EXPLORATORY ANALYSIS OF SOCIAL E-HEALTH BEHAVIOR

Spencer Acadia, B.A., M.A., M.L.S.

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APPROVED:

Nicole Dash, Committee Co-chair
Brenda McCoy, Committee Co-chair
James Swan, Committee Member
Abigail Tilton, Committee Member
Daniel G. Rodeheaver, Chair of the Department of Sociology
Mark Wardell, Dean of the Toulouse Graduate School

Extant literature has documented well that people seek health information via the internet as patients and consumers. Much less, however, is known about interaction and creation behaviors in the development of new online health information and knowledge. More specifically, generalizable sociodemographic data on who engages in this online health behavior via social media is lacking in the sociological literature. The term “social e-health” is introduced to emphasize the difference between seeking behaviors and interaction and creation behaviors.

A 2010 dataset of a large nationally representative and randomly sampled telephone survey made freely available from the Pew Research Center is used to examine social e-health behavior according to respondents’ sociodemographics. The dependent variable of social e-health behavior is measured by 13 survey questions from the survey. Gender, race, ethnicity, age, education, and income are used as independent variables. Logistic regression analysis was used to determine the odds of engagement in social e-health behavior based on the sociodemographic predictors.

The social determinants of health and digital divide frameworks are used to help explain why socioeconomic variances exist in social e-health behavior. The findings of the current study suggest that predictable sociodemographic patterns along the dimensions of gender, race, age, education, and income exist for those who report engaging in social e-health behavior. This study is important because it underscores the fact that engagement in social e-health behavior is differentially distributed in the general U.S. population according to patterned sociodemographics.
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CHAPTER I
INTRODUCTION

Statement of the Problem

Extant literature has documented well that people seek health information via the internet as consumers and patients (Atkinson, Saperstein, & Pleis, 2009; Baker, Wagner, Singer, & Bundorf, 2003; Brodie et al., 2000; Dickerson et al., 2004; Fox, 2011b; Hsu et al., 2005; Rice, 2006; Ybarra & Suman, 2006). Much needed, however, is research beyond online health information seeking behaviors towards a greater understanding of behaviors that are interactive and creative in the internet medium. Gurak and Hudson (2006, p. 29) noted that “most popular accounts about e-health focus on the use of the web by patients and health seekers to search for information [but] e-health and its implications go well beyond internet searching.” Thus, while there is recognition that e-health research should move ahead of seeking behaviors, literature is only beginning to emerge where interactive and creative behaviors are explored.

A central piece of the missing literature on interactive and creative internet health behavior is the question of who is engaging in these activities. Josefsson (2006, p. 145) noted that sociodemographic variables such as “education, income, sex” and more “are important factors that should be considered profoundly in future work [on e-health],” yet scant research has attempted to understand the sociodemographic implications of people who monitor their own health, create online health information and knowledge, and actively participate in e-health behavior through the internet.

Scarce is the sociological literature reporting the social demography of online interactive and creative e-health behaviors, and even scarcer is literature where multiple
sociodemographic variables and their relationships with multiple online interactive and creative behaviors are considered. Cotten and Gupta (2004, p. 1799) illustrated the fact that more “multivariate level research is needed that investigates the interrelationships among internet usage [and] sociodemographic characteristics” related to e-health behavior. Much of what is known about e-health beyond information seeking is rooted in limited-variable case study analyses and not generalizable to larger populations.

At hand is the following problem: A lot of research is available on online health information seeking behaviors, but not on interaction and creation behaviors. Very little generalizable information is known about the social demography of people who do and do not use the internet to actively manage their health, interact with others, and create their own online health content through social e-health media such as blogs, online support groups, social networking sites, and mobile health applications. Not knowing the sociodemographics of these users impedes e-health research because population-specific nuances cannot be used as a guide to craft future research. Sociodemographic research on social e-health behavior specifically is needed to tailor future investigations into why sociodemographic patterns for this behavior exist and how disparity gaps may be closed. By understanding the social demography of social e-health behavior, future studies can be created to examine the relevancy, outcomes, and effectiveness of this behavior specifically among disenfranchised sociodemographic populations.

Purpose of this Study

The purpose of the current study was to add to the sociological literature on e-health in a way that filled an obvious gap—the lack of extant generalizable and
multivariate research on the sociodemographic distribution of interaction and creation e-health behavior. As mentioned in the previous section, Josefsson (2006) noted that social demographics should be a key point of e-health research, while Cotten and Gupta (2004) called for more multivariate research involving e-health and social demography. Even more recently in a study of migrant health, Goodall, Ward, and Newman (2010, p. 28) wrote in that “there is little research on the effects of…socioeconomic status, education, [and] gender…on the use of information and communication technology."

Following the recognized need for more sociodemographic research, six hypotheses were tested using a quantitative approach to analyze interaction and creation e-health behavior in the contexts of gender, race, ethnicity, age, education, and income. So that the results would be meaningful for the greater population, secondary analysis of data from a large nationally-representative, randomly sampled telephone survey was used to conduct multivariate logistic regression. The dependent variable of social e-health was created by combining responses to thirteen individual e-health behavior questions from the survey that involved some interactive and/or creative element. Because social demography had a central role in my study, I used a blended framework of both the social determinants of health and digital divide concepts.

The current study is important for two reasons. First, if the sociodemographics of people engaging in these social e-behaviors are known then the distribution of this behavior can be examined much in the same way that the distribution of health itself is commonly analyzed in sociological and population-based research. Second, if interaction and creation behaviors are distributed according to generalizable
sociodemographic patterns that are unfavorable for socially subjugated populations, researchers could determine the relevancy of social e-health for these populations, assess these populations’ social e-health skills and literacy, and investigate the potential value of socially participatory behaviors toward better health outcomes and maintenance among these populations.

What is Social E-Health?

In my study, I introduce the term social e-health as a convenient way to classify together those online health behaviors that are interactive and creative. Social e-health connotes the idea of online technologies and behaviors that are socially and technologically interactive and creative, dependent on the back-and-forth health-related reciprocal contributions of individuals over an internet platform. This term is not currently used in the existing literature, but is helpful in separating the non- and less-social forms of e-health (e.g., electronic patient records, electronic medication prescriptions, telemedicine, health information seeking on the internet, etc.) from those that have socially and technologically interactive and creative components. The word social intentionally has been used to describe this type of e-health because the interactivity and creation of new health information and knowledge is dependent on the reflexive, social nature of individual agents in society.

Some examples of social e-health are the use of general social media sites such as Facebook®, Twitter®, MySpace®, and LinkedIn® to communicate about health; use of health-specific social media sites such as PatientsLikeMe® to track and monitor health and communicate about health with others; posting comments on health blogs,
health news sites, and other related websites; and use of any combination of communication technologies, including use of e-mail, texting, and mobile applications, or apps, to monitor, track, and share one’s own health outcomes. In essence, social e-health can be thought of as Web 2.0 applied to health and medicine. Web 2.0 is a general term used to describe the “second wave of the world wide web, one that allows individuals to publish, collaborate, and share experiences with other like-minded individuals or groups” (Deshpande & Jadad, 2006, p. 333).

Defining the Social Demographics

Gender, race, ethnicity, age, education, and income were central to the current study. Typical definitions found in many dictionaries, encyclopedias, and introductory textbooks of sociology were used to define overall the six sociodemographic variables in my study (American Sociological Association, 2003; Bury, 2004; Crompton, 2006; Hunt, 2006; Kerbo, 2000; Kimmel, 2008; Lawson & Garrod, 2012; Newman, 2006; Pitchford, 2001; Phillipson, 2006; Ryan, 2011; Turner, 2006; White, 2006).

In short, gender referred to the self-identification of respondents as either male or female. Because the data were self-reported, the term gender rather than sex was preferred in the current study as no evidence was present to confirm or deny any biological characteristics of respondents. Race referred to the self-identification of respondents to the racial category (e.g., white, black, etc.) with which they most identified. Ethnicity referred to the self-identification of respondents as either identifying with a Hispanic ethnicity or not. Age referred to the self-identification of respondents to how long in years they have been alive. Education referred to the self-reported level of
formal learning achieved from an educational institution. Finally, income referred to the self-reported amount by respondents of 2009 annual monies obtained from all sources in U.S. dollars before taxes.

Social Determinants of Health and the Digital Divide

I blended together the social determinants of health and digital divide frameworks to understand how social e-health behavior is sociodemographically distributed. The social determinants of health framework is the notion that health occurs as a function of sociodemographic variables such as gender, race, ethnicity, age, education, and income—this relationship has been well demonstrated in the medical sociological literature. Similarly, the digital divide framework is the idea that technology, particularly the internet and access to it, and technological literacy, particularly internet skills, are unequally distributed in the population based on social demography—this relationship has been well demonstrated in the social and technological literature, especially with regards to online health information seeking behavior.

Because both health and technology are socially allocated along these sociodemographic dimensions, I combined the social determinants of health and digital divide frameworks into one and used it as a foundation around which to build the argument that social e-health behavior—having elements of both health and technology—is, too, distributed according to social demographic factors. Via the current study, I have demonstrated this phenomenon in two ways. First, I examined the existing literature through this merged framework to illustrate that, prior to this study, very little was known about generalizable, multivariate sociodemographic relationships
specifically for social e-health. Second, using generalizable data I tested six hypotheses in line with what would be sociodemographically predicted based on what is known from the social determinants of health and digital divide frameworks—that socially and economically disenfranchised populations would be less likely to engage in social e-health behavior.
CHAPTER II
LITERATURE REVIEW

This chapter is divided into four sections. First, an in-depth discussion of the social determinants of health and digital divide frameworks is provided to serve as the backdrop for the current study. Second, a review of e-health generally and computer-mediated communication is given as a necessary introduction to better understand the use of the internet by patients and consumers for health purposes. Third, an overview of the literature on online health information seeking behavior discusses what is known regarding the relationships between health information seeking and the internet. The last section delves into e-health interaction and creation behavior by reviewing some of the literature dealing explicitly with the much unexplored social e-health landscape.

Why Social Determinants of Health and the Digital Divide Are Important

A social determinants of health framework is fundamental to understanding how health and illness occur disproportionately across human populations. Research from medical sociology and other fields has recognized that sociodemographic factors such as gender, race, ethnicity, age, education, and income impact human health outcomes and experiences. Generally, research has confirmed that disenfranchised groups and low-socioeconomic populations (e.g., women, lesbian/gay/bisexual/transgendered populations, racial and ethnic minorities, the elderly, the financially poor, the uneducated, and the disabled) often have a higher burden of chronic disease, acute illness, and stress response, as well as view their own health unfavorably, when

Although the precise mechanisms through which social factors impact health are not always known, interdisciplinary research and data has made clear that many aspects of human health are shaped by sociodemographic determinants and yield substantial evidence to validate the reality that health is socially distributed.

Likewise, a digital divide framework is central to understanding how access to and skills of using technology, especially internet technology, are differentially distributed in the general population according to socioeconomic patterns. Digital divide is the phenomenon where people are denied access to computers, the internet, and the
general literacy needed to operate the equipment correctly and navigate the online environment due largely to socioeconomic factors and other social barriers (Banerjee & Hodge, 2007; Gorski, 2003; Mansell, 2002; Mossberger, Tolbert, & Stansbury, 2003; Robison & Crenshaw, 2010; Stern, 2010; van Dijk, 2005; van Dijk & Hacker, 2003; Warschauer, 2003). Digital divide is a classic example of the haves and have-nots where people in higher socioeconomic groups often have no problem accessing and using computers and the internet, yet those in lower socioeconomic groups have much difficulty doing so. The latest data from the U.S. Census Bureau (2013, p. 5) show that males (69%) and females (70%) are equally represented in internet access, but non-Hispanic whites have more internet access (75%) than blacks (60%) and Hispanics of any race (54%); the 18 to 34 age group have more internet access (82%) than the older 65+ age group (46%); people with incomes of $100,000+ have the most internet access (87%), while those with incomes of less than $25,000 have the least (50%); and people with a completed college education have the most internet access (90%), while those with a less-than-high school education have the least (32%).

With mobile technologies increasing among all segments of the population (Fox, 2010; Fox & Duggan, 2012), an argument could be made that the digital divide is narrowing. One study (Wietfeldt et al., 2010) did not find any statistically significant sociodemographic differences on internet use when used generally or for health purposes specifically among 194 visitors to two university clinics and suggested that a digital divide no longer exists. However, the authors failed to draw attention to the fact that 11% of the sample reported an annual household income of at least $1 million; this is crucial to note because it suggests that their sample is not in any way representative
of a normally distributed population. The scientific consensus as echoed by Kreps and Neuhauser (2010, p. 330) is that while “internet usage among all populations is continuously increasing, digital divides still remain for people who have less education, lower incomes, or who are older than 65.” Indeed, the divide is likely to remain or widen further because disadvantaged populations simply cannot catch up to the same level of technological standards attained by advantaged populations due to unequal social distributions of technology.

