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The Use of Technology for Seeking Health Information in Persons with Cancer

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Walden University
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Abstract

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Jasvir Zonobi

MS Computer Science, San Jose State University 1992

BS Computer Science, San Jose State University, 1989

Doctoral Study Submitted in Partial Fulfillment

of the Requirements for the Degree of

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Abstract

Cancer is a growing public health concern. The U.S. cancer prevalence nearly doubled from 8.1 million in 1996 to 15.5 million in 2016 and is expected to rise by an additional 68% from 2016 to 2040. Many cancer survivors use technology (e.g., smartphones) for health information seeking (HIS) for health-related self-efficacy (HRSE) to self-manage the health issues (e.g., physical impairment, chronic disease) they face. However, limited research exists regarding cancer survivors' use of HIS technology for HRSE. The self-efficacy theoretical framework, multiple logistic regression analyses, and the data from 2019 Health Information National Trends Survey were used in the current study to assess the impact of the use of technology for HIS on HRSE and HIS experiences, as well as the relationship between sociodemographic and clinical factors with the use of technology for HIS. Most (80.2%) survivors used HIS technology. The use of technology for HIS did not significantly predict HRSE (OR = 0.91, 95% CI = 0.54-1.54) nor positive HIS experiences (OR =1.15, 95% CI = 0.75-1.79), $p > .05$. Age, education, and income independently predicted technology-based HIS, $p < .05$, with persons under the age of 65 years, those with greater than high school education, and those earning over $20,000 having greatest odds of using technology for HIS. The HIS-technology’s potential to improve HRSE is not fully understood. More research is needed to inform its use in the survivorship programs to reduce disparities and barriers in survivors’ health information access for improved cancer outcomes. Current and future studies on the research gaps can lead to positive social change by providing evidence for effective survivorship interventions for HRSE to help survivors self-manage their health-related quality of life.

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Dedication

I dedicate this dissertation to those who provide selfless service to the betterment of the world. I dedicate this dissertation to those who enable and empower individuals, families, and communities with education and health information to help them live their lives to the fullest and transform the public health scenario. Among those are persons who supported my lifelong passion for learning and being a social change agent.

I dedicate this to my husband, parents, siblings, and family, who provided the loving and learning environment, and they taught me *the good of all* core tenet of positive social change by example. They encouraged education towards this end and emphasized that *true education* is applying the knowledge for a positive impact on others rather than just for a personal benefit. Despite never having attained a college degree, both my parents were social change agents whose community-wide impact continues to thrive well past their lives. I am proud of my husband, his brother, and my nieces and nephews for their advocacy and support for persons with disabilities and for improving environmental and public health.

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I also express my sincere gratitude to Paul Randolph for his review and valuable feedback throughout the draft process, and his feedback helped me improve the accessibility of the content in this dissertation document.

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Section 1: Foundation of the Study and Literature Review

Introduction

Cancer is a growing public health problem. Cancer incidence has been on the rise given early disease detection, as well as population growth, namely an increase in the elderly population (Alfano et al., 2019). Similarly, cancer survival rates have increased with advances in the treatment of cancer (Alfano et al., 2019; Bluethmann et al., 2016). Commensurate with the increase in the incidence and survival rates, the overall cancer prevalence is rising and is expected to grow to 26.1 million by 2040 (from 8.1 million in 1996) (Alfano et al., 2019; Roser & Ritchie, 2019; Rowland, 2016). Cancer survivors (i.e., persons diagnosed with cancer, irrespective of their treatment status or the time since diagnosis [Lavoie Smith et al., 2012]) are faced with a variety of health-related concerns such as reduced health-related quality of life (HRQOL), chronic diseases, cancer recurrence, and treatment-induced secondary cancers (American Cancer Society [ACS], 2016; Andreotti et al., 2015; Cohen & Derubeis, 2018; Demoor-Goldschmidt & De Vathaire, 2019; Smith & Bass, 2019). Therefore, addressing the health needs for cancer survivors is an important public health matter.

One approach to support cancer survivors is to encourage health information seeking (HIS) and provide easily accessible patient-centered health-information resources for the self-management of cancer given that HIS has been demonstrated to be positively correlated with self-care behaviors of disease prevention and management (Finney Rutten, Agunwamba, et al., 2016; Miller et al., 2018; Shneyderman et al., 2016), and a reduction of fatalist beliefs (Emanuel et al., 2018). Most (70–90%) cancer survivors seek health information from a variety of sources (Bigsby & Hovick, 2018; Chua et al., 2018; Finney Rutten, Agunwamba, et al., 2016; Holmes et al., 2017). Electronic sources of health information such as the Internet, health-related social media and YouTube videos are easily accessible via technologies such as computers and smartphones, and these sources afford anonymity and interactivity, such as online chat functions (Jacobs et al., 2017; Wang et al., 2012). However, it is presently not well understood how the use of technology for HIS (i.e., looking for health or medical information on the Internet using a computer, smartphone, or other electronic means; participating in health-related online forums for persons with similar health issues; or watching a health-related video on an internet website, e.g., YouTube; Domínguez & Sapiña, 2017; Jackson et al., 2016; Zucco et al., 2018) may impact cancer survivors' ability to manage their personal health-related goals (i.e., health-related self-efficacy) and to find relevant patient-centered health information. It is also not clear which types of cancer survivors (according to sociodemographic and clinical variables) are most inclined to use, and find benefit from, technology for HIS.

My objective for the current study was to assess the relationship between cancer survivors' use of technology for HIS with their health-related self-efficacy, HIS experiences, and survivors' characteristics (sociodemographic and clinical) for the use of technology for HIS. Understanding the impact of technology-based HIS on the health-related self-efficacy could lead to positive social change by helping public health practitioners and clinicians identify appropriate resources, namely sources to improve the accuracy, as well as the accessibility of health-information sources. Understanding the patients’ characteristics associated with technology-based HIS behaviors could inform health promotion policies and self-management programs targeting cancer survivors.

In this section, I will introduce the research problem and describe the gaps in the scientific knowledge regarding technology-based HIS behaviors among cancer survivors who seek HIS. I will also discuss the purpose of the study, including the study variables, the research questions and corresponding hypotheses, and the guiding theoretical framework for this study. I will also discuss the research design and methodology, along with the study assumptions and limitations. I will also provide a comprehensive review of the current literature on the study variables. Finally, I will conclude this section by providing a summary and a brief introduction to Section 2.

Problem Statement

There is a gap in the collective knowledge about the use of technology for HIS among cancer survivors who seek health information. Although HIS among cancer survivors has risen from 66.8% in 2003 to 80.8% in 2013 (Finney Rutten, Agunwamba, et al., 2016; Kobayashi & Smith, 2016), there is a high prevalence of unmet health information needs among cancer survivors to address their physical and psychological needs (Nekhlyudov et al., 2017; van Leeuwen et al., 2018). Up to 75% of the cancer survivors reported concerns with accessing self-care cancer health information (Hall et al., 2018; Hébert & Fillion, 2017; Iyer et al., 2017; McGinty et al., 2016; Pongthavornkamol et al., 2019; Vogel et al., 2017).

Fatalistic beliefs, sociodemographic factors, and multiple cancer diagnoses are well-documented predictors of HIS behaviors (Bustillo et al., 2017; Finney Rutten, Agunwamba, et al., 2016; Greenberg et al., 2018; Medeiros et al., 2015; Miller et al., 2018). However, it is not clear what type of sociodemographic and clinical factors are more likely to influence the use of technology for HIS than others. Additionally, there is evidence to suggest that negative HIS experiences are associated with fatalistic beliefs (Amuta et al., 2017; Arora et al., 2008; Waters et al., 2016), low health literacy (Kobayashi & Smith, 2016), and low self-esteem (Emanuel et al., 2018). However, it was not clear how the use of technology for HIS impacted HIS experiences among cancer survivors who seek health information.

There was also a paucity of literature regarding the use of technology for HIS and how this serves to benefit cancer patients either by efficient information access through preferred sources (Jacobs et al., 2017), impact of technology-based HIS behaviors (e.g., participation in online peer support, improving knowledge) on disease-related self-care to prevent or arrest disease (Jamal et al., 2015), HRQOL (Bachmann et al., 2016), and health-related decisions (Finney Rutten, Agunwamba, et al., 2016). Such information would be valuable because understanding the characteristics of HIS behaviors, persons' experience with the use of technology for HIS, and their impact on the self-confidence and competence of persons with cancer would contribute to the scientific knowledge for improving self-care interventions for persons with cancer. However, no researchers had examined the impact of the cancer survivor's clinical and sociodemographic factors on their use of technology for HIS nor the impact of the use of technology for HIS on their ability to take good care of their health or the HIS experiences of cancer survivors who seek health information.

There was a gap in the collective knowledge about the characteristics of cancer survivors who seek health information, how they used it, how they felt about it, and how they benefited from it. These gaps can limit the effectiveness of the public health systems for supporting self-management for helping cancer survivors attain or retain a satisfactory HRQOL, particularly in the changing landscape. Understanding these factors is a first and essential step in preventing cancer recurrence, improving HRQOL concerns for cancer survivors, and, more generally, addressing the notable public health concern of cancer. The evidence on the impact of the use of technology for HIS on self-efficacy and HIS experiences could inform evidence-based public health interventions for the self-management of cancer. Cancer survivors' personal factors (sociodemographic and clinical) and their use of technology for HIS might reveal new insights about their needs in a changing sociodemographic and technological landscape. These insights can be used to update the public health knowledge about recency and relevancy of cancer survivorship knowledge and improve cancer survivorship interventions for satisfactory HRQOL and reduce public health burden.

Purpose of the Study

The purpose of this quantitative study was to assess the association between use of technology for HIS and health-related self-efficacy, as well as the HIS experiences and personal factors among persons with cancer who seek health information. As health education and access to useful health information are the means to developing the knowledge and practice of healthy lifestyle behaviors (World Health Organization, 2012), accessible cancer health information would be an important factor for improving survivors' HRQOL, assuring compliance with treatment regimens, and reducing the cancer recurrences rates. I conducted this study to assess the impact of the use of technology for HIS (independent variable) on the health-related self-efficacy (dependent variable: low to none, full or high) among cancer survivors who seek cancer health information, the use of technology (used technology or did not use technology) for HIS (independent variable) on the positive HIS experiences (dependent variable) among cancer survivors who seek cancer health information, and cancer survivors' personal factors (sociodemographic and clinical factors) on the use of technology for seeking health information among cancer survivors who seek cancer health information.

Research Questions (RQs) and Hypotheses

The current study was conducted to address the research gaps noted above and specifically to address the following research questions:

Research Question 1 (RQ1): What is the relationship between the use of technology for HIS and self-efficacy (Low or none, Full or high) in one's ability to take care of their health among cancer survivors who seek health information?

$H_0$1: There is no relationship between the use of technology for HIS and health-related self-efficacy among cancer survivors who seek health information.

$H_1$1: There is a significant relationship between the use of technology for HIS and health-related self-efficacy among cancer survivors who seek health information.

Research Question 2 (RQ2): What is the relationship between the use of technology for HIS and positive HIS experiences (positive: not frustrated and did not take too much effort; negative: otherwise) among cancer survivors who seek health information?

$H_0 2$: There is no relationship between the use of technology for HIS and positive HIS experiences among persons with cancer who use technology than those who do not.

$H_1 2$: There is a significant relationship between the use of technology for HIS and positive HIS experiences among cancer survivors who use technology than those who do not.

Research Question 3 (RQ3): What is the relationship between a) survivors' sociodemographic characteristics (age, sex, race, education level, income) and the use of technology for HIS, and b) clinical factors (diagnosis of diabetes, hypertension, heart diseases, lung diseases, arthritis, depression) and the use of technology for HIS among cancer survivors who seek health information?

$H_0 3_a$: There is no relationship between the survivors' sociodemographic characteristics and their use of technology for HIS among cancer survivors who seek health information.

$H_1 3_a$: There is a significant relationship between the survivors' sociodemographic characteristics and their use of technology for HIS among cancer survivors who seek health information.

$H_0 3_b$: There is no relationship between the survivors' clinical characteristics and their use of technology for HIS among cancer survivors who seek health information.

H_13_b: There is a significant relationship between the survivors' clinical characteristics and their use of technology for HIS among cancer survivors who seek health information.

Theoretical Framework

The theoretical framework for this study was Bandura's self-efficacy theory. This theory posits that people's confidence or belief in their capabilities influence their behavior through cognitive, motivational, affective, and selective processes (Bandura, 1997). Persons with high self-efficacy take on challenges, set challenging goals, maintain a commitment to goals, and attribute failures to a deficiency in knowledge (Bandura, 1994). In contrast, persons with low self-efficacy avoid difficult tasks, dwell on low personal aptitude rather than overcoming the barriers, and become victims of stress (Bandura, 1994). The processes for developing self-efficacy involve enhancing cognitive abilities with knowledge and practice, motivation with expected outcomes and expectancy-value, and capacity to exercise self-influence, affective learning with the ability to cope with challenges and regulating thought processes (Bandura, 1994). The three efficacy-processes interact with the choice-related processes (selective processes) of the self-efficacy theory for decision-making (Bandura, 1994). As a result, knowledge, confidence, and practice of the self-efficacy theory influence action. These are relevant to persons with cancer as their behaviors will dictate their self-care behaviors of cancer-recurrence and quality of life. Per the self-efficacy theory, activated patients who develop knowledge and skills would then, in turn, develop their personal agency (cognitive and selective processes) for knowledge and skills of self-efficacy for better health.

I selected this theory because improving health-related self-efficacy is one of the goals of self-management interventions. Self-efficacy (self-assessed belief in the ability to perform tasks such as acquire new behaviors or control existing behaviors) is a mediator of behavior change (Finney Rutten, Hesse, et al., 2016; Strecher et al., 1986). Self-efficacy is domain-specific, and it involves performing cognitive tasks such as reasoning and problem solving (Kleitman & Stankov, 2007). Therefore, the self-efficacy domains could include decision-making (discerning between good and bad information, a decision about using specific resources), self-care (e.g., problem recognition, use of resources, taking health action), and learning (e.g., seeking health information, developing personal agency) self-efficacy. Thus, public health professionals promote patient engagement and provide access to health education and resources to enhance patients' skills and confidence in the self-management of their health goals (Grover & Joshi, 2015). The four concepts in the self-efficacy theory predict self-efficacy in the desired outcomes: patient activation would lead to patient engagement in the self-care (via the motivational process), and increased knowledge and experience would increase the confidence in identifying and solving health problems (e.g., health-related self-efficacy). Beliefs about the action and its expected value would motivate ways to overcome challenges (via the affective process) such as frustration with HIS and improve HIS self-efficacy among patients motivated to address the health issue. Effective choices (via the choice process informed by the cognitive and affective processes) would inform the utilization of cost-effective resources (decisional self-efficacy). Therefore, these four conceptual processes of the self-efficacy theory map directly to the self-efficacy domains of the three research questions in the current study.

The self-efficacy theory posits that increased access to knowledge for a desired goal would increase the person's ability to attain that goal. Cancer survivors who seek cancer health information using a readily available technology would seek to enhance their confidence in their ability to take good care of their health. Therefore, survivors' aim of self-management and this theoretical underpinning provided a rationale to investigate the extent to which one's use of technology for HIS is correlated with their personal agency for taking good care of their health (health-related self-efficacy), which was my aim of the first research question.

As self-efficacy develops from experience and perseverance in attaining the desired goals, motivated persons with knowledge would be expected to take on challenges to overcome the obstacles and enhance knowledge with practice. Finding cancer health information can be time-consuming, and technology may serve as a means for more efficient information-gathering, and consequently, persons who use technology for HIS might have different experiences than those who do not. As a result, cancer survivors with high self-efficacy could overcome information access barriers by exploring different options, including using technological tools for developing their HIS-seeking agency to meet their health information needs (HIS self-efficacy). In the past 10 years, there has been substantial growth in technology-enabled health information (Wang et al., 2012) and the self-efficacy theory also posits a reciprocal impact of a person's experience (i.e., HIS) on their personal agency (i.e., HIS self-efficacy and HIS experiences). Therefore, my purpose of the second research question was to explore the association between the use of technology (i.e., engagement of the selective process and self-influence theoretical concepts) for HIS (overcoming challenges and barriers to information) and the positive experience with HIS (finding information rather than being frustrated or being overwhelmed).

Cancer survivors with short- and long-term treatment side effects or comorbidities are likely to face unique health information challenges. The affective process of the self-efficacy theory deals with learning to cope with challenges such as comorbidities (e.g., depression, diabetes, arthritis, heart disease) that can impair cognitive and physical functions. The self-efficacy theory posits that motivated persons would overcome their challenges to attain the goal, and readily accessible technology may remove the barriers to do so. As such, cancer survivors might use multiple technologies (e.g., watch health videos, participate in online communities, use wearables to monitor and track symptoms) to access health information for improving their health. This premise was the subject of my evaluation in the third research question. The self-efficacy theory also posits the interaction between the affective process (learning to cope with challenges), cognitive process (knowledge and skills), and motivation (to improve HRQOL) guide the selection process (whether to use one or more technologies) for self-efficacy of health action (e.g., to seek health information).

Nature of the Study

The nature of the study design was a quantitative secondary data analysis of a nationally representative population survey. Quantitative study designs are used to test hypotheses, the effect of the predictor variables(s) on the predicted variables, and quantitative correlational designs measure the relationship between the variables and estimate the strength of the relationship (Burkholder et al., 2016). I used the quantitative correlational design to measure the relationship between the sociodemographic and clinical characteristics of the persons with cancer and their use of technology for HIS, between the technology-based HIS and HIS experience, and between technology-based HIS and self-reported confidence. I employed a correlational design, using a cross-sectional dataset, to assess the relationship between the study variables in each research question, and to test the hypotheses about the relationships. The study population was cancer survivors who sought cancer health-information for disease management.

The study population was the adult cancer survivors in the US who sought cancer health-information for disease management. The use of technology for HIS (used technology, did not use technology) was the independent variable in RQ1 and RQ2 (Table 1). Sociodemographic (age, race, sex, education, income) and clinical (diagnosis of diabetes, high blood pressure, heart disease, lung disease, or depression) factors were the independent variables in RQ3a and RQ3b, respectively (Table 1). Health-related self-efficacy (Low or none, Full or more) was the dependent variable in RQ1. Positive HIS experiences (positive, negative) was the dependent variable in RQ2. The use of technology for HIS was the dependent variable in RQ3.

Table 1

Study Variables for each RQ

RQ	Dependent variable (DV)	Independent variable (IV)	Potential confounding variable (CV)
RQ1	Health-related self-efficacy	The use of technology for HIS	Survivor's self-reported health status Survivor's self-reported health literacy
RQ2	Positive HIS experiences	The use of technology for HIS	Survivor's self-reported health status Survivor's health literacy
RQ3a	The use of technology for HIS	Survivors' sociodemographic variables: Age, Race, Sex, Education, and Income	Survivor's self-reported health status
RQ3b	The use of technology for HIS	Survivors' clinical variables: diagnosis of diabetes, high blood pressure, heart disease, lung disease, and depression or anxiety	Survivor's self-reported health status

I used the most recent dataset collected using the Health Information National Trends Survey (HINTS). HINTS is a cross-sectional nationally representative self-administered mail and web survey of the U.S. adults on the information environment, access, and use of health-related information (National Cancer Institute [NCI], n.d.). HINTS contains data on who is looking for health information, how they sought cancer health-information, HIS experiences, use of the technology (including participation and use of social media) to find information, their health status and diagnoses of chronic diseases (including cancers), and self-reported confidence (NCI, 2018). The dataset is publicly available for researchers and health professionals in multiple formats with a self-attested agreement to the HINTS Data Terms of Use policies (NCI, 2020b). Therefore, the HINTs dataset was used because it has the data required to conduct the proposed study, and it is publicly available.

I used IBM SPSS software to process the data to generate the descriptive and inferential statistics to address the research questions. Full details on the statistical methodology are described in Section 2 in this document, including a description and justification for the selected statistical tests and potential threats to internal and external validity.

Literature Review

Literature Search Strategy

I searched Google Scholar, CINAHL, and Medline databases for peer-reviewed literature on the study variables or concepts. I selected the articles that were published within the recent 5 years (after 2014) to develop the intellectual heritage on the study variable(s) and topic. I extended the search criteria to include studies since 2000 for the seminal works on the theoretical concepts and operationalization of the study variables for trends in and application of the concepts and variables by other researchers. Due to the remarkable advances in consumer-accessible technology and exponential growth in the information web pages, results from older literature on a researched subject would only be useful for the foundational understanding rather than current conclusions on the subject. I used the terms related to the study topic (cancer), population (e.g., survivors), concepts (e.g., self-efficacy, health information, quality of life) and variables (e.g., the Internet, YouTube for the technologies for the use of technologies for HIS, frustrating or too much information of positive HIS experiences, and cancer comorbidities such as diabetes and depression [Table 1] as variables in the survivor's clinical characteristics) to define the search keywords.

I used the following search keywords*: cancer health information-seeking behavior, health information seeking cancer outcomes, internet online cancer patients, cancer information-seeking experience, frustration too much information seeking health information + cancer, trusted cancer information sources, cancer self-management, cancer quality of life, cancer + self-efficacy, social media and cancer, YouTube + cancer + health-information, cancer + health-related use + YouTube, health-related use +social media, self-confidence + cancer + health-information seeking, cancer + chronic conditions, cancer + comorbid, cancer + diabetes + health-information seeking, cancer + arthritis + health-information, cancer + asthma OR COPD + health-information, cancer + lung OR respiratory disease + health-information, cancer + heart OR cardiovascular disease + health-information, cancer + mental health OR depression + health-information.* For literature related to the key variables and concepts, I first reduced the result set to only those articles that contained the word 'cancer" and "survivor, patients, or persons with" in the article's title or abstract. Then, I selected the literature on chronic conditions to address the concerns of limited or no research on a search criterion such as the cancer comorbidities.

Literature Related to Key Concepts

As described in the theoretical framework, I used the self-efficacy theory to assess the impact of HIS behaviors on cancer survivor's health-related self-efficacy rather than predict the behaviors of health (e.g., HIS) posited by other theories such as the health belief model, theory of planned behavior, and social cognitive theories (LaMorte, 2018b, 2018a; Rosenstock, 1974). As the four conceptual processes (cognitive, motivational, affective, and decisional) influence self-efficacy in the desired outcome such as health self-efficacy (e.g., health-related self-efficacy), HIS self-efficacy (e.g., positive HIS experiences), and decisional self-efficacy (e.g., selection of tool such as the use of technology for HIS), I included literature review on the role of the these four conceptual processes in HIS and the self-management of cancer in this section.

Cognitive

Because the cognitive process depends on the personal agency (the person's knowledge of and personal practical experience with the self-care resources) for the self-efficacy of the desired goal, the personal agency would be impacted by the person's health literacy. Health literacy refers to the ability to find, access, interpret, and use health information and system resources for health decisions for action (Poureslami et al., 2016; Shneyderman et al., 2016; S. G. Smith et al., 2010). The personal agency develops from personal interest or experience with the health issue through HIS (self-learning) or healthcare or health promotion systems (Abubakari et al., 2016). Therefore, any limitations in the accessibility of health information due to internal or external controls, particularly among persons who seek health information, could impact the person's health literacy (and personal agency) and health-related outcomes.

There is evidence that health literacy is correlated with health self-efficacy (Finney Rutten, Hesse, et al., 2016; Peters et al., 2019). Finney Rutten and Hesse et al. (2016) conducted a secondary analysis of the 2013 HINTS cross-sectional dataset to examine the impact of patient-provider communication and health self-efficacy among Americans with multiple chronic illnesses (e.g., diabetes, cardiovascular, respiratory, arthritis, depression). Finney Rutten and Hesse et al. found a positive and significant association between health literacy (access to health information from patient-provider communications) and health self-efficacy ($n = 3000$, $\beta = 0.26$, $p < .0001$). Finney Rutten and Hesse et al. also reported lower levels of health self-efficacy among persons with higher burden of chronic diseases (i.e., one or more) as compared with persons without chronic illnesses (zero conditions: $\beta = 11.06$, $p < 0.0001$ versus one chronic condition: $\beta = 7.82$, $p < 0.0002$). Peters et al. (2019) reported a similar association between health self-efficacy and disease burden among patients ($n = 848$) with multiple morbidities at seven primary care practices in England. These findings were credible because of the sample size, agreements between these two studies of different populations (the U.S. versus England) and contexts (healthcare in the U.S. versus universal healthcare in England) using different study designs (secondary versus primary) and study instruments (HINTS 4 versus multiple self-efficacy questionnaires used by Peters et al.). Finney Rutten and Hesse et al. (2016) and Peters et al. (2019) both reported mental health (e.g., depression) as a potential confounder of health-related self-efficacy, although only Peters et al. (2019) provided a theoretical basis (self-efficacy theory) for the study and Finney Rutten and Hesse et al. (2016) did not. The data in these studies on the cognitive processes of self-efficacy demonstrated that health literacy is a predictor of HIS, health outcomes, and health-related self-efficacy.

Finney Rutten and Hesse et al. (2016) recommended that future studies examine the association between the levels of health self-efficacy and HIS behaviors because the authors believed that persons with high health self-efficacy might be more likely to seek health information than their counterparts with lower health self-efficacy. Peters et al. (2019) noted further research is needed on the clustering of diseases for awareness on the self-efficacy needs of persons with enhanced need of self-management.

In summary, mental access to health information and mental health issues such as depression could impact self-efficacy outcomes (e.g., health-related self-efficacy and HIS self-efficacy), even among the motivated and activated cancer survivors engaged in the self-management of their HRQOL and developing their ability to care for their health. However, health literacy may be inadequate without patient engagement or activation.

