2008.11.008

Wang, C., Wu, X., & Qi, H. (2021). A Comprehensive Analysis of E-Health Literacy Research Focuses and Trends. *Healthcare (Basel)*, *10*(1). https://doi.org/10.3390/healthcare10010066

Wang, H., Ho, A. F., Wiener, R. C., & Sambamoorthi, U. (2021). The Association of Mobile Health Applications with Self-Management Behaviors among Adults with Chronic Conditions in the United States. *Int J Environ Res Public Health*, *18*(19). https://doi.org/10.3390/ijerph181910351

Wang, Q., Tao, C., Yuan, Y., Zhang, S., & Liang, J. (2023). Current Situations and Challenges in the Development of Health Information Literacy. *Int J Environ Res Public Health*, *20*(3). https://doi.org/10.3390/ijerph20032706

Wang, X., & Cheng, Z. (2020). Cross-Sectional Studies: Strengths, Weaknesses, and Recommendations. *Chest*, *158*(1s), S65–s71. https://doi.org/10.1016/j.chest.2020.03.012

Wang, Y., Song, Y., Zhu, Y., Ji, H., & Wang, A. (2022). Association of eHealth Literacy with Health Promotion Behaviors of Community-Dwelling Older People: The Chain Mediating Role of Self-Efficacy and Self-Care Ability. *International Journal of Environmental Research and Public Health*, *19*(10), 6092.

Wannheden, C., Åberg-Wennerholm, M., Dahlberg, M., Revenäs, Å., Tolf, S., Eftimovska, E., & Brommels, M. (2022). Digital Health Technologies Enabling Partnerships in Chronic Care Management: Scoping Review [Review]. *J Med Internet Res*, *24*(8), e38980. https://doi.org/10.2196/38980

Warren-Findlow, J., Basalik, D. W., Dulin, M., Tapp, H., & Kuhn, L. (2013). Preliminary validation of the Hypertension Self-Care Activity Level Effects (H-SCALE) and clinical blood pressure among patients with hypertension. *J Clin Hypertens (Greenwich)*, *15*(9), 637–643. https://doi.org/10.1111/jch.12157

Watson, K. B., Wiltz, J. L., Nhim, K., Kaufmann, R. B., Thomas, C. W., & Greenlund, K. J. (2025). Trends in Multiple Chronic Conditions Among US Adults, By Life Stage, Behavioral Risk Factor Surveillance System, 2013-2023. *Preventing Chronic Disease*, *22*, E15. https://doi.org/10.5888/pcd22.240539

Wayment, A., Wong, C., Byers, S., Eley, R., Boyde, M., & Ostini, R. (2020). Beyond Access Block: Understanding the Role of Health Literacy and Self-Efficacy in Low-Acuity

Emergency Department Patients. *Ochsner J*, *20*(2), 161–169. https://doi.org/10.31486/toj.19.0047
Widaman, K. F., & Revelle, W. (2023). Thinking thrice about sum scores, and then some more about measurement and analysis. *Behav Res Methods*, *55*(2), 788–806. https://doi.org/10.3758/s13428-022-01849-w
Wieczorek, M., Meier, C., Vilpert, S., Reinecke, R., Borrat-Besson, C., Maurer, J., & Kliegel, M. (2023). Association between multiple chronic conditions and insufficient health literacy: cross-sectional evidence from a population-based sample of older adults living in Switzerland. *BMC Public Health*, *23*(1), 253. https://doi.org/10.1186/s12889-023-15136-6
Wigal, J. K., Creer, T. L., & Kotses, H. (1991). The COPD Self-Efficacy Scale. *Chest*, *99*(5), 1193–1196. https://doi.org/10.1378/chest.99.5.1193
Wigfall, L. T., & Tanner, A. H. (2018). Health Literacy and Health-Care Engagement as Predictors of Shared Decision-Making Among Adult Information Seekers in the USA: a Secondary Data Analysis of the Health Information National Trends Survey. *Journal of Cancer Education*, *33*(1), 67–73. https://doi.org/10.1007/s13187-016-1052-z
Wilkowska, W., & Ziefle, M. (2012). Privacy and data security in E-health: Requirements from the user's perspective. *Health Informatics Journal*, *18*(3), 191–201. https://doi.org/10.1177/1460458212442933
Williams, R. B. (2008). Psychosocial and Biobehavioral Factors and Their Interplay in Coronary Heart Disease. *Annual Review of Clinical Psychology*, *4*(Volume 4, 2008), 349–365. https://doi.org/https://doi.org/10.1146/annurev.clinpsy.4.022007.141237
Willis, E., & Royne, M. B. (2017). Online Health Communities and Chronic Disease Self-Management. *Health Communication*, *32*(3), 269–278. https://doi.org/10.1080/10410236.2016.1138278
Wilson, I. B., & Cleary, P. D. (1995). Linking Clinical Variables With Health-Related Quality of Life: A Conceptual Model of Patient Outcomes. *JAMA*, *273*(1), 59–65. https://doi.org/10.1001/jama.1995.03520250075037
Witte, J. S., Greenland, S., Haile, R. W., & Bird, C. L. (1994). Hierarchical regression analysis applied to a study of multiple dietary exposures and breast cancer. *Epidemiology*, *5*(6), 612–621. https://doi.org/10.1097/00001648-199411000-00009
World Health Organization. (2019). *WHO guideline: recommendations on digital interventions for health system strengthening.* Geneva: World Health Organization Retrieved from https://iris.who.int/server/api/core/bitstreams/c3c53f30-23cc-48d0-a3b5-c05ddd7f5349/content
World Health Organization. (2020, December). *The top 10 causes of death*. https://www.who.int/news-room/fact-sheets/detail/the-top-10-causes-of-death
World Health Organization. (2024, December). *Noncommunicable diseases*. https://www.who.int/news-room/fact-sheets/detail/noncommunicable-diseases
Wu, Y., Wen, J., Wang, X., Wang, Q., Wang, W., Wang, X., Xie, J., & Cong, L. (2022). Associations between e-health literacy and chronic disease self-management in older Chinese patients with chronic non-communicable diseases: a mediation analysis. *BMC Public Health*, *22*(1), 2226. https://doi.org/10.1186/s12889-022-14695-4
Xesfingi, S., & Vozikis, A. (2016). eHealth Literacy: In the Quest of the Contributing Factors [Original Paper]. *Interact J Med Res*, *5*(2), e16. https://doi.org/10.2196/ijmr.4749