The digital divide singular may be best thought of as digital divides plural; that is, there are a variety of gaps that have emerged along sociodemographic dimensions thanks to computer and internet technology. While strides have been made to reduce or neutralize digital divide (Atkinson & Gold, 2002), a new divide—called the broadband gap—adds another chasm between those who have and do not have access to high-speed internet and cannot benefit from many streaming and/or cloud-based multimedia interactive programs that require high internet connection speeds. Matusitz and Breen (2007, p. 108) note that “the main barriers that must be addressed are literacy, intercultural differences, language, technology access, and education,” suggesting that all of these barriers represent a pluralistic representation of digital divide.

A well-known principle is Hart’s (1971) inverse care law which states that those who can benefit most from health care are the least likely to receive it. Applied to health in the context of technology, the law could be restated as an inverse health technology law to say that those who can benefit most from online health technologies are least likely to receive them (Cotten & Gupta, 2004; Glied & Lleras-Muney, 2008; Wyatt & Sullivan, 2005; Ziebland, 2004). In fact, the internet may actually “exacerbate existing
socioeconomic health disparities” (Wald, Dube, & Anthony, 2007, p. 221) because it creates one more of many forms of division between the advantaged and disadvantaged. Crilly, Keefe, and Volpe (2011, p. 1163) state matter-of-factly that “health information technology is currently designed to benefit primarily populations already connected to such systems.” In addition, for those that do have access, the quality of the internet (e.g., its speed and reliability of connection) can be a factor in how often and for what reasons it is used (Skinner, Biscope, & Poland, 2003).

In terms of health, Glasgow (2007, p. S119) notes that “e-health digital divide issues include amount of participation across users at different levels of health literacy, computer experience, and types of connections to the internet.” The number and severity of chronic conditions also may serve as a gap and create barriers to social e-health (Ayers & Kronenfeld, 2007; Fox, 2011c; Fox & Purcell, 2010). Orgad (2006) suggests that gaps in cultural literacy dictate internet use for health purposes in terms of differences in culture, differences in culture online, and differences in online culture. Thus, research has made clear that digital divide in the circumstance of health is a complex phenomenon composed of numerous elements, central of which is social disparity.

Several studies of internet use among HIV/AIDS patients illustrate well digital divide in a health-related context. In 2009, Shacham, Stamm, and Overton conducted a study on general technology use of 515 patients at an HIV/AIDS clinic. Results showed that the majority of the sample when stratified by sex and race was represented by black males (54%) and black females (60%). About half of all males had some college education (48%), but 64% of all females had only a high school or less-than-high school
education. A large majority (45% men and 60% women) reported an income of less than $10,000 and close to 30% of both sexes indicated they were homeless. Forty-four percent reported never using the internet. Logistic regression results confirmed that internet usage was higher among white, educated males with higher salaries. The sociodemographic distribution of the entire sample, however, was illustrative of a typical HIV/AIDS-infected cross-section (i.e., low-income black males) who would not likely benefit from any type of online-based health services due to lack of continued, reliable internet access as well as technological and health literacy skills.

An earlier study of HIV/AIDS patients (Mayben & Giordano, 2007) found a similar pattern in that 35% of the sample reported not having internet access at all and those that did had higher levels of income and education. A later study of mostly black male HIV/AIDS patients (Samal et al., 2011) reported that 55% did not use the internet to search for health-related information. However, those who did use the internet for this purpose were more likely to be younger, better educated, well salaried, and more compliant in their antiretroviral therapy. The results from these HIV/AIDS studies are indicative a digital divide based not only on typical sociodemographic factors such as race, income, and education, but also along the dimension of illness.

Evidence suggests, too, that even when differential groups are provided the same internet technology services, actual usage remains unequally distributed. In 2005, a longitudinal study by Hsu et al. examined e-health behaviors conducted through a no-cost integrated delivery system (IDS) of users over a period of four years. Via the IDS, users could engage in behaviors such as setting up appointments, refilling prescriptions, and submitting medical questions to be answered by a nurse. The authors found that
the gap between use of this service from 1999 to 2001 widened when race and socioeconomic status was considered. As time went on the number of whites who used the IDS increased while the number of non-whites decreased. Moreover, users classified in high-socioeconomic groups used the IDS with more frequency than did those in low-socioeconomic groups and adapted the technology at faster rates. The authors concluded that, while people of all sociodemographic types are using e-health services, the digital divide between them is actually widening because high-socioeconomic and white groups are using e-health technologies at accelerating rates compared to slower rates of use among low-socioeconomic and non-white groups.

Many other studies on digital divide and health exist (Bolam, McLean, Pennington, & Gillies, 2006; Borzekowski & Rickert, 2000, 2001; Dickerson et al., 2004; Gallagher & Doherty, 2009; Goodall et al., 2010; Hardey, 2001), but the current study is unique in that it explicitly draws attention to the similarities of digital divide(s) and the social determinants of health as compatible frameworks that, when combined, are ideal for analyzing health experiences, outcomes, and behaviors occurring in both sociodemographic and technological contexts. Conceptually, then, the social determinants of health and digital divide frameworks can be successfully merged into a core approach for analyzing the intersection of health and technology—in this case, social e-health. The former of these underscores the importance of sociodemographic factors regarding health, while the latter emphasizes the prominence of sociodemographics regarding technology. Both frameworks fall in line with each other and, when combined, provide an excellent sociological basis for explaining how patterns of social e-health behavior are evident according to social demographic characteristics.
Before discussing internet health seeking behavior and social e-health along with their social demographics, a very brief discussion on general e-health and computer-mediated communication (CMC) will be helpful. This brief review is only meant to define e-health and CMC to contextualize the extensive discussions to follow—seeking behaviors and interaction and creation behaviors as types of CMC-directed e-health.

General E-Health and Computer-Mediated Communication: A Brief Review

A short discussion of e-health generally and computer-mediated communication is needed to build upon the remainder of the current study. Electronic health, or e-health, is an umbrella term encompassing a wide range of technologies aimed at improving human health. Simply stated, e-health “includes the use of the internet or other electronic media to disseminate health related information or services” (Gustafson & Wyatt, 2004, p. 1150). Eng (2002, p. 267) defines e-health as “the use of emerging information and communication technology, especially the internet, to improve or enable health and health care.”

Ongoing debates about what constitutes e-health and its various forms are plentiful in the existing literature (Ahern, Kreslake, & Phalen, 2006; Della Mea, 2001; Eysenbach, 2001; Gurak & Hudson, 2006; Jones et al., 2005; Matusitz & Breen, 2007; Neuhauser & Kreps, 2003; Oh, Rizo, Enkin, & Jadad, 2005; Pagliari et al., 2005; Wyatt & Sullivan, 2005). A definitional consensus supports generally the conceptualization of e-health as the use of electronic, technological, and internet-connected systems to distribute information among and between healthcare providers and other constituents,
as well as deliver a wide-range of health and medical services to patients. In addition, e-health enables patients, caregivers, family members, and other interested parties to interact with each other for advice, information, and support.

E-health technologies are used often by medical professionals, insurance companies, pharmaceutical organizations, and other health care sectors to connect, first, with each other in transferring information internally about patients and, second, with patients in the external delivery and fulfillment of health services. Also, patients themselves use e-health technologies to communicate in return to health care organizations as well their own friends, families, and others in their social networks about their health conditions. Thanks to the internet, patients increasingly are connecting with other patients who share similar health conditions and incorporating them into their social support and information networks (Mo, Malik & Coulson, 2009).

Indeed, Orizio and Gelatti (2010, p. 30) have recognized that “three categories of actors involved in the health world whose role has been influenced by the internet [are] health professionals, health organizations, and patients/citizens.”

Ever since internet technology became widely commercialized in the early 1990s, people have used it to seek, locate, and share with others information, data, and knowledge about health and medicine (Cullen, 2006; Mittman & Cain, 2001; Preece & Ghozati, 2001; Rice, 2001). Ziebland (2004, p. 1783) notes that “health sites and discussion lists are widely used and are among the most popular resources on the web.” When e-health technology is used between people to communicate, it becomes a type of computer-mediated communication (CMC). At its most basic, CMC is defined as any type of human communication occurring through any type of computer technology.
often involving the internet (Herring, 1996, 2004; Thurlow, Lengel, & Tomic, 2004). CMC allows communication between people to transpire without the constraints of time and space while fostering virtual relationships and networks (Caplan, 2001).

CMC has been agreed upon by researchers as having a number of characteristics in common (Eysenbach, 2008, p. 280; Neuhauser & Kreps, 2003, pp. 10-11; Wright & Bell, 2003, p. 40), particularly as it concerns the social elements of e-health behavior. These include:

- E-health is most effective when users can identify with it on both rational and emotional levels, and when it relates to specific events, purposes, or contexts within users’ lives
- E-health is most effective when messages to users are tailored to their particular needs and situations rather than generic, one-size-fits-all messages
- E-health is most effective when communication between users is interactive and participatory rather than a one-way street, in part because participation and interaction can facilitate social, emotional, and psychological therapeutic support
- E-health can empower users to discuss sensitive or stigmatized health issues more comfortably than in face-to-face encounters, in part by the reduction of social status and physical cues
- E-health can provide access to interactive online information sources, including people such as physicians, health care personnel, and other patients with similar health concerns that would not otherwise be available
- E-health can permit users to access health information from many internet sources (e.g., static websites, interactive forums, chat sites, etc.) before even consulting a medical professional

As evident by the aforementioned characteristics, e-health and CMC together constitute a social engagement between technology and its users, and between users through technology. Because of this social engagement, the creation of the term social e-health is warranted. As mentioned in Chapter 1, social e-health moves beyond online
information seeking and spotlights the interaction and creation aspects of e-health. However, before an in-depth discussion on the interactive and creative behaviors that make up social e-health can be given, a detailed review of online health information seeking is needed. Such a discussion is required to better understand the differentiation between seeking versus interaction and creation behaviors, as well as create a social demographic thread throughout this study.

Online Health Information: Who Is Searching For It and What Are They Searching For?

The seeking of online health information is a type of e-health. Moreover, online health information seeking could be considered a type of computer-mediated communication insofar as users are interacting with technology and communicating through the medium of a static website. For example, authors for the popular medical website WebMD® communicate indirectly with their readers by writing and posting articles on the site. This is an example of a one-way communication relationship. Online health information seeking behavior such as this constitutes an indirect form of CMC, but is indeed a type of e-health occurring over an internet platform.

In their pursuit of gathering and understanding health information, people nowadays often turn to the internet as a supplement to, but not necessarily a replacement for, health information provided by their own health care practitioner if they have one (Fox 2011a, 2011b). Ongoing research known as the Internet and American Life Project (IALP) aims to explore and measure general internet usage and general online behaviors using survey data collected in the United States. IALP started in 2000
(Pew, 2012) and was the beginning of a systematic assessment of people’s general internet use as well as their use of the internet for obtaining health information.

IALP research has shown that people use the internet to seek and locate health-related information and knowledge. In 2000, Rainie and Fox reported that 55% of U.S. internet users obtained health information online. Two years later, that percentage had climbed to 62% (Fox & Rainie, 2002). From 2003 to present, the percentage of U.S. internet users who report seeking health information online has consistently remained around 70% to 80% (Fox, 2005, 2006, 2008, 2011b, 2012; Fox & Duggan, 2013b; Fox & Fallows, 2003; Fox & Jones, 2009). European data are similar (Andreassen et al., 2007). Also, the American public is increasingly using mobile devices to access health information. Fox (2010) reported that close to 20% of people with mobile phones have used the internet on their devices to locate health information online; two years later, that number increased to over 30% (Fox & Duggan, 2012).

Recent IALP data (Fox, 2011b) show that, of the percentage of people who go online to search for health information, 65% are women; 63% are white, 47% black, and 45% identify as Latino/a; the majority (81%) are college graduates; and the majority (83%) report incomes of at least $75,000. The age group of 18-29 is represented by 71% of users and the percentages decrease as the age ranges of groups increase. Therefore, IALP data provides statistically generalizable evidence that internet users looking for health information online are likely to be white, female, college graduates, on the youngest end of adult age groups, and/or earn an income of at least $75,000. These data lend confirmation of digital divide with regards to health information seeking via the internet—that populations advantaged with higher incomes, higher education statuses,
and being white are more likely than disadvantaged populations to go online for health information.