Motivation

As discussed before, patients must actively self-manage their health for health self-efficacy. *H*ealth literacy and fatalistic beliefs predict patient activation (S. Jiang, 2017; Kobayashi & Smith, 2016; Palmer et al., 2014). Lower quality of patient-provider communications reduces the likelihood of patient activation and consequential self-management of their health (Palmer et al., 2014). Per Kobayashi and Smith (2016), fatalistic beliefs and lower levels of health literacy were associated with lower levels of patient activation. Thus, persons who seek health information for themselves must believe in their ability to control their health outcomes. The use of technology for HIS among cancer survivors would indicate activated patients.

It is expected that activated patients would seek information to overcome health literacy gaps for decision and health self-efficacy. Most cancer survivors (i.e., those ever diagnosed with cancer) seek health information to address the health issues they face from cancer and its treatments (Finney Rutten, Agunwamba, et al., 2016; Finney Rutten, Hesse, et al., 2016; Jiang et al., 2017; Miller et al., 2018; Shneyderman et al., 2016; Somera et al., 2016). Such cancer survivors who seek health information would be among the activated survivors motivated to either address a health or health literacy gap.

Activated patients have a greater likelihood of greater levels of self-confidence in their ability to perform self-care tasks such as making health decisions (Palmer et al., 2014) or the use of technology for HIS (S. Jiang, 2017). S. Jiang (2017) confirmed that patient activation mediated the effects of the use of social media on the emotional well-being of the study participants in the 2013 HINTS survey ($\beta = 0.12$, $p < .05$, $n = 459$). Activated persons with high health literacy and HIS self-efficacy would be expected to use the tools that enhance their access to health information for their desired health self-efficacy. Moreover, a study of activated survivors and motivated persons such as cancer survivors who seek health information would avoid the potential confounding effect of patient activation on health self-efficacy.

Affective

As discussed before, per the affective process in the self-efficacy theory, a person's motivation to perform an activity for a goal is mediated by the expected value of the goal. A person's affective attitudes (e.g., positive or negative feelings, stress, knowledge, beliefs) influence the perceived value of the outcome of the effort towards the activity for the desired goal (Rimer & Brewer, 2015). HIS is a resource-consuming activity because it involves individuals actively searching for the health information from various sources rather than passively scanning information while doing other tasks (Shim et al., 2006). Individuals tend to seek health information from the sources they trust, accommodate their personal preferences, or have a positive experience with (Clauser et al., 2011). The resources to seek quality, relevant, and accessible health information from sources such as the print media (e.g., books, magazines), mass media, online sites (e.g., websites, virtual communities), people (e.g., family, friends, other survivors), and healthcare professionals (Somera et al., 2016) might vary widely. Furthermore, individual HIS behaviors (the way people seek health information) and their preferences (Jacobs et al., 2017) might impact the perceived value of the options for their HIS activity. Although the actual value of HIS could depend on the survivors' HIS behaviors, an expected value of HIS could be the enhanced personal agency for the self-management of the desired aim, such as attaining a satisfactory HRQOL. The expectation of finding ways to cope with health issues (Miller et al., 2018; Mooney et al., 2017), self-care or treatment options, and save money or time (Holmes et al., 2017; Zucco et al., 2018) might explain the high prevalence of HIS among cancer survivors in the U.S. (Finney Rutten, Agunwamba, et al., 2016; Jacobs et al., 2017; Miller et al., 2018; Mooney et al., 2017; Somera et al., 2016).

Miller et al. (2018) found that childhood cancer survivors ([CCS] aged 15 to 25 years, *n* = 193) recruited from two cancer care centers in Los Angeles reported seeking health information to cope with their unmet psychosocial needs. Miller et al. (2018) found that CCS diagnosed with cancer at two cancer care centers in Los Angeles sought health information from multiple sources. Miller et al. (2018) also found that most of them reported seeking health information from any source (63%) and healthcare providers (65.3%). Miller et al. found that the use of technology for HIS was not significantly associated with race (Hispanic: 37.1% and non-Hispanic: 36.4%, $p = .11$); however, the study findings might not be generalizable due to the sampling design (two clinics in one city) and nonrepresentative sample (Hispanic 54% and non-Hispanic: 45%). Miller et al. also found a positive and significant ($p < .01$) association between HIS behaviors and sex, insurance, follow-up self-efficacy and post-traumatic growth among the study participants. Miller et al. found a positive but not significant association between HIS behaviors and race, education, and depression symptoms. Miller et al. also found that age, sex, post-traumatic growth, and health insurance were predictors of the use of technology for HIS, and females were 2.76 times more likely to use technology for HIS than males (adjusted odds ratio [OR] = 2.76, 95% confidence interval [CI] = 1.39, 5.47, $p < .01$). Miller et al. confirmed the role of affective process in cancer survivors' HIS behaviors.

The need to address unmet health needs was also the motivation for searching reliable and relevant health information among the participants in the studies by Mooney et al. (2017) and Somera et al. (2016). Mooney et al. (2017) used a mixed-method design to understand the HIS behaviors among CCS and young adults (under 40). Mooney et al. (2017) reported that most (92%) of the study participants in the focus group reported using technology for HIS ($n = 25$; 100% non-Hispanic White, 68% female) to find reliable and quality cancer health information unique to their health needs. Somera et al. (2016) compared the HIS behaviors of adults in Guam ($n = 510$) with the adults in the U.S. ($n = 3969$). Somera et al. found about 70% of the respondents in Guam and the U.S., samples searched the Internet on health and medical topics, and nearly 80% of them searched it for themselves. Somera et al. also found that for a strong need for health information, a higher percentage of the Guam sample searched the Internet (Guam: 45.8%; U.S.: 39.4%), while a higher percentage of Americans sought health information from the healthcare providers (Guam: 38.2%, US: 52.2%). Moreover, persons with income from $35,000 to $49,999 in the Guam sample were more likely to seek cancer-related health information than their counterparts in Guam with higher or lower income (OR = 3.13, 95% CI = 1.08, 9.08), whereas the odds of cancer-related HIS among the U.S. sample were higher among those with a higher income than their counterparts with lesser income (Somera et al., 2016). These findings suggest that healthcare access and ease of search using technology for understanding disease symptoms and evaluating self-treatment versus clinical treatment decisions may have influenced a high prevalence of technology-based HIS in U.S. and Guam (Somera et al., 2016). However, a comparison between the 2011 HINTS sample of U.S. adults and the 2013 Guam sample could lack study validity if the technology and health-information availability changed substantially between 2011 and 2013 in Guam, the U.S., or both. Although Somera et al. (2016) did not examine the HIS behaviors among cancer survivors these findings provide evidence that information seekers aim to gain financial or knowledge benefit from the HIS activity. S. Jiang and Liu (2020) and Finney Rutten and Agunwamba et al. (2016) analyzed the HINTS cross-sectional datasets for the trends in the HIS behaviors among cancer survivors. Both authors reported a high prevalence of HIS among cancer survivors (70%). Among cancer survivors in the US, HIS increased from 53.5% in 2011 to 69.2% in 2017 (S. Jiang & Liu, 2020), and the cancer-related HIS increased from 66.8% in 2003 to

80.8% in 2013 (Finney Rutten, Agunwamba, et al., 2016). However, HIS self-efficacy has been decreasing, despite an increasing percentage of persons with information-seeking skills (S. Jiang & Liu, 2020). S. Jiang and Liu (2020) suggested it might be due to the differences in the amount of information found in the online versus traditional sources. S. Jiang and Liu recommended further research on health-related self-efficacy and HIS behaviors, which was one of my aims of the current study.

Although individual's beliefs and sociodemographic and clinical characteristics (e.g., multiple cancer diagnoses) influence the HIS behaviors, race and insurance status were not significant predictors of HIS among cancer survivors who sought health information (Finney Rutten, Agunwamba, et al., 2016), presumably due to the motivation to address the health need. However, health insurance mediated the preferred health information source, such as the use of health information technology (HIT) for accessing cancer-related information (from healthcare provided resources) among the insured rather than uninsured survivors (Miller et al., 2018). Fatalism had a mild influence on the relationship between health literacy and HIS behaviors among the 2013 HINTS study participants who had ever sought information and believed in fatalism (Kobayashi and Smith, 2016). Kobayashi and Smith (2016) used the New Vital Signs (NVS) health literacy assessment tool used to measure the person’s ability to read and comprehend health information. As health literacy refers to the mental (read, comprehend, process, and interpret information) and material (e.g., for everyday use of the information) access for self-management of health (Peerson & Saunders, 2009), the use of NVS was appropriate for assessing the cognitive health literacy (the ability to read and comprehend health information). Although Kobayashi and Smith (2016) demonstrated the relationships between health literacy and HIS behaviors, they did not examine the relationship among activated cancer survivors nor persons with lingering physio-psychological health concerns with or without cognitive impairment. The processes associated with the source for searching and retrieving health information could impact the amount of information found (too much or too little), quality of the retrieved information, the effort in retrieving the information. Those experiences can impact future HIS behaviors, knowledge, and self-management self-efficacy. In summary, individuals' need to cope with their health issues was the motivation for seeking health information among survivors, and their health literacy, beliefs, and sociodemographic and clinical characteristics (e.g., multiple cancer diagnoses) had some influence on the HIS behaviors.

Selective Process

The choice process involves making decisions about the medium or methods to attain the desired goal established per the interaction between the cognitive, motivational, and affective processes. Easy-to-use technologies can facilitate technology literacy, self-care, and learning (Fischer et al., 2014), and reciprocally greater reliance on technology for self-care and learning. Some healthcare providers provide patient portals for patient-provider communications and tracking health information to member patients (Demiris et al., 2019). However, the membership, authentication and security concerns for accessing patient portals and health information technology (HIT) platforms are among the barriers in the patient’s adoption of HITs for HIS (Jackson et al., 2016) Information-seekers might avoid technology that makes life more difficult and this may become a barrier to learning and self-care. Therefore, the decision about the use of a specific medium (e.g., technology) for self-care activity (e.g., seeking health information) would depend on the person's access to the medium.

Greenberg et al. (2018) analyzed seven iterations of the HINTS datasets from 2003 to 2014 ($n = 33749$) to compare the use and acceptance of technology among rural and urban U.S. adults. Greenberg et al. (2018) reported an uptake in the access and use of the Internet in the rural and urban settings across the seven years. However, Greenberg et al. (2018) found that the rural population ($n = 6043$) had lower odds of regular access (reliable connection) to the Internet (OR = 0.70, 95% CI = 0.61, 0.80), electronic health records (OR = 0.59, 95% CI = 0.45, 0.78), or electronic communications with their doctors (OR = 0.62, 95% CI = 0.49, 0.77) than their urban counterparts. The lower odds of electronically accessing the healthcare systems might be explained by the lower health insurance rates among the rural than the urban population (Greenberg et al., 2018).

S. Jiang and Liu (2020) also performed a trend analysis of the HINTS *2011* ($n = 563$), 2013 ($n = 459$), and 2017 ($n = 504$) data on Internet access, usage, and the health-related adoption of HIT (for health-related activities HIS such as emailing a doctor or participating in online forums) among cancer survivors. They also confirmed a significant increase ($p < .001$) in internet access (by 12% to 71.4%), mobile connectivity (*75%),* and the adoption rate of HIT (30%) among cancer survivors. Although they did not examine the regular reliability of connection between rural and urban populations, increased mobile connectivity has the potential to increase regularly reliable online connection. Nonetheless, digital divide between population subgroups such as the urban and rural due to material access could impact the cancer survivor's decision to select technology for HIS to manage health or the impact of the use of technology for HIS on their health self-efficacy and HIS experiences.

The benefits of technology for patient activation and health promotion are well documented (Jackson et al., 2016; Shneyderman et al., 2016). Technology is a communication medium that allows health promoters to engage patients in self-care behaviors and promote reliable online health information websites, videos, and interactive support channels. Noting a 10% increase in the use of social media for obtaining and generating health information from 67% in 2012 to 74% in 2014, Jackson et al. (2016) analyzed the 2013 HINTS data ($n = 2284$) to determine the impact of the use of social media (per the Communication Channel theory) on the patient's use of HIT for tracking health information and communicating with healthcare professionals using email or text and tracking their health. Jackson et al. (2016) found HIT engagement was significantly associated with social media use (visited a social media network: OR =2.00, 95 % CI = 1.33, 3.01, $p < .001$; watched health-related YouTube videos: OR = 2.25, 95 % CI = 1.51, 3.34, $p < .0001$; shared health-related information on social media: OR = 2.22, 95 % CI = 1.33, 3.71, $p < .002$). They also found that the likelihood of having Internet access was higher among respondents with a family history of cancer, χ^2 (2, $N = 1264$) =14.37, $p = .02$, or better health status, χ^2 (1, $N = 1966$) = 49.39, $p <.0001$. Several researchers reported a positive association between the technology-based HIS and screening adherence (Shneyderman et al., 2016), healthy behaviors (Miller et al., 2018), and improved psychosocial and emotional health with the participation in the online social support services (Bouma et al., 2015; Domínguez & Sapiña, 2017). Therefore, HIS technology use can be a means to better access to health information for better health.

In summary, per the selective process of the theory of self-efficacy, persons would continue to use a medium for the desired self-efficacy until the medium no longer serves their purpose. Cancer survivors who use technology for HIS would be expected to have some level of technology literacy because technology-based HIS depends on the person's technology literacy skills to search, share, and exchange health information (oral, electronic, visual, written) (Poureslami et al., 2016). Even the cancer survivors with adequate levels of technology literacy could experience access or connection disruptions (i.e., due to the rural/urban digital divide).

Per the cognitive concept, health literacy (access to health information) and mental health (i.e., depression) could be confounders for predicting a person's self-confidence and HIS experiences. Although health insurance and financial constraints can also mediate the material access to the interventions (affordability of the prevention or treatment), persons with a high health self-efficacy might seek more affordable alternatives. Per the selective concept, digital divide could be a confounder for predicting the use of technology for HIS and HIS experiences among cancer survivors who seek health information.

Literature Related to Key Variables

This section presents literature review on the study variables: *the use of technology for HIS*, *health-related self-efficacy*, *positive HIS experiences*, and *survivor's sociodemographic and clinical characteristics*. This section presents the real-world definition of each variable used by other scientists (including measurements, operationalization, and study methods), seminal and recent scientific knowledge about each variable, and the gaps in the knowledge.

Use of Technology for HIS

The *use of technology for HIS* was a predictor variable in RQ1 and RQ2 and predicted variable in RQ3. As discussed above, individuals have options for searching health-information, and how individuals seek health information is a controllable and operationalizable HIS construct for decision-making and health actions. Several academic and industry thought leaders recommended the use of electronic devices such as computers, mobile and smartphones, and tablets to access electronically available health information (Haase, 2019). Scientists also recommended the online availability of health information and support resources for survivorship for anytime accessibility via the Internet or mobile apps (Allsop et al., 2018; Davis et al., 2019; Hochstenbach et al., 2015). Commonly used online cancer survivorship resources include public websites, virtual cancer communities and support groups, online cancer education sources (Fischer et al., 2014). Consumers use a web browser or mobile app on a smartphone to search and access information on the Internet or electronic health platforms (Bouma et al., 2015; Y. Jiang et al., 2017). The Internet is one of the most common sources of health information for 92% of the young adults aged 18-39 years (Mooney et al., 2017), 60% of the adult survivors of childhood cancers (Miller et al., 2018), and adults with internet literacy skills (Jacobs et al., 2017). Between 36% to 60% of the cancer survivors also used social media platforms (e.g., shared information on internet sites, watched health-related YouTube videos) for psychosocial support (Miller et al., 2018) and emotional well-being (S. Jiang, 2017). Therefore, participation in an online forum or support group (Jackson et al., 2016), the use of the Internet, social media, and YouTube videos (Domínguez & Sapiña, 2017; Zucco et al., 2018) are means of seeking HIS.

However, the use of mobile health (i.e., mHealth) apps that connect with healthcare or private electronic health systems were not commonly associated with HIS. Y. Jiang et al. (2017) studied the acceptance and use of electronically accessible health information source (i.e., eHealth) and mHealth apps (for HIS, accessing patient portals, patient-provider communications) among cancer survivors using the 2014 HINTS dataset (*n*=3677). Y. Jiang et al. (2017) found that most of the study participants reported having Internet access (73.9%), trusted online cancer information (68.9%), and the importance of electronic access to personal health information (67.7%). However, less than half had electronic means (40.4%) or mobile apps (23.4%) to access health-information, and less than half (44.7%) had an interest in electronic patient-provider communications involving medical information (Y. Jiang et al., 2017). The use of wearable technologies for tracking physical activity (e.g., Fitbit) was only effective for activity but not for inactivity nor for awareness about the importance of avoiding unhealthy behaviors such as sedentary behaviors (N. H. Nguyen et al., 2017). The use of mHealth was effective in engaging patients in their follow-up care (Rico et al., 2017), achieving health behavior goals, making appointments, and tracking their health (Bhuyan et al., 2016). However, nearly half (45%) of the users who downloaded mHealth apps on their devices stopped using it at some point (Bhuyan et al., 2016). Bhuyan et al. (2016) reported short-term use of mHealth apps for health maintenance, and the younger age (relative to each 10-year increment), insured, and urban respondents were more likely to use mHealth apps than their counterparts for health maintenance. Bhuyan et al. (2016) also found good health, normal weight (not obese), confidence in the ability to take care of themselves, and multi-morbidity were significant predictors of the use of mHealth app. The studies revealed that persons tend to use wearable technologies and mHealth apps to maintain or track health rather than seek for HIS to address health issues. Therefore, wearable technologies and mHealth apps would not commonly used technologies for HIS. Instead, the commonly used technologies via electronic devices such as computers, smartphones, and tablets *for HIS* would be searching the Internet, viewing YouTube videos, and participating in online forums and support groups with similar health conditions.

The use of each technology (used Internet, participated in social media, watched YouTube video) is commonly measured in terms of yes or no values (Domínguez & Sapiña, 2017; Jackson et al., 2016; S. Jiang & Liu, 2020). Jackson et al. (2016) used the HINTS yes/no questions (*have you participated in an online forum or support group for people with a similar health or medical issues, have you shared health information on social networking sites, such as Facebook or Twitter, have you watched a health-related video on YouTube)* for the use of social media and YouTube. S. Jiang and Liu (2020) also used the HINTS yes/no survey questions to measure Internet use for HIS. Domínguez and Sapiña (2017) asked the yes/no question about the use of Internet, social media, and YouTube for HIS in their semi-structured questionnaire used to guide their qualitative study on the accessibility, advantages and concerns of Internet use among adolescents and young adults with cancer (*n* = 20). Zucco et al. (2018) also asked yes/no type questions for antibiotic-related information-seeking on the Internet and social media forums. Therefore, the *use of technology for HIS* could also be a categorical variable with two attributes (Did not use any technology: no Internet usage, health-related online forums participation, and Watched YouTube video; Used technology: used Internet, participated in health-related social media forums or groups, or watched health-related video on YouTube). The corresponding type of technology used for HIS could be the Internet, online forums, or YouTube.

There is growing body of research on the predictors, prevalence, and trends of technology-based HIS and the association between technology-based HIS and patient’s engagement in the use of HIT and healthy behaviors. Zucco et al. (2018) found a high prevalence of Internet use and health-related social media participation among the parents of children in six schools in Italy for making antibiotic-related medical decisions, including self-medication without consultation with physicians (Used Internet: 90%, *n* = 885; social media: 49%, *n* = 751). Although Zucco et al. did not study cancer-related health decisions, the authors found a potential motivation for HIS (i.e., healthcare costs or financial ability) and parents who use Internet or social media for their children’s health might do the same for their health.

Jackson et al. (2016) also confirmed a rising trend in the use of Internet and social media participation. Jackson et al. also reported a high prevalence of Internet use (78%, *n* = 2284) and social media (76 %; *n* = 1632) participation among Americans who responded to the 2013 HINTS 4 Cycle 3 survey. Jackson et al. also found a higher likelihood of HIT engagement among the users of social media.

Holmes, Bishop, and Calman (2017) used mixed methods design to study the motivation for the use of the Internet for finding information for making decisions on the use of complementary (for managing HRQOL) and alternative medicine (for better treatment options) among breast cancer survivors. Holmes et al. (2017) used the Theory of Planned Behavior to design the study, and selected breast cancer survivors who had completed medical treatment (mean age = 56 years), were internet users and had completed treatment. Holmes et al. (2017) conducted interviews until data saturation (*n* = 11), and they found the Internet use played a key role in the women's decision-making process and the self-management of cancer side-effects and treatment. Most of the study participants reported searching the Internet and participating in online forums to find information because their healthcare professionals lacked knowledge or time to address their unmet cancer-related health information needs (Holmes et al., 2017). As a result, unmet health information from healthcare motivated them to use the Internet and online forums to find information despite disapproval from social networks or healthcare providers (Holmes et al., 2017). Although Holmes et al. examined the use of the Internet and online forums for seeking health information among cancer survivors, these authors did not examine the relationship between *the use of technology for HIS* and *health-*

related self-efficacy in caring for themselves. The small sample size, lack of considerations for comorbidities would limit the generalization of the study findings (Holmes et al., 2017). Holmes et al. did not explain the quantitaive and qualitative design elements and variables of each section. However, the study confirmed the importance of assessing the *use of technology for HIS* among cancer survivors, and the current study would expand upon the findings by Holmes et al. (2017).

Studies on the correlates of *the use of technology for HIS* were limited to patients' engagement in healthy behaviors and HIT engagement. Jackson et al. (2016) explored the association between the use of Internet, online social media forums, and YouTube and HIT engagement but not HIS. None of the studies assessed the impact of *the use of technology for HIS* on *health-related self-efficacy* and *positive HIS experiences*. Although Y. Jiang et al. (2017) recognized the importance of HIS, the authors did not examine the technology-based HIS nor the relationship between the *use of technology and HIS*, *health-related self-efficacy*, HIS experiences nor clinical factors such as diagnosis of diabetes, hypertension, heart disease, lung disease, or mental health. Although Bhuyan et al. (2016) studied the use of mHealth apps for HIS behaviors, they did not include the use of other technologies (Internet, health-related online social media forums, YouTube) nor the influence of the *use of technology for HIS* on self-reported confidence in caring for their health (i.e., *health-related self-efficacy*). Literature search did not produce any other literature that covered these gaps, despite the benefits of HIS and potential of technology in improving access to health information for enhancing self-confidence in the self-management of health.

In summary, *the use of technology for HIS* surfaced as a supportive factor in cancer survivorship interventions for the self-management of satisfactory HRQOL. Findings on *the use of technology for HIS*, disparities in access to technology for HIS (Greenberg et al., 2018), the impact of internet in reducing or perpetuating disparities in health information availability (Jacobs et al., 2017) and the use and acceptance of technology for self-management (Greenberg et al., 2018; Y. Jiang et al., 2017) help guide public health priorities in improving access to health information and reducing disparities in health outcomes. Clinical trials on the use of technology for patient engagement in the self-care and monitoring activities demonstrated that the use of technology in self-management serve to better public health (Hall et al., 2018; N. H. Nguyen et al., 2017; Rico et al., 2017).

However, there were still many gaps in the scientific understanding about the *use of technology for HIS*. Most studies included the sociodemographic predictors (e.g., age, sex, race) of HIS behaviors and Holmes et al. (2017) and Mooney et al. (2017) shed light on cancer survivors' motivation for seeking HIS (i.e., closing health information gaps for self-care). As noted above, the impact of cancer survivor's *use of technology for HIS* on their *health-related self-efficacy* and *positive HIS experiences* among cancer survivors who seek health information was lacking in all studies in the literature review.

S. Jiang and Liu (2020) recommended the need for more research on technology based HIS among cancer survivors. Abubakari et al. (2016) recommended future research on barriers or promoters of self-management which can inform different forms of health promotion, including the use of digital platforms (i.e., the use of technology) for enhancing knowledge and self-care efficacy for self-management programs. Greenberg et al. (2018) recommended future studies examine the impact of *the use of the technologies* on patient-reported outcomes. One patient-reported outcome of interest is the self-confidence needed for self-management. In the current study, I aimed to close some of these gaps by exploring the health-related self-efficacy with *the use of technology for HIS* to contribute to the growing body of knowledge about HIS and health-related self-efficacy.

Domínguez and Sapiña (2017) recommended a broader study of the use of social media and participation in social networks for better self-management of their unmet needs. Jackson et al. (2016) recommended continued monitoring of the HIS behaviors and predictors of HIS behaviors for continuous improvement in the public health interventions and for changing landscape. I used these recommendations and the evidence on the rising trends on *the use of technology for HIS* to justify continued research on the use of technology for HIS for self-management.

Health-Related Self-Efficacy

Health-related self-efficacy was the predicted variable in RQ1. Self-confidence is a self-assessed measure (or strength) of self-efficacy, and the level of confidence is positively correlated with self-efficacy (Kleitman & Stankov, 2007). Measuring confidence involves cognitive processing involving recognition, inference, intuition, guessing, and openness to new knowledge and experiences (Kleitman & Stankov, 2007). A high confidence rating corresponds with immediate recognition from experience or knowledge and inference from logical analysis and conclusion in the absence of readily available evidence (Kleitman & Stankov, 2007; Roediger & DeSoto, 2014). In contrast, the lowest level of confidence is associated with guessing (Kleitman & Stankov, 2007). Therefore, self-confidence is the level certainty (or uncertainty) persons hold in their ability to perform tasks for their personal goals, and a very high self-confidence score would correspond with high self-efficacy for personal health goals. More specifically, self-confidence in taking care of health would refer to a one's ability to recognize and solve health issues by making health decisions and taking actions (e.g., engaging appropriate healthcare and social services) to attain the desired health goal (Foster & Fenlon, 2011; Y. Jiang et al., 2017; Miller et al., 2018). Therefore, in the current study, self-reported self-confidence in taking care of health refers to health-related self-efficacy (i.e., one's assessment of their ability to take good care of their health).