Xiang, J., & Stanley, S. J. (2017). From online to offline: Exploring the role of e-health consumption, patient involvement, and patient-centered communication on perceptions of health care quality. *Computers in Human Behavior*, *70*, 446–452. https://doi.org/https://doi.org/10.1016/j.chb.2016.12.072

Xie, B. (2011). Older adults, e-health literacy, and collaborative learning: An experimental study. *Journal of the American Society for Information Science and Technology*, *62*(5), 933–946. https://doi.org/https://doi.org/10.1002/asi.21507

Xie, L., & Mo, P. K. H. (2023). Comparison of eHealth Literacy Scale (eHEALS) and Digital Health Literacy Instrument (DHLI) in Assessing Electronic Health Literacy in Chinese Older Adults: A Mixed-Methods Approach. *International Journal of Environmental Research and Public Health*, *20*(4), 3293.

Xie, Z., Liu, K., Or, C., Chen, J., Yan, M., & Wang, H. (2020). An examination of the socio-demographic correlates of patient adherence to self-management behaviors and the mediating roles of health attitudes and self-efficacy among patients with coexisting type 2 diabetes and hypertension. *BMC Public Health*, *20*(1), 1227. https://doi.org/10.1186/s12889-020-09274-4

Xu, L., Li, T., He, W., Cao, D., Wu, C., & Qin, L. (2023). Prevalence of sufficient physical activity among general adult population and sub-populations with chronic conditions or disability in the USA. *Eur J Public Health*, *33*(5), 891–896. https://doi.org/10.1093/eurpub/ckad132

Xu, R. H., Zhou, L. M., Wong, E. L., & Wang, D. (2021). The Association Between Patients' eHealth Literacy and Satisfaction With Shared Decision-making and Well-being: Multicenter Cross-sectional Study. *J Med Internet Res*, *23*(9), e26721. https://doi.org/10.2196/26721

Yang, K., Hu, Y., & Qi, H. (2022). Digital Health Literacy: Bibliometric Analysis. *J Med Internet Res*, *24*(7), e35816. https://doi.org/10.2196/35816

Yang, X., Yang, N., Lewis, D., Parton, J., & Hudnall, M. (2021). Patterns and Influencing Factors of eHealth Tools Adoption Among Medicaid and Non-Medicaid Populations From the Health Information National Trends Survey (HINTS) 2017-2019: Questionnaire Study [Original Paper]. *J Med Internet Res*, *23*(2), e25809. https://doi.org/10.2196/25809

Yang, Y.-M., Chan, H.-Y., Ho, Y.-F., Lin, H.-W., Wang, C.-C., Wang, T., & Huang, Y.-M. (2026). Charting the path to better diabetes outcomes: Revealing psychosocial influences on medication adherence through the information-motivation-behavioral skills model among adults with type 2 diabetes. *Research in Social and Administrative Pharmacy*, *22*(1), 96–106. https://doi.org/https://doi.org/10.1016/j.sapharm.2025.08.010