On gender, much research shows that women use the internet more than men to seek health information online (Atkinson et al., 2009; Baker et al., 2003; Brodie et al., 2000; Hsu et al., 2005; Rice, 2006; Shade, 2004; Warner & Procaccino, 2007; Ybarra & Suman, 2006), especially when they are better educated (Pálsdóttir, 2003). Digital divide might predict that men would be more likely than women to engage in online health seeking behaviors because males are a socially advantaged group. Thus, the fact that women—not men—are the primary seekers of health information online might be opposite of what would be expected. That women engage in this behavior more so than men, however, is not surprising for two reasons. One, in social systems women often take on the caregiver role and going online is one way to gather caregiving information. Two, in social systems men often shun visiting the doctor and avoid showing concern over their health. To the extent that online health information seeking shows concern for health, it stands to reason that men would not be likely to engage in this behavior, or at least publically acknowledge doing so.

IALP data (Fox, 2011b, p. 2) indicate that “34% of internet users have read someone else’s commentary or experience about health or medical issues on an online news group, website, or blog; 25% have watched an online video about health or medical issues; 24% have consulted online reviews of particular drugs or medical treatments; 16% have consulted online rankings or reviews of doctors or other providers; and 15% have consulted online rankings or reviews of hospitals or other medical facilities.” Thirty-five percent of adults have gone online to self-diagnose their
conditions based on presenting symptoms (Fox & Duggan, 2013b). These data confirm that online health information seekers look at many different topics on a variety of health issues and many explore a wide range of websites.

In 2002, Fogel, Albert, Schnabel, Ditkoff, and Neugut identified and talked with 251 women with breast cancer at a university teaching hospital. They later mailed a questionnaire to the women to gain more information about their use of the internet to obtain health information; 188 responded. The results showed that 42% reported using the internet to seek health information. More importantly, the odds of using the internet for health information purposes were three times greater for those who had a college-level education and incomes of greater than $60,000 compared with those who did not have a college education and incomes of less than $60,000. Race and age were not statistically significant; neither were the elapsed time since diagnosis or cancer stage. In this study, education and income, but not race or age, played an important role in online health information seeking.

In their analysis of 274 primary care clinic patients who reported using the internet for obtaining health information, Diaz et al. (2002) found that the odds of patients going online to seek health information were two times greater for those who had a college education and higher incomes relative to those who had no college education and lower incomes. Also, the odds of patients aged less than 60 of engaging in this behavior were three times higher than those older than 60. The mean age for the sample was 46, almost 60% female, and nearly all white. In terms of topics, 68% went online to look for information about diet and nutrition, 58% about drug side effects, and 41% about complementary and alternative medicine. Sixty percent believed that the
health information they were able to get online was equal to or better than the
information received by their physician. Education, income, and age were significant
predictors of online health information seeking.

In 2004, Cotton and Gupta analyzed the sociodemographics of people who
sought health information online and compared them with those who did so offline. At
the time, very little was known about the sociodemographics of online health information
seekers in general terms. Most prior studies on internet health information seekers had
been dedicated to examination of people with specific illnesses, from specific locations
such as clinics and hospitals, and/or who used specific websites, forums, or support
groups. Cotton and Gupta used 2000 data from the General Social Survey (GSS). The
sample size was moderately large (N = 385) and the authors’ results showed that
younger age, higher income, and higher education were predictive factors in the
likelihood of users going online to search for health information. Gender and race were
not statistically significant, but descriptively the majority of online health seekers were
female (64%) and white (83%).

Also in 2004, Dickerson et al. surveyed the self-reported online health
information seeking behaviors of patients at three primary health care clinics. Using
logistic regression with the total sample size interviewed (N = 315), the authors
determined that education level and race were the only statistically significant
sociodemographics in the study that predicted online health-seeking behavior. Blacks
were 45% less likely than whites to search online for health information. The odds of
engaging in this behavior for those who attended college were over four times as great
as those who never attended college. Of those who used the internet for health
purposes, 80% of them reported going online to locate information about a specific physical illness; 57% sought information about nutrition and fitness; 36% sought information about a specific doctor, hospital, or medication; 32% looked for information on complementary and alternative medicine; and 19% looked for information about mental health.

As much IALP data and other research have shown, the typical online health information seeker is younger in age, female, and white with high levels of education and income, and sometimes in fair to poor physical and/or mental health (Baker et al., 2003; Eastin & Guinsler, 2006; Gallagher & Doherty, 2009; Houston & Allison, 2002; Jadad et al., 2001; Koch-Weser, Bradshaw, Gualtieri, & Gallagher, 2010; Pandey, Hart, & Tiwary, 2003; Robinson, Flowers, Alperson, & Norris, 1999; Ybarra & Suman, 2006). Exceptions do exist, however.

Findings surrounding users’ age have been inconsistent; one study found that people in the age group 50-64 were more likely than those in the 30-49 age group to use standard e-health technologies (Hsu et al., 2005), while another study found that age was not an adequate predictor of e-health use at all (van Deursen & van Dijk, 2011). Results from some studies (Houston & Allison, 2002; Kim & Kwon, 2010) suggested that the age of people seeking health information may depend largely on what type of illness they have (e.g., a person looking for information about cancer may be older by virtue of the fact that cancer occurs with more frequency in older persons), as well older users’ own beliefs that online searching may be too complex for them or irrelevant to their needs. Nonetheless, most studies do conclude that older people are
less likely to use internet technology, including use for health-related purposes (Goodall et al., 2010; Selwyn, 2004).

Regarding education, an Australian study found that the majority of pain clinic patients (52%) who had searched online for health information lacked education beyond secondary level (i.e., high school) (Corcoran, Haigh, Seabrook, & Schug, 2010). Such a finding is opposite of what would be expected given what is known about the strong relationship between education, health, and technology.

Findings regarding online health information seekers’ current state of health do not always suggest they are in fair to poor health. Cotten and Gupta (2004) indicated that the majority of online health information seekers reported being in good (48%) or excellent (38%) health, not fair (9%) or poor (5%). A study involving five-year internet data from over 15,000 women with some form of gynecological cancer showed that an overwhelming 90% of those with ovarian cancer self-reported being in good health (Markman, Markman, Belland, & Petersen, 2006). Results from Koch-Weser et al. (2010) showed that the majority of patients seeking health information reported their health as good (40%), whereas only around 15% reported poor and fair. The health statuses of online health information seekers likely vary dependent on the type and stage of their medical condition as well as their general social and economic security.

A percentage of online health information seekers who themselves may be in good or bad health act as caregivers and seek health information on behalf of an ill family member (e.g., child, parent, or spouse). Middle-aged females especially may engage in surrogate searching due to their increased likelihood of caring both for their young children and aging parents (Fattah, 2000). Once again, the IALP data (Fox,
2011b) confirm that seeking health information online by proxy is common as 50% of people who go online to get health information report doing so on behalf of someone else.

Despite the popularity of utilizing the internet to seek information about health by consumers and patients, physicians have remained skeptical about the benefit versus risk potential of online health information seeking. Research indicates that some physicians and other health care professionals have expressed concern over the credibility, accuracy, and quality of online health information and believe the potentiality of patient harm to be a realistic threat (Adelhard & Obst, 1999; Ahmad, Hudak, Bercovitz, Hollenberg, & Levinson, 2006; Berland et al., 2001; Eastin, 2001; Gagliardi & Jadad, 2002; McLeod, 1998; Risk & Dzenowagis, 2001; Roberts & Copeland, 2001; Walji et al., 2004). A review of nearly 80 articles where online health information was evaluated showed that 70% of those articles questioned the quality of websites, whereas only 9% had a favorable impression of website content quality (Eysenbach, Powell, Kuss, & Sa, 2002).

Numerous studies and reports have found frequent content errors, omissions, and misleading information related to health issues and topics, as well as expressed skepticism about how favorable is the online health information and further asked how can the quality of such websites be measured systematically for reliability, validity, and accuracy (Abbott, 2000; Barnes et al., 2003; Benigeri & Pluye, 2003; Bichakjian et al., 2002; Biermann, Golladay, Greenfield, & Baker, 1999; Cheh, Ribisl, & Wildemuth, 2003; Gallagher & Doherty, 2009; Gottlieb, 2000; Griffiths & Christensen, 2000; Hoffman-Goetz & Clarke, 2000; Ipser, Dewing, & Stein, 2007; Jadad & Gagliardi, 1998; Kunst,
Groot, Latthe, Latthe, & Khan, 2002; Li, Irvin, Guzmán, & Bombardier, 2001; Mathieu, 2007; Meric et al., 2002; Risk & Petersen, 2002; Suarez-Almazor, Kendall, & Dorgan, 2001; Tamm, Raval, & Huynh, 2000). Pandolfini and Bonati (2002, p. 583) noted that while the quality of health information on websites had improved since their prior study five years earlier (Impicciatore, Pandolfini, Casella, & Bonati, 1997), significant errors and omissions remained on many websites and the authors called for continued “monitoring [of] health information on the internet for accuracy, completeness, and consistency.”

However, extant research shows that “reports of patients coming to harm as the result of online advice are rare, whereas accounts of those who have obtained better care, averted medical mistakes, or saved their own lives are common” (Ferguson & Frydman, 2004, p. 1148). Indeed, multiple studies and reports have suggested that patients gain more benefit than they do harm from accessing and reading online health information about, as well as incorporating online behavioral interventions into, their health care (Balas et al., 1997; Dickerson et al., 2004; Eysenbach, 2003; Ferguson & Kelly, 1999; Jones et al., 1999; Krishna, Balas, Spencer, Griffen, & Boren, 1997; Lewis, 1999; Rimer et al., 2000; Sandvik, 1999). In 2001, Smith concluded succinctly that nearly no substantial reported evidence exists of patients experiencing harm due solely from information obtained online. Nearly a decade later, Neuhauser and Kreps (2010, p. 9) agreed that “the first 15 years of scientific evidence about the use of e-health interventions suggest that, overall, such strategies are gaining rapid acceptance worldwide, improve user engagement, and often show significant positive effects on health behaviors in diverse populations and across a wide range of health conditions.”
Nonetheless, calls for continued, interdisciplinary investigation on the reliability of online health information remain (Adams, 2010a; Adams & de Bont, 2007; Adams, de Bont, & Berg, 2006).

Historically, physicians have been the keepers and dispensers of health information and medical knowledge through social and power roles created out of intense professionalization, institutional authority, specialized medical training, and heavily bureaucratized, hierarchical systems (Conrad, 2005; Foucault, 1973; Goode, 1960; Lupton, 2012; Parsons, 1951; Starr, 1982; Turner, 1995; Zola, 1972), especially in America with the rise of the American Medical Association (AMA) in year 1847 (Freidson, 1970; Hyde & Wolff, 1954). Although much power is still held in the hands of mainstream biomedical physicians, medical de-professionalization has been occurring over time due to increased governmental regulations; controls imposed by managed care corporations; and a growing unhappy, skeptical, highly-critical patient populace (Light, 1993; Mechanic, 2004; Pescosolido, Tuch, & Martin, 2001; Potter & McKinley, 2005; Ritzer & Walczak, 1988; Waitzkin, 2000). Fogel et al. (2002, Introduction, paragraph 2) write that “many patients no longer feel comfortable with [doctors’] paternalistic approach and are becoming more insistent about being fully informed and participating in their treatment decision-making.”

Indeed, much evidence has been collected showing that the landscape of the patient-physician relationship continues to be altered (Blumenthal, 2002; Dansky, Thompson, & Sanner, 2006; Dedding, van Doorn, Winkler, & Reis, 2011; Ferguson, 1998; Gerber & Eiser, 2001; Glodé, 1996; Goldsmith, 2000; Hardey, 1998, 2001; Hollander & Lanier, 2001; Kivits, 2006; Mandl, Kohane, & Brandt, 1998; McKinlay &
Via internet technology, patients are given control to search for health information online before, during, and after a physician consult leading to a destabilization and redefinition of the conventional physician-dominant medical models of health care.

Studies have been mixed showing that some physicians feel threatened when patients present to them internet information or dismiss reviewing the information with their patients, while other physicians may be supportive—or at least accepting—of their patients’ online health information seeking habits as long as the information they obtain is deemed credible and beneficial (Anderson, 2004; Chen & Siu, 2001; Coiera, 1996; Hart, Henwood, & Wyatt, 2004; Helft, Hlubocky, & Daugherty, 2003; Henwood, Wyatts, Hart, & Smith, 2003; Jadad, 1999; Shaw & Baker, 2004; Thorne, Nyhlin, & Patterson, 2000). Even when physicians want to become more involved in their patients’ online health information seeking activity, a recent Australian study questioned whether or not general practitioners really even know how to determine the optimal websites for their patients by stating that “health care practitioners need to improve their own skills in internet use with respect to steering patients to reliable health websites” (Usher, 2009, p. 43).