Health-related self-efficacy, as a measured level of health self-efficacy, would be measured by an ordinal rank or Likert scale. Several researchers used the HINTS questionnaire item "*the ability to take good care of health*" with the 5-point scale (*Completely confident, Very confident, Somewhat confident, A little confident, Not confident at all) response options for* measuring health-related self-efficacy (Bhuyan et al., 2016; Finney Rutten, Hesse, et al., 2016; S. Jiang & Liu, 2020). The Perceived Medical Condition Self-Management questionnaire also uses the 5-point scale to measure HIV self-efficacy (Wild et al., 2018) and diabetes self-efficacy (Abubakari et al., 2016). Peters et al. (2019) used the 10-point Chronic Disease Scale (about how well someone feels) to measure health self-efficacy to study the association between health-related self-efficacy and HRQOL. However, Peters et al. (2019) did not explain how the Chronic

Disease Scale was adopted to measure confidence in the ability to take care of their health. Literature search did not produce any other studies that used a 10-point scale or the Chronic Disease Scale to measure self-confidence. Therefore, the 5-point scale is a commonly used measure of health-related self-efficacy.

Although seeking health information is vital for the self-management of diseases, studies on the correlation between HIS and health self-efficacy were limited. Abubakari et al. (2016) found perceived health-related self-efficacy significantly explained the variability in the self-management of diabetes, and the time since the diagnosis and the disease severity significantly predicted the *health-related self-efficacy* in the self-management of diabetes. Finney Rutten and Hesse et al. (2016) reported the number of chronic diseases inversely related with self-care self-efficacy. Abubakari et al. (2016) used the self-efficacy theory to study the association between the level of health self-efficacy and the degree of adherence to eight self-management activities of diabetes. Abubakari et al. (2016) used several standard health questionnaires (e.g., Perceived Diabetes Self-Management Scale, Perceived Medical-Condition Self-Management Scale) to collect data on the various self-management elements such as disease severity, perceived control and the number of symptoms. Abubakari et al. (2016) reported a significant association between disease severity, time since diagnosis, and long-term perceptions about diabetes were significant in predicting patient's self-confidence in the self-management of their health. For instance, Abubakari et al. (2016) found self-confidence explained the variability in the adherence to the self-monitoring of blood glucose by 14% ($\beta = 0.66$; 95% CI = 0.07, 1.25; $p < 0.05$) and foot care by 18%

($\beta = 0.28$; 95% CI = 0.06, 0.49; $p < 0.01$). However, the study sample ($n = 123$) was too small to examine the eight predictors of self-management. Despite this limitation, the study was guided by the self-efficacy theory, and the definition and operationalization of *health-related self-efficacy* used in the study were consistent with other studies. Therefore, disease severity (or physical disabilities) might be confounders of self-confidence.

Finney Rutten and Hesse et al. (2016) performed a secondary analysis of the HINTS 2012-2013 dataset to study the impact of patient-centered communications on patient's health self-efficacy. Finney Rutten and Hesse et al. (2016) found that positive patient-provider communications were significantly and positively associated with self-confidence among persons ($n = 3630$, $\beta = 0.26$, $p < 0.0001$). Moreover, the increasing number of chronic diseases (one condition: $\beta = 11.06$, $p < 0.0001$; two conditions: $\beta = 7.82$, $p = 0.0002$ and depression/anxiety were significantly (no depression: $\beta = 4.34$, $p < .01$) associated with reduced levels of health-related self-efficacy. As a result, depression and the number of chronic diseases might be confounders of health self-efficacy.

Peters et al., (2019) collected data from 15 primary care practices in one region of England (n=848 from 2983 eligible) and well-established questionnaires (Long-Term Conditions Questionnaire, European Quality of Life [EuroQol] 5 Dimension 5 Level, EuroQol Visual Analog Scale, Disease Burden Impact Scale) to collect data on the various health conditions examined in the study. Despite using a different scale to measure the ability to take care of health, Peters et al., (2019) also found that the presence of severe physical or mental disability significantly impacted health-related self-efficacy. Agreements in the findings among these studies across different contexts (cultural, country) and data collection instruments add to the strength of the evidence that disease burden and severity of the issue could be potential confounders of *health-related self-efficacy*.

S. Jiang and Liu (2020) studied the trends of material (ease of Internet access) and mental (trust in online information; HIS skills) axes of the digital divide and the impact of the digital divide on HIS among cancer survivors. Based on 2011, 2013, and 2017 iterations of the HINTS survey, S. Jiang and Liu (2020) reported an increase in the material access over time ($F[2, 1523] = 15.58$, $p < .001$), and participants did not report any significant differences in the mental access of digital divide over time. Both material and mental access were significantly associated with HIS behaviors, and the trust dimension of the mental access was significantly associated with HIS, while the association between HIS and the HIS skills dimension was not significant (S. Jiang & Liu, 2020). The findings of this study add to evidence that the digital divide in the material access could be a confounder of self-efficacy, which was more prominent among the rural than the urban population (Greenberg et al., 2018). Greenberg et al. (2018) did not examine *the use of technology for HIS* among activated cancer survivors for self-management nor decisional or self-care self-efficacy. These upward trends in the material access to online health information sources and increasing trends in the technology-based HIS are the foundational elements in helping cancer survivors close any gaps in their cognitive factors for health self-efficacy.

To date, scientific knowledge on the impact of *the use of technology for HIS* and *health-related self-efficacy* among cancer survivors who seek health information was limited to none. Studies on the correlates of self-confidence either lacked an examination of the relationship between technology-based HIS and health-related confidence among cancer (S. Jiang &Liu, 2020), or studies on this association targeted population other than the cancer survivors (Finney Rutten & Hesse et al., 2016). Finney Rutten and Hesse et al. (2016) studied health self-efficacy among the U.S. population with chronic conditions, including cancer (*n* = 419; 9% of the respondents). However, Finney Rutten and Hesse et al. included cancer in the summative counts of other diseases and did not present information specifically for the cancer survivors. Although Peters et al. (2019) separated their findings among cancer survivors, the study examined the relationship between disease burden and self-efficacy rather than HIS and self-efficacy. Other studies on self-efficacy targeted other chronic diseases such as Type 1 and Type 2 diabetes (Abubakari et al., 2016) and HIV (Wild et al., 2018). As a result, none of the studies assessed the influence of technology based HIS on self-reported self-efficacy (i.e., health self-efficacy) nor on the HIS experiences, particularly cancer survivors who seek health information, even though self-efficacy and self-confidence are the expected outcomes of self-management interventions.

In summary, per the literature review, *health-related self-efficacy* is commonly measured with a Likert scale with response options varying from no confidence (unable to take care) to excellent (having no barriers to taking good care of health). Although there is much research on some self-efficacy domains as predictors or predicted variables, the literature search did not produce any recent studies which explored the relationship between technology-based HIS and *health-related self-efficacy*, particularly among cancer survivors. However, the data on HIS behaviors in the reviewed studies revealed health literacy (ability to access health information), depression, and debilitating medical conditions (i.e., poor or less than good health status) are potential confounders of HIS and health-related self-confidence, and consequently the *health-related self-efficacy*.

Positive HIS Experiences

The variable, *Positive HIS experiences,* was the predicted variable in RQ2. HIS experiences with any source can impact information-seekers' access to health information. HIS experience has four dimensions: effort, frustration, quality concerns, comprehension (Paige et al., 2019). High levels of effort to get or find the needed health information can overwhelm or frustrate the information-seekers and lead to negative experiences while the opposite to a positive experience. There is evidence that *positive HIS experiences* reduce anxiety and improve health-related communications and self-care abilities (Emanuel et al., 2018). Therefore, per these dimensions of HIS experience, *positive HIS experience* would correspond with health-information seeker disagreeing with frustration, effort, poor quality, and inaccessibility of health information.

Due to the presence of a four- and five-point Likert scale used in the U.S. versus other countries, Paige et al. (2019) examined the validity of the four-point Likert scale used in the HINTS survey instruments for measuring HIS experiences. The four-point Likert scale has four response options (Strongly agree, somewhat agree, somewhat disagree, strongly disagree), and the five-point Likert scale has an "agree" option in the center (Paige et al., 2019). For instance, S. Jiang and Street (2017) used the 5-point Information Seeking Experience Scale, which includes agree as the midpoint response. Paige et al. (2019) conducted a study on the construct validity of the HINTS scale with an online survey of U.S. adult participants with one or more chronic diseases (*n*=684). Paige et al. (2019) found that persons with chronic diseases were less likely to select the “agree” response and concluded that the 4-point scale was sufficiently adequate for measuring HIS experience. However, Paige et al. (2019) noted that the inclusion of agreeing does not threaten the construct reliability. The HINTS instrument uses a four-point scale (Strongly Agree, Somewhat Agree, Somewhat Disagree, Strongly Disagree) (Emanuel et al., 2018; Finney Rutten, Agunwamba, et al., 2016; S. Jiang & Liu, 2020; Waters et al., 2016). As a result, positive and negative experiences can be constructed from the agree and disagree response options, where positive HIS experiences could correspond with the disagreement response options for each dimension of the HIS experience, and negative with the agreement options.

Recent studies on the HIS experiences among cancer survivors were extremely limited, and a few studies on the subject lacked an explanation of the data measurement and design for the HIS experience variables. Chua et al. (2018) studied two dimensions (quality concern and comprehension), and Mooney et al. (2017) studied effort. Both Chua et al. (2018) and Mooney et al. (2017) discussed their respective HIS dimensions in terms of positive or negative, and both studies lacked an explanation of the measurement design. Holmes et al. (2017) used a qualitative study approach to gain deeper insights on the participant’s positive/negative (dichotomous) quality-related HIS experiences, and it appeared to be delineated along the agree or disagree sentiments. Therefore, there was also precedence for constructing positive of negative experiences along the agree and disagree delineators from a multi-point scale.

An association between the educational level and beliefs and HIS experiences was reported in multiple studies (Emanuel et al., 2018; Holone, 2016; S. Jiang & Street, 2017; Waters et al., 2016). Among the cancer survivors who sought health information and responded to the 2011-2012 HINTS 4 survey, Emanuel et al. (2018) found lower educational levels had a significant influence on the fatalist beliefs and the negative HIS experiences ($n = 3070$, $\beta = -.19$, $p < .001$), and negative HIS experiences also predicted fatalistic beliefs ($\beta = .22$, $p < .001$). These findings were consistent across three samples (Emanuel et al., 2018), and were consistent with the findings by Waters et al. (2016) among the participants of the 2013 HINTS dataset. Waters et al. (2016) also found a significant negative association between HIS experiences with pessimistic beliefs and lower belief in the multifactorial model of cancer causation. Waters et al. (2016) did not study technology-based HIS experiences.

A positive association between *positive HIS experiences* and health outcomes was reported by S. Jiang and Street (2017). Per the user-media-message framework, S. Jiang and Street (2017) found *positive HIS experiences* significantly moderated the association between technology-based HIS and perceived social support ($\beta = 0.12$, $p < 0.05$), which indirectly affected the support-mediated physical, emotional, and psychological outcomes. S. Jiang and Street (2017) studied a one-way path from Internet use to health status. However, they did not consider the diversity of technology (e.g., smartphones, social media networks, YouTube) for HIS nor the experiences of cancer survivors. However, S. Jiang and Street (2017) used a convenient sampling design, which can result in the researcher or response bias. Moreover, frustration can also emerge from pop-up advertisements on the web page, computer and Internet speed, and unknown search algorithms that rank and order the web content (Holone, 2016). However, any pop-up, connectivity, and search engine challenges would difficult to isolate in any population-wide uncontrolled study.

Chua et al. (2018) studied the prevalence of HIS behaviors, HIS experiences, among other factors, among 411 cancer patients, selected from a National Cancer Center in Singapore. Chua et al. (2018) examined the understandability of the information found on the Internet. They found about nearly half (49%) of the respondents searched the Internet first, and nearly (46.6%) of them found the information was easily comprehensible. Although their findings are non-generalizable due to non-representative population and lacking considerations for the diversity of technology, they highlighted the importance of research on the technology-based HIS for cancer survivors and examining the impact of the HIS technologies on the HIS experiences.

Mooney et al. (2017) conducted a qualitative study to examine cancer survivors' HIS experiences using internet resources. Mooney et al. (2017) confirmed the previously reported challenges of difficulty in locating relevant and trusted information on the internet (e.g., too much information on the internet, not specific to the unmet needs, not trustworthy). However, the study by Mooney et al. (2017) had a small and non-representative sample (*n* = 25; sex: males = 8, females = 17; Race: 100% White, 24 non-

Hispanic White and 1 Hispanic White) and was limited to the experiences of adolescents and young adult survivors of cancer (aged 18 – 39 years).

Holmes et al. (2017) had also examined cancer survivors’ HIS experiences in their mixed-methods study. The study participants reported positive HIS experiences (not getting upset or frustrated with the vast amounts of information on the Internet) and concerns about the legitimacy of the information. Because the study was guided by the theory of planned behavior, the findings (of positive HIS experience), the findings might not address complex predictors of HIS experiences, such as physical or mental disabilities. The study was also not generalizable due to its small sample size (*n* = 11), non-representative population (breast cancer survivors, mean age = 56 years), and the guiding theoretical framework. Moreover, the study lacked transparency in the research design and methodology, which makes it difficult to assess the validity of the constructs and findings. However, cancer survivors’ motivation for technology based HIS (closing the health information gaps for health decision and action) and the reported experiences with HIS, and their health outcomes suggest that the use of technology might serve to improve self-management interventions. In the current study, I aimed to contribute to the research started by Holmes et al. (2017) by enhancing the scientific understanding of technology-based HIS among cancer survivors.

There was a significant demand on future research on HIS experiences, even though scientific knowledge on the predictors, prevalence, and impacts of HIS experiences on health outcomes was growing. As discussed before, Finney Rutten, Agunwamba, et al. (2016) also described the increased likelihood of HIS among cancer survivors following diagnosis or experience of treatment-related side effects and the increasing trends towards greater HIS. Among cancer survivors, Finney Rutten, Agunwamba, et al. (2016) found the HRQOL and unmet health information for managing HRQOL was a significant predictor of HIS. Multiple scientists called for future research to investigate HIS experiences in relation to new information-seeking modes and sources. Small-scale studies by Holmes et al. (2017) and Mooney et al. (2017) highlight the importance of continued research on HIS experiences. Emanuel et al. (2018) recommended future reseach on the affective components (e.g., frustrating experiences) of HIS, and Waters et al. (2016) recommended future studies examine the technology based HIS experience. Finney Rutten, Agunwamba, et al. (2016) recommended future studies examine the cancer survivors' HIS experiences to inform interventions for better self-management of cancer by cancer survivors. The need for understanding HIS experiences from secondary sources (other than health professionals) among cancer survivors was also proposed by Germeni, Bianchi, Valcarenghi, and Schulz (2015) for assessing patient needs and developing evidence-based and targeted information provisioning. In particular, the protocol proposed by Germeni et al., (2015) recommended collecting data on survivor becoming frustrated or overwhelmed by the information. S. Jiang and Liu (2020) recommended additional studies on the technology-based HIS behaviors, which was an undertaking of the current study.

Even though there were a limited number of studies on HIS experiences, and most studies on chronic conditions and HIS were old and lacked focus on cancer survivors, those studies confirmed the importance of the research on HIS experiences for informing public health policy. A few additional studies that explored HIS experiences were outdated and may not have accurately reflected the current experiences. Wigfall and Friedman (2016) conducted a systematic and scoping review of the use of HINTS datasets for HIS. The literature review presented on the concepts and variables confirmed earlier findings by Wigfall and Friedman (2016), who found 22 experimental studies focused on HIS behaviors. Four of the studies were on the predictors of HIS behaviors, and 18 on the association between HIS behaviors and various cancer outcomes such as cancer knowledge, information-seeking self-efficacy, beliefs, and prevention behaviors among cancer information seekers. Except for one, all studies reviewed by Wigfall and Friedman were published between 2006 and 2015. Several studies reviewed by Wigfall and Friedman, such as Arora et al. (2008) and Vanderpool et al. (2009), reported a high prevalence of negative HIS experiences among cancer survivors who sought health information. Conflicting but non-generalizable findings of cancer survivors' HIS experiences were reported by Chua et al. (2018), Holmes et al. (2017) and Mooney et al. (2017). No other studies were found on HIS experiences among cancer survivors who seek health information. Both Holmes et al. (2017) and Mooney et al. (2017) confirmed HIS experiences impact cancer survivors' health outcomes and self-management abilities.

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In summary, positive HIS experiences are important for the self-management of cancer, and negative HIS experiences can promote fatalistic beliefs and avoidance of healthy behaviors. The literature also confirmed that education level, urbanicity (for material access), and mental health could be confounders of HIS experiences. Moreover, current literature on HIS experience was limited and old, and many reseachers recommended further study on HIS experiences, particularly relative to the use of technology for HIS, for internvention planning. By studying RQ2, I aimed to close some of these gaps in the collective knowledge.

Survivors' Sociodemographic Characteristics

Survivor's sociodemographic characteristics *were a set of predictor variables in RQ3a.* All studies in the literature review included descriptive or inferential statistics on the sociodemographic characteristics of their study participants. *As per the literature review on HIS and the use of technology, age, sex, education, and income were associated with HIS and y*ounger age, female sex, higher educational attainment level, un- or under-insured, and reliable internet access and higher income were associated with technology-based HIS (Abubakari et al., 2016; Bhuyan et al., 2016; Jacobs et al., 2017; Sedrak et al., 2020; Shneyderman et al., 2016). There was some evidence that race was not a predictor of technology-based HIS (Finney Rutten, Agunwamba, et al., 2016; Miller et al., 2018; Rooks et al., 2019) and the evidence on the association between technology-based HIS and income was non-conclusive (Somera et al., 2016). Miller et al. (2018) reported age, sex, insurance status, and race influenced HIS. Jacobs et al. (2017) found age, socioeconomic status, gender, education, and internet skills predicted primary sources of information among cancer survivors who sought health-information. Younger survivors had a higher likelihood of using the Internet as a first source of health information than older adults, and older survivors with family history of cancer were more likely to prefer healthcare providers (Finney Rutten, Agunwamba, et al., 2016;

Jacobs et al., 2017). Somera et al. (2016) confirmed the predictors (education, age, income) of the use of the Internet for HIS, and females were more likely to seek HIS than males in Guam and the US. The digital divide between urban and rural identified by Greenberg et al. (2018) could impact any population without the affordability of a reliable internet connection. Moreover, the accelerated access to telehealth (American Speech-Language-Hearing Association, 2020; Federal Communications Commission, 2020) and online learning due to the 2019 coronavirus pandemic (C. Li & Lalani, 2020) might soon reduce the digital divide in technology-based HIS noted by Greenberg et al. (2018). Therefore, urbanicity did not surface as a direct predictor of HIS or confounder of health-related self-efficacy as motivated persons could switch to another accessible HIS source, and those using technology for HIS were assumed to have sufficiently reliable internet access for health-related self-efficacy.

A person's race and educational attainment have been linked to the trust in the health information source (Richardson et al., 2012), and violation of trust and privacy can result in individuals disassociating from the source. Per a 2013 study, persons' age, sex, race, and education were independent and significant predictors of the user's protective practices on the Internet (e.g., younger age: $\beta = -.20$, $p < .001$, higher education: $\beta = .27$, $p < .001$) and social networking sites ($n = 1002$, younger age: $\beta = -.41$, $p < .001$; Whites race: $\beta = .09$, $p < .05$; female gender: $\beta = .10$, $p < .05$; higher education: $\beta = .27$, $p < .001$) (Xie et al., 2019). Income did not significantly predict users' online privacy or protective practices on the Internet, $\beta = -.03$, $p = .19$, and social networking sites, $\beta = -.00$, $p = .92$ (Xie et al., 2019). Consequently, the study on the influence of age, sex, race, education, and income on technology-based HIS would be necessary to update the knowledge because technology and socioeconomics can impact anyone's behaviors. These sociodemographic variables were generally measured as nominal for sex (female, male), categorical for race/ethnicity, ordinal for education, and ordinal or continuous for age and income (Bhuyan et al., 2016; Jacobs et al., 2017; Shneyderman et al., 2016).

Survivors' Clinical Characteristics

Survivor's clinical characteristics were a set of predictor variables *in RQ3b.* Chronic diseases such as depression, cardiovascular diseases, diabetes, and respiratory issues such as difficulty breathing are among the cancer comorbidities due to the well-documented long-term adverse effects of cancer treatments (Arndt et al., 2017; Cohen & Derubeis, 2018; Dehghani et al., 2020; van Leeuwen et al., 2018). There were higher odds of HIS among persons with these chronic diseases and lower odds of health-related self-efficacy among persons with multimorbidity and depression (Finney Rutten, Hesse, et al., 2016; Rooks et al., 2019). As a result, the clinical factors, in the current study, included ever having a clinical diagnosis of the following: diabetes or high blood sugar (yes/no); high blood pressure or hypertension (yes/no), a heart condition such as heart attack, angina, or congestive heart failure (yes/no); chronic lung disease, asthma, emphysema, or chronic bronchitis (yes/no); depression or anxiety disorder (yes/no).

The literature search resulted in no recent research on HIS among cancer survivors with chronic comorbidities. Due to the limited knowledge on the clinical factors of cancer survivors and their HIS behaviors, literature review scope was expanded to the study of HIS among persons with chronic conditions because the significance of

HIS for self-management self-efficacy of chronic illnesses is well documented (Bhuyan et al., 2016; Dean et al., 2017). Bhuyan et al. (2016) used the 2014 HINTS survey to examine the use of mHealth apps for HIS among U.S. adults. Bhuyan et al. (2016) used the HINTS survey items with yes/no response for having a clinical diagnosis of diabetes, high blood pressure or hypertension, heart conditions, and respiratory conditions. They categorized the chronic diseases into zero, one, and two or more chronic conditions, and they reported that multimorbidity significantly increased the odds of using mHealth for self-management as compared to no comorbidities. The findings may be limited because Bhuyan et al. (2016) grouped the population into three races (White, African American, Other) and considered the count of comorbidities (rather than specific conditions). The findings by Bhuyan et al. (2016) provided a basis to identify the personal factors associated with technology-based HIS among cancer survivors.

Guided by the theory of uncertainty management, Rooks et al. (2019) tested their hypothesis that there is an association between the number of chronic illnesses and HIS, and that race/ethnicity would not influence the relationship. Rooks et al. (2019) also analyzed the 2007 U.S. Health Tracking Household Survey (HTHS) dataset. They found a significant and positive association between the number of chronic illnesses and HIS, and there were no differences in the association due to race or ethnicity. Although race is associated with socioeconomic status and health insurance with health literacy and healthcare access, race did not influence HIS behaviors among information-seekers (Rooks et al., 2019).

Both Rooks et al. (2019) and Bhuyan et al. (2016) reported consistent findings (a positive correlation between the number of chronic conditions and HIS) even though the two studies were conducted using different datasets and data sources collected seven years apart (2007 versus 2014). Dean et al. (2017) also used the 2007 HTHS survey to examine the relationship between HIS, predisposing factors sociodemographic factors, and health-related self-efficacy (e.g., prevent symptoms, communicate with the doctor, know when to get medical care) among persons with chronic disease. Dean et al. (2017) found urbanity, education, and usual source of healthcare (i.e., health insurance) predicted the association between HIS and self-efficacy among persons with chronic diseases. However, Dean et al. (2017) did not explore technology-based HIS, and the study did not explicitly consider cancer survivors. Sedrak et al. (2020) conducted a secondary analysis on the 2014 Women’s Health Initiative (WHI) dataset collected using the WHI Extension Study Supplemental Questionnaire (Form 156) to understand how older patients with chronic illnesses use technology for HIS. Sedrak et al. (2020) found 60% of the older adult women with chronic conditions used technology and internet for health-related information, and recently diagnosed patients and patients with any cancer were more likely to use the Internet for HIS. However, Sedrak et al. (2020) limited the study to postmenopausal women, and the data is from 2014, while the technology and information landscape may have changed widely. Unfortunately, all the studies on the clinical factors relied on old datasets that might not apply to the modern digital era, and none of the studies targeted cancer survivors.

Dean et al. (2017) suggested further research to address the digital divide-related disparities. By studying the technology-based HIS among cancer survivors with chronic comorbidities, the study would close the information gaps about predisposing and enabling factors for improving access to health-related information. Sedrak et al. (2020) recommended further studies to understand technology-based HIS behaviors better among persons with chronic illnesses, which was my aim in studying RQ3.

In summary, the main insights from the literature review on the association between chronic diseases, HIS behaviors, and health-related self-efficacy were that persons with greater disease burden had a higher need for health information, greater disease burden was associated with HIS behaviors, and that multimorbidity mediated health-related self-efficacy. Prior research on the personal predictors of HIS and chronic diseases and the theoretical foundation served as my basis to study RQ3 because prior studies have not explored a relationship between the cancer survivors’ sociodemographic and clinical characteristics and their use of technology for HIS among cancer survivors who seek cancer.