Ye, J. F., Zheng, S., Ao, S. H., Yan, C. D., Lai, Y., Lai, Z., & Zhao, X. (2024). How does patient-centered communication work? Trend analysis of mediation through cancer worry and health self-efficacy, 2011–2020. *Journal of Health Psychology*, *29*(10), 1164–1178. https://doi.org/10.1177/13591053241228437

Yeoh, E. K., Wong, M. C. S., Wong, E. L. Y., Yam, C., Poon, C. M., Chung, R. Y., Chong, M., Fang, Y., Wang, H. H. X., Liang, M., Cheung, W. W. L., Chan, C. H., Zee, B., & Coats, A. J. S. (2018). Benefits and limitations of implementing Chronic Care Model (CCM) in primary care programs: A systematic review. *International journal of cardiology*, *258*, 279–288. https://doi.org/https://doi.org/10.1016/j.ijcard.2017.11.057

Yu, S., Wan, R., Bai, L., Zhao, B., Jiang, Q., Jiang, J., & Li, Y. (2023). Transformation of chronic disease management: Before and after the COVID-19 outbreak [Mini Review]. *Frontiers in Public Health*, *11*. https://doi.org/10.3389/fpubh.2023.1074364

Zaghloul, H., Fanous, K., Ahmed, L., Arabi, M., Varghese, S., Omar, S., Al-Najjar, Y., El-Khoury, R., Gray, J., Rakab, A., & Arayssi, T. (2025). Digital Health Literacy in Patients With Common Chronic Diseases: Systematic Review and Meta-Analysis. *J Med Internet Res*, *27*, e56231. https://doi.org/10.2196/56231

Zahnd, W. E., Del Vecchio, N., Askelson, N., Eberth, J. M., Vanderpool, R. C., Overholser, L., Madhivanan, P., Hirschey, R., & Edward, J. (2022). Definition and categorization of rural and assessment of realized access to care. *Health Services Research*, *57*(3), 693–702. https://doi.org/https://doi.org/10.1111/1475-6773.13951

Zangger, G., Mortensen, S. R., Tang, L. H., Thygesen, L. C., & Skou, S. T. (2024). Association between digital health literacy and physical activity levels among individuals with and without long-term health conditions: Data from a cross-sectional survey of 19,231 individuals. *Digit Health*, *10*, 20552076241233158. https://doi.org/10.1177/20552076241233158

Żarnowski, A., Jankowski, M., & Gujski, M. (2022). Public Awareness of Diet-Related Diseases and Dietary Risk Factors: A 2022 Nationwide Cross-Sectional Survey among Adults in Poland. *Nutrients*, *14*(16), 3285.

Zeng, B., Rivadeneira, N. A., Wen, A., Sarkar, U., & Khoong, E. C. (2022). The Impact of the COVID-19 Pandemic on Internet Use and the Use of Digital Health Tools: Secondary Analysis of the 2020 Health Information National Trends Survey [Original Paper]. *J Med Internet Res*, *24*(9), e35828. https://doi.org/10.2196/35828

Zhang, C., Mohamad, E., Azlan, A. A., Wu, A., Ma, Y., & Qi, Y. (2025). Social Media and eHealth Literacy Among Older Adults: Systematic Literature Review. *J Med Internet Res*, *27*, e66058. https://doi.org/10.2196/66058

Zhang, C., & Yang, J. (2024). Personalizing Physical Activity for Glucose Control Among Individuals With Type 2 Diabetes: Are We There Yet? *Diabetes Care*, *47*(2), 196–198. https://doi.org/10.2337/dci23-0063

Zhang, L., Li, H., Huang, T., Yang, M., Yu, X., & Liu, Y. (2025). Nutritional self-management in chronic diseases: a conceptual analysis. *Front Public Health*, *13*, 1680903. https://doi.org/10.3389/fpubh.2025.1680903

Zhang, X., Bi, R., Wang, X., Bu, Y., Liu, X., Liu, Y., Cui, R., Wang, Y., & Li, H. (2025). Physical activity health literacy in patients with chronic diseases: a concept analysis. *Front Public Health*, *13*, 1673391. https://doi.org/10.3389/fpubh.2025.1673391

Zheng, B., & Agresti, A. (2000). Summarizing the predictive power of a generalized linear model. *Statistics in Medicine*, *19*(13), 1771–1781. https://doi.org/https://doi.org/10.1002/1097-0258(20000715)19:13<1771::AID-SIM485>3.0.CO;2-P

Zoellner, J., Connell, C., Bounds, W., Crook, L., & Yadrick, K. (2009). Nutrition literacy status and preferred nutrition communication channels among adults in the Lower Mississippi Delta. *Prev Chronic Dis*, *6*(4), A128.