Wald et al. (2007, p. 221) suggest that for those physicians who view their patients’ online health information seeking behavior favorably might do so because “the patient [is] perceived as proactive [and] makes an effort to become knowledgeable.” Some research shows, however, that patients may be reluctant to share internet-obtained information with their doctors for fear that the physician may feel insulted,
adversely judge them, tell them it is not their responsibility to seek outside information, not have time to go over the information with them, or make them feel inferior or patronized (Henwood et al., 2003; Imes, Bylund, Sabee, Routsong, & Sanford, 2008).

McMullan (2006) identified three types of relationships that may form when internet information is introduced by the patient into the patient-physician interaction:

- **Health professional-centred relationship**: The health professional feels threatened by the information the patient brings and responds defensively by asserting their expert opinion
- **Patient-centred relationship**: The health professional and patient collaborate in obtaining and analysing the information
- **Internet prescription**: The health professional will guide patients to reliable health information websites (p. 24)

Wald et al. (2007) view the current state of the patient-physician relationship in a triadic way; the patient-physician dyad has now become the patient-web-physician triad. Such a view suggests that internet use for health information purposes has become so salient and engrained into everyday consumer life that such behaviors are now mainstays for patient health consumption, and that the medical and health industry would be wise to understand that consumers and patients will continue to use the internet as a medium through which they get health information, with or without their physician’s approval.

Gurak and Hudson (2006, p. 29) note that “in terms of information gathering, the internet has leveled the playing field—patients and consumers have access to much of the same health information and guidelines as physicians.” Adding some credence to Gurak and Hudson’s claim, one report found that close to 45% of the time physicians confirmed a self-diagnosis from patients who self-diagnosed themselves using online information prior to consulting their physician (Fox & Duggan, 2013b). This finding is
important because it suggests one of the following might be occurring: nearly half of all people are able to accurately diagnose themselves without physician involvement because the quality of medical information online is sufficiently complete and understandable enough; the health literacy of consumers is high enough that, irrespective of the quality of online medical information, they are sufficiently health literate to understand their own symptoms, match them up with the information they find online, and be accurate nearly half of the time; or physicians themselves are increasingly aware that people go online to seek medical information and self-diagnose even before a visitation and have decided to succumb to this reality, challenging only about half of those situations. Naturally, all three of these scenarios favor advantaged sociodemographic groups as they are the ones most likely to have internet access and a physician to go to in the first place. In addition, as predicted by digital divide, the advantaged are most likely to have the skills to find and navigate health websites and feel emboldened enough to discuss health information they found online with their physician.

In Hardey’s (2001) study, 132 mostly U.S. websites containing personal accounts of health experiences were examined along with questionnaire responses from authors of 74 of those sites. Analyses showed that one main impetus for seeking online health information and creating online outlets for health advice and support was due to dissatisfaction with one’s physician and/or health care system. This finding has been replicated in other studies (Chen & Siu, 2001; Jenkins, Fallowfield, & Saul, 2001; Kivits, 2006). However, Hardey concluded that users preferred to manage their personal health care with physician-provided advice and treatment along with internet
information. Hardey’s conclusion suggests that consumers and patients are happy using both physician and internet input in a complementary fashion when needing healthcare (Kivits, 2006; Pandey et al., 2003) and that doctor-patient relationships in general have taken on a mutual participatory aspect where physicians and their patients work together in provider-consumer exchanges toward optimal health outcomes (Calabretta, 2002; Cockerham, Lueschen, Kunz, & Spaeth, 1986; Warren, Weitz, & Kulis, 1998; Ziebland, 2004). Case studies do exist, however, where physicians fully and sometimes aggressively exert their authority without patient or family regard (Rier, 2000; Weitz, 1999).

A final point to make regarding health information seeking is that while most existing literature on this subject is directed towards understanding more about patient and consumer behavior, they are not the only ones using the internet to look for health information. A few studies have examined the online health information seeking behaviors of physicians and other health care professionals. This body of research shows that physicians and other health personnel—as much as 90% surveyed in 2002—use the internet to find information about professional development, including involvement in professional organizations, continuing education courses, and upcoming conferences; writings by other physicians and researchers to keep abreast of the latest medical research; and use of proprietary websites and databases to look for journal articles, clinical trials, drug information, and statistical data (Murero, 2006; Rice & Katz, 2006). Therefore, doctors, too, use the internet to locate health information, knowledge, and data, though for different purposes when compared with their patients and general consumers.
In sum, research shows that online health information seeking behaviors by patients and consumers occur mostly among advantaged sociodemographic groups such as whites, the highly educated, and the wealthy, while occurring less so among marginalized populations such as blacks, Hispanics, the less educated, and the economically poor. Women are more likely than men to seek health information online, as are younger age groups compared to older age groups. The sociodemographic distribution of people seeking health information online can be explained by the same social distribution approach used for health generally. The social determinants of health framework illustrates how health and illness are differentially distributed in the population based on factors such as gender, race, ethnicity, age, education, and income. So too, the digital divide framework explains how technology and its use are varyingly distributed across the population based on the same sociodemographics. When taken together, these two frameworks optimally provide the sociodemographic contexts to elucidate the distributional relationships between both health and technology combined. Just as patterns of online health information seeking are evident by gender, race, ethnicity, age, education, and income, so too should online interaction and creation behaviors show similar distributions.

Social E-Health: Interaction and Creation

Behaviors—What Do(n’t) We Know?

Not all e-health users stop at searching. Though some people use the internet for seeking and consuming health information only passively, many also use the internet as a vehicle for actively engaging with others by creating their own online health content
through creation of blogs, profiles, comments, postings, and support groups. Adams (2011, p. 1070) wrote that “website users become information producers, changing their current roles from message recipients to message senders, and creating room for new information users to emerge…through a blending of consumption and production.” Hardey (2001, p. 288) noted that “users of health services have also become significant providers of health information and advice.”

As explained in Chapter 1, social e-health is an extension of regular e-health in that it explicitly involves online health behaviors between social actors that are interactive and creative much in the way that Adams (2011) and Hardey (2001) envision. As Kivits (2009, p. 684) contended,

> It remains important to examine online spaces dedicated to health information and practices of information seeking in order to better understand the contribution of the use of the internet to the construction of health understandings and knowledge … seeking health information on the internet must not be restricted to a linear reading of information and an unreflective use of the medium. [italics mine] (pp. 684-685)

Thus, social e-health moves beyond the more static and one-way health information seeking behavior towards dynamic, interactive, creative, and multi-way behaviors. Social e-health involves synchronous and asynchronous communication over the internet via social networking media. This media may include social networking and share-your-experience sites, blogs, review sites, health tracking apps and sites, support groups, chat sessions, e-mail, text messaging, and alerts—essentially any type of computer-mediated communication (CMC) occurring on the internet where health information between social actors can be shared. Social e-health is not a term used currently in the literature; it is introduced here intentionally to emphasize the inherent
social aspects of e-health behaviors wherein individuals collect and share information with each other through online interactive and creative processes.

Social e-health is important to study for several reasons. First, as presented in the literature review below, social e-health is becoming a standard way people are collecting and sharing health information, as well as comprehending better their own and others’ health experiences and outcomes. Second, the academic sociological literature on social e-health behavior is slim and more research on the topic is needed. Much of the research that does exist is based on case studies and anecdotal evidence rather than generalizable population-based data. To be sure, case studies are critical in understanding social e-health but so too is research using large randomly sampled datasets, especially when analyzing social demography. Before examining what little is known about the sociodemographics of social e-health, a discussion of its inherent social aspects is required to accentuate the social in social e-health.

Research has established that internet technology in general enables the cultivation of virtual relationships, develops communal ties between individuals, and increases the social capital of participating individuals and groups, even if no face-to-face interaction has occurred (Brennan & Fink, 1997; Konijin, Utz, Tanis, & Barnes, 2008; Polkosky, 2008; Tanis, 2008; Utz, 2008). In the social e-health environment specifically, research shows that online support groups, forums, and blogs can act as social communities and extensions of social networks wherein people become connected around a common theme, usually a specific medical condition or health event that promotes a sense of homophily (Wright, 2000). This phenomenon falls much in line with self-verification theory (Swann & Read, 1981) where people seek out,
identify with, and befriend others who match most closely with their own experiences. These relationships when developed online may be classified as weak tie networks (Granovetter, 1973, 1982) wherein people communicate regularly and intimately with others, yet are not particularly attached to them in the same way as they might be to those with whom they have face-to-face relationships.

The characteristics of what makes a virtual community has been discussed and debated in the literature (Baym, 1998; Bays & Mowbray, 2001; Burrows & Nettleton, 2002; Burrows, Nettleton, Pleace, Loader, & Muncer, 2000; Jones, 1998; Rheingold, 1993; Slevin, 2000). In many ways, virtual communities established online are built with the same aspects fundamental to the establishment of real life communities including participation, solidarity, reciprocity, support, trust, and respect for others (Herring, 2004; Kling & Courtright, 2004; Surratt, 2001). Also, the development of emotional attachment among community members is common (Neuhauser & Kreps, 2003). Social e-health provides socially sanctioned, electronic pathways through which virtual communities centered in health are created by individuals seeking other individuals with whom they can identify, share experiences, and develop new health knowledge through casual online social interaction. These communities are symbolic of unique social networks formed in virtual space and reliant on interactivity not unlike the face-to-face interaction of traditional social encounters.

A key component of social e-health is interactivity, defined as “the degree to which the user can assert his or her agency” in a given interaction (Sundar, 2008, p. 64). Studies have found that user assertion of influence and control in a medium (e.g., the internet) is related to the perceived interactivity of that medium (Brennan &
Fink, 1997; Street & Rimal, 1997; Sundar 2007). Chamberlain (1996, p. 46) described interactivity as the “most important feature of new media technology” and, to be sure, interaction is a fundamental characteristic driving social e-health. Interactivity is important for social e-health because patient-technology and patient-patient interactions through interactive, communicative, and participatory technology can yield favorable health behaviors (Neuhauser & Kreps, 2003, 2010). Thus, interactivity occurring in online space through technology between individuals about health is considered a key element of social e-health because it helps foster improved health outcomes and motivation toward better health behaviors (Atkinson & Gold, 2002; Rice, 2001; Rubin & Rubin, 2001; Street & Rimal, 1997).

Another main idea behind social e-health is reflexivity, the notion that people are expected to contribute to the society in which they belong (Adams, 2011; Garfinkel, 1967; Giddens, 1991). In essence, this is an extension of social constructivism (Berger & Luckmann, 1967; Blumer, 1969; Blumer & Morrione, 2004). One method of contribution to society is the sharing of information about one's personal experiences, opinions, and outcomes with the society that helped produced them. This information is formed through self-interactions via internal, personal reflection and by external, social interactions with others via communication and exchange of ideas and knowledge (Bourdieu & Wacquant, 1992) and can be viewed as dramaturgical insofar as people often act according to what is expected of them to be judged favorably by others and society at large (Goffman, 1959).

Reflexivity then is a property whereby people define their everyday lives through the social interactions that define those lives. Inherent in reflexivity is the notion that
reciprocity between individuals and society is required; that is, as people accrue results from social interactivity there is an expectation that they will in turn share those results with the society that helped produce them. In the reflexive sense, society helps individuals make meanings of information and knowledge and, in turn, individuals reciprocate by sharing their meanings with society.

The notion of reflexivity helps explain partially why people are driven to share their health experiences over the internet. A cross-national sample of share-your-experience websites related to health policy and reform was examined by Adams in 2011. A primary purpose of the sites was to provide a platform for discussion of experiences users have had with the health care system in their respective country. Sharing their experiences on the websites, users added to the health care system dialogue by making their own posts and responding to others’ posts. Adams argues that the health care systems of today allow and expect patients to take on increasing roles in the production, maintenance, and alteration of their own health thanks in part to the rise of the internet. One way these demands are met is through the solicitation of user participation by governments, businesses, health organizations, physicians, and other patients in sharing personal experiences as well as evaluating products and services in online community environments.