Health Literacy

Per the self-efficacy theory and the literature review on the study variables, the ability to access health information (i.e., health literacy) was identified as a confounder for health-related self-efficacy in RQ1 and positive HIS experiences in RQ2. Health literacy has been long recognized as a determinant of health and healthy behaviors (Ashrafi-Rizi et al., 2018; Luong et al., 2012; Zide et al., 2016) and healthcare access and utilization (Nielsen-Bohlman & Panzer, 2004). In a study on the association between education and health literacy (*n* = 409) among college students in the junior and senior grades, Ickes and Cottrell (2010) found that higher levels of education are not correlated with higher levels of health literacy. In contrast, in a secondary analysis of the 2007 HINTS dataset, Richardson et al. (2012) reported that education level influenced HIS behaviors and confidence in obtaining health information (*n* = 3,243, confidence OR = 50.44, 95% CI = 0.30, 0.63). Both Ickes and Cottrell (2010) and Richardson et al. (2012) confirmed that education is an enabler of HIS behaviors. Similarly, although health insurance is an enabler of access to health care, having health insurance is not known to enhance the ability to read, comprehend, or process health information. However, James et al. (2018) reported that the level of health insurance literacy (knowledge about health insurance and the ability to access insurance) significantly moderated healthcare utilization among college students in the southern U.S. (*n* = 1450).

Arnold et al. (2017) conducted a quasi-experimental study to test the effectiveness of health literacy intervention using colorectal screening kit for colorectal cancer-related self-efficacy in 8 Federally Qualified Health Centers by giving the kits to all participants, education to one group, and nurse support for screening to the second group. About half (54%) of the participants had less than high school education. They measured self-efficacy by asking questions about their confidence in their ability to perform the screening tasks (request a test, complete it, mail it), and knowledge and beliefs about the test. They found that screening and mailing in self-efficacy significantly increased in the supported group (*p* < .0001) and decreased in the education arm (*p* <.001 for getting and mailing it and *p* < .0003 for completing it). However, they found an overall increase in the colorectal screenings in all groups. This study provided evidence that health literacy is a confounder of health-related self-efficacy.

S. Jiang and Beaudoin (2016) noted that prior literature demonstrated higher health literacy among patients who used internet-connected sources for seeking health information than other patients. The authors used the 2013 HINTS 4 Cycle 3 sample (n = 3173) to test their hypothesis that internet use is positively associated with health literacy. They constructed a dichotomous health-related internet use (yes or no) using the same definition defined in the current study for the use of technology for HIS. They retained their hypothesis (β = 17, $p < .001$) and found that education had a direct effect on the motivation for health-related internet use (β = .14, $p < .001$) and health literacy (β = .16, $p < .001$). They used the responses to the HINTS questions about person's knowledge about five healthy behaviors (i.e., knowledge of three vaccine-preventable cancers, tobacco use, food labels) to calculate respondent's health literacy score from zero to five, where a "0" indicated a lack of knowledge on the behavior and "1" knowledge. While the use of the food labels was appropriate for assessing participant's health literacy, the lack of knowledge or awareness about the other four measured elements (NCI, 2013) might not imply the inability to access or find the information when needed. Therefore, the study might have lacked construct validity. The authors also cautioned about the validity of the health literacy scale for it had not been validated by prior research and recommended considering other types of information processing.

Other researchers measured health literacy with the self-reported confidence in their ability to obtain or access health or medical information when needed (Bangerter et al., 2019; Richardson et al., 2012). Richardson et al. (2012) used a dichotomous measure of health literacy (low, high), where low corresponded with the “somewhat,” “a little,” or “no” confidence responses and high with “completely” or “very confident” responses to the 2007 HINTS question about the self-reported ability to obtain and access health and medical information. Bangerter et al. (2019) used a 5-point ordinal measure with values ranging from no confidence to completely competent. Bangerter et al. also used the 2017 HINTS 5 Cycle 1 instrument for their study on caregiver’s self-confidence in seeking health information.

Health Status

Health status is a measure of health and people living disease, and disability-free lives are among the principle objectives of Healthy People 2020 (Koh et al., 2011). Health status was one of the predictors of the HIS behaviors (Abubakari et al., 2016; Jacobs et al., 2017; Rooks et al., 2019; Shneyderman et al., 2016), health-related self-efficacy (Finney Rutten, Hesse, et al., 2016; Peters et al., 2019), and HIS experiences (S. Jiang & Street, 2017). Persons with less than good health could be most in need of patient-centered health information to better their health (Blanch-Hartigan et al., 2016). However, persons with poorer health status are more likely to report less healing relationships (Wald $F = 9.08$, $p < .001$) such as patient-provider communications (Blanch-Hartigan et al., 2016). In contrast, persons with good health had higher odds of higher levels of health literacy (OR = 1.23, 95% CI = 1.02, 1.48) (Miyawaki et al., 2015). Therefore, health-related self-efficacy and positive HIS experiences may be impacted by a person’s health status.

Health status can be measured as poor or good (Jackson et al., 2016; Miyawaki et al., 2015) or on an ordinal scale ranging from poor to excellent health (Abraham et al., 2017; Manor et al., 2000). Jackson et al. (2016) classified self-reported fair or poor health status responses in the “poor” category and good, very good, and excellent health status responses into the “good” category. Others classified health status into three categories: poor, fair, and good (Zhao et al., 2020) or excellent, good, and poor/fair (Blanch-Hartigan et al., 2016).

Literature Review Summary

Various clinical trials, conducted by health professionals, provided evidence that technologies such as mobile apps, texting, and health tracking devices were associated with increased patient engagement, self-efficacy of the targeted activities such as medication adherence, tracking health, self-confidence in specific activities, and self-esteem (Awick et al., 2017; N. H. Nguyen et al., 2017; Rico et al., 2017). As the administrators of clinical trials maintain control over the study parameters for each participant from the start to the end of the study, the findings of the clinical trials cannot be generalized to uncontrolled environments in which cancer survivors live and seek health information from any information source, irrespective of the information accuracy or reliability. However, the findings of clinical trials provided a basis for testing *the use of technology for HIS* in the real-world setting without clinical control.

Although there was much literature on the general predictors of the preference or use of technology for information-seeking, no studies to date had examined the association between the cancer survivors’ characteristics (sociodemographic and clinical) and the use of technology for HIS. Given the premise of self-management interventions in controlling chronic conditions and the role of technology in enabling timely access to health information, it was imperative to answer questions about the association between *survivors' use of technology for HIS* and their *health-related self-efficacy* and *positive HIS experiences*, and the association between *survivor's characteristics* (*sociodemographic* and *clinical*) and their *use of technology for HIS* among activated cancer survivors for improving public health interventions. As per the literature review, many researchers had documented the prevalence, trends, and predictors of HIS behaviors, the use of technology for HIS, and HIS experiences to inform the self-management public health interventions for cancer survivors. Ongoing research on technology-based HIS, predictors of HIS behaviors, HIS experiences, and health information seeker's characteristics were also indicators of the importance of examining those factors. Several researchers reported on the current disparities in eHealth and mHealth access and the trends in the Internet connectivity, access, and use.

The prevalence, trends, predictors, and correlates between the use of technology and HIS were documented in many studies. However, the impact of technology-based HIS on health-related self-efficacy and HIS experiences among cancer survivors were generally missing. Instead, future studies on the association between the health-related self-efficacy and technology-based HIS were recommended (Domínguez & Sapiña, 2017; Finney Rutten, Hesse, et al., 2016; Greenberg et al., 2018; Jackson et al., 2016; S. Jiang & Liu, 2020), which was my aim in studying RQ1.

There were several studies on the association between HIS experiences and health beliefs and healthy behaviors. However, the literature on the association between the *use of technology for HIS* and HIS experiences among cancer survivors was limited to specific subpopulation and was potentially outdated. The gaps in the knowledge and the interaction between the four processes in the self-efficacy theory provided a basis to explore the relationship between *the use of technology for HIS* and HIS experiences. Moreover, several researchers recommended closing this research gap (Finney Rutten, Agunwamba, et al., 2016; Germeni et al., 2015; S. Jiang & Liu, 2020), which was my aim in studying RQ2.

While the demographics of health-information seekers were documented in several studies, the literature on the association between the *use of technology for HIS* and survivors’ clinical factors among cancer survivors who seek health information was none to limited. Instead, most of the research was on other chronic diseases, possibly because cancer survivorship was recognized as a chronic health issue after the increase in cancer survival rates (Nekhlyudov et al., 2017). Moreover, Jackson et al. (2016) recommended regularly updating the association between the sociodemographic characteristics of the health information seekers and their HIS behaviors and how those technologies help them address their health needs. Therefore, RQ3a was studied for up-to-date knowledge and RQ3b to close the knowledge gap about technology-based HIS among cancer survivors.

Definitions

Cancer Survival: refers to the amount of time a person lives after the initial cancer diagnosis, and it does not guarantee cancer- or disease-free health status (NCI, 2019).

Cancer Survivor: refers to any living person who has a clinical diagnosis of cancer, irrespective of the time since the diagnosis or the treatment status areas *(Lavoie Smith et al., 2012).*

Health-Related Quality of Life (HRQOL): refers to the level of the physical, mental, emotional, social, psychosocial function that enables or impairs independent and healthy living (Arndt et al., 2017).

Health-I*nformation* S*eeking (HIS):* refers to individuals actively searching for, rather than passively scanning or listening to, health-related information from any source (Shim et al., 2006).

Health-I*nformation* S*eeking* B*ehavior:* refers to the way (e.g., reading print or digital/online media, watching or listening to health audio or video, communicating with health professionals, participating in discussions) people search for information (Jacobs et al., 2017).

Health-Related Self-Efficacy: refers to the persons' confidence and ability to attain desired health goals, such as managing treatment side-effects preventing disease recurrence or progression (Greenberg et al., 2018). One way to measure it is by measuring the person's self-confidence (the level of a self-reported measure of the ability to perform a task) in taking good care of their health, and the confidence can vary from no confidence (no self-efficacy) to extreme confidence (high self-efficacy) in performing the tasks to attain the desired health goal (Awick et al., 2017; Kleitman & Stankov, 2007; Vithessonthi & Schwaninger, 2008).

Positive Health Information Seeking Experience (Patient HIS Experience): refers to the low or tolerable degree of challenge in terms of effort and non-frustrating amount of information when searching for health information (Paige et al., 2019).

Second and Secondary Cancers: both refer to new cancer diagnoses following the diagnosis of an original cancer diagnosis. The second cancers may be caused by the same or different exposures (e.g., environmental or lifestyle), while the secondary cancers are caused by cancer treatments such as radiation or chemotherapy (Demoor-Goldschmidt & De Vathaire, 2019; Hoekstra et al., 2018).

Self-Reported Health Literacy: refers to the person's self-reported ability to obtain or access health or medical information when needed (Bangerter et al., 2019; Richardson et al., 2012).

Self-Reported Health Status: refers to the self-reported measure of health, ranging from poor to excellent, and persons with disease or disability might experience poor health (Koh et al., 2011).

Survivor's Clinical Factors: refer to the survivor having a clinical diagnosis of well-documented cancer treatment-related chronic illnesses. In this study, clinical factors pertain to a survivor ever having a diagnosis of diabetes or high blood sugar, high blood pressure or hypertension, a heart condition, lung diseases, and depression/anxiety disorder (Arndt et al., 2017; Cohen & Derubeis, 2018; Dehghani et al., 2020; van Leeuwen et al., 2018).

Survivor's Sociodemographic Factors: in the current study, these refer to the survivor's age, race, sex, education, and income as these factors are known to influence the HIS behaviors (Abubakari et al., 2016; Bhuyan et al., 2016; Jacobs et al., 2017; Sedrak et al., 2020; Shneyderman et al., 2016) and trust in the information source (Richardson et al., 2012).

The use of Technology for HIS: refers to a person seeking health information from electronic health information sources by looking for health or medical information on the Internet using a computer, smartphone, or other electronic means, participating in social media with persons with similar health issues or watching a health-related video on YouTube to search for health information (Domínguez & Sapiña, 2017; Jackson et al., 2016; Zucco et al., 2018). Survivors who do not search electronic sources by searching the Internet, do not participate in health-related social media, and do not watch health-related videos on YouTube would be considered those who do not use technology for HIS.

Scope and Delimitation

The research scope of the study was to examine the use of technology for HIS among cancer survivors who seek health information to generate evidence for use in cancer survivorship intervention planning. Only the use of the Internet for searching medical and health information, participation in health-related online forums, and watching health-related YouTube were considered in scope for the use of technology for HIS. Writing blogs, the use of social media (e.g., Twitter, Facebook, Instagram) platforms for non-health-related purposes (e.g., socializing), email, texting, and the use of eHealth systems and mHealth apps were considered out-of-scope for the current study. Furthermore, only data on the use of technology for HIS by cancer survivors, aged 18 years or older, who seek health information for self (i.e., self or both self plus someone else, but not exclusively for someone else) were to be included in the current study. Cancer survivors of any age who did not report seeking health information were to be excluded from the current study. The results of the current study were to be generalizable to the specific technologies (searching for health information on the Internet, participating in health-related online forums, or watching health-related videos on YouTube) among the U.S. adult cancer survivors represented in the HINTS dataset.

Assumptions

It was assumed that the study participants searched health information for the self-management of cancer and satisfactory HRQOL. This assumption was necessary to conclude health-related self-efficacy as measured by the self-reported confidence in their ability to take good care of their health. It was also assumed that the study participants provided accurate responses to the study questions associated with the study variables and about searching for health information. As some of the web-based experience might be impacted by the device features (e.g., speed, memory), connection speeds, and browser settings (Ng et al., 2017; Wang et al., 2012), it was assumed the respondents who reported using the in-scope technology for HIS had adequate network connectivity with satisfactory speed for performing other internet-related tasks.

Limitations

Secondary data sources have many limitations, such as constraints of the sampling design, sample size, data cleanup or handling the missing data methods, and unavailability of information on the variables or covariates for the study. As the HINTS dataset was a self-administered survey conducted via mail or web, it might have response variability that can lead to invalid response or missing data due to full or partial nonresponse (McKnight & McKnight, 2010). Self-administered surveys could be subject to recall or information bias. The HINTS data source lacked information on cancer stage, and the differences in cancer stage and the total amount of time spent searching for HIS can affect patients' health status, the effect of emotional health on HIS behaviors and experiences, or their use (or confidence to apply) the health information (Evans et al., 2007; Kim et al., 2013).

Public Health Significance of the Study

There was a knowledge gap in the use of technologies such as computer and smartphone to access health information among persons with cancer to seek health information, their HIS experiences and their impact on their abilities to improve their health such as reducing the risk of cancer recurrence and improve quality of life against the cancer fatalism backdrop. Optimization of intervention for cancer survivors is needed to avoid cancer patients exchanging one poor health outcome with another (Rowland, 2016). This study findings could be used to identify the modality of information that is optimal for cancer survivors in enhancing their cognitive agency to improve cancer survivors' quality of life and self-care of cancer symptoms, treatment side-effects, and prevent (or delay) cancer recurrence. As such, the key social change implications of the study are identifying optimal modality of cancer health-information for cancer survivors to inform improvements in the technology-based HIS to reduce the long-term need for health care resources and morbidity due to cancer treatment. The study findings could provide insights on another HIS tool for more effective cancer care management with targeted public health intervention to enhance patients' knowledge for self-efficacy and enhance the overall public health. Addressing these information gaps help reduce cancer survivors' barriers to attaining a satisfactory HRQOL, controlling cancer relapse, and preventing the preventable second and secondary cancers. The study findings could also provide insights on the barriers to delivering optimal health information to the right persons at the right time for improved outcomes among persons with cancer. As such, the social change implications for this research are a reduction in the cancer-related burden on cancer survivors, their families, healthcare, and public health resources. Therefore, the aim of this study is to advance scientific knowledge to improve health communications, information, and promotion strategies for improving the individual level of cancer interventions to improve cancer patients' quality of life and reduce preventable cancer recurrences to reduce societal cancer burden. Understanding the HIS behaviors of persons with cancer, and their experiences with health-information technologies for information-seeking would inform and enable public health practitioners to ensure that these individuals are receiving the optimal information in an optimal manner for meeting their health information needs.

Summary

Cancer is a growing public health concern, despite the scientific progress in early detection and treatment of cancer. Cancer survivors are faced with new health-related challenges during and post-treatment, many of which can be self-managed with an enhanced personal agency for self-care. Per the self-efficacy theory, personal cognitive factors (knowledge, goals, expected value) predict health self-efficacy, and personal cognitive factors can be developed or enhanced with HIS, education, and practice. Per this theory, the HIS tools that remove barriers to health information would produce positive HIS experiences, which in turn, would result in a reciprocal increase in the use of the tool for future health information needs. In recent years, there has been an increase in the technology use and a decrease in the digital divide in the material access to technology for information seeking per the literature review. However, there were gaps in the literature about the understanding of how the use of technology for HIS impacts the cancer survivor’s health-related self-efficacy or their HIS experiences. Several researchers also recommended continued monitoring of HIS behaviors among cancer survivors. I have described in this Section how the current study was performed to address the research gaps that were identified in the literature review. In the next section, Section 2, I described the research design and methodology for answering the proposed research questions.

Section 2: Research Design and Data Collection

Introduction

The purpose of this quantitative study was to assess the relationship between cancer survivor's use of technology for HIS and their health-related self-efficacy, positive HIS experiences, and personal factors among cancer survivors who seek health information. Several researchers recommended more research on the use of technology for HIS among cancer survivors for better self-management of cancer survivors' unmet health needs (Abubakari et al., 2016; Domínguez & Sapiña, 2017; Hesse et al., 2017; S. Jiang & Liu, 2020). Jackson et al. (2016) recommended continued monitoring of the HIS behaviors for continuous improvement in the public health interventions and to keep pace with the ever-changing technological landscape. I selected these research questions to close the research gaps in the use of technology for HIS among cancer survivors, and to enhance the understanding of the association between cancer survivors' use of technology for HIS and their health-related self-efficacy, positive HIS experiences, and their personal factors for the planning and provisioning of the self-management interventions in the public health arena.

In this section, I will describe and justify the research design and the rationale, methodology, and ethical considerations. Within the Methodology section, I will describe the study population, sample size, sampling procedures for data collection, instrumentation, data analysis, and threats to validity. I will conclude this section with a discussion on the ethical considerations relative to the HINTS dataset and a summary of the section before reporting the study findings in the next Section.

Research Design and Rationale

I designed this study as a secondary analysis of the nationally-representative 2019 HINTS Cycle 5 cross-sectional dataset using the quantitative correlational design to test the hypotheses associated with each research question. I used this dataset because national data sources provide full transparency and documentation to the data collection and management design, which are necessary for minimizing researcher bias, increasing study validity, and availing the data to any researcher for study reproduction (A. K. Smith et al., 2011). I selected the most recent HINTS dataset for recency and relevancy for public health planning. Because a correlational secondary analysis design is used for testing hypotheses about the relationship between the predicted and predictor variables without manipulating any factors or seeking to find a causal inference (Burkholder et al., 2016), I used correlational secondary analysis to measure the relationship between the independent variables (IVs) and dependent variables (DVs), while controlling for the potential confounding variables, shown in Table 2 to answer the following research questions (RQs):

RQ1: What is the relationship between the use of technology for HIS and the health-related self-efficacy among cancer survivors who seek health information, while controlling for the potential confounders (Table 2)?

RQ2: What is the relationship between the use of technology for HIS and positive HIS experiences among cancer survivors who seek health information, while controlling for the potential confounders (Table 2)?

RQ3 consists of two separate questions (a and b) examining the relationship between survivors' characteristics (sociodemographic and clinical factors), which are IVs measured at categorical or ordinal levels [Table 2]) and their use of technology for HIS among cancer survivors who seek health information while controlling for the potential confounders as follows:

RQ3a: What is the relationship between the cancer survivors' sociodemographic IVs (Age, Sex, Race, Education, and Income) and their use of technology for HIS among cancer survivors who seek health information, while controlling for potential confounding by their self-reported health status and clinical factors (Table 2)?

RQ3b: What is the relationship between cancer survivor's clinical dichotomous IVs (Diabetes diagnosis, High blood pressure diagnosis, Heart disease diagnosis, Lung disease diagnosis, Depression diagnosis) and the use of technology for HIS among cancer survivors who seek health information, while controlling for potential confounding by their self-reported health status?

Table 2

Description of the Independent Variables (IVs), Dependent Variables (DVs), and Covariates (CVs)

Variable (Measure)	Description	Valid values	Role in RQs
The use of technology for HIS (Categorical)	Measures whether the cancer survivor used the technology to search for health information	0=Did not use technology 1=Used technology	IV: RQ1, RQ2 DV: RQ3a, RQ3b
Health-related Self-efficacy (Categorical)	Measures the extent to which the cancer survivor reported having the ability to take care of their health.	0=Low or none 1=Full or high	DV: RQ1
Positive HIS experiences	Measures whether the cancer survivor reported positive (was	0=No 1=Yes	DV: RQ2

Variable (Measure)	Description	Valid values	Role in RQs
(Categorical)	neither overwhelmed nor frustrated) or negative (felt overwhelmed or frustrated) experience in searching for health information		
Sociodemographic variables:			
Age (Ordinal)	Measures the age category of the cancer survivor in the sample	1=under 50 years, 2=50-64 years, 3=65-74 years, 4=75 years or older	IV: RQ3a
Sex (Categorical)	Measures the survivor's self-reported gender (male or female)	0=Female 1=Male	IV: RQ3a
Race (Categorical)	Measures survivor's self-reported race	1=Non-Hispanic White, 2=Non-Hispanic Black or African American, 3=Hispanic, 4=Asians and Others	IV: RQ3a
Education (Ordinal)	Measures the survivor's self-reported highest educational attained level category	1=High school graduate or less 2=Some college or vocational training; 3=Bachelor's degree; 4=Post baccalaureate degree	IV: RQ3a
Income (Ordinal)	Measures the survivor's self-reported annual household income category	1=under $20,000, 2=$20,000--$49,999; 3=$50,000--$99,999; 4=$100,000 or more	IV: RQ3a
Survivor's clinical variables:			
Diabetes diagnosis (Categorical)	Measures whether a doctor or health professional ever told survivor had diabetes or high blood sugar	0=No 1=Yes	CV: RQ3a IV: RQ3b
Blood pressure diagnosis (Categorical)	Measures whether a doctor or health professional ever told survivor had high blood pressure	0=No 1=Yes	CV: RQ3a IV: RQ3b
Heart disease diagnosis (Categorical)	Measures whether a doctor or health professional ever told the survivor had a heart condition such as heart attack or angina	0=No 1=Yes	CV: RQ3a IV: RQ3b
Lung disease diagnosis (Categorical)	Measures whether a doctor or health professional ever told the survivor had chronic lung disease such as asthma	0=No 1=Yes	CV: RQ3a IV: RQ3b

Variable (Measure)	Description	Valid values	Role in RQs
Depression or anxiety diagnosis (Categorical)	Measures whether a doctor or health professional ever told the survivor had depression or anxiety	0=No 1=Yes	CV: RQ3a IV: RQ3b
Potential covariate variables:			
Self-reported health literacy (Categorical)	Measures the cancer survivor self-reported ability to obtain or access health or medical information	0=Low 1=High	CV: RQ1, RQ2
Self-reported health status (Categorical)	Measures cancer survivor’s self-reported health status	0=Less than good 1=Good or better	CV: RQ3a, RQ3b

Methodology

Population

The target population of the study was the U.S. adults (aged 18 years and older) who ever had a cancer diagnosis and seek health information for themselves. Many cancer survivors reported unmet health information needs (Faller et al., 2017; Hudson et al., 2012). Nearly all cancer survivors reported actively seek health information (e.g., on symptoms, alternative or complementary treatment options, side effects), and nearly half of them reported using technology to find cancer-related health information (Bigsby & Hovick, 2018; Chua et al., 2018; Finney Rutten, Agunwamba, et al., 2016; Holmes et al., 2017). Therefore, the target population was adult cancer survivors in the U.S. who sought health information for themselves.

Sampling Procedures

According to NCI (2019), the HINTS survey administrators targeted civilian, noninstitutionalized adults living in the U.S. Sampling started with first randomly selecting a nonvacant residential address (including P.O. boxes), and then selecting an adult within the selected residential address using the Next Birthday Method. The HINTS survey administrators selected 23,430 addresses comprising 16,740 addresses in high-minority areas and 6,690 in the low-minority concentration population areas (NCI, 2019). They oversampled high-minority concentration population for proportional sampling and to reduce nonresponse bias. The HINTS survey participants were randomly selected to participate via paper only (Paper Only) or via paper or web (Web pilot or Web Bonus groups) with a $2 prepaid financial incentive, and the Web Bonus group was promised an additional $10 upon completed response via the Web. The HINTS 5 Cycle 3 dataset was collected in 2019 (paper: January 22 to April 30; Web: January 29 to May 7) using a self-administered mailed or web-accessible questionnaire. They offered all participants in all groups the option to respond via paper (in English or Spanish), but via the Web (in English) only to those in the Web Pilot or Web Bonus groups. They also used a well-published protocol for the invitation to participate, follow-up, and reminders. The overall response rate was 30.5%, with a 22.2% response rate in the high-minority concentration strata and 33.4% in the low-minority strata (NCI, 2019).

The responses were scanned using TeleForm, manually validated (by comparing scanned copy with survey form), and the dataset was cleaned up or edited for missing or invalid values (NCI, 2019). Over 97% (5,427) responses to the HINTS 5 Cycle 3 (paper and web) survey were complete, and the remaining were incomplete or contained bad data (NCI, 2019). Detailed data collection, quality control, and management procedures and specifications are well-documented and publicly available from the HINTS website (NCI, 2019b). The quality control procedures included the rules for data cleanup, editing, recoding to missing or invalid values, and imputing the measured values (Westat, 2019). Those procedures have been verified for scientific utility and credibility (Finney Rutten et al., 2020). The NCI has also published summary statistics from each cycle and how-to guides and tutorials for using the dataset for research (Moser & Murray, 2020).