Adams’ (2011) research drew upon reflexivity to explain why people engage in online e-health behaviors by writing that “people, both individually and as members of social groups, actively draw on available knowledge in order to monitor their actions and the contexts in which these take place” (p. 1070). In doing so, Adams continued, “individuals must not only negotiate the available options for themselves but they must
also contribute to a collective understanding by reporting the results of choices made” (p. 1075). Wenger’s (1998) concept of community is similar, as Hodgetts, Bolam, and Stephens (2005) wrote:

This concept is used to refer to a group of people engaged in shared activities through which learning occurs, expertise develops, meaning is constructed, and social relationships are negotiated. Through the enactment of rituals enabling the pursuit of a shared enterprise, group members (re)produce social relations and become embedded within specific subcultures. (p. 130)

Thus, interactive online social e-health enables people to share health information based on their own knowledge, experiences, and meanings for the benefit of others by giving back to society new health information and contributing to the sense-making processes of other people having similar health circumstances. Moreover, the act of sharing benefits the people themselves who share because it can raise their self-esteem. Plus, the potential to gain social support from others is maximized by publically acknowledging one’s own health conditions and creating an e-health identity with which others may more easily identify. The idea that the reciprocal behaviors of giving and sharing yields increased self-esteem of the giver and increase the likelihood of receiving in return has been discussed in the classic work *The Gift* by Marcel Mauss (1925).

Users of social e-health practice reflexive behaviors by first discovering, learning about, and monitoring their own health by observing others’ online accounts of health experiences as sources of real-life, real-world health knowledge. Then, users begin to actively employ information gained from the personal accounts of others into the health contexts developed from their own lived experiences. Users begin to recognize that, similar to the people who shared their health experiences online, they too can share their experiences for others to read. Such recognition may stem from a feeling of
obligation, desire to help others, or decision to become a part of a collective. As individuals become more deeply involved in others’ online health narratives, they may begin to feel a sense of commitment to and identification with e-health communities. Thus, the interactivity afforded by social e-health gives users the privilege to learn about health from real people like themselves while at the same time conditioning those users to actively and habitually contribute to an ongoing exchange of health-related ideas and experiences.

Plus, social e-health moves the creation and acquisition of health knowledge away from conventional physician-dependent models and allows patients themselves to become experts on their own illness conditions. Hardey (2001, p. 402) noted that “reflexive construction and publication of health narratives forms part of the reconfiguration of health expertise that is available to internet users.” Neuhauser and Kreps (2003, p. 13) noted that “people create health within their own settings” and Fox, Ward, and O’Rourke (2005, p. 1300) wrote that “growth in health information availability [online] has transformed the patient into a reflexive consumer.” Because reflexivity depends on a person’s synthesis of information and (re)creation of knowledge, reflexive thought and behavior often is created from one’s unique personal and social experiences. A part of this uniqueness is the ability to customize and personalize the new health knowledge that is to be shared with others.

Research has already made clear that customized and personalized health information in general is more effective for improving health learning and behavioral change when compared to health information that is not customized and personalized (Atkinson & Gold, 2002; Bastani, Maxwell, Bradford, Das, & Yan, 1999; Brug, Glanz,
van Assema, Kok, & van Breukelen, 1998; Bull, Holt, Kreuter, Clark, & Scharff, 2001; Cline & Haynes, 2001; Kreuter & Wray, 2003; Lipkus, Lyna, & Rimer, 1999; Marcus et al., 1998; Revere & Dunbar, 2001; Rimer et al., 1999; Skinner, Campbell, Rimer, Curry, & Prochaska, 1999). Customization is an important element of online social networking and interactivity because it fosters a sense of agency by allowing users to personalize their online profiles, decide what information to share or not share, and to some extent control the appearance of their internet presence (Kalyanaraman & Sundar, 2008; Sundar, 2008).

The social e-health environment overall has adapted similar customizations that afford users the ability to become more participatory and accountable in their own individualized and personalized health experiences (Kivits, 2006; Kreps & Neuhauser, 2010; Neuhauser & Kreps, 2003, 2010). Examples of social e-health personalization include tailoring online health profiles to reflect real-life health circumstances; writing and posting personal online health stories as a type of self-therapeutic release from which others may learn; and connecting online with others who may be similar to them health-wise for seeking advice on and reflecting upon shared health problems. Such customizations are important because they give people options to express their health and illness identities, as well as manage the extent to which those identities are revealed and shared through maintaining comfortable social distance.

Many customizable and interactive options such as uploading images, posting status updates and comments, and sending friend requests to other users are available on standard social networking platforms like Facebook, Instagram®, Pinterest®, and Twitter. Many of these same features often are available on interactive social e-health
websites such as CureTogether®, Inspire®, and PatientsLikeMe. These social e-health sites permit users to input into their public profile personal health data including medical diagnoses, medication types and dosages, height, weight, blood pressure, and more. In this way, users can create their own e-health identity by personalizing their profile with past and current health data, track theirs—and others’—health outcomes over time, and seek social support from other users who match up with their own similar health characteristics. Users may decide to openly reveal any and all information about their health lives or choose to guard their identities through careful attempts at preserving as much anonymity as possible.

The commonalities found in interactive online social e-health are that the internet provides a way for people to search for, gather, and interpret health information and data provided by others in online public and proprietary domains; create their own online personalities through customization and personalization features afforded by social e-health technologies; interact with others regarding their own health concerns via online support groups, forums, blogs, health tracking, and other interactive internet media; and feel a sense of community by connecting with others who share similar health conditions and/or who seek others for social support. For social e-health to be at its most effective, it must be “participatory, deeply meaningful, empathetic, empowering, interactive, personally relevant, contextually situated, credible, and convenient” (Neuhauser & Kreps, 2003, p. 18). Neuhauser and Kreps (2010, p. 9) asserted that the “enhanced features of interactivity, multimodality, mass customization, and the opportunity for users to also be producers” are key qualities for maximal social e-health
penetration. These qualities are noted in the literature as being fundamental for optimal health communication over electronic media (Atkinson & Gold, 2002; Eysenbach, 2001).

Through interaction over internet media and by creation of their own content, e-health users have become social e-health users by both consuming and producing health information. Moreover, users’ contributions to the virtual health environment stimulate ongoing worldwide conversations on health and medical topics. Four forms of specific social e-health activity highlighted in the current study are: blogs, online support groups, share-your-experience websites, and mobile health apps.

Blogs have increasingly become a platform for consumers and patients to document their first-hand health experiences for world-wide audiences and an everyday resource for people across the world to gain unique health information and knowledge through the personal accounts (Kennedy, 2004). Health blogs serve as digital diaries for patients in documenting their health experiences through personal narratives and may have a cathartic, therapeutic value in that patients are able to organize and express their feelings and thoughts into a readable medium for further reflection and active participation. Blog authors and readers can respond to comments on the blog, creating streams of asynchronous conversations similar to those found in internet support group forums, message boards, and other share-your-experience formats. Adams (2010b, p. 90) used the phrase “push-button publishing” to describe the ease with which consumers and patients can make available online their own health content via blogs and other web platforms.

In the same vein, online support groups and forums allow people to share their own health experiences while at the same time learn from the experiences of others.
These interfaces serve as message boards on which users engage in reciprocal conversations about health topics. According to Tannis (2008):

Web forums are easily accessible locations where people can give and receive support and where people who are interested can browse through the postings in an attempt to find the information they need. This makes them a good place not only for people who suffer from some kind of condition themselves, but also for their close relatives or caregivers. They can very easily visit web forums in order to increase their level of understanding and knowledge about the specific situation another is facing. (pp. 291-292)

Thus, online support groups can serve many of the same purposes as blogs insofar as both provide opportunities for users to express themselves, experience some therapeutic value in doing so, and reach out to other online users for information, emotional support, and social camaraderie. Research on empathy in online support groups and forums show that many users of these interfaces are empathetic to others’ health issues and situations (Preece, 1998, 1999; Preece & Ghozati, 1998, 2001). Thus, a favorable aspect of connecting with others online is the feeling of empathy that the involved agents feel as they share their health experiences in supportive environments.

The majority of blog and support group research is focused not on social demography but on the social, emotional, and psychological support these media provide. Notwithstanding, limited sociodemographic findings are available, mostly pertaining to gender. Research suggests that social e-health involvement by women more than men tends to exhibit qualities of empathy, compassion, emotion, encouragement, and nurturance, while involvement by men more so than women focuses on research findings, diagnostic facts, symptoms, medical news, practical issues, and less emotionally-driven discourse (Burri, Baujard, & Etter, 2006; Drentea & Moren-Cross, 2005; Klemm et al., 2003; Klemm, Hurst, Dearholt, & Trone, 1999;
In one of the largest blog studies available, Miller, Pole, and Bateman (2011) content analyzed nearly 1,000 health blogs from 2007 and 2008, 60% of which were authored by women. Results revealed that on average men’s blogs tended to include greater emphasis on health product and service advertisement; health news, research, and technology; and health policy and law, while women’s blogs favored discussion of nutrition; diseases and disabilities such as mental health, reproductive issues, and cancer; and personal experiences. Results indicated also that the majority of male-authored blogs (37%) were written by physicians who blogged as medical professionals, while the majority of female-authored blogs (65%) were written by women blogging as patients, consumers, and caregivers. Other health blog research has showed that women were more likely than men to use RSS feeds as a way to share information and post information that contained personally identifiable information about themselves (Kovic, Lulic, & Brumni, 2008; Sundar, Edwards, Hu, & Stavrositu, 2007).

Preece and Ghozati (2001) concluded that “a high number of empathetic messages in an online group is associated with the presence of women” (p. 251) and “the ratio of males to females…appears to influence empathetic communication” (p. 254). The study by Miller et al. (2011) suggested that women do seem to be more willing than men to seek connections with others and establish supportive networks online via interactive e-health behaviors. Thus, some evidence suggests that gender may be predictive of certain social e-health behaviors.
However, other research shows that gender effects may not be as prevalent or influential in e-health behavior. A study by Salem, Bogat, and Reid (1997) found no main or interaction effects in the postings made by men and women in an online support group for depression. Analyses of online breast and prostate cancer message boards have found only some statistically significant gender differences between types and topics of postings (Blank & Adams-Blodnieks, 2007; Blank, Schmidt, Vangsness, Monteiro, & Santagata, 2010; Gooden & Winefeld, 2007; Ravert, Hancock, & Ingersoll, 2004). A study by Seale (2006) found that empathetic, caring, and supportive communication styles were exhibited by women in online discussion groups for breast and prostate cancer, as well as by men in the breast but not prostate cancer group. Additional studies have demonstrated that men, similar to women, sometimes display characteristics of compassion and encouragement in health-related online social support seeking behaviors (Malik & Coulson, 2008; Nicholas, McNeill, Montgomery, Stapleford, & McClure, 2003).

Prior research agrees that a disproportionate number of online support group and forum users are women (Atkinson et al., 2009; Chou, Hunt, Beckjord, Moser, & Hesse, 2009; Hausner, Hajak, & Spießl, 2008). That women may be more likely than men to engage in e-health and social e-health behaviors such as information seeking, blogging, and online support groups is reasonable given that women tend to coordinate health services for both their families and themselves and experience greater morbidity. Women are socially constructed to assume the role of caregiver in many health situations, especially when seeking and coordinating care for their families (Auerbach & Figert, 1995; Miller et al., 2011) and are more likely to actively seek health information.
than men (Cotten & Gupta, 2004). Some existing evidence shows that primary caregiver responsibility may create additional emotional and psychological strain on women who already may be doubly burdened with domestic affairs (e.g., raising children and housework) and employment responsibilities (Bird, 1999; Neal, Ingersoll-Dayton, & Starrels, 1997; Simon, 1995; Yee & Schulz, 2000). Also, research suggests that because care-giving roles are time-consuming, many female caregivers simply do not have adequate time to engage in optimal healthy and health-promoting behaviors and may be more likely to prioritize others' health and well-being over their own (Bird & Rieker, 2008; Johnson & Repta, 2012; Lillie-Blanton, Martinez, Taylor, & Robinson, 1993). Thus, a gendered division of labor effect may be influencing women's behaviors and participating in e-health activities simply may be the easiest and most convenient option. Plus, going online may yield more meaningful support for women than that offered by family and/or physician.

Females, however, are not always the majority users in mixed-gender research. In a study on social e-health use of patients with spina bifida ($N = 63$), 60% were male (Chan & Dicianno, 2011). In the same study, the majority (68%) of users had only a high school-level education, a finding contrary to what digital divide would predict.

Not much is known about race and blog research as it pertains to health, but two studies explicitly concerned with blacks are important to note. Research by Della, Griffin, Eroğlu, Bernhardt, and Wells (2013) showed that more than 50% of general African-American blogs reviewed in their study recognized health in some fashion and that this percentage is consistent with the larger general blogger population. Research by Kvasny and Igwe (2008) showed that blogs can be used as a health education and
promotion tool among African-Americans in the fight against the spread of HIV/AIDS and could be more reliable than other black social outlets (e.g., television stations/programs and churches/church services aimed at black audiences).

Much more prevalent is research on the supposed social, emotional, and psychological support provided through blogs and support groups due in part to the stigmas attached to many forms of illness. Social stigmas associated with illness (Brown, 1995; Bury, 2000; Goffman, 1963; Radley, 1994; Zola, 1972) may be reduced by text-based online support groups because users can share information and experiences freely with less fear of being shamed, judged, or socially exiled (Berger, Wagner, & Baker, 2005; Fife & Wright, 2000; Reidpath, Chan, Gifford, & Allotey, 2005; Wright & Bell, 2003) and may lead to greater feelings of empowerment, self-esteem, self-confidence, and enhanced coping mechanisms (Bolam et al., 2006). Feelings of empowerment are commonly reported by users of e-health technology (Åkesson, Saveman, & Nilsson, 2007; Pandey et al., 2003).

On the subject of empowerment via online support groups, van Uden-Kraan, Drossaert, Taal, Seydel, and van de Laar (2009) surveyed 528 users (94% female, mean age = 44) of breast cancer, fibromyalgia, and arthritis internet groups to determine in what ways specifically involvement in these groups led to their empowered feelings. The authors found that the patients’ exchange of illness information, getting recognition of illness from others, and sharing illness experiences led to increased empowerment by being better informed about their illness, enhancing their social well-being, and elevating their confidence when discussing their illness with their physicians. Though they acknowledge that online empowerment is seen often as non-specific, highly
personal, and difficult to empirically measure, Barak, Boniel-Nissim, and Suler (2008, p. 1878) concluded that the “impact of writing, expressing emotions, gathering information and improving knowledge, developing interpersonal relationships, and bettering decision making skills generate a personal sense of empowerment.” However, in a critical analysis of 50 breast cancer websites and online support groups, Pitts (2004) cautioned that the perceived online empowerment of women should be interpreted with care as some illness narratives appear as if the writers are empowered yet still approach and describe their illness within the frameworks of biomedicine and defer their fate to the biomedical profession.

Barker’s (2005, 2008) research involving fibromyalgia showed that online support groups provided social and psychological strength to people who shared an illness that was largely questioned and contested in modern biomedicine. Thus, patients were able to use the internet space for support, but also to engage in sociological, political, and philosophical discussions about the skepticism of their illness among the medical profession, becoming one’s own expert on their contested illness, and seeking physician compliance in a medical system that disbelieved them.

In a 2011 study, Dickins, Thomas, King, Lewis, and Holland identified and interviewed 44 bloggers (mean age = 34, 82% female) who blogged about their own lived experiences of obesity and overweightness, particularly about fat acceptance. Fat acceptance is:

A consumer-based movement comprised of individuals…who question the dominant discourse of health reporting and information about obesity … [it includes] acceptance of one’s own body and relinquishment of the idea that one’s body is unacceptable if it does not conform to a societal ideal of thinness. (p. 1681)
The bloggers reported that writing about their experiences in the fat acceptance community helped them self-accept their obesity in an otherwise thinness-driven culture. Through their blogs, they were able to talk to others who helped them cope with stigmatization of their obesity and promote a sense of empowerment toward developing their own identity unconfined to hegemonic societal norms. In an earlier study (Fox et al., 2005) on an online obesity forum, participants openly shared their personal experiences of being overweight and drew upon each other's stories for emotional and social support. Users of the forum saw it as way to help them manage their overweight condition and medical treatments from day-to-day.

Using participant observation on an entire sample of 40 individuals and interviewing a subset of that sample \( n = 25 \), a Norwegian study of a breast cancer online support group (Sandaunet, 2008) revealed that women felt insecure about their futures and experienced feelings of isolation and loss. Participation in the support group, however, gave the women social, emotional, and informational resources that helped them manage their social and psychological discomfort. The main reason women cited for participating in the group was that they wanted to find other women who were in similar illness situations as them. Høybye, Johansen, and Tjørnhøj-Thomsen (2005) studied a Scandinavian online support group for breast cancer where the participating women \( N = 15 \), mean age 41) all had a breast cancer diagnosis, underwent breast surgery, and received either chemotherapy or radiation treatments. The women reported that the group served as a coping mechanism by providing them a sense of hope, emotional support, and a therapeutic outlet. The authors concluded that:

Writing and sharing a story in an internet support group can lead to the articulation and transformation of the individual experience of illness by offering a
mode of action … the illness is not just experienced submissively, as women progressed from isolation to active participation in a new social context. (p. 216)

In the end, involvement in the group made the women feel empowered and less stigmatized.

Armstrong, Koteyko, and Powell (2012) studied a diabetes online support group (\(N = 17\), all white, 65% female) based in the United Kingdom for six months. The authors’ findings revealed that users of the group engaged mostly in conversations revolving around diabetes self-management, treatments for diabetes, and ways to emotionally cope with having diabetes. Overall, users reported feeling empowered through information sharing, having more self-confidence, and experiencing a greater sense of independence and control over their illness specifically and their lives in general.

A study of message boards on a parenting website that included discussion on pregnancy, childbirth, and maternal health (Drentea & Moren-Cross, 2005) found that both emotional and informational support among the female members was common regarding topics such as stress, frustration, and various health symptoms pertinent to both the mothers and babies. Despite some topics that elicited disagreement and argumentative statements (e.g., how to properly breastfeed, what are the best childrearing techniques, etc.), the authors concluded that “the social support received by the women themselves was important for mitigating stress and improving their well-being” (p. 931).

While most studies examining online health interaction show positive, supportive results, some experiences with blogs, online support groups, and other interactive social media such as listservs may be detrimental to certain population segments. In 2010, a
randomized controlled study by Salzer et al. showed that 78 women with breast cancer—mostly white, college-educated, and having incomes greater than $40,000—who used an internet peer-support listserv became more distressed and rated their quality of life lower the more they continued using the listserv. A randomized controlled study by Kaplan, Salzer, Solomon, Brusilovskiy, and Cousounis (2011) showed that 300 individuals—mostly white, college-educated females with a mean age of 47—diagnosed with a schizophrenic spectrum or an affective disorder exhibited more distress when using interactive online peer-support listservs and bulletin boards. The results of these two studies provide evidence that are opposite of those concluding positive effects of using interactive online health tools for mental health improvement (Chang, Yeh, & Krumboltz, 2001; Corrigan, 2006; Houston, Cooper, & Ford, 2002).

Also, websites and discussion groups do exist that encourage behaviors detrimental to health. Online pro-suicide groups (Alao, Soderberg, Pohl, & Lola Alao, 2006; Biddle, Donovan, Hawton, Kapur, & Gunnell, 2008) and pro-anorexia groups (Brotsky & Giles, 2007; Day & Keys, 2008), for example, encourage users to engage in suicidal and anorexic behaviors that are unhealthy and fatal. Thus, not all websites, blogs, and support groups that are health-related promote healthy behaviors and outcomes.

In general, extant research suggests that participation in virtual support groups, forums, and online health programs mostly have positive effects on users’ health experiences and outcomes (Barak, Boniel-Nissim, & Suler, 2008; Barak & Grohol, 2011; Eysenbach, Powell, Englesakis, Rizo, & Stern, 2004; Ferguson & Kelly, 1999; Kral, 2006; Radin, 2006). However, as noted, there are some reports in the literature of
potential harm (Cline & Haynes, 2001; Crocco, Villasis-Keever, & Jadad, 2002; Cullen, 2006; Scheerhorn, 1997) as well as inconclusive results (Bessell et al., 2002). Plus, as with any type of health-related website, health blogs and support groups can suffer from the same problems of misinformation, lack of quality control, and similar characteristics common to any consumer- and patient-created media (Larkin, 2005).

Turning now to share-your-experience health websites, these are sites specifically designed for users to communicate with each other about their health and illness experiences through narrative postings and comments as well as health data tracking. Research involving these sites is only beginning to appear in the sociological literature. Examples of these types of sites include CareTogether, Inspire, and PatientsLikeMe. The latter of these has become one of the most popular. As of 2011, the PatientsLikeMe website had over 80,000 registered users (Frost, Okun, Vaughn, Heywood, & Wicks, 2011), but has grown to more than 200,000 in just two years (Bradley, 2013; Upbin, 2013).

The primary method of communication between PatientsLikeMe members is through the website’s forums that are very similar to traditional asynchronous online support group interfaces—a user begins a topic discussion and other users post their responses to the original post and subsequent responses. The forums are moderated by PatientsLikeMe employees. Frost and Massaglia (2008) found three main recurring themes in comments posted in the PatientsLikeMe forums:

- Asking advice of a user with a particular experience
- Offering advice to a user with a specific symptom or health problem
- Fostering relationships based on shared attributes (Discussion section, paragraph 2)
In a more recent study (Wicks et al., 2010), users of PatientsLikeMe reported having favorable opinions of and experiences with the site. Survey responses of over 1,300 PatientsLikeMe users showed that 72% rated the site as helpful to them and 57% said the site was beneficial for learning about side effects from medications and other treatments. Just over 40% indicated that the site connected them with other people who had helped them understand more about their health conditions and treatments. In terms of specific disease diagnoses, more men than women reported having amyotrophic lateral sclerosis (ALS) (67%) and HIV (70%), while more women than men reported multiple sclerosis (81%), Parkinson’s (54%), fibromyalgia (98%), and mood disorders (76%). Close to 60% of all users reported that the site was useful in helping them manage their symptoms and 70% reported that the site helped them cope with their illnesses. A little less than two-thirds of respondents reported that the site helped them feel less self-conscious about and more empowered over their illness. Though 66% of users reported that their physicians were supportive of their use of the site, nearly 40% reported that they questioned the diagnoses given to them by their physicians and 12% reported changing physicians directly as a result of health information they obtained on the site. The researchers concluded overall that people who used the interactive features of the site such as health data tracking and forums reported greater perceived benefits and quality of life from using the site.

Ascertaining one’s sociodemographic and health data based on profile entry on share-your-experience websites such as PatientsLikeMe is problematic because people online can take on any identity they wish as well as fabricate or falsify their own health information. Thus, there is no way to be completely certain if users of these sites are
male, female, black, white, young, old, etc. based solely on the observation of online profiles and postings, nor is it possible to determine the accuracy of any health data, commentary, or information provided by the user about their own health status. These same cautions apply to research involving blogs and online support groups, so the limitations are not new.

One of the features on many share-your-experience health websites such as PatientsLikeMe is that users can input their own health data into their profile for tracking purposes. The information is visible to other users who visit the profile, so it is possible for others to track any users’ health data as well. Tracking one’s own health data using the internet is growing in popularity (Fox, 2010). Examples of health data to be tracked might be weight, blood pressure, blood sugar levels, number and types of medications, and much more. Health data tracking options are growing on general health websites, as well as physician, pharmacy, and health insurance websites.

Increasingly, people use apps on their mobile devices to track their health. Data has shown that anywhere from a little less than 10% to close to 20% of people with mobile phones use apps to help track and monitor their own health (Fox, 2011b; Fox & Duggan, 2012, 2013a). Those who use mobile health apps are likely to be black and Latino/a, female, and aged 18-29 with high education and income; whites and the 30-49 age group follow closely behind (Fox & Duggan, 2012, p. 12). Research has shown that blacks use text messaging for health purposes more than whites (Denizard-Thompson, Feireisel, Stevens, Miller, & Wofford, 2011). In addition, compared with other racial groups, more blacks track indicators of health and symptoms in some form or fashion—from memory, on paper, or online (Fox & Duggan, 2013a). The use of mobile health
apps presents a unique opportunity for sociodemographic research because, opposite of what might be expected from a digital divide framework, whites are shown to use this technology less frequently than both blacks and Hispanics.

Tracking health data has become a social behavior as recent reports have indicated that one-third of people who tracked their health shared it with someone else (Fox & Duggan, 2012, 2013a). Sharing tracked data has become easier through use of mobile health apps. Burgeoning research already has begun to show that people are using mobile apps in greater numbers, especially health apps, and users of these apps appear to find their use favorable (Brendryen, Drozd, & Kraft, 2008; Campbell & Kelley, 2008; Kim & Kim, 2008; Kristjánsdóttir et al., 2011; Patrick et al., 2009; Pjenenborg et al., 2010; Shapiro et al., 2010; Whittaker et al., 2011).