Sample Size

The required sample size is a function of the significance level for rejecting the null hypothesis and the desired effect size or strength of the relationship between the IV and DVs that must be detectable or a meaningful measure of the relationship between the variables. Logistic regression models are used to compute the odds of one of many outcomes in the presence of one or more exposures, and the strength of measure the association (i.e., the odds ratio [OR]) between the predictor and predicted variables (Sperandei, 2014). As the response variables in all three RQs were binomial (Table 2), I used the binary logistic regression models and OR to estimate the sample size. The OR is a widely used measure of association (none with OR=1, positive or higher with OR >1, negative or lower with OR <1) and effect size per unit change in the exposure (H. Chen et al., 2010; Szumilas, 2010). Pseudo R-squared is a measure of the variability explained by the logistic model, and the exponential of the beta coefficient is the OR in logistic regression (University of California, Los Angeles [UCLA]: Statistical Consulting Group, n.d.). A two-tailed significance level of 5% (Type 1 error: α=.05), statistical power of .8 (Type 2 error: $\beta = .2$), medium effect size ($2.5 \leq \text{OR} \leq 3$), and R^2 of .16 are recommended or accepted in scientific research for correlational studies research (H. Chen et al., 2010; Ferguson, 2009; Frankfort-Nachmias & Leon-Guerrero, 2016; Hsieh, 1989; Wilson, 1999). I used G*Power 3.1.9.4 software by Faul et al. (2007) to compute the sample size for logistic regression by performing the “a priori: compute required sample size-given α, power, and effect size” power analysis for z-tests using $\alpha = .05$, $\beta = .2$, binomial distribution, equal exposure (x-param=.5), equal and unequal H0 probability for the unadjusted and adjusted R^2 (Table 3). A minimum of 273 cases were needed to detect a medium effect (2.5 ≤ adjusted OR ≤ 3.0) at $R^2 = .16$ (Table 3).

Table 3

*Sample Size Estimates Produced by G*Power 3.1.9.4*

Binomial distribution; α = .05, β =.2, x-parm=.5	OR	Estimated sample size	
		$R^2 = 0$ (unadjusted)	$R^2 = .16$ (adjusted)
	1.5	778	926
	2	276	328
Equal probability: Pr (Y=1 | X=1) H_0=.5	**2.5**	**164**	**196**
	3	119	142
	3.5	81	114
	1.5	936	1114
	2	308	366
Unequal probability: Pr (Y=1 | X=1) H_0=.25	**2.5**	**173**	**206**
	3	119	142
	3.5	92	109
	1.5	1319	1570
	2	420	500
Unequal probability: Pr (Y=1 | X=1) H_0=.15	**2.5**	**229**	**273**
	3	155	184
	3.5	117	139

Instrumentation and Operationalization of the Constructs

I used the HINTS 5 Cycle 3 survey instrument (NCI, 2019b, 2019a) to operationalize the study variables. HINTS was sponsored by the NCI as noted above and was developed by the Health Communications and Informatics Research Branch of the Division of Cancer

Control and Population Sciences (NCI, 2020c). The HINTS instrument was designed by a group of behavioral scientists, clinicians, and health communications experts to complement the existing health datasets such as the National Health Interview Survey and Behavioral Risk Factors Surveillance System of relevance to health sciences (Hesse et al., 2017).

HINTS 5 Cycle 3 sociodemographic variables were calibrated using the 2017 American Community Survey by the U.S. Census Bureau, and the cancer and health insurance-related questions were calibrated with the 2017 National Health Interview Survey, per the "*Overview of the HINTS 5 Cycle 3 Survey and Data Analysis Recommendations*" dated January 2020 (NCI, 2019c). The HINTS survey instrument has been used to track the access and use of health technology for health (G. T. Nguyen & Bellamy, 2006) and informing national policies about health technologies (Hesse et al., 2017). HINTS design and methodology was grounded in the Findable, Accessible, Interoperable, and Reusable principles because the dataset can be processed by multiple statistical software (e.g., SPSS, SAS, STATA) and the HINTS administrators provide tutorials, webinars, and bundled packages (Finney Rutten et al., 2020). The Westat Institutional Review Board (IRB) approved the instrumentation and administration of the HINTS survey (Finney Rutten et al., 2020).

The HINTS survey instruments are used to measure constructs associated with HIS, cancer prevention (e.g., screening) knowledge, attitudes, and behaviors, cancer risk perceptions, healthcare use and access, technology use and access, health status, self-reported confidence in HIS and attaining health goals, and sociodemographic (Finney

Rutten et al., 2020; NCI, 2019a). The HINTS survey has been used in over 500 peer-reviewed studies (Finney Rutten et al., 2020; Westat, 2019), including for local research in Guam (Somera et al., 2016) and Puerto Rico (Tortolero-Luna et al., 2010).

The HINTS datasets, including the HINTS 5 Cycle 3 dataset, are freely available from the NCI with a self-attested agreement that the data would not be sold or repacked for sale, and it can be downloaded from the HINTS website (NCI, 2020c). No other permissions are required to access the dataset. Although the HINTS data are readily available, I sought approval from the university's IRB for the use of this secondary data before starting any data analysis for the current study.

Operationalization of the Study Variables

The HINTS survey includes the variables required for this study. The responses to HINTS survey questions A1 ("*have you ever looked for information about health or medical topics from any source?*") M1 ("*have you ever been diagnosed as having cancer?*"), and A3 ("*the most recent time you looked for information about health or medical topics, who was it for?*") were used to select cases that represented cancer survivors who sought health information. Cases with a "yes" response to both Questions A1 and M1 and with either "Myself" or "Both myself and someone else" to Question A3 were selected for the study. Then, the IVs, DVs, and the covariates in the study, shown in Table 2, were operationalized as explained next.

The use of technology for HIS was the predictor variable in RQ1 and RQ2 and the predicted variable in RQ3. As a measure of whether the survivor used technology for HIS, it was set to be a dichotomous variable (Table 2). This variable was used to capture the study participants' responses about their use of a computer, smartphone, or other electronic means to look for health or medical information for self on the Internet, participation in health-related online forums, or watching online health-related videos for HIS. Internet use is positively associated with participation in online forums and online group chats (Shklovski et al., 2006) and the use of social media (online chat groups and YouTube) to higher Internet use (Simsek et al., 2014). Moreover, the users of Internet might participate in health-related social media platforms and YouTube videos based on the results of their Internet search. Similarly, persons who participate in health-related social media or watch health videos on YouTube might find links to Internet sites for searching for more information. As a result, the use of one of these online technologies can be a catalyst for the use of the other technology; these technologies have a high collinearity and covariance, irrespective of its detectability in the current sample. Therefore, it was categorized as a dichotomous variable to address the potential covariance and collinearity between the technology options for HIS. The variable was set to “Used technology” if the participants responded with a “Yes” to any of the following HINTS survey questions:

- B5a (*In the past 12 months, have you used a computer, smartphone, or other electronic means to look for health or medical information for yourself: yes/no?)*
- B14d (*In the past 12 months, have you used the internet to participate in an online forum or support group for people with a similar health or medical issue: yes/no?*)

- B14e (*In the past 12 months, have you used the internet to watch a health-related video on YouTube: yes/no?*)

Otherwise, it was set to “Did not use technology” if the participant responded with a “no” to all three questions. A combination of nonresponse and “no” response to the three questions was treated as invalid data. These questions and the approach were used by (Bangerter et al., 2019) to construct a dichotomous variable for using the Internet.

Health-related self-efficacy was the predicted variable in RQ1, and it was measured as a level of confidence in the survivors’ self-care abilities. As discussed in the literature review, it is often measured as a rank-ordered scale ranging from no confidence to extremely high confidence. The level of self-confidence is an indicator of optimal (full ability) or suboptimal (none to low ability) confidence, where the suboptimal (i.e., low self-confidence) negatively impacts self-care decision making and action for the self-management of health (Chuang et al., 2013; Eilander et al., 2016; Foster & Fenlon, 2011). Several researchers interpreted the multilevel ordinal results in terms of high or low confidence (Chuang et al., 2013; Eilander et al., 2016; Foster & Fenlon, 2011). Chan (2013) collapsed five categories into three (low, somewhat, high), and Hochbaum (1954) into two (high, low) categories. Therefore, health-related self-efficacy was decided to be a dichotomous variable, and it was measured using the response to the HINTS survey item F2 (“*Overall, how confident are you about your ability to take good care of your health?*”). The participant’s response was collapsed from the five categories (Extremely confident=1 to Not confident at all=5) to two categories (Low, High). This variable was set to “Full or high” for those who reported being “Completely confident” or “Very confident” and to “Low or none” for “Somewhat confident,” “A little confident,” or “Not at all confident.”

Positive HIS experience was the predicted variable in RQ2. As a measure of whether the cancer survivor had a positive or negative experience searching the health information, was a dichotomous variable. It was based on participant’s response to the effort and frustration dimensions of HIS experiences using the HINTS survey items A4a (“*It took a lot of effort to get the information*”) for effort and A4b (“*You felt frustrated during your search for the information*”) for frustration. The variable was set to “No” if the participant responded with “strongly agree” or “somewhat agree” to either A4a and A4b, and “Yes” with a “Somewhat disagree” or “strongly disagree” response to both A4a or A4b. Nonresponse to either question was treated as an invalid response.

The sociodemographic variables were cancer survivor’s age, race, sex, education, and income (Table 2). These variables were predictor variables in RQ3a. Responses to the HINTS survey items O1 (“*what is your age*”), O5 (*Are you of Hispanic, Latino, or Spanish origin?*), O6 (“*what is your race*”), O9 (“*mark your sex*”), O3 (“*what is the highest grade or level of schooling you completed*”), and O12 (“*what is your combined pre-tax annual household income from all sources in the past year*”) were used to collect data on these variables. Per the HINTS 5 Cycle 3 codebook, the responses were derived as follows into HINTS variables: age in “AgeGrpA” and “AgeGrpB”; ethnicity and race in “RaceEthn5” and “RaceEthn7”; educational attainment level in “EducA” and “EducB”; sex in “SelfGender”; income in “IncomeRanges_IMP” (NCI, 2020b). More granular information is available from “EducB” than “EducA” (NCI, 2020b). The O12 response used for IncomeRanges_IMP was corrected with the highest range in case the respondent selected multiple income ranges or imputation in case of nonresponse (Westat, 2019).

Because cancer is most prevalent among persons older than 50 years (Guy et al., 2017), the IV Age in RQ3a was operationalized using the HINTS variable AgeGrpB, which has categories for above and below 50 years, rather than AgeGrpA with all persons aged 45 or older grouped into the “45+” category (NCI, 2020b). For the same reason, participants aged under 50 years were grouped into the “under 50 years” category. Therefore, values in AgeGrp were classified into the most appropriate category of Age (under 50 years=1, 50-64 years=2, 65-74 years=3, 75 years or older= 4), as shown in Table 4.

The IV Race in RQ3a was operationalized using the HINTS variable RaceEthn5 because some of the representative sample (e.g., .2%) in the entire HINTS dataset for several classifications in the RaceEthn7 was very small (e.g., unweighted: 10 American Indian and Alaskan Native, 11 for Hawaiian or other Pacific Islanders) for meaningful analysis (NCI, 2020b), which could have been even smaller within the target population. In RaceEthn5, persons who responded as being “Native Hawaiian,” “Samoan,” “Guamanian or Chamorro,” “Other Pacific Islander” or multiracial were classified into the “Other” category. Persons who responded as being “Asian Indian,” “Chinese,” “Filipino,” “Japanese,” “Korean,” “Vietnamese,” or “Other Asian” were classified as

"Asian" (NCI, 2020b). Therefore, Race was set to the values of RaceEthn5, as shown in Table 4.

The HINTS variables "SelfGender", "EducB", and "IncomeRanges_IMP" were used to set the IVs Sex, Education, and Income (NCI, 2020b). The computation of Education from "EducB" and Income from "IncomeRanges_IMP" is shown in Table 4.

Table 4

Calculating the Age, Race, Education, and Income

Variable	Participant's response	Computed value
Age	AgeGrpB = "1" or "2"	Age=under 50 years
	AgeGrpB = "3"	Age=50-64 years
	AgeGrpB = "4"	Age=65-74 years
	AgeGrpB = "5"	Age=75+ years
Education	EducB= "1" or "2"	Education= High School graduate or less
	EducB ="3"	Education= Some college or vocational training
	EducB ="4"	Education= Bachelor's degree
	EducB ="5"	Education= Post baccalaureate degree
Race	RaceEthn5 = "1"	Race = Non-Hispanic White
	RaceEthn5 = "2"	Race = Non-Hispanic Black or African American
	RaceEthn5 = "3"	Race = Hispanic
	RaceEthn5 = "4" or "5"	Race = Asians and Others
Income	IncomeRangesIMP= "1", "2", or "3"	Income=under $20,000
	IncomeRangesIMP= "4" or "5"	Income =$20,000-$49,999
	IncomeRangesIMP= "6" or "7"	Income =$50,000-$99,999
	IncomeRangesIMP= "8" or "9"	Income =$100,000 or more

Survivor's clinical diagnosis of diabetes, high blood pressure, heart disease, lung disease, and depression or anxiety were the clinical variables that were potential confounders in RQ3a and IVs in RQ3b. The HINTS survey items about ever being told by a health professional about F6a ("*diabetes or high blood sugar*"), F6b ("*high blood* *pressure or hypertension*”), F6c (“*a heart condition such as heart attack, ...*”), F6d (“*chronic lung disease, asthma, ... ”*)*,* and F6e (“*depression or anxiety*”) were used to operationalize diabetes diagnosis, blood pressure diagnosis, heart disease diagnosis, lung disease diagnosis, and depression or anxiety diagnosis, respectively. As the response options for the questions and the variables are both dichotomous, the yes/no responses were used directly.

Self-reported health-literacy was a dichotomous covariate that was a potential confounder in RQ1 and RQ2. As per the literature review, HINTS survey items A5 (“*Overall, how confident are you that you could get advice or information about health or medical topics if you needed it*?”) was used in several studies to operationalize *self-reported health literacy*, and the same will be used in the current study. The responses to A5 were categorized into two groups (Low or none, Full or high). The variable was set to “Full or high” for “Very confident” and “Completely confident” participant responses. Otherwise, it was set to “Low or none” for “Somewhat confident,” “A little confident’, “Not confident at all responses.

Self-reported health status was dichotomous covariate and a potential confounder in RQ1, RQ2, RQ3a, and RQ3b. In the literature review, poor physical and mental health were identified as a confounder of self-confidence and positive HIS experience. HINTS survey item F1 (“*In general, would you say your health is*?”) was used to operationalize this variable. A response of “Poor’ or “Fair” were mapped to “Less than good” and other valid response options (“Excellent”, “Very good”, and “Good”) were mapped to “Good or better” as was done in the studies by Jackson et al. (2016) and Miyawaki et al. (2015).

Data Quality Assurance

The HINTS team reviewed the survey responses to each question for validity and nonresponse (Westat, 2019). They implemented the hot-deck imputation procedure for nonresponse to age, sex, race, education, and income (NCI, 2020b). They used the highest order response for Income and Education ranges if the participant selected multiple responses to these mark-only-one questions (NCI, 2020b). When imputation or editing was not possible for the study variables, they recoded the responses with error-specific negative values to indicate invalid (e.g., nonconforming or failed skip tests) or missing data (NCI, 2020b). Therefore, negative values and missing values for any of the study variables were treated as invalid data for listwise exclusion from the analysis.

Data Analysis Plan

I used IBM SPSS version 24 for performing the data analyses. I began by performing descriptive analyses for all variables under investigation. I then conducted inferential analyses, both unadjusted and adjusted, to examine the relationship between the independent variables and dependent variables for the various research questions.

Descriptive Analyses

The count and percentage frequency distributions are among the descriptive statistics used for univariate analyses of categorical variables (Frankfort-Nachmias & Leon-Guerrero, 2016). Categories with too few responses in the variables with three or more categories should be collapsed to avoid bias due to classification errors (Shen & Gao, 2008). As all variables were categorical (Table 2), I generated frequency distribution and percentages for the distribution of responses, as well as verifying required data assumptions for the analysis. I also examined the response to variables with three or more categories and collapsed the categories with too few responses in such variables to avoid bias due to classification errors. I also generated the graphical displays, e.g., pie charts, for the visual analysis or display of the data for the study variables.

Inferential Analyses

Binomial logistic regression model (henceforth referred to as logistic regression model) were used because of the dichotomous outcomes (Statistics Solutions, n.d.; UCLA Statistical Consulting, n.d.; Wagner, 2016) in all three RQs. The assumptions of the logistic regression model (i.e., predict dichotomous outcomes, one or more categorical or continuous IVs, independence of observations, mutually exclusive response categories, the existence of a relationship between IVs and DVs, and the independence of covariates) must be verified for reliable models and results (McDonald, 2014; Wagner, 2016). I verified several of these assumptions during the study design and verified the remaining during the hypothesis testing. I ensured the first assumption was met for predicting “High” or “Low” health-related self-efficacy, “Yes” or “No’ positive HIS experiences, and the “use” or “nonuse” of technology for HIS in RQ1, RQ2, and RQ3 respectively. I also verified that the assumptions about one or more categorical or continuous IVs, independence of observations, and mutually exclusive response categories were already met per the HINTS survey design and the operationalization of the variables (Table 2). I verified the assumptions about the covariance and multicollinearity during the hypothesis testing.

Variables with three or more categories (k >2) without a rank order must be transformed into k-1 dummy variables to meet the assumptions about the measurement level for the linear regression (McDonald, 2014; Wagner, 2016). As a result, I transformed the racial categories into dummy dichotomous variables, used the non-Hispanic Whites as the reference category, and set the reference category to the zero value in the dummy variables. I did not transform age, education, and income because they were ordinal variables.

For each RQ, I used the bivariate logistic regression model to examine the unadjusted effect associations and the multiple logistic regression to control for confounders and the adjusted effects, as described next. These analyses were also used to check the remaining assumptions (i.e., the relationship between IV and DV and the independence of covariates) of the logistic regression analysis and to fit the model for the inferential analysis. For all analyses, I used the significance threshold value of .05 as my level of statistical significance.

Unadjusted Analyses.

Following the descriptive analyses, I began the inferential analyses by examining the unadjusted correlation between the outcome predictors in each RQ using the most appropriate correlation factors, which according to Virginia Commonwealth University (n.d.) were the phi-coefficient (for binary variables) or Cramer’s V (for variables with three or more categories). Then, I used the logistic regression analysis to examine the effect (unadjusted odds ratio and the corresponding 95% confidence intervals) of each IV on the outcome in each RQ (Table 2) without adjusting for the potential confounders.

Adjusted Analyses.

Next, multivariable logistic regression models were fit for each RQ to control for potential confounding. A first step in the building of the multivariate models was to examine all pairwise correlations between the IVs to assess whether any of these are variables were strongly related to one another and, therefore, could lead to collinearity issues. I then built the logistic regression models by forcing all independent variables into the model (apart from any covariates that might be related to other variables). Because a greater than ten value of the variance inflation factor ([VIF] > 10) is a strong indicator of multicollinearity between the predictor variables (Allison, 1999; Fox, 1991; Obi, 2014), I checked the multicollinearity assumption by examining the VIF for the final models. I chose a VIF greater than ten to suggest that multicollinearity was present. Should this happen, I planned to remove the covariates that might be leading to the collinearity issues and produce revised multiple logistic models.

I also calculated the Hosmer-Lemeshow statistic for the adjusted model to assess the overall fit of the model. Should the Hosmer-Lemeshow statistic have a $p < 0.05$ (suggesting lack of fit), I planned to carefully examine the model to identify the reason(s) for the lack of fit and make refinements accordingly, e.g., systematically recategorizing or removing/replacing predictor variables until there was no further evidence of lack of model fit.

I applied the data analysis methods and the logistic models for each RQ to test the corresponding null hypothesis described in Section 1. More specifically, I conducted three multiple logistic regression models, one for each RQ, as summarized in Table 5.

Table 5

Data Analysis Plan by RQ

RQ	Dependent variable	Independent variables	Potential confounding variables	Test purpose	Statistical test
RQ1	Health-related self-efficacy (dichotomous)	The use of technology for HIS (dichotomous)	Self-reported health literacy (dichotomous) Self-reported health status (dichotomous)	Identify the odds of predicting the health-related self-efficacy with the use of technology for HIS while controlling for potential confounders.	Multiple logistic regression for predicting the odds of health-related self-efficacy.
RQ2	Positive HIS experiences (dichotomous)	The use of technology for HIS (dichotomous)	Self-reported health literacy (dichotomous) Self-reported health status (dichotomous)	Identify the odds of positive HIS experience with the use of technology for HIS, while controlling for potential confounders.	Multiple logistic regression for predicting the odds of positive HIS experiences.
RQ3a	The use of technology for HIS (dichotomous)	Age (ordinal) Race (nominal) Sex (dichotomous) Education (ordinal) Income (ordinal)	Clinical variables (dichotomous)	Identify the odds of using technology for HIS with each sociodemographic, while controlling for the potential confounders.	Multiple logistic regression for predicting the odds of the use of technology for HIS.
RQ3b	The use of technology for HIS (dichotomous)	Dichotomous diagnosis of: Diabetes High Blood Pressure Heart diseases Lung diseases Depression or anxiety	Self-reported health status (dichotomous)	Identify the odds of using technology for HIS with each clinical variable, while controlling for potential confounders.	Multiple logistic regression for predicting the odds of the use of technology.

Threats to Validity

Biases in the design, implementation, and analysis processes can threaten the study validity. Selection, response, and information biases (e.g., participant selection, time, history, maturation) in the design, conclusions without considering confounders, and gaps in the operationalization of the theoretical concepts or constructs can impact the study results (i.e., internal validity) and the generalizability of the results (i.e., external validity) (Drost, 2011; Fink, 2013). The study validity can also be affected by differences in the settings in a controlled experiment versus the real-world life setting (Drost, 2011). Cultural, social, or ecological differences in the population in different settings (e.g., cancer survivors in the U.S. versus India or England) could also limit the ability to extrapolate the study findings (Drost, 2011) of any study, including non-experimental studies, even after controlling for the known confounders (e.g., self-reported health literacy, self-reported health status). The findings of the current study cannot be generalized to future settings with different types of technologies for HIS behaviors or U.S. healthcare policies (e.g., universal health care, testing, education system) because the study design involves secondary analysis of the 2019 cross-sectional HINTS 5 Cycle 3 dataset. Therefore, the threats to external validity were addressed by ensuring internal validity and generalizing the study findings on the associations and measures only to the targeted population.

The design was free from threats to the internal validity from the selection, history, time, maturation, and statistical regression biases. First, the selection, maturation, or history biases were not possible with the HINTS dataset because of the HINTS sampling (random), instrument design (about past 12 months), and data collection design (a specific point in time). Second, the HINTS surveyor addressed the potential for nonresponse by some subgroups (e.g., racial or ethnic groups) by oversampling the groups with a greater likelihood of nonresponse to minimize the selection and response bias that can threaten the internal validity and providing weights to adjust for nonresponse (Fuller, 1974). However, as the HINTS survey was a self-administered questionnaire, any information bias (due to false claims within valid options) was not detectable in the current study, and such information bias would result in systematic differences in all studies using the responses with false claims. A study's internal validity can also be threatened by statistical regression errors such as issues with the measurements of the construct, unaccounted alternative explanation, nonreliability of the regression analyses, or invalid conclusions (Drost, 2011). These threats were addressed by using a reliable instrument, proactively addressing the potential confounders in the data analysis, providing transparency in the data analysis plan (including validating the assumptions of the regression model), and justifying the inferences. As the current study was designed as a correlational study, the findings were limited to reporting association and not causal inferences.

Ethical Procedures

For the current study, I did not require access to any of the participant's personally identifiable data, and I used the publicly available HINTS dataset. HINTS administrators used a randomly generated unique identification number for each selected participant, provided financial incentives and pre-stamped envelopes, and offered a web option to all recruited participants (Westat, 2019) to ensure equitable and ethical participant selection and data collection. The HINTS survey questionnaire did not collect any personal data, and the stored responses do not contain any personal data (Westat, 2019). Therefore, the use of these secondary data through the HINTS survey did not present ethical issues related to any of the following items: treatment of human subjects, data collection, privacy concerns, conflict of interest, or power differentials. An application to Walden's IRB was submitted to obtain and analyze the HINTS data for the current study, and the IRB approval was secured before starting the study analysis. The data access did not present any ethical concerns as the HINTS dataset is freely available to researchers who agree to the online terms and conditions and provide a personal email address. Before downloading the dataset, the HINTS administrators required a researcher to agree via self-attestation (by clicking on the "agreement" button) to the online terms and conditions presented on the download website and provide email address. I accepted all the terms and provided my email address in the same manner

Summary

In Section 2, I described the study design and methods to assess the impact the use of technology for HIS on the cancer survivor's health-related self-efficacy and positive HIS experiences and the impact of the survivor's sociodemographic and clinical characteristics on the survivor's use of technology for HIS. I provided a rationale for conducting a quantitative and correlational study using the 2019 cross-sectional HINTS dataset from the NCI and provided information on the target population, sample size, and the study variables. I described the data collection design and procedures and the acceptability of the dataset within the scientific community for science research. I also described the data quality assurance and data analysis plans for the study, including the details on the descriptive and inferential statistics model for each proposed research question and to draw insights. In the next section, Section 3, I presented the study results based upon the methodologies described in the present Section.

Section 3: Presentation of the Results and Findings

Introduction

The purpose of the study was to assess whether there is a significant relationship between cancer survivor’s use of technology for HIS and their health-related self-efficacy, positive HIS experiences, and their sociodemographic and clinical factors among cancer survivors who seek health information (Table 6).