An ever-increasing body of research has shown that physicians, health care providers, public health officials, and researchers are finding ways to use blogs, online support groups, mobile health apps, and other social media to communicate health information with their own patients and the masses. The specific methods and strategies by which communication occurs vary, but an abundance of studies have shown use of interactive websites, social media marketing campaigns, telemedical applications, public health promotion, and online behavioral modification programs (Bae, Lee, Yoon, & An, 2006; Carr et al., 2008; Cook, Billings, Hersch, Back, & Hendrickson, 2007; Dalton, 2008; Gosselin & Poitras, 2008; Grant et al., 2006; Hurling et al., 2007; Kalichman, Benotsch, Weinhardt, Austin, & Luke, 2002; Kim, Lee, & Kim, 2013; McFarlane, Kachur, Klausner, Roland, & Cohen, 2005; Moore et al., 2008; Nijland, van Gemert-Pijnen, Boer, Steehouder, & Seydel, 2008; Riper et al., 2009; Riper
et al., 2008; Schulz, Rubinelli, Mariotti, & Keller, 2009; Tate, Jackvony, & Wing, 2003; Tate, Wing, & Winett, 2001). Some in the medical establishment, however, have been hesitant to adapt these new technologies (Bodenheimer & Grumbach, 2003; Brooks & Menachemi, 2006; Patt, Houston, Jenckes, Sands, & Ford, 2003; Rich & Fletcher, 2013) due to “fear of increased demand on time, confidentiality issues, liability concerns, and lack of reimbursement” (McMullan, 2006, p. 26). Nonetheless, though results have been varied “emerging evidence provides support for the beneficial effects of online interactive e-health programs” (Ahern, 2007, p. S75).

In sum, research on blogs and online support groups shows that its users are mostly women—this finding consistently appears when examining what is known about social e-health. Beyond gender, the literature is scarce with sociodemographic, statistically generalizable data on who is and is not engaging in social e-health behavior. Very little is known about share-your-experience websites and only small pockets of data are beginning to appear with regards to online health data tracking and use of mobile health apps. Using the social determinants of health and digital divide frameworks, a reasonable assertion would be that the same sociodemographic patterns found in online health information seeking would apply also to interaction and creation e-health behavior because at the root of each is use of the internet for health purposes. Existing sociological literature, however, has not made this association clear.
CHAPTER III

RESEARCH METHODS

Univariate frequency data and multivariate logistic regression results of reported social e-health behavior by gender, race, ethnicity, age, education, and income were analyzed using 2010 data from a large, nationally representative and randomly sampled telephone survey. The dependent variable of social e-health was obtained by collapsing responses to thirteen variables having to do with online interaction and creation behaviors. Logistic regression was used to determine the odds of engaging in social e-health behavior according to respondents’ sociodemographics. Gender, race, ethnicity, age, education, and income were used as the sociodemographic predictor variables because extant literature as discussed in Chapters 1 and 2 has demonstrated that these are key factors in the social determinants of health and digital divide.

Research Question

This study asked: Is there a difference in social e-health behavior according to gender, race, ethnicity, age, education, and income?

Hypotheses

Using quantitative analysis, the following six hypotheses were tested. One hypothesis was developed for each of the six sociodemographic characteristics based on outcomes that would be expected from the social determinants of health and digital divide frameworks.
Hypothesis 1 (H1): Concerning gender, women are more likely than men to engage in social e-health behavior.

Hypothesis 2 (H2): Concerning race, non-whites are less likely than whites to engage in social e-health behavior. Also, persons in the racial category of other are less likely than blacks to engage in this behavior.

Hypothesis 3 (H3): Concerning ethnicity, non-Hispanics are more likely than Hispanics to engage in social e-health behavior.

Hypothesis 4 (H4): Concerning age, as age increases people are less likely to engage in social e-health behavior.

Hypothesis 5 (H5): Concerning education, persons with at least some college education are more likely than those without any college education to engage in social e-health behavior. Also, college graduates are more likely than those with only some college to engage in this behavior.

Hypothesis 6 (H6): Concerning income, persons with income greater than $40,000 are more likely than those with income less than $40,000 to engage in social e-health behavior. Also, persons in the $40,000 to under $75,000 income range are less likely than those with income of at least $75,000 to engage in this behavior.

Dataset

The current study used an existing dataset (N = 3,001) of a nationally representative random-digit dialing (RDD) telephone survey conducted by Princeton Survey Research Associates International in 2010 for the Pew Research Center. Respondents were contacted either by landline or cellular telephone and survey
interviews were conducted in either English or Spanish. Over 53,000 landline numbers and 17,000 cellular numbers were dialed. The response rate for completed landline interviews was 13.6% and 17% for cellular interviews. Complete sampling techniques have been explained in the Pew report for this dataset (Fox, 2011b, p. 21-23). The dataset along with an accompanying copy of the telephone questionnaire and report were freely available and downloaded from the Pew Research Center website in March 2012. The complete dataset was imported into and analyzed using SPSS® software versions 20 and 21.

A standardized weight variable was included with the dataset. This variable was activated in SPSS such that each case was assigned an appropriate sample weight to correct for disproportionate sampling as well as bias from non-response and missing data common in telephone surveys. Details on how the weights were calculated are available in the Pew report for this dataset (Fox, 2011b, pp. 21-23). All $N$ and $n$ sample sizes reported in the current study represent unweighted values even though the dataset was weighted during analysis. The decision to report unweighted rather than weighted sample sizes was made because unweighted values represent the actual sample sizes (i.e., the real number of cases) whereas weighted sample size values do not reflect true sample sizes (i.e., the number of cases are influenced by the weights).

Filtering strategies were used on the full dataset ($N = 3,001$) in an attempt to increase accuracy and interpretability of results. As the focus of analyses in the current study involved online behaviors, the number of respondents who identified themselves as non-internet users ($n = 936$) was filtered out from the dataset. Filtration on this criterion yielded a new sample size of $N = 2,065$. For this new sample size, all system-
missing and non-response data as well as respondent answers of don’t know and refused for all variables were left in the dataset but coded as missing so that those cases would be excluded from valid sample sizes during analysis.

As mentioned, the dependent variable of social e-health behavior was created by combining thirteen individual survey questions that in some way dealt with interaction and creation e-health behavior. Influential and outlying cases for each of the thirteen survey questions were determined by Pearson standardized residual ($z$) analysis. Pearson standardized residuals were chosen over Studentized and deviance residuals because the values are larger and outliers more easily detectable (Menard, 2002, 2010). A stringent criterion of $z = \pm 2.00$ was applied such that all cases having a standardized residual with at least an absolute value of 2.00 were eliminated. Application of this strict criterion, though reducing the sample size, ensured that all cases that might potentially influence the final results were removed. A total of $n = 593$ outlying cases were eliminated with this criterion bringing the total sample size to $N = 1,472$ up to this point.

After the thirteen variables were collapsed into one variable, Pearson standardized residual analysis was used to check for outliers and influential cases on the newly-combined variable. This time, however, a less-stringent criteria for removal of outlying cases was set at $z = \pm 4.00$ on the basis that the majority of influential cases were already removed in the previous step and, thus, the threshold could be more relaxed. Using this criterion, only five additional outlying cases were eliminated resulting in a sample size of $N = 1,467$. After accounting for missing cases ($n = 884$), final multivariate logistic regression was conducted with a final sample size of $N = 583$. 
Table 1

A List of All Variables Used in this Study along with Original Coded and Re-Coded Values

<table>
<thead>
<tr>
<th>Variable</th>
<th>Survey Question</th>
<th>Original Coding</th>
<th>My Re-coding</th>
</tr>
</thead>
<tbody>
<tr>
<td>Social</td>
<td>n/a</td>
<td>Coding</td>
<td></td>
</tr>
<tr>
<td>E-Health(^1)</td>
<td></td>
<td>0 = no; ≥1 = 1 = Yes</td>
<td></td>
</tr>
<tr>
<td>Survey Question Q24a</td>
<td>Have you ever signed up to receive e-mail updates or alerts about health or medical issues?</td>
<td>1 = Yes; 2 = No; 8 = Don't Know; 9 = Refused</td>
<td>0 = No; 1 = Yes; 98 = Don't Know; 99 = Refused</td>
</tr>
<tr>
<td>Survey Question Q24d</td>
<td>Have you ever gone online to find others who might have health concerns similar to yours?</td>
<td>1 = Yes; 2 = No; 8 = Don't Know; 9 = Refused</td>
<td>0 = No; 1 = Yes; 98 = Don't Know; 99 = Refused</td>
</tr>
<tr>
<td>Survey Question Q24e</td>
<td>Have you ever tracked your weight, diet, or exercise routine online?</td>
<td>1 = Yes; 2 = No; 8 = Don't Know; 9 = Refused</td>
<td>0 = No; 1 = Yes; 98 = Don't Know; 99 = Refused</td>
</tr>
<tr>
<td>Survey Question Q24f</td>
<td>Have you ever tracked any other health indicators [besides weight, diet, or exercise] or symptoms online?</td>
<td>1 = Yes; 2 = No; 8 = Don't Know; 9 = Refused</td>
<td>0 = No; 1 = Yes; 98 = Don't Know; 99 = Refused</td>
</tr>
</tbody>
</table>

(table continues)
<table>
<thead>
<tr>
<th>Variable</th>
<th>Survey Question</th>
<th>Survey Question Q25a</th>
<th>Survey Question Q25b</th>
<th>Survey Question Q25c</th>
<th>Survey Question Q25e</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Have you ever posted comments, questions, or information about health or medical issues in an online discussion, a listserv, or other online group forum?</td>
<td>Original Coding</td>
<td>1 = Yes; 2 = No; 8 = Don’t Know; 9 = Refused</td>
<td>My Re-coding</td>
<td>0 = No; 1 = Yes; 98 = Don’t Know; 99 = Refused</td>
</tr>
<tr>
<td></td>
<td>Have you ever posted comments, questions, or information about health or medical issues on a blog?</td>
<td>Original Coding</td>
<td>1 = Yes; 2 = No; 8 = Don’t Know; 9 = Refused</td>
<td>My Re-coding</td>
<td>0 = No; 1 = Yes; 98 = Don’t Know; 99 = Refused</td>
</tr>
<tr>
<td></td>
<td>Have you ever posted comments, questions, or information about health or medical issues on a social networking site such as Facebook, MySpace, or LinkedIn?</td>
<td>Original Coding</td>
<td>1 = Yes; 2 = No; 8 = Don’t Know; 9 = Refused</td>
<td>My Re-coding</td>
<td>0 = No; 1 = Yes; 98 = Don’t Know; 99 = Refused</td>
</tr>
<tr>
<td></td>
<td>Have you ever posted comments, questions, or information about health or medical issues on a website of any kind, such as a health site or news site that allows comments and discussion?</td>
<td>Original Coding</td>
<td>1 = Yes; 2 = No; 8 = Don’t Know; 9 = Refused</td>
<td>My Re-coding</td>
<td>0 = No; 1 = Yes; 98 = Don’t Know; 99 = Refused</td>
</tr>
</tbody>
</table>