My research questions (RQs) and corresponding hypotheses were as follows:

RQ1: What is the relationship between the *use of technology for HIS* (independent dichotomous variable) and health-related self-efficacy (dependent dichotomous variable) among cancer survivors who seek health information, while controlling for the potential confounders? The null hypothesis (H_o) is that there is no relationship between the independent and dependent variables in RQ1 and the alternative hypothesis (H_1) is that there is a significant relationship between these study variables in RQ1.

RQ2: What is the relationship between the *use of technology for HIS* (independent dichotomous variable) and positive HIS experience (dependent dichotomous variable) among cancer survivors who seek health information, while controlling for the potential confounders? The H_o is that there is no relationship between the independent and dependent variables in RQ2 and the H_1 is that there is a significant relationship between these study variables in RQ2.

RQ3: What is the relationship between survivor’s a) sociodemographic independent nominal variables (age, race, education, income) and their *use of technology for HIS* (dependent dichotomous variable) and b) clinical independent dichotomous variables (diagnosis of diabetes, high blood pressure, heart disease, lung disease, and depression/anxiety) and their *use of technology for HIS* (dependent dichotomous variable) among cancer survivors who seek health information, while controlling for the potential confounders? The H_o is that there is no relationship the between the independent and dependent variables in RQ3 and the H_1 is that there is a significant relationship between these study variables in RQ3.

In Section 3, I will present the results and findings of the analyses. Following the introduction, I will describe the data collection methods, the survey timeframe, and the sample characteristics. Next, I will present the descriptive statistics, inferential analysis of the survey data, the results analysis, and key findings of the results for each RQ. Finally, I will conclude this section by providing the answers to each RQ and briefly introducing Section 4 on the practical application of the findings and social change implications.

Data Collection of the Secondary Data Set

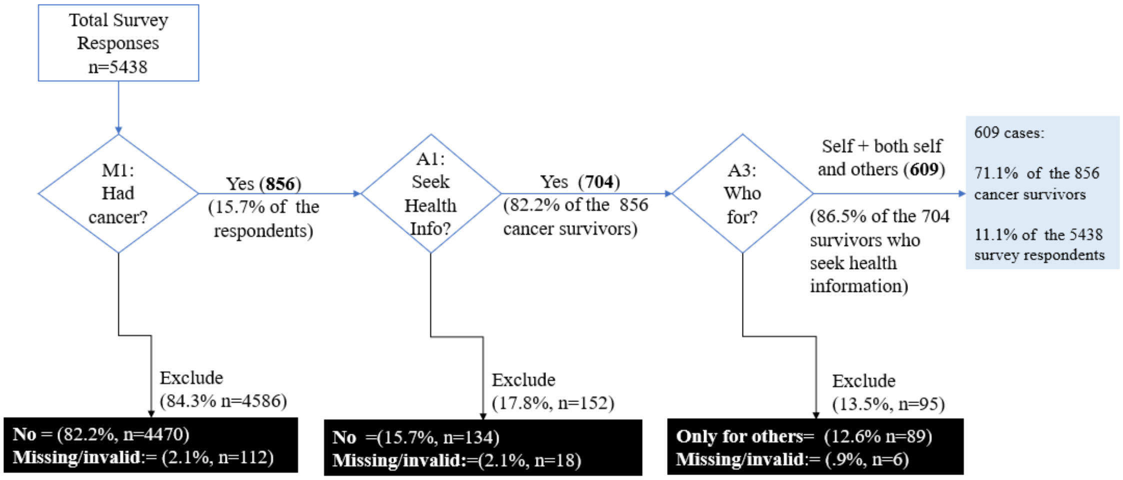
I used the nationally representative secondary data from the HINTS 5 Cycle 3, funded by the NCI. It was fielded from January 22 to May 7, 2019, to obtain a stratified sample of 23,470 (71.4% high-minority, 28.6% low-minority) randomly selected adults (using the Next Birthday method) from the randomly selected nonvacant residential addresses in the 52 U.S. states (Westat, 2019). The HINTS researchers used the 2013–2017 American Community Survey to designate the areas with more than 34% African American or Hispanic population as high-minority and all others as low-minority concentration population areas (Westat, 2019). The data were collected in two modes:

January 22 to April 30 for paper-only, and January 29 to May 7 for the paper or web option (Westat, 2019). The downloaded HINTS data set had responses from a total of 5438 participants, which corresponded with an overall response rate of 30.5%, the high-minority response rate of 22.2%, and the low-minority response rate of 33.4% (Moser & Murray, 2020; Westat, 2019). Each participant self-administered the survey and responded by either mailed-in surveys or the web form (Westat, 2019).

I used a subsample of only those cases in which the participants reported being cancer survivors and seeking health information for themselves were considered in the current study using the process described in Figure 1. First, I selected cancer survivors among the survey respondents by selecting only those who reported having ever had a cancer diagnosis (856 cancer survivors representing 15.7% of survey respondents). Then, I selected only the subset of cancer survivors who reported seeking health information *(n*=704 or 82.2% of the cancer survivors). I further limited the subsample to only those cancer survivors who sought the health information for themselves and not exclusively for others, which resulted in a total of 609 cases representing 86.5% of the 704 cancer survivors who reported seeking health information (Figure 1). The subsample of 609 cancer survivors who reported seeking health information for themselves represented 71.1% of the cancer survivors and 11.1% of all the survey respondents in the 2019 HINTS 5 Cycle 3 data set (Figure 1). These 609 cases representing the cancer survivors who sought health information were included in the current study, and all other cases were excluded from the study sample.

Figure 1

Study Sample



After computing the study variables (Table 6) according to the operationalization plan described in Section 2, I analyzed the study subsample *(n*=609) for invalid data in each variable and its impact on each research question.

Table 6

Codebook for the Study Variables

Variable	Measurement	Values
Use of technology for HIS	Nominal	0 = Did not use technology 1 = Used technology -1 = Invalid or missing data
Health-related self-efficacy	Nominal	0 = Low or none 1 = Full or high -1 = Invalid or missing data
Positive HIS Experiences	Nominal	0 = No, 1 = Yes, -1 = Invalid or missing data
Self-reported health literacy	Nominal	0 = Low or none 1 = Full or high -1 = Invalid or missing data
Self-reported health status	Nominal	0 = Less than good 1 = Good or better

Variable	Measurement	Values
		-1 = Invalid or missing data
Age	Nominal	1 = Under 50 years, 2 = 50 – 64 years 3 = 65 – 75 years 4 = 75 years or older -9 = Invalid or missing data
Sex	Nominal	0 = Female 1 = Male -1 = Invalid or missing data
Race	Nominal	1 = Non-Hispanic White 2 = Non-Hispanic Black or African American 3 = Hispanic 4 = Non-Hispanic Asians and Others. -9 = Invalid or missing data
Education	Nominal	1 = High school graduate or less 2 = Some college or vocational training 3 = Bachelor’s degree 4 = Post baccalaureate degree -9 = Invalid or missing data
Income	Nominal	1 = under $20,000 2 = $20,000--$49,999 3 = $50,000--$99,999 4 = $100,000 or more -9 = Invalid or missing data
Diabetes	Nominal	0 = No, 1 = Yes, -9 = Invalid or missing data
High blood pressure	Nominal	0 = No, 1 = Yes, -9 = Invalid or missing data
Heart disease	Nominal	0 = No, 1 = Yes. -9 = Invalid or missing data
Lung disease	Nominal	0 = No, 1 = Yes, -9 = Invalid or missing data
Depression or anxiety	Nominal	0 = No, 1 = Yes, -9 = Invalid or missing data

The study sample had 272 invalid responses across the study variables, and the invalid response rate ranged from 0.5 to 9.7 % for all variables (Table 7). Invalid response rates was the highest for *positive HIS experiences (n*=43), sex (*n*=57), and race (*n*=59), were 7.1%, 9.4%, and 9.7%, respectively as shown in Table 7.

Table 7

Number Invalid Values by Variable in the Study Sample

Variable	*n*	%
Use of Technology for HIS	14	2.3
Health-related self-efficacy	7	1.1
Positive HIS experiences	43	7.1
Age	8	1.3
Race	59	9.7
Sex	57	9.4
Income	8	1.3
Education	3	0.5
Diabetes	14	2.3
High blood pressure	13	2.1
Heart disease	8	1.3
Lung disease	10	1.6
Depression or anxiety	14	2.3
Self-reported health-literacy	3	0.5
Self-reported health-status	11	1.8
Total number of invalid values	272	3.0

Further analysis of listwise exclusion of cases with invalid values for a variable necessary for the RQ-specific analysis resulted in 581 (95.4%) valid cases for RQ1, 543 (89.2%) for RQ2, and 484 (79.5%) for RQ3 (Table 8). The final sample size for each RQ met the minimum sample size of 273 required to detect a medium effect at α =.05 and β = .2, as presented in Section 2. In the results section below, I will present the results by RQ.

Table 8

RQ-Specific Subsample Selection Criteria

RQ	Exclusion criteria	Valid cases: *N* (% of 609)
RQ1	Listwise exclusion of the invalid cases for the: • use of technology for HIS, • health-related self-efficacy, • self-reported health-literacy, and • self-reported health status.	581 (95.4)
RQ2	Listwise exclusion of the invalid cases for the: • use of technology for HIS, • positive HIS experiences, • self-reported health-literacy, and • self-reported health status.	543 (89.2)
RQ3	Listwise deletion of invalid cases for the: • use of technology for HIS, • each sociodemographic variable (age, sex, race, education, and income), • each clinical variable (diabetes, high blood pressure, heart disease, lung diseases, depression/anxiety), and • self-reported health status.	484 (79.5)

Study Results

I conducted multiple logistic regression analyses to investigate the relationship between cancer survivors' use of technology for HIS and their health-related self-efficacy (RQ1), positive HIS experiences (RQ2), and personal factors (i.e., socio-demographic factors in RQ3a and clinical factors in RQ3b). Unadjusted (univariable) and multiple (adjusted) logistic regression models were run to compute the odds ratio (OR), which is the the exponentiated β (Exp [β]), for the relationship between each independent variable and the outcome variable. Given the differences in the analysis samples, the results of the descriptive and logistic regression analysis for each RQ are presented by RQ.

RQ1: The Relationship Between the use of Technology for HIS and Health-Related Self-Efficacy

In RQ1 on the relationship between the survivors' use of technology for HIS (predictor variable) and their health-related self-efficacy (outcome variable), their self-reported health literacy and self-reported health status were the potential confounders. As noted in Table 8, the RQ1 analyses were based on a sample of *N* = 581. Most of these participants had full or high health-related self-efficacy (Figure 3).

RQ1 Univariate Analyses

As shown in Table 9, a majority of the cancer survivors reported using technology for HIS (*n* = 466, 80.2%), having a full or high health-related self-efficacy (*n* = 393, 67.6%), full or high self-reported health literacy (*n* = 379, 65.2%), and good or better self-reported health status (*n* = 439, 75.6%). Most cancer survivors, irrespective of their use of technology for HIS, reported full or high health-related self-efficacy (66.1% [79 of 115] who did not use technology; 68.0% [317 of 499] who used technology). Nearly three-quarters (*n* = 106, 74.6%) of the 142 survivors with less than good self-reported health status reported having low or no health-related self-efficacy. Most of the survivors with full or high self-reported health literacy (*n* = 288, 76%) and good or better self-reported health status (*n* = 357, 81.3%) reported having a full or high health-related self-efficacy. The sample had more females (n = 282, 48.4%) than males (*n* = 251, 43.2%), 65 years or older (*n* = 370, 62.1%) than under 65 years (*n* = 204, 35.1%), non-Hispanic Whites (*n* = 427, 73.5%) than other racial groups (*n* = 104, 17.9%), earning under $50,000 (*n* = 308, 55.6%) than $50,000 or more (*n* = 266, 45.8%), and had bachelors or higher degree (*n* = 286, 58.5%) than some college education or less (*n* = 266, 39.2%). Most participants in each sociodemographic category, except for the Hispanic and those earning under $20,000, reported having full or high health-related self-efficacy.

Table 9

RQ1 Summary Statistics for the Study on the Relationship Between the Use of Technology and Health-Related Self-Efficacy

Variables (V) and categories	Sample (*N*=581)		Health-related self-efficacy			
			Low or none		Full or high	
	n	%	*n*	% within V	*n*	% within V
Use of technology for HIS						
Did not use technology	115	19.8	39	33.9	76	66.1
Used technology	466	80.2	149	32.0	317	68.0
Self-reported health literacy						
Low or none	202	34.8	97	48.0	105	52.0
Full or High	379	65.2	91	24.0	288	76.0
Self-reported health status						
Less than good	142	24.4	106	74.6	36	25.4
Good or better	439	75.6	82	18.7	357	81.3
Sex						
Female	282	48.5	79	28.0	203	72.0
Male	251	43.2	87	34.7	164	65.3
Missing or invalid data	48	8.3	22	45.8	26	54.2
Age						
Under 50 years	45	7.8	11	24.4	34	75.6
50-64 year	159	27.4	52	32.7	107	67.3
65-74 years	202	34.8	66	32.7	136	67.3
75 years or older	168	28.9	58	34.5	110	65.5
Missing or invalid data	7	1.20	1	14.3	6	85.7
Race						
Non-Hispanic White	427	73.5	122	28.6	305	71.4
Non-Hispanic Black or African American	42	7.2	13	31.0	29	69.0
Hispanic	33	5.7	17	51.5	16	48.5

Variables (V) and categories	Sample (*N*=581)		Health-related self-efficacy			
			Low or none		Full or high	
	n	%	*n*	% within V	*n*	% within V
Non-Hispanic Asian or Other	29	5.0	11	37.9	18	62.1
Missing or invalid data	50	8.6	25	50.0	25	50.0
Income						
Under $20,000	84	14.5	43	51.2	41	48.8
$20,000--$49,999	182	31.3	65	35.7	117	64.3
$50,000--$99,999	164	28.2	39	23.8	125	76.2
$50,000--$99,999	144	24.8	37	25.7	107	74.3
Missing or invalid data	7	1.2	4	57.1	3	42.9
Education						
High school graduate or less	104	17.9	44	42.3	60	57.7
Some college or vocational training	188	32.4	63	33.5	125	66.5
Bachelor’s degree	152	26.2	40	26.3	112	73.7
Post baccalaureate degree	134	23.1	40	29.9	94	70.1
Missing or invalid data	3	0.5	1	33.3	2	66.7
Health-related self-efficacy						
Low or none	188	32.4	-	-	-	-
Full or high	393	67.6	-	-	-	-

Unadjusted Logistic Regression Analysis for RQ1

I conducted three unadjusted logistic regression analyses investigate RQ1 on the relationships between each predictor variable (use of technology for HIS, self-reported health literacy, and self-reported health status) and the dependent variable, health-related self-efficacy. The use of technology for HIS was not significantly associated with health-related self-efficacy, $p > .05$ (Table 10). Both self-reported health literacy (OR = 2.92; 95% CI = 2.03, 4.20) and self-reported health status (OR = 12.82; 95% CI = 8.19, 20.06) were significantly associated with health-related self-efficacy.

Table 10

Unadjusted Logistic Models for Predicting Health-Related Self-Efficacy

Predictor	β	S.E.	Wald	df	*p*-value	Odds ratio	95% CI LL - UL
Use of technology for HIS							
Used technology	0.09	0.22	0.16	1	.691	1.09	0.71 - 1.68
Self-reported health literacy							
Full or high	1.07	0.18	33.56	1	< .001	2.92	2.03 - 4.20
Self-reported health status							
Good or better	2.55	0.22	124.64	1	< .001	12.82	8.19 - 20.06

Note: CI = Confidence interval; LL = Lower limit, UL= Upper limit.

Multiple Logistic Regression Analysis for RQ1

I conducted a multiple logistic regression analysis to investigate the relationship between survivors' use of technology for HIS (the independent variable of interest) and their health-related self-efficacy (the outcome variable) while controlling for self-reported health literacy and self-reported health status. The logistic regression model was statistically significant, $\chi^2(3) = 179.92$, $p < .05$, and it explained 37.2% (Negelkerke R^2) of the variability in health-related self-efficacy. The model correctly classified 79.7% of the cases, and its sensitivity and selectivity rates for predicting health-related self-efficacy were 90.8% (Full or high) and 56.4% (Low or none), respectively. There was no evidence of the lack of model fit based upon the Hosmer and Lemeshow goodness-of-fit statistic of 3.15, $p > .05$ (Table 11).

Controlling for survivor's self-reported health literacy and self-reported health status, the use of technology for HIS (the predictor variable of interest) was not a significant contributor to the model (p >.05), and it was not a significant predictor of health-related self-efficacy (OR = 0.91; 95% CI = 0.54, 1.54 [Table 11]). Both self-reported health literacy and self-reported health status were significant predictors of health-related self-efficacy, $p < .05$. The odds of full or high health-related self-efficacy were 3.39 times higher with “Full or high” than with “Low or no” self-reported health literacy (OR = 3.39; 95% CI = 2.20, 5.22; $p < .05$). The odds of full or high health-related self-efficacy were 13.99 times higher with “Good or better” than with “Less than good” self-reported health status (OR= 13.99; 95% CI = 8.73, 22.44; $p < .05$).

Table 11

Multiple Logistic Model for Predicting Health-Related Self-Efficacy

Predictor	β	S.E.	Wald	df	*p*-value	Odds ratio	95% CI LL – UL
Constant	-1.81	0.32	31.16	1	<.001	0.16	
Use of technology for HIS							
Used technology	-0.01	0.26	0.13	1	.72	0.91	0.54 - 1.54
Self-reported health literacy							
Full or high	1.22	0.22	30.80	1	<.001	3.39	2.20 - 5.22
Self-reported health status							
Good or better	2.64	0.24	120.08	1	<.001	13.99	8.73 - 22.44
Model predictive capacity = 79.7% (full or high = 90.8%, low or none= 56.4%).							
Hosmer Lemeshow goodness of fit statistic = 3.15, *p*-value = .676							

Note: CI = Confidence interval; LL = Lower limit, UL= Upper limit.

I ran diagnostic tests to identify correlated predictors and the presence of multicollinearity between them (i.e., VIF ≥ 10). The predictors of health-related self-efficacy were not highly correlated with each other ($|\Phi| < 0.4$), and there was no evidence of multicollinearity (VIF < 10) between them (Table 12). Based on the results of these diagnostics and the nonsignificant contributions of the use of technology for HIS to the model, I failed to reject the null hypothesis in RQ1 that there is no relationship between survivors' use of technology for HIS and their health-related self-efficacy.

Table 12

Correlation Between the Predictors of Health-Related Self-Efficacy

Variable	Correlation between the covariates			VIF
	Use of technology for HIS	Self-reported health literacy	Self-reported health status	
Use of technology for HIS	-	Φ =.046, p =.27	Φ=.039, p = .35	1.003
Self-reported health literacy	-	-	Φ =.081, p = .05	1.008
Self-reported health-status	-	-	-	1.008

RQ2: The Relationship Between the use of Technology for HIS and Positive HIS Experiences

In RQ2 on the relationship between the survivors' use of technology for HIS (predictor variable) and their positive HIS experiences (outcome variable), the potential confounders were their self-reported health literacy and self-reported health status. As shown in Table 8, the RQ2 analyses were based on the sample size of N = 543.

RQ2 Univariate Analysis

As shown in Table 13, a majority of the cancer survivors reported using technology for HIS (n = 443, 81.6%), having positive HIS experiences (n = 310, 57.1%), full or high self-reported health literacy (n = 355, 65.4%), and good or better self-reported health status (n = 410, 75.5%). Most of the survivors who used (n = 256, 57.8%) and did not use technology for HIS (n = 54, 54.0%) reported having positive HIS experiences. A majority of the survivors with any self-reported health status (less than good [51.9%] and good or better [58.8%]) and a full or high self-reported health literacy

(71.8%) reported having positive HIS experiences. About 58% of the female (*n* = 260, 47.9%) and male (*n* = 237, 43.6%) participants reported having positive HIS experiences. Most (60% ±5%) of the participants aged under 75 years and half of the 151 participants aged 75 years or older (*n* = 77, 51.0%) reported having positive HIS experiences. A little over third (37.0%) of the participants in the Asians or Other and over half (57-68%) in the other racial groups reported having positive HIS experiences. About half (49.7%) of those earning $20,000-$49,999 and around 60% ± 3% of the rest earning under $20,000 or $50,000 or more reported having positive HIS experiences.

Table 13

RQ2 Summary Statistics for the Study on the Relationship Between the Use of Technology and Positive HIS Experiences

Variables (V) and categories	Sample (*N*=543)		Positive HIS experiences			
			No		Yes	
	n	%	*n*	% within V	*n*	% within V
Use of technology for HIS						
Did not use technology	100	18.4	46	46.0	54	54.0
Used technology	443	81.6	187	42.2	256	57.8
Self-reported health literacy						
Low or none	188	34.6	133	70.7	55	29.3
Full or High	355	65.4	100	28.2	255	71.8
Self-reported health status						
Less than good	133	24.5	64	48.1	69	51.9
Good or better	410	75.5	169	41.2	241	58.8
Sex						
Female	260	47.9	110	42.3	150	57.7
Male	237	43.6	100	42.2	137	57.8
Missing of invalid data	46	8.5	23	50.0	23	50.0
Age						
Under 50 years	45	8.3	20	44.4	25	55.6
50-64 year	154	28.4	64	41.6	90	58.4

Variables (V) and categories	Sample (*N*=543)		Positive HIS experiences			
			No		Yes	
	n	%	*n*	% within V	*n*	% within V
65-74 years	188	34.6	71	37.8	117	62.2
75 years or older	151	27.8	74	49.0	77	51.0
Missing or invalid data	5	0.9	4	80.0	1	20.0
Race						
Non-Hispanic White	401	73.8	166	41.4	235	58.6
Non-Hispanic Black or African American	40	7.4	13	32.5	27	67.5
Hispanic	30	5.5	13	43.3	17	56.7
Non-Hispanic Asian or Other	27	5.0	17	63.0	10	37.0
Missing or invalid data	45	8.3	24	53.3	21	46.7
Income						
Under $20,000	75	13.8	31	41.3	44	58.7
$20,000--$49,999	169	31.1	85	50.3	84	49.7
$50,000--$99,999	152	28.0	61	40.1	91	59.9
$50,000--$99,999	140	25.8	52	37.1	88	62.9
Missing or invalid data	7	1.3	4	57.1	3	42.9
Education						
High school graduate or less	92	16.9	48	52.2	44	47.8
Some college or vocational training	176	32.4	78	44.3	98	55.7
Bachelor’s degree	145	26.7	61	42.1	84	57.9
Post baccalaureate degree	128	23.6	45	35.2	83	64.8
Missing or invalid data	2	0.4	1	50.0	1	50.0
Positive HIS experiences						
No	233	42.9	-	-	-	-
Yes	310	57.1	-	-	-	-

Unadjusted Logistic Regression Analysis for RQ2

I conducted three unadjusted logistic regression analyses to investigate RQ2 on the relationship between the predictor variables (use of technology for HIS, self-reported health literacy, and self-reported health status) and positive HIS experiences (the outcome variable). The use of technology for HIS and self-reported health status were not significant predictors of positive HIS experiences, $p > .05$ (Table 14). Self-reported health literacy significantly contributed to the model ($p < .05$) for predicting positive HIS experiences (OR = 6.17; 95% CI = 4.17, 9.11; $p < .05$).

Table 14

Unadjusted Logistic Regression Model for Predicting Positive HIS Experiences

Predictor	β	S.E.	Wald	df	*p*-value	Odds ratio	95% CI LL - UL
Use of technology for HIS							
Used technology	0.15	0.22	0.48	1	.490	1.17	0.75 - 1.80
Self-reported health literacy							
Full or high	1.82	0.20	83.52	1	<.001	6.17	4.17 - 9.11
Self-reported health status							
Good or better	0.28	0.20	1.95	1	.163	1.32	0.89 - 1.96

Note: CI = Confidence interval; LL= Lower limit; UL= Upper limit.

Multiple Logistic Regression Analysis for RQ2

I conducted a multiple logistic regression analysis to investigate the relationship between the use of technology for HIS (independent varialbe of interest) and positive HIS experiences (the outcome variable), while controlling for self-reported health literacy and self-reported health status (Table 15). The model was statistically significant, $\chi^2(N = 543, 3) = 93.13$, $p < .05$, and it explained 21.2% (Negelkerke R^2) of the variability in positive HIS experiences. The model correctly classified 71.5% of the cases. Its sensitivity and selectivitiy rates for predicting positive HIS experiences were 82.3% (Yes) and 57.1% (No), respectively. There was no evidence of the lack of model fit per the nonsignificant Hosmer and Lemeshow goodness-of-fit statistic of 0.22, $p > .05$ (Table 15). Controlling for self-reported health literacy and self-reported health status, the use of technology for HIS was not a significant predictor of positive HIS experiences (OR = 1.13; 95%

CI = 0.70, 1.82; *p* > .05). Self-reported health literacy was a significant contributor to the model, *p* < .05. Survivors with “Full or high” self-reported health literacy had 6.1 times higher odds of positive HIS experiences than their counterparts with “Low or none” self-reported health literacy (OR = 6.10; 95% CI = 4.13, 9.02; *p* < .05). Self-reported health status did not contribute to the model, and it was not a significant predictor of positive HIS experiences, *p* > .05, OR = 1.16, 95% CI [0.75, 1.79].

Table 15

Adjusted Logistic Regression Models for Predicting Positive HIS Experiences

Predictors	β	S.E.	Wald	df	*p*-value	Odds ratio	95% CI LL - UL
Constant	-1.09	0.30	13.32	1	<.001	0.38	
Use of technology for HIS							
Used technology	0.12	0.24	.24	1	.623	1.13	0.70 - 1.82
Self-reported health literacy							
Full or high	1.81	0.20	82.21	1	<.001	6.10	4.13 - 9.02
Self-reported health status							
Good or better	0.15	0.22	0.46	1	.498	1.16	0.75 - 1.79
Model overall predictive capacity: 71.5% (Yes = 82.3%, No =57.1%)							
Hosmer Lemeshow goodness of fit statistic = .222, *p*-value =.99							

Note: CI = Confidence interval; LL= Lower limit; UL= Upper limit.

The lack of evidence of multicollinearity (VIF < 10) and the nonsignificant correlation between the predictor variables ($|\Phi| < .4$, *p* >.05) indicated that the assumptions of logistic regression were not violated (Table 16). As a result, I failed to reject the null hypothesis in RQ2 that there is no relationship between the survivors’ use of technology for HIS and their positive HIS experiences.

Table 16

Correlation Between the Predictors of Positive HIS Experiences

Predictor	Correlation between the predictors			VIF
	Use of technology for HIS	Self-reported health literacy	Self-reported health status	
Use of technology for HIS	-	Φ = .02, *p* = .58	Φ =.03, *p* =.52	1.001
Self-reported health literacy	-	-	Φ =.08, *p* = .06	1.007
Self-reported health status	-	-	-	1.007

RQ3: The Relationship Between Survivor Characteristics and the Use of Technology for HIS

In RQ3, I aimed to assess the impact of the survivors' sociodemographic (age, sex, race, education, and income) and clinical (diabetes, high blood pressure, heart disease, lung disease, or depression/ anxiety) factors (predictor variables) on their use of technology for HIS (outcome variable). For this study on the relationship between the use of technology for HIS and each of the personal factors, I presented RQ3 as two questions: one to look at the sociodemographic (RQ3a) and the other at the clinical (RQ3b) variables. Survivors' self-reported health status was a potential confounder in RQ3. The RQ3 analyses, discussed next, were based on a sample of *N* = 484 (Table 8).

RQ3 Univariate Analysis

Tables 17 and 18 show the sociodemographic and clinical characteristics of the study participants, respectively. As shown in Table 17, most cancer survivors used technology (*n* = 395, 81.6%), had good or better self-reported health status (*n* = 375, 77.5%). were aged 50 years or older (*n* = 443, 91.5%), females (*n* = 259, 53.5%), and non-Hispanic Whites (*n*=392, 81.9%), had some college education or higher degree (*n* = 401, 82.9%), and earned $50,000 or higher (*n* = 269, 55.9%).

As shown in Table 17, most cancer survivors in each sociodemographic category reported using technology for HIS. About 80% ±3% of the survivors with any self-reported health status (79.8% with less than good and 82.1% good or better) or *sex* (83.8% females and 79.1% males) used technology for HIS.

Table 17

RQ3 Summary Statistics on the Survivors' Socio-demographic Factors and their use of Technology for HIS

Variable (V) and category	Sample (*N*=484)		Use of technology for HIS			
			Did not use technology		Used technology	
	n	%	*n*	% within V	*n*	% within V
Self-reported health status						
Less than good	109	22.5	22	20.2	87	79.8
Good or better	375	77.5	67	17.9	308	82.1
Age						
Under 50 years	41	8.5	2	4.9	39	95.1
50-64 year	136	28.1	9	6.6	127	93.4
65-74 years	174	36.0	29	16.7	145	83.3
75 years or older	133	27.5	49	36.8	84	63.2
Sex						
Female	259	53.5	42	16.2	217	83.8
Male	225	46.5	47	20.9	178	79.1
Race						
Non-Hispanic White	392	81.0	78	19.9	314	80.1
Non-Hispanic Black or African American	37	7.6	7	18.9	30	81.1
Hispanic	28	5.8	3	10.7	25	89.3
Non-Hispanic Asian or Other	27	5.6	1	3.7	26	96.3
Education						

Variable (V) and category	Sample (*N*=484)		Use of technology for HIS			
			Did not use technology		Used technology	
	n	%	*n*	% within V	*n*	% within V
High school graduate or less	83	17.1	34	41.0	49	59.0
Some college or vocational training	149	30.8	29	19.5	120	80.5
Bachelor’s degree	132	27.3	14	10.6	118	89.4
Post baccalaureate degree	120	24.8	12	10.0	108	90.0
Income						
Under $20,000	56	11.6	20	35.7	36	64.3
$20,000 - $49,999	159	32.9	39	24.5	120	75.5
$50,000 - $99,999	142	29.3	21	14.8	121	85.2
$100,000 or more	127	26.2	9	7.1	118	92.9
Use of technology for HIS						
Did not use technology	89	18.4	-	-	-	-
Used technology	395	81.6	-	-	-	-

Participants under 50 years accounted for 8.5% (*n* = 41) of the sample. Of the persons aged 50 years or older (*n* = 443, 91.5%), those aged 50-64 years (*n* = 136), 65 - 74 years (*n* = 174), and 75 years or older (*n* = 133) accounted for 28.1%, 36.0%, and 27.5% of the sample, respectively. The use of technology for HIS was higher among the younger than older survivors for each age category, and most survivors in each age category used it. Of the 41 survivors aged under 50 years, only two reported not using technology for HIS, which necessitated collapsing the first two age categories (“under 50 years” and “50 – 64 years”) into the new “under 65 years” category (*n* = 177). Nearly all survivors under 65 years (*n* = 166, 93.8%) and three-quarters of those 65 years or older (*n* = 229, 74.6%) reported using technology for HIS. Most of the 307 survivors aged 65 years or older (83.3% of the 65 - 74 years and 63.2% of the 75 years or older) reported using technology for HIS. Over 80% of the survivors in each race category also reported using technology for HIS.

The sample had more females (*n* = 259, 53.5%) than males (*n* =225, 46.5%). About 80% of the females (*n* = 217, 83.8%) and males (*n* = 178, 79.1%) reported using technology for HIS.

Non-Hispanic Whites (*n* = 392), non-Hispanic Blacks and African Americans (*n* = 37), Hispanic (*n* = 28), and non-Hispanic Asians and Others (*n* = 27) accounted for 81.0%, 7.6%, 5.8%, and 5.6% of the sample, respectively. The proportion of the non-Hispanic Whites in the sample was consistent with the 2017 prevalence by race for the 5-year cancer survival rates (Whites: 81.1%) statistics published by the Centers for Disease Control and Prevention ([CDC], 2020). Between 80% and 96.3% of the study participants in any racial subgroup reported using technology for HIS. Its use was lower among the non-Hispanic Whites than the other racial groups. The *use of technology for HIS* among non-Hispanic Whites (*n* = 392), non-Hispanic Black of African Americans (*n* = 37), Hispanic (*n* = 28), and non-Hispanic Asian or Other (*n* = 27) was 80.1%, 81.1%, 89.3%, and 96.3%, respectively. Hispanic and non-Hispanic Asians and Other race categories were re-categorized into “Hispanic and Others” (*n* = 55) because only three of the 28 Hispanic and one of the 27 non-Hispanic Asian or Others reported not using technology for HIS. Among the 55 Hispanic and Others, 92.7% (*n* = 51) reported using technology for HIS.

Less than 20% of the study participants attained high school graduation or less education (17.1%, *n* =83), and the majority reported having attained higher than high school education (82.9%, *n* = 401). Of the 401 survivors with greater than high school educational attainment, 30.8% (*n* = 149) had some college education, 27.3% (*n* = 132) bachelors degree, and 24.8% (*n* = 120) post-baccalaureate degree. The use of technology for HIS among the participating survivors with high school or less education (*n* = 83), some college *(n* = 149), bachelor's degree *(n* = 132), and post-baccalaureate degree *(n* = 120) was 59.0%, 80.5%, 89.4%, and 90.0%, respectively. The higher education categories had a higher percentage of survivors using technology for HIS than the lower educational attainment categories.

Most (88.4%, *n* = 428) of the study participants reported earning $20,000 or higher and 11.6% (*n* = 56) under $20,000. The 428 survivors who earned $20,000 or more were distributed approximately equally (30% ± 3.8%) across the three income categories: 32.9% (*n* = 159) earned $20,000-$49,999; 29.3% (*n* = 142) $50,000-$99,999; and 26.2% (*n* = 127) $100,000 or more. The use of technology for HIS for the income categories ranged from 64.3% to 92.9%, and the percentage of participants using it was higher in the higher than the lower-income categories (64.3% for those earning under $20,000, 75.5% for $20,000-$49,999, 85.2% for $50,000-$99,999, and 92.9% for $100,000 or more).

As shown in Table 18, most survivors had high blood pressure *(n* = 288, 59.5%). Most survivors in the study did not have a diagnosis of diabetes (*n* = 344, 71.1%), heart disease (*n* = 410, 84.7%), lung disease (*n* = 416, 86.0%), or depression or anxiety (*n* = 382, 78.9%). Most survivors, irrespective of their diagnosis of the targeted health conditions, used technology for HIS. Except in the case of a depression or anxiety diagnosis, the use of technology for HIS was higher among the survivors without than among those with the studied disease: 84.9% (*n* = 292) without and 73.6% (*n* = 103) with diabetes; 86.7% (*n* = 170) without and 78.1% (*n* = 225) with high blood pressure*;* 83.9% (*n* = 344) without and 68.9% (*n* = 51) with heart disease; and 81.7% (*n* = 340) without and 80.9% (*n* = 55) with lung disease. A higher proportion of the participants with depression or anxiety (84.3%, *n* = 84) than without it (80.9%, *n* = 309) used technology for HIS.

Table 18

Summary Statistics on the Survivor's Clinical Factors and their use of Technology for HIS

Variable (V) and categories	Sample (*N*=484)		Use of technology for HIS			
			Did not use technology		Used technology	
	n	%	*n*	% within V	*n*	% within V
Diabetes						
No	344	71.1	52	15.1	292	84.9
Yes	140	28.9	37	26.4	103	73.6
High blood pressure						
No	196	40.6	26	13.3	170	86.7
Yes	288	59.4	63	21.9	225	78.1
Heart disease						
No	410	84.7	66	16.1	344	83.9
Yes	74	15.3	23	31.1	51	68.9
Lung disease						
No	416	86.0	76	18.3	340	81.7
Yes	68	14.0	13	19.1	55	80.9
Depression or anxiety						
No	382	78.9	73	19.1	309	80.9
Yes	102	21.1	16	15.7	86	84.3

RQ3 Unadjusted Logistic Regression Analyses

I conducted several logistic regression analyses to investigate the unadjusted relationship between the use of technology for HIS (the outcome of interest) and each predictor (age, sex, race, education, income, diabetes, high blood pressure, heart disease, lung disease, depression or anxiety, and self-reported health status). Sex, race, lung disease, depression or anxiety, and self-reported health status were not significant predictors of the use of technology for HIS, p > .05 (Table 19). Age, education, income, diabetes, high blood pressure, and heart disease significantly predicted the use of technology for HIS, p <.05.

Table 19

Unadjusted Logistic Regression Analyses for Predicting Survivors' use of Technology for HIS Based on the Their Personal Factors

Predictors of the use of technology for HIS	β	S.E.	Wald	*p*-value	Odds ratio	95% CI LL - UL
Sex						
Female (Reference)						
Male	-0.31	0.24	1.74	.187	0.73	0.46 - 1.16
Age						
Under 65 years (Reference)						
65-74 years	-1.10	0.37	8.82	.003	0.33	0.16 - 0.69
75 years or older	-2.17	0.36	36.60	<.001	0.11	0.06 - 0.23
Race						
Non-Hispanic White (Reference)						
Non-Hispanic Black or African American	0.06	0.44	0.02	.886	1.07	0.45 - 2.51
Hispanic and Others	1.15	0.53	4.65	.031	3.17	1.11 - 9.03
Education						
High school graduate or less (Reference)						
Some college or vocational	1.05	0.30	12.00	.001	2.87	1.58 - 5.21

Predictors of the use of technology for HIS	β	S.E.	Wald	*p*-value	Odds ratio	95% CI LL - UL
training						
Bachelor’s degree	1.76	0.36	24.04	<.001	5.85	2.89 - 11.84
Post baccalaureate degree	1.83	0.38	23.56	<.001	6.25	2.98 - 13.08
Income						
under $20,000 (Reference)						
$20,000--$49,999	0.53	0.33	2.57	.109	1.71	0.89 - 3.29
$50,000--$99,999	1.16	0.37	10.12	.001	3.20	1.56 - 6.55
$100,000 or more	1.98	0.44	19.97	<.001	7.28	3.05 -17.40
Diabetes						
No (Reference)						
Yes	-0.70	0.24	8.29	.004	0.50	0.31 - 0.80
High blood pressure						
No (Reference)						
Yes	-0.61	0.25	5.66	.017	0.55	0.33 - 0.90
Heart disease						
No (Reference)						
Yes	-0.86	0.28	9.00	.003	0.43	0.24 - 0.74
Lung disease						
No (Reference)						
Yes	-0.06	0.33	0.03	.867	0.95	0.49 - 1.82
Depression or anxiety						
No (Reference)						
Yes	0.24	0.30	0.63	.429	1.27	0.70 - 2.29
Self-reported health status						
Less than good (Reference)						
Good or better	0.15	0.27	0.30	.583	1.16	0.68 - 1.99

Note: CI = Confidence interval; LL= Lower limit; UL= Upper limit.

RQ3 Multiple Logistic Regression Analysis

I conducted a multiple logistic regression analysis to investigate the impact of survivors’ sociodemographic (age, sex, race, education, and income) and clinical variables (diabetes, high blood pressure, heart disease, lung disease, and depression or anxiety) on their use of technology for HIS (the outcome variable) while controlling for their self-reported health status. The model was significant, $\chi^2(N = 484, 17) = 101.78$, $p < .05$, and it explained 30.8% (Negelkerke R^2) of the variability in the use of technology for HIS. The model correctly classified 82.9% of the cases, and its accuracy was 95.7% for predicting the use and 25.8% for the nonuse of the use of technology for HIS (Table 20). There was no evidence of the lack of model fit based upon the Hosmer and Lemeshow goodness-of-fit statistic of 5.95, $p > .05$.

Table 20

Adjusted Logistic Regression Analysis for Predicting the use of Technology for HIS

Predictors of the use of technology for HIS	β	S.E.	Wald	df	*p*-value	Odds Ratio	95% CI LL - UL
Constant	1.01	0.60	2.79	1	.095	2.74	
Sex							
Female (Reference)							
Male	-0.35	0.28	1.54	1	.215	0.71	0.41 - 1.22
Age							
Under 65 years (Reference)							
65 - 74 years	-0.92	0.40	5.13	1	.024	0.40	0.18 - 0.88
75 years or older	-1.99	0.41	23.67	1	<.001	0.14	0.06 - 0.30
Race							
Non-Hispanic White (Reference)							
Non-Hispanic Black	0.08	0.50	0.03	1	.866	1.09	0.41 - 2.88
Hispanic and Others	0.91	0.61	2.24	1	.135	2.47	0.75 - 8.10
Education							
High school graduate or less (Reference)							
Some college or vocational training	1.05	0.35	9.07	1	.003	2.85	1.44 - 5.65
Bachelors' degree	1.62	0.42	14.66	1	<.001	5.05	2.20 - 11.56
Post baccalaureate degree	1.58	0.45	12.45	1	<.001	4.83	2.01 - 11.59
Income							
Under $20,000 (Reference)							
$20,000-$49,999	0.85	0.40	4.48	1	.034	2.34	1.07 - 5.16
$50,000-$99,999	1.25	0.44	8.30	1	.004	3.51	1.49 - 8.23
$100,000 or more	1.66	0.53	9.69	1	.002	5.28	1.85 - 15.04

Predictors of the use of technology for HIS	β	S.E.	Wald	df	p-value	Odds Ratio	95% CI LL - UL
Diabetes							
No (Reference)							
Yes	-0.50	0.30	2.80	1	.095	0.61	0.34 - 1.09
High blood pressure							
No (Reference)							
Yes	0.24	0.31	0.60	1	.438	1.27	0.69 - 2.35
Heart disease							
No (Reference)							
Yes	-0.44	0.34	1.63	1	.202	0.65	0.33 - 1.26
Lung disease							
No (Reference)							
Yes	-0.01	0.39	0.00	1	.971	0.99	0.46 - 2.11
Lung disease							
No (Reference)							
Yes	0.329	0.36	0.82	1	.365	1.39	0.68 - 2.83
Self-reported health status							
Less than good							
Good or better	-0.42	0.34	1.58	1	.209	0.65	0.34 - 1.27

Model's prediction capacity = 82.9% (95.7%: used technology, 25.8%: did not use technology).

Hosmer lemeshow goodness-of-fit statistic = 5.951, p-value=.653

Note: CI = Confidence interval; LL= Lower limit; UL= Upper limit.

The adjusted analysis resulted in age, education, and income being significant contributors to the model for predicting the use of technology for HIS, $p < .05$. However, two sociodemographic variables (sex and race), all clinical variables (diabetes, high blood pressure, heart disease, lung disease, depression or anxiety), and self-reported health status were not significant contributors to the model, $p > .05$ (Table 20). Controlling for the self-reported health status, other sociodemographic and the clinical variables, the predictor variable (age) contributed significantly to the model (Table 20). Survivors 65 years or older had significantly lower odds of using technology for HIS than their counterparts under 65 years ($p < .05$). The odds of using technology for HIS for survivors aged 65-74 years were 0.40 times of those under 65 years (OR = 0.40; 95% CI = 0.18, 0.88), and for 75 years or older had 0.14 times of those under 65 years (OR = 0.14; 95% CI = 0.06, 0.30).

The predictor variable (education) had a significant and independent association with the use of technology for HIS ($p < .05$). The odds of using technology for HIS were 2.85 times with college education (OR = 2.85; 95% CI = 1.44, 5.65), 5.05 times with a bachelors' degree (OR = 5.05; 95% CI = 2.20, 11.56), and 4.83 times with a post-baccalaureate degree (OR = 4.83; 95% CI = 2.01, 11.59) as compared with those with high school or less education.

The predictor variable (income) was significantly and independently associated with and a significant predictor of the use of technology for HIS, $p < .05$ (Table 20). The estimated odds of survivors use of technology for HIS were 2.34 times higher with earnings of \$20,000-\$49,999 (OR = 2.34; 95% CI = 1.07, 5.16), 3.51 times with \$50,000-\$99,999 (OR = 3.51; 95% CI = 1.49, 8.23), and 5.28 times with \$100,000 or more (OR = 5.28; 95% CI = 1.85, 15.04) as compared to those earning under \$20,000 (Table 20).

There was no evidence of the violation of the assumptions of logistic regression per the lack of evidence of highly correlated predictors of the use of technology for HIS ($|\varphi| < .4$) or the multicollinearity between them, VIF < 10 (Table 21).

Table 21

RQ3 Correlation Between the Predictors of the use of Technology for HIS

Variable	Relationship (phi, phi-c) between the variables(a)										
	1	2	3	4	5	6	7	8	9	10	VIF
SRHS	0.06	0.05	0.07	0.13*	0.09*	0.15*	0.08	0.19*	0.16*	0.13*	1.10
1 Age	-	0.14*	0.16*	0.07	0.11*	0.14*	0.31*	0.19*	0.08	0.16*	1.21
2 Sex	-	-	0.10	0.12	0.14*	0.04	0.07	0.13*	0.02	0.12*	1.07
3 Race	-	-	-	0.09	0.11*	0.09	0.08	0.06	0.01	0.06	1.08
4 ED	-	-	-	-	0.25*	0.12	0.13*	0.08	0.12	0.10	1.22
5 INC	-	-	-	-	-	0.14*	0.12	0.06	0.13*	0.22*	1.30
6 Diabetes	-	-	-	-	-	-	0.28*	0.19*	0.03	0.01	1.14
7 High BP	-	-	-	-	-	-	-	0.17*	0.04	0.01	1.19
8 Heart D	-	-	-	-	-	-	-	-	0.06*	0.06	1.10
9 Lung D	-	-	-	-	-	-	-	-	-	0.17*	1.05
10 Dep/ Anx	-	-	-	-	-	-	-	-	-	-	1.09

[a] the column headers 1 – 10 correspond to the variables designated by the number in the variable column; * = $p < .05$, High BP = High blood pressure, SRHS = self-reported health status, INC = Income, Heart D = heart disese, Lung D = Lung disease, Dep/Anx = Depression or anxiety

Consequently, I rejected the null hypothesis in RQ3a with the evidence of a significant relationship between sociodemographic factors and use of technology for HIS, and I failed to reject the null hypothesis in RQ3b without the evidence of a significant relationship between clinical factors and the use of technology for HIS. However, statistically significant evidence against the null hypothesis in RQ3a served as evidence of a significant relationship between some of the survivors' characteristics and their use of technology for HIS.

Summary

I conducted multiple logistic regression to investigate the relationship between cancer survivor's use of technology for HIS and their health-related self-efficacy (in RQ1), positive HIS experiences (in RQ2), and personal factors (in RQ3) among cancer survivors who seek health information for themselves. I presented the results of each analysis, summarized the findings, and presented the conclusions. The results were not statistically significant for RQ1 and RQ2, in that I did not find evidence to suggest that using technology for HIS significantly predicted health-related self-efficacy (RQ1) or positive HIS experiences (RQ2) among cancer survivors who sought health information, after controlling for potential confounding variables. I found that sociodemographic factors, i.e., age, income, and education of the survivors who sought health information were significant independent predictors of their use of technology for HIS (RQ3). Clinical factors, such as diabetes and heart disease were not significantly associated with the use of technology for HIS (RQ3), however. In Section 4, I will interpret these findings, recommend future research, and provide social change implications of the findings.

Section 4: Application to Professional Practice and Implications for Social Change

Introduction

The purpose of this quantitative study was to close the gaps in the scientific knowledge about the characteristics of cancer survivors who use technology for HIS, how it benefits their health-related self-efficacy, and how they feel about its use. I used the HINTS 5 Cycle 3 cross-sectional survey to measure the use of technology for HIS, health-related self-efficacy, positive HIS experiences, and the sociodemographic (age, sex, race, education, and income), and clinical (diabetes, high blood pressure, heart disease, lung disease, and depression or anxiety) factors of the participating cancer survivors who sought health information. As described in Section 2, the HINTS surveyors used a stratified sampling design and surveyed nationally representative adults in the U.S. to ensure generalizability.

I conducted this study because cancer survivors face various health issues during their survivorship, and many of them use technology to seek health information for the self-management of their HRQOL, as discussed in Section 1. I used a correlational study design and conducted multiple regression analyses to examine the relationship between the survivors' use of technology HIS and their health-related self-efficacy, positive HIS experiences, and sociodemographic and clinical factors. The results, presented in Section 3, did not show a statistically significant influence of the survivors’ use of technology for HIS on their health-related self-efficacy (OR = 0.91; 95% CI = 0.54, 1.54 $p > .05$, $N = 581$ [Table 11]) or the positive HIS experiences (OR = 1.15; 95% CI = 0.75, 1.79; $p > .05$, $N = 543$ [Table 15]). Several sociodemographic factors (i.e., age, education, and income) significantly predicted use of technology for HIS, $p < .05$ (Table 20). However, the other two sociodemographic factors (sex and race), clinical characteristics (diabetes, high blood pressure, heart disease, lung disease, and depression or anxiety), and self-reported health status were not significant predictors of the use of technology for HIS ($p > .05$, $N = 484$ [Table 20]). In this section, I will interpret these findings within the self-efficacy theoretical framework, discuss the study's limitations, propose future research recommendations, and discuss the findings' social change implications.

Interpretation of the Findings

This study advanced an understanding of the technology for HIS and key goals of cancer survivorship self-management interventions. The current study confirmed that a high percentage of cancer survivors use technology for HIS (80.2% ± 1.6%), and it is 20 to 40% higher than previously reported (Chua et al., 2018; Finney Rutten, Agunwamba, et al., 2016; S. Jiang & Liu, 2020; Miyawaki et al., 2015; Mooney et al., 2017). Self-management interventions promote HIS behaviors to improve health literacy and self-efficacy (Grover & Joshi, 2015) in performing tasks such as taking good care of their health or finding health information. Per the self-efficacy theory, domain knowledge plays a role in the development of the domain-specific personal agency. As technology-based HIS enables access to external health information (i.e., knowledge), I conducted multiple logistic regression analyses to understand the influence of survivors' use of technology for HIS (i.e., accessing external knowledge source) on their health-related self-efficacy and positive HIS experiences. I also conducted multiple logistic regression analyses to understand the impact of their sociodemographic and clinical factors (as the affective and selective components of the Self-efficacy theory) on their use of the technology for HIS. In the first question, my goal was to understand the effects of the technology-based HIS on health-related self-efficacy, which is a key goal of health self-management interventions. In the second research question, I sought to understand the effects of the technology-based HIS on positive HIS experiences to reduce barriers to health self-management barriers. The third research question was designed to identify the current predictors of using technology for HIS to inform health promotion strategies based on the latest predictors of HIS behaviors.

Health-related self-efficacy

Concerning the first research question, I did not find a statistically significant relationship between the use of HIS-technology and health-related self-efficacy. Developing health agency (i.e., health-related self-efficacy), per the personal agency concept of the self-efficacy theory, requires the generation of new knowledge rather than just possessing (internally or externally) knowledge (Bandura, 1997). As such, survivors who prefer to rely on external sources for self-care might not experience any health agency gains. Therefore, the self-efficacy theory's cognitive process and personal-agency concept can explain the nonsignificant association between survivors' use of technology for HIS and health-related self-efficacy. These findings also show that health literacy and health status, rather than the tool used to find health information, are essential considerations for health self-management interventions.

Consistent with past research, full or high self-reported health literacy and good or better self-reported health status (i.e., low or no morbidity burden) were significantly and positively correlated with health-related self-efficacy (Finney Rutten, Hesse, et al., 2016; Peters et al., 2019). As the first to examine the impact of technology-based HIS on health-related self-efficacy among the cancer survivors who seek health information, this study contributed new knowledge about technology-based HIS to the body of scientific knowledge. As discussed in Section 2, the past studies examined: the acceptance and adoption of healthcare technology (Rahman et al., 2016); the impact of health-related self-efficacy on technology-based HIS (Miller et al., 2018); the impact of technology-based HIS on health (S. Jiang & Street, 2017), the adoption of healthy behaviors (Song et al., 2015), and improved patient-centered communications (Finney Rutten, Hesse, et al., 2016) and patient engagement (McAllister et al., 2012); and, the impact of HIS behaviors on patient's health-related self-efficacy (Go & You, 2018). The current study enhanced the scientific understanding of HIS-mechanisms driving health-related self-efficacy and closed the same gap identified by Finney Rutten et al. (2016). The findings supported earlier research about health literacy being a significant positive predictor of health-related self-efficacy (Finney Rutten, Hesse, et al., 2016; Peters et al., 2019).

The negative relationship between technology-based HIS and health-related self-efficacy may be explained by many factors impeding cognitive storage or processing the information retrieved from the external sources. Many online health information sources lack patient-centered, accessible, and scientifically vetted health information (ACS, 2016; Cleveland Clinic, 2014), making it difficult to develop new knowledge (i.e., personal agency) from the searched information. Second, survivors may seek health information or support to cope with unmet health needs (e.g., unmet psychosocial needs, new or acute issues) to improve their HRQOL (Bouma et al., 2015; Willems et al., 2016), making it unnecessary to store information for future use if they can easily retrieve it next time. The convenience of anytime access to the external knowledge may reduce demand for the cognitive processes involved in developing the personal agency just as scanning information was negatively associated with health knowledge (Wigfall & Friedman (2016). Moreover, many searched HIS to improve their communications with their healthcare providers as many reported using it to close information gaps for treatment decisions, self-diagnosis, second opinions, acceptance of the diagnosis, and self-empowerment for provider communications (Holmes et al., 2017; Mayoh et al., 2011; Zucco et al., 2018). In such cases, technology-based HIS might impact the survivors' health literacy (for navigating their healthcare decisions) rather than self-care ability to control cancer or HRQOL without engaging healthcare professionals' support. Technology as an enabler of control over what to learn and when (Go & You, 2018), the HIS for purposes other than developing personal agency may not substantially change the person's health-related self-efficacy. Therefore, although not significant, it is noteworthy that the negative effects of technology-based HIS on health-related self-efficacy still have a practical significance, given the high percentage of survivors seeking health information (82.2%, Figure 1 in Section 3) and most of them (80.2%) used technology for HIS (Table 9).

The high prevalence of technology-based HIS, despite low health-related self-efficacy, may be explained by the fact that any HIS technology is a tool for accessing external knowledge rather than internal knowledge. Given self-efficacy is situation-, task-, and domain-specific (Bandura, 1997), survivors would need new information for new health issues. Given the ubiquity of online health information sources (Ernst, 2015), some survivors might also opt to rely on external information sources rather than develop internal knowledge.

As observed in nonhealthcare domains, consumers’ technology use and adoption tend to be driven by its relative advantage in performing procedural tasks, convenience, complexity, and the immediate rather than future gratification from its use (Charness & Boot, 2015; Pantano & Priporas, 2016; Sun et al., 2013). The wide adoption of Global Positioning Systems (GPS) can be attributed to the ease of use and efficiency of the GPS-based systems in the immediate gratification in addressing real problems such as finding a vehicle or key location, automatic re-routing for missing a planned exit versus getting lost with paper maps (Ciccarellia et al., 2011) or finding wandering clients (pets, persons with cognitive impairments) using the alternative methods (Wherton et al., 2019). Patients also use technology for HIS to find better health information from online sources to address their dissatisfaction with healthcare providers' health communications (Holmes et al., 2017; Tan & Goonawardene, 2017; Tustin, 2010). However, users without confidence in their ability to do the task (e.g., calculate, graph) and without mental engagement with the tool's output (e.g., calculations, health information) may not recognize errors or limitations of the technology (McCulloch et al., 2013; Thomas et al., 2007). A reliance on technology rather than mental knowledge can impair cognitive function for lacking demand and activation of the neuronal processes involved in the cognitive processing of the information in the persons’ memory (Gruber et al., 2001).

Therefore, the use of convenient and easy to use technology to access the health information resources can reduce the demand for internal knowledge and cognitive processes for developing the agency needed for health-related self-efficacy among survivors who do not mentally engage with the searched content.

Positive HIS experiences

The multiple regression analysis did not result in a statistically significant relationship between the use of technology for HIS and positive HIS experiences, which indicated that general-purpose HIS technologies for searching online health information might be insufficient for attaining positive HIS experiences. Moreover, the high prevalence of negative HIS experiences among the survivors with lower education, lower-income, less than good health status, and low or no health literacy, and some of the minority racial/ethnic subgroups (Table 13) indicate potential inequities in the HIS access, and it also shows the untapped potential for improving survivorship HRQOL.

These findings extended the body of knowledge about the relationship between technology-based HIS and HIS experiences. The current study added new information to the scientific body of knowledge on the relationship between the use of technology for HIS and positive HIS experiences and the confounders (self-reported health literacy and self-reported health status). The study findings support prior research about a high prevalence (i.e., over 30%) of negative HIS experiences among cancer survivors (Bernat et al., 2016; Vanderpool et al., 2009; Wigfall & Friedman, 2016). These findings serve as the first step towards closing the literature gaps identified by Jiang and Liu (2020), Waters et al. (2016), and Germeni et al. (2015) on the understanding of the technology-based HIS experiences to inform cancer survivorship interventions. Although clinical trials demonstrated the benefits of technology (e.g., mobile apps, short text messages, emails) in improving patients' access to health information (Greenberg et al., 2018; Y. Jiang et al., 2017; Rico et al., 2017), the current study did not provide any statistically significant evidence of those benefits with the use of a general-purpose technology for health information search. The approximately equal proportion of survivors experiencing negative or positive HIS experiences with and without technology-based HIS (Table 13) indicate there may be survivorship information gaps in the health information sources (healthcare, family, print media, and online sources). Patients who lack access to survivorship care plans (SCP) for health self-management would be at a disadvantage in managing their health. Long-term survivors (i.e., five or more years) such as the adult survivors of childhood cancers or those without healthcare access have consistently lacked access to comprehensive SCPs (Birken et al., 2018; Iyer et al., 2017). Even 40% to 75% of cancer survivors who received cancer-related health information from their healthcare providers had difficulty accessing the information for health-related decisions and action (Hall et al., 2018; Hébert & Fillion, 2017; McGinty et al., 2016; Pongthavornkamol et al., 2019; Vogel et al., 2017). The past research suggests that a lack of health information may be an underlying reason for such a high prevalence of negative, rather than positive, HIS experiences among the survivors who seek health information with and without HIS-technology use.

A higher prevalence of negative HIS experiences without using HIS technology (46.0%) than with it (42.2%) further indicates potential gaps in health information availability. The study confirms the high prevalence of negative HIS experiences (43.0%) in the past, including in 2016 (McCloud et al., 2016) and (42.6%) 2009 research (Vanderpool et al., 2009). These indicate no or little improvement in the survivors' HIS experiences in the past 10 years. The findings indicate disparities in the positive HIS experiences for some survivors (75 years or older, non-Hispanic Asians and Others race, earning $20,000-$49,999, high school or less education). A small percentage of non-Hispanic Asians and those of other races included in this category having positive HIS experiences (37% [Table 13]), even though nearly all of them used technology for HIS (96.3%), may indicate disparities in the health information or the access to health information. More non-Hispanic Asians using technology for HIS than non-Hispanic Whites and health information disparities were also reported by Nguyen and Bellamy (2006). Given HIS behavior is a significant mediator of health self-efficacy (Y. Chen & Feeley, 2014), these disparities in the positive HIS experiences may negatively influence their access to health information and, consequently, their health-related self-efficacy. These specific factors might confound the potential of these factors to influence their positive HIS experiences.

The nonsignificant relationship and the persistently high prevalence of negative HIS experiences may be due to the factors such as the HIS skills, practice, computer skills (McCloud et al., 2016), or the assumptions described in Section 1 such as device features and HIS-related environmental factors. As survivors expect some value (affective reason) for the effort put into the HIS activity (Bandura, 1997), survivors searching readily available information in multiple modes (health-related web, social media, or videos) might encounter less effort or frustration than those searching for rare or previously unreported side-effects or a combination of health issues. Survivors with early stage-diagnosis of treatable cancers might have different unmet health information needs than those diagnosed with secondary or second cancers. Survivors aiming to get targeted search results to their needs may become frustrated with non-targeted search results. Nonetheless, negative HIS experiences (in terms of effort and information overload), with any HIS means, could discourage further HIS or switch to better or alternative HIS means (McCloud et al., 2016). Survivors with perpetuating negative HIS experiences may form fatalistic beliefs for attaining a satisfactory HRQOL.

Use of Technology for HIS

To study the third research question, I ran multiple logistic regression to predict HIS technology use based on the survivors' sociodemographic and clinical factors and their self-reported health status. The highly prevalent (≥ 80%) use of technology for HIS among survivors of any sex, self-reported health status, age under 75 years, racial/ethnic group, with college or higher education, and income of $50,000 or more (Table 17) indicates ubiquity of the HIS technology in the US. Fewer (60% ± 5%) low socioeconomic persons (high school or less education and earning under $20,000) using technology for HIS is consistent with prior research attributing disparities in the digital divide to the survivors' socioeconomic status, internet skills, preferred HIS source, or their trust in online versus other HIS sources (Jacobs et al., 2017; Nicolaije et al., 2016; Wigfall & Friedman, 2016). These findings suggest that low socioeconomic survivors may be at a disadvantage in accessing online health information sources.

The analysis showed that three sociodemographic factors (age, education, and income) significantly and independently predicted using technology for HIS (Table 20). Technology use for HIS was not significantly different, $p > .05$, for sex, race, self-reported health status, or clinical diagnosis of diabetes, high blood pressure, heart disease, lung disease, and depression/anxiety; as such, these factors did not significantly predict the use of technology for HIS. These findings indicate that after controlling for survivors' health, their sociodemographic factors remain predictors of HIS behaviors and that the increased burden of cancer comorbidities has little impact on technology use for HIS among the cancer survivors in the US.

Consistent with past research, age, education, and income were correlated with higher technology-based HIS behaviors (Finney Rutten, Agunwamba, et al., 2016; Jacobs et al., 2017; Miller et al., 2018). The results indicated that younger age (under 65 years than 65 years or older), higher education (with a college or higher education than with a high school or less), and higher-income (earning $20,000 or higher income than earning less) were significantly associated with higher use of technology for HIS. Although race, sex, self-reported health status as significant predictors of online HIS among the general U.S. adult population (J. Li et al., 2016), those linkages were not evident among the U.S. cancer survivors in the current study. The significant linkage between self-reported health status and online HIS among the general U.S. population in 2012 (J. Li et al., 2016) was not confirmed among the cancer survivors in the current study.

The findings confirm prior research on younger age being significantly correlated with technology-based HIS (Finney Rutten, Agunwamba, et al., 2016; Jacobs et al., 2017) and extended the meaning of "younger age" in the past research (under 40 years) and the current study (under 65 years). The past findings based on the pre-2014 data showed a higher prevalence of technology-based HIS among those under 40 years than over 40 years (Finney Rutten, Agunwamba, et al., 2016; Jacobs et al., 2017; Shneyderman et al., 2016), while the current study showed no substantial differences among those under 65 years. Instead, a similarly high prevalence of technology-based HIS (95% ± 2%) between those under 50 (95.1%) and 50 to 64 years (93.4%) can be explained by the rapid rise in mobile-device ownership across age groups (Pew Research Center, 2019), the increased material access to internet infrastructure and connectivity (Greenberg et al., 2018; S. Jiang & Liu, 2020), and those representing the under 40 years age group in the pre-2014 research now reaching the 50-64 age group. The differences in the technology-based HIS may be influenced by healthcare access to Americans 65 years or older. Prior research indicated that older adults in this age group preferred and trusted their healthcare providers rather than online sources (Jacobs et al., 2017). Nonetheless, over 80% of the 65 to 74 year and 63% of the 75 years or older using technology for HIS (Table 17) indicate that most older survivors seek HIS from online sources.

Consistent with prior knowledge, higher education and higher income were significantly associated with higher odds of technology-based HIS (Jacobs et al., 2017; Miller et al., 2018), and consequently, the negative effects of their inverse on survivors' access to health information. Survivors without healthcare access, such as adult survivors of childhood cancers, who do not use HIS technology would lack access to online health resources.

The study supported prior research of no significant correlation between race/ethnicity and technology-based HIS (Dean et al., 2017; Finney Rutten, Agunwamba, et al., 2016; Jacobs et al., 2017; Kobayashi & Smith, 2016; Rooks et al., 2019). These findings can be explained by the fact that most (about 80% or more) Americans across racial/ethnic background own smartphone (Pew Research Center, 2019), as supported by 80% of the survivors in each racial group in the study used technology for HIS (Table 17). Among the general U.S. population between 2002 and 2012, Li et al. (2016) found race/ethnicity to be a significant predictor of online HIS. A cancer diagnosis may be a significant predictor of technology-based HIS than other clinical factors, given that over 80% of the survivors used technology for HIS.

Consistent with some prior research, sex was not significant predictor of technology-based HIS (Finney Rutten, Agunwamba, et al., 2016; Kobayashi & Smith, 2016). However, these findings were inconsistent among the young survivors aged under 35 (Jacobs et al., 2017; Miller et al., 2018). Among these young adults, Miller et al. (2018) found females were more likely than males to use technology, and Jacobs et al. (2017) found significant linkage only in 2014 than the earlier 2011 to 2013 population samples. Since Jacobs et al. (2017) studied the HIS behaviors among all U.S. adults, rather than the cancer survivors, the current study extended the existing knowledge that the differences in the HIS behaviors by sex found in the general U.S. adult population may not apply to the cancer survivors in the U.S. It warrants further investigation on the HIS behaviors by sex among the young adults (under 35 years) versus older adults (under 65 years).

Limitations of the Study

Due to the cross-sectional study design, the results cannot infer any causal links between the predictor and predicted variables. The current study is generalizable to adult U.S. cancer survivors who seek health information under similar contexts. The small number of participants in the younger age, such as under 50 years and minority racial/ethnic groups such as Asians and American Indians limits the generalizability of the subpopulation groups' findings. Moreover, HIS experiences can be measured along with any combination of the four dimensions, as described in Section 2, rather than the just two dimensions (effort and frustration) used to operationalize positive HIS experiences in the current study. Therefore, the generalizability of the findings is limited to the effort and frustration dimensions only.

Per the Self-efficacy theory, survivors' HIS-related agency (HIS skills and practice) and health-related agency (health knowledge and practice) predict both HIS experiences (e.g., reduced effort or frustration with HIS agency) and health-related self-efficacy (retrieval and interpretation of the most relevant information) to manage the unmet health issue. The significantly higher odds of HIS frustration among persons without a medical problem than with a medical condition (McCloud et al., 2016) suggest that persons with medical problems might have different levels of effort expectation or search vocabulary for better search experience. However, I did not consider survivors' HIS skills, HIS frequency and duration, the HIS motivation (e.g., prevention, treatment, or control decision), survivor's health (e.g., cancer stage, recurrence factors), treatment context (during or post-treatment), the HIS environment (e.g., devices or connectivity), or the context (e.g., health insurance). Therefore, the findings of the relationship between the use of technology for HIS and health-related self-efficacy and positive HIS experiences may not be generalizable to survivors with varying levels of HIS agency, health agency, or HIS context. Instead, the findings are generalizable to cancer survivors in the U.S. who seek health information within the study design parameters.

Except for the above-noted limitations, the findings are reliable and generalizable for the lack of evidence of threats to internal or external validity. As discussed in Section 2, the results are based on the data source, study instrument, and data collection design widely accepted and used by scientists for peer-reviewed scientific literature. The analysis models had a predictive accuracy of 90.8% for full or high health-related self-efficacy (Table 11), 82.3% for positive HIS experiences (Table 15), and 95.7% for using technology for HIS (Table 20). This study can be repeated for dependability and confirmability by using the design discussed in Section 2 and performing the multiple logistic regression analysis on the 2019 HINTS 5 Cycle 3 data described in Section 3.

Recommendations

Although the current study advanced knowledge about how survivors use technology for HIS, how they benefit from it, and how they feel about it, many questions remain unanswered. More studies are needed to fully assess how best to integrate HIS technology for effective cancer survivorship interventions and remove diverse groups' barriers to health information. Due to the small number of minority participants in the current study, future studies may be focused on minority U.S. subpopulations such as

American Indians/Native Americans, Pacific Islanders, and Asians. Other studies may test the hypotheses in dissimilar healthcare and sociopolitical contexts.

Just as the current study confirmed that external knowledge searched via a tool did not significantly impact survivors' health agencies, future research can examine the impact of accessing external health knowledge on health literacy, given health literacy is a significant predictor of health-related self-efficacy. Understanding the association between technology-based HIS and health literacy can provide meaningful insights for addressing cancer survivors' unmet health information needs.

Future studies can expand the contribution of the current study on the association between technology-based HIS and positive HIS experiences by examining survivors' HIS motivation (e.g., prevention, control, coping, saving money or time), HIS skills, and cancer experience (e.g., early-stage, late-stage, during or post-treatment) to better understand their barriers to health information and informing effective and targeted survivorship interventions.

Future studies can expand the current finding of HIS experiences from different sources. There are many public and nonprofit cancer-related health information and education resources such as the nonprofit organizations (e.g., ACS, American Lung Association [ALA]) and public health agencies (e.g., NCI), with a mission to improve patient lives (ACS, 2016; ALA, n.d.; Cleveland Clinic, 2014) as well as healthcare providers and other private health information sources. Understanding the positive or negative impact of the HIS from and use of the health information from those different sources (e.g., public, healthcare, academic, and non-regulated distributors of health information) on survivors’ HIS experiences and health outcomes can provide further insights on the information or implementation gaps in survivorship interventions. For instance, understanding the relationship between using technology for HIS and pubic online health information such as the CDC, NCI, and virtual support groups on physical and psychosocial health outcomes following the HIS activity can help health educators develop effective communication strategies to improve self-care survivorship interventions.

Considering past research on the perceived usefulness of HIS technology and health consciousness (motivated and seeking benefits) for health action (Zhang et al., 2019), understanding the impact of the HIS with and without technology on their knowledge, expected, and actual health outcomes could provide insights into the specific improvements in cancer survivorship interventions.

Given that lower-income and lower-educational attainment are also among the predictors of lower health healthcare access (Barber et al., 2017; Johnson et al., 2020), health-related self-efficacy and self-management (Farley, 2020), future research is recommended to understand the lower socioeconomic survivors’ barriers to technology-based HIS among, given the anytime and anywhere availability of the public online health information sources.

Implications for Professional Practice and Social Change

The findings may improve cancer survivorship interventions and survivors' barriers to attaining a satisfactory HRQOL. As a new study, the study documented survivors' self-efficacy outcomes using HIS technology to self-manage their HRQOL.

The evidence against the significant impact of the technology on health-related self-efficacy or positive HIS experiences and the high prevalence of negative HIS experiences among cancer survivors documented the gaps in the US's self-management survivorship interventions. Addressing survivor unmet health information needs to self-manage the negative treatment effects on physical, mental, and emotional health and the associated degraded HRQOL (Arndt et al., 2017; Faller et al., 2017; Hall et al., 2018; Hébert & Fillion, 2017; Lindqvist et al., 2017; Loeb et al., 2010; Pongthavornkamol et al., 2019; van Leeuwen et al., 2018; Vogel et al., 2017; Voss et al., 2015). The findings also showed that many survivors with negative HIS experiences could not find health information resources despite the many reliable online health information sources for cancer interventions. These findings have practically significant implications on the development and promotion of cancer survivorship self-management interventions.

Professional Practice

The absence of a statistically significant relationship between the use of technology for HIS and health-related self-efficacy and positive HIS experiences implies the need to improve online health information, the searchability, and the accessibility of online health information. Given the ubiquity of the online health information sources, HIS technology, and the survivors' growing demand for health information, public health communicators must consider online sources in availing personalized health information needed by the diverse survivors in the US.

While technology-based HIS may not significantly impact health-related self-efficacy, a technology designed specifically to support health-information seeking may help survivors self-manage specific health issues for a better HRQOL. Consumers tend to use technology for immediate gratification (Lee & Ma, 2012). Recognizing online information sources can be availed to anyone with HIS technologies, HIS technology has the potential to transform self-management interventions and removing survivor's barriers to health information if it can provide the immediate gratification consumers seek from the use of any tool. Otherwise, consumers will replace any tool which fails to deliver the desired outcomes within expectations. Widely adopted technologies (e.g., interactive maps and trip planning, glucose meters) rely on quality information (e.g., up-to-date maps and user location, highly sensitive glucose readings), intuitively easy to use user interface, and immediate results. Therefore, any health promotion and self-management strategies that depend on general-purpose HIS technologies would benefit from ensuring accuracy, relevancy, and accessibility of the agency's multimorbidity health information. The current study's findings support integrating purposeful, rather than general-purpose, HIS technology for providing targeted health information for improving survivorship HRQOL outcomes (Allsop et al., 2018; Davis et al., 2019; Hochstenbach et al., 2015; Howell et al., 2019). Purposeful HIS-technology (e.g., a publicly available health browser) that produces targeted results for the need and overcomes any search environment-related issues (e.g., browser tracking, content prioritizing content based on the commercial rather than seeker's need) might reduce survivors' barriers to positive outcomes in the desired health goal. Therefore, investing in targeted HIS technologies, void of commercial conflicts of interest, can help reduce disparities in disadvantaged survivors' (such as those with inadequate health insurance, e.g., uninsured and underinsured) access to health information for attaining a satisfactory HRQOL.

Recognizing the high prevalence of the technology-based HIS even among cancer survivors aged 65 years or older, health practitioners need to consider developing health infrastructure to serve personalized health information to improve the survivors' HIS experiences and their ability to search for health information. Interactive and publicly managed health information infrastructure and resources can help survivors attain a satisfactory HRQOL using tools already available to them without burdening the healthcare system.

The findings of lower age and higher education and higher income having higher odds of technology-based HIS served as evidence that sociodemographic factors impact health information distribution and, consequently, equities in health benefits. Therefore, survivorship program planners should continue to include sociodemographic factors in planning, implementing, monitoring, and evaluating the survivorship interventions. Similarly, policymakers and program managers should address gaps in their programming to reduce disparities and improve disadvantaged subpopulations' access to health information.

Positive Social Change

The study's positive social change implications include contributing new scientific evidence on HIS technology's impact on self-management public health programs' key goals. The study findings provide unique insights into the relationship between the survivors' use of technology for HIS and its impact on their health-related self-efficacy, HIS experiences, and sociodemographic and clinical factors. Public health professionals can use the findings and insights on these factors to inform effective survivorship education, health promotion, research, and interventions. The insights about the potential negative impacts of the technology-based HIS on health-related self-efficacy can be used to guide the key goals and measures of success of cancer survivorship interventions. Similarly, public health professionals can use the information about little-to-no improvement in survivors' HIS experiences in the past ten years to prioritize the public or private policy to promote the health information' searchability and accessibility to reduce survivors' access barriers to health information. Public health professionals can also use the findings of sociodemographic factors, after controlling for health and clinical factors, continue to be predictors of HIS behaviors to inform public policy to address disparities in the digital divide in access to online health information sources.

Conclusion

In this quantitative correlational study using the 2019 HINTS cross-sectional dataset, I examined the relationship between survivors' use of technology for HIS and their health-related self-efficacy, positive HIS experiences, and sociodemographic and clinical factors. Most survivors across sociodemographic and clinical groups used technology for HIS. Its use varied by comorbidity, and its use was higher among survivors with than without depression or anxiety and among those without than with diabetes, high blood pressure, heart disease, and lung disease. Survivors' use of technology for HIS was significantly influenced by their age, income, and education but no other study factors. Their use of technology for HIS was not significantly related to their health-related self-efficacy, positive HIS experiences, sex, race, self-reported health status, and clinical factors.

Despite the substantial advances in scientific knowledge and the availability and affordability of the HIS technology in the US, the study revealed that HIS technology's potential in reducing the disease burden on healthcare and public health resources is yet to be realized. Therefore, further research is required to fully assess how best to integrate HIS technology in survivorship interventions to help survivors address their unmet health information needs, to reduce the disparities and barriers to health information for the self-management of their HRQOL. The lower odds of technology-based HIS among the low socioeconomic survivors compared with their higher socioeconomic counterparts confirmed disparities in survivors' access to online health information sources. However, technology being used by most of the survivors indicated that public health professionals must address any underlying health information and accessibility gaps to realize the potential of the HIS technology for improving underscore the need to focus cancer survivorship on searchable and accessible content to remove access barriers to online health information sources. The high prevalence of negative HIS experiences indicated potential gaps in searchability and accessibility of targeted health information for survivors' needs. Future research is necessary to understand and close any gaps in the online health information and how HIS technology nay be used in facilitating search and access to online health information for helping survivors attain their health goals.

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