*(table continues)*
<table>
<thead>
<tr>
<th>Variable</th>
<th>Survey Question</th>
</tr>
</thead>
<tbody>
<tr>
<td>Survey Question Q26b</td>
<td>Have you ever used a social networking site to start or join a health-related group?</td>
</tr>
<tr>
<td></td>
<td>Original Coding</td>
</tr>
<tr>
<td></td>
<td>1 = Yes; 2 = No; 8 = Don’t Know; 9 = Refused</td>
</tr>
<tr>
<td></td>
<td>My Re-coding</td>
</tr>
<tr>
<td></td>
<td>0 = No; 1 = Yes; 98 = Don’t Know; 99 = Refused</td>
</tr>
<tr>
<td>Survey Question Q26c</td>
<td>Have you ever used a social networking site to follow your friends’ personal health experiences or health updates?</td>
</tr>
<tr>
<td></td>
<td>Original Coding</td>
</tr>
<tr>
<td></td>
<td>1 = Yes; 2 = No; 8 = Don’t Know; 9 = Refused</td>
</tr>
<tr>
<td></td>
<td>My Re-coding</td>
</tr>
<tr>
<td></td>
<td>0 = No; 1 = Yes; 98 = Don’t Know; 99 = Refused</td>
</tr>
<tr>
<td>Survey Question Q29d</td>
<td>Have you ever posted a review online of a doctor?</td>
</tr>
<tr>
<td></td>
<td>Original Coding</td>
</tr>
<tr>
<td></td>
<td>1 = Yes; 2 = No; 8 = Don’t Know; 9 = Refused</td>
</tr>
<tr>
<td></td>
<td>My Re-coding</td>
</tr>
<tr>
<td></td>
<td>0 = No; 1 = Yes; 98 = Don’t Know; 99 = Refused</td>
</tr>
<tr>
<td>Survey Question Q29e</td>
<td>Have you ever posted a review online of a hospital?</td>
</tr>
<tr>
<td></td>
<td>Original Coding</td>
</tr>
<tr>
<td></td>
<td>1 = Yes; 2 = No; 8 = Don’t Know; 9 = Refused</td>
</tr>
<tr>
<td></td>
<td>My Re-coding</td>
</tr>
<tr>
<td></td>
<td>0 = No; 1 = Yes; 98 = Don’t Know; 99 = Refused</td>
</tr>
<tr>
<td>Survey Question Q29f</td>
<td>Have you ever posted your experiences with a particular drug or medical treatment online?</td>
</tr>
<tr>
<td></td>
<td>Original Coding</td>
</tr>
<tr>
<td></td>
<td>1 = Yes; 2 = No; 8 = Don’t Know; 9 = Refused</td>
</tr>
<tr>
<td></td>
<td>My Re-coding</td>
</tr>
<tr>
<td></td>
<td>0 = No; 1 = Yes; 98 = Don’t Know; 99 = Refused</td>
</tr>
<tr>
<td>Variable</td>
<td>Survey Question</td>
</tr>
<tr>
<td>----------</td>
<td>-----------------------------------------------------</td>
</tr>
<tr>
<td>Gender</td>
<td>What is your gender? Are you male or female?</td>
</tr>
<tr>
<td>Race</td>
<td>What is your race? Are you white, black, Asian, or some other race?</td>
</tr>
<tr>
<td>Ethnicity</td>
<td>Are you of Hispanic or Latino origin or descent, such as Mexican, Puerto Rican, Cuban, or some other Latin American background?</td>
</tr>
<tr>
<td>Age</td>
<td>What is your age?</td>
</tr>
</tbody>
</table>
Table 1 (continued).

<table>
<thead>
<tr>
<th>Variable</th>
<th>Survey Question</th>
</tr>
</thead>
<tbody>
<tr>
<td>Education</td>
<td>What is the last grade or class you completed in school?</td>
</tr>
<tr>
<td></td>
<td><strong>Original Coding</strong></td>
</tr>
<tr>
<td></td>
<td>1 = None or Grades 1-8; 2 = High School Incomplete Grades 9-11; 3 = High School Graduate or GED Certificate; 4 = Technical, Trade, or Vocational School After High School; 5 = Some College but No 4-Year Degree, Includes Associates; 6 = College Graduate B.S., B.A., or Other 4-Year Degree; 7 = Post-Graduate Training or Professional School After College; 8 = Don’t Know; 9 = Refused</td>
</tr>
<tr>
<td></td>
<td><strong>Survey Re-coding</strong></td>
</tr>
<tr>
<td></td>
<td>1 = Less Than High School; 2 = High School Graduate; 3 = Some College; 4 = College Graduate and Above; 9 = Don’t Know and Refused</td>
</tr>
<tr>
<td></td>
<td><strong>My Re-coding</strong></td>
</tr>
<tr>
<td></td>
<td>1 = Less Than High School and High School; 2 = Some College; 3 = College Graduate; 9 = Don’t Know and Refused</td>
</tr>
<tr>
<td>Income</td>
<td>Last year in 2009, what was your total family income from all sources before taxes?</td>
</tr>
<tr>
<td></td>
<td><strong>Original Coding</strong></td>
</tr>
<tr>
<td></td>
<td>1 = Less than $10,000; 2 = $10,000 to under $20,000; 3 = $20,000 to under $30,000; 4 = $30,000 to under $40,000; 5 = $40,000 to under $50,000; 6 = $50,000 to under $75,000; 7 = $75,000 to under $100,000; 8 = $100,000 to under $150,000; 9 = $150,000 or more; 98 = Don’t Know; 99 = Refused</td>
</tr>
<tr>
<td></td>
<td><strong>My Re-coding</strong></td>
</tr>
<tr>
<td></td>
<td>1 = Less than $40,000; 2 = $40,000 to under $75,000; 3 = $75,000 or more; 98 = Don’t Know; 99 = Refused</td>
</tr>
</tbody>
</table>

1 This variable was not in the original dataset. It was created by collapsing the subsequently listed Survey Question variables.

2 In the dataset were two education variables, one as originally coded and one that was already re-coded for simplification. The already re-coded variable was re-coded by me to collapse the less than high school and high school graduate categories.
All variables from the dataset that were used in the current study required some form of recoding, including the thirteen survey questions that were combined to create the single social e-health variable. Table 1 lists all thirteen e-health survey questions that were combined to create the social e-health behavior variable, as well as all six sociodemographic variables. The Table contains the original coding values from the dataset and their re-coded values as used in the current study.

Logistic regression estimated all results using an iterative maximum likelihood method, not the least squares criteria used in linear regression (DeMaris, 1992; Harrell, 2001; Hosmer & Lemeshow, 2000, 2012; Menard, 2002, 2010; Wright, 1995). Maximum likelihood requires large sample sizes of at least 50 cases per predictor variable (Aldrich & Nelson, 1984). This requirement was met by the dataset.

Variables

Social E-Health Behavior

The dependent variable of social e-health behavior was obtained by combining thirteen separate survey questions. A list of the thirteen questions used is provided in Table 1. These thirteen questions were chosen from the survey to represent social e-health because they each involve some type of online interactive or creative e-health behavior. A fourteenth question from the survey (Q25d) was considered for inclusion as it pertained to Twitter and other status updating sites but was eliminated because it added too many missing cases to the analyses. Answers to all thirteen questions were recorded originally in the dataset as yes, no, don’t know, or refused. For the current
study, a no response was set to a value of 0 and a yes response to a value of 1. All
don’t know and refused responses were re-coded as missing.

Once all the values were appropriately set for each of the thirteen survey
questions, the variables were collapsed into the dependent variable of social e-health.
This single variable was then re-coded such that any value of one and greater was
counted as yes and set to 1 which indicated that social e-health behavior had occurred
for that respondent. All values of zero were counted as no and set to 0 which indicated
that social e-health behavior had not occurred for that respondent.

Gender

The independent variable of gender was represented by answers to a single
question in the 2010 survey that asked respondents to indicate whether they were male
or female. Answers to this question were recorded originally in the dataset as 1 = male
and 2 = female; there were no don’t know, refused, or missing responses. For the
current study, a male response was re-coded as a reference category to a value of zero
and a female response to a value of one.

Race

The independent variable of race was recorded originally in the dataset as eight
categories as follows: white, black or African-American, Asian or Pacific Islander, mixed
race, Native American or American Indian, other, don’t know, and refused. The four
categories of Asian or Pacific Islander, mixed race, Native American or American
Indian, and other each contained very few respondents and were collapsed into a single
category labeled other. The category of white was coded as 1, black coded as 2, and other coded as 3. All don’t know, refused, and system missing responses were set as missing.

Race was then re-coded as three dummy variables; this was necessary to obtain comparison categories for the three possible combinations of comparisons—white versus black, white versus other, and black versus other. For these comparisons, white was the reference category for black and other, while black was the reference category for other—this ensured that all combinations without redundancy were accounted for in the final model. For the first dummy variable, black was set to a value of 1, while white and other to a value of 0. For the second dummy variable, other was set to a value of 1, while white and black to a value of 0. For the third dummy variable, white was set to 0, while black and other to a value of 1. With this dummy coding scheme, the three possible comparisons across categories were possible.

**Ethnicity**

This survey question asked respondents if they were of Hispanic or Latino origin. As such, the ethnicity variable was concerned only with the Hispanic-Latino ethnicity and was recorded originally in the dataset as 1 = yes and 2 = no, while 8 and 9 represented don’t know and refused, respectively. For the current study, a no response was re-coded as a reference category to a value of 0 and a yes response to a value of 1. All don’t know, refused, and system missing responses were set as missing. Because neither Latino nor Hispanic is considered a race (U.S. Census Bureau, 2011b).
collapsing the ethnicity variable into the other race category or including it as its own category within race would have been inaccurate.

Age

The independent variable of age was originally recorded at the interval-ratio level in the 2010 survey and remained as such in the current study. Raw, non-centered values of age were used and no re-coding was needed.

Education

The dataset contained two education variables. The first variable had nine total categories. The second variable collapsed the first into four categories of less than high school, high school graduate, some college, college graduate, don’t know, and refused. Because the category of less than high school had few respondents, it was merged with the high school graduate category in the current study. Thus, a response of less than high school or high school graduate was simply termed high school and set to a value of 1, some college to a value of 2, and college graduate to a value of 3. All don’t know, refused, and system missing responses were set as missing.

Education was then re-coded as three dummy variables; this was necessary to obtain comparison categories for all possible combinations of comparisons—high school versus some college, high school versus college graduate, and some college versus college graduate. For these comparisons, high school was the reference category for some college and college graduate, while some college was the reference category for college graduate—this ensured that all combinations without redundancy
were accounted for in the final model. For the first dummy variable, some college was
set to a value of 1, while high school and college graduate to a value of 0. For the
second dummy variable, college graduate was set to a value of 1, while high school and
some college to a value of 0. For the third dummy variable, the category of high school
was set to a value of 0, while some college and college graduate to a value of 1. With
this dummy coding scheme, the three comparisons across all categories were possible.

Income

The independent variable of annual 2009 U.S. income before taxes was recorded
originally in nine categories as follows: less than $10,000; $10,000 to under $20,000;
$20,000 to under $30,000; $30,000 to under $40,000; $40,000 to under $50,000;
$50,000 to under $75,000; $75,000 to under $100,000; $100,000 to under $150,000;
$150,000 or more; don’t know; and refused. For the current study, the nine categories
were collapsed into three. The category values and titles were 1 = under $40,000; 2 =
$40,000 to under $75,000; and 3 = $75,000 or more. All don’t know, refused, and
system missing responses were set as missing.

Income was then re-coded as three dummy variables; this was necessary to
obtain comparison categories for all possible combinations of comparisons—under
$40,000 versus $40,000 to under $75,000; under $40,000 versus $75,000 or more; and
$40,000 to under $75,000 versus $75,000 or more. For these comparisons, under
$40,000 was the reference category for $40,000 to under $75,000 and $75,000 or more,
while $40,000 to under $75,000 was the reference category for $75,000 or more—this
ensured that all combinations without redundancy were accounted for in the final model.
For the first dummy variable, $40,000 to under $75,000 was set to a value of 1, while under $40,000 and $75,000 or more to a value of 0. For the second dummy variable, $75,000 or more was set to a value of 1, while under $40,000 and $40,000 to under $75,000 to a value of 0. For the third dummy variable, under $40,000 was set to 0, while $40,000 to under $75,000 and $75,000 or more to a value of 1. With this dummy coding scheme, the three comparisons across all categories were possible.

Statistical Procedures

Univariate Analysis

Univariate frequency distribution tables were constructed for all six sociodemographic variables, as well as the social e-health variable and all thirteen survey questions that were used to create that variable. These Tables are presented in Appendix A. All Tables for dichotomous and categorical variables (A.1 through A.19) include raw frequency data, valid percentages, and total sample sizes. The Table for the single continuous variable of age (A.20) included the mean, median, mode, standard deviation, minimum and maximum values, range, skewness, and kurtosis.

Dummy Coding

variables of race, education, and income had three categories ($k$), the corresponding number of new dummy variables to represent each original variable had to be created ($k - 1$). This re-coding resulted in six newly-created dummy variables—two for race, two for education, and two for income. This coding scheme allowed one reference category to be assigned that was compared against the other two categories. Using race as an example, white was used as a reference category, while black and other were used as comparison categories (i.e., white versus black and white versus other). However, an ordinal extension to the coding scheme was made to allow the third possible comparison where black was the reference category for other (i.e., black versus other). This extension treated categorical variables as ordinal. The extension resulted in the creation of three more dummy variables—one for race, one for education, and one for income. This completed all possible combinations for the comparisons without statistical redundancy. An illustration of the dummy coding used in this study with race as an example is provided in Table 2.

In Table 2, the inclusion of dummy race A and dummy race B allows for the comparisons white versus black and white versus other in logistic regression. When dummy race A is replaced with dummy race C, however, the last comparison of black versus other is made possible in logistic regression. This same logic was applied to the education and income variables.
Table 2

Illustration of Traditional Dummy Coding ($k - 1$) with Ordinal Extension Using Race as an Example

<table>
<thead>
<tr>
<th></th>
<th>Traditional Dummy Coding ($k - 1$)</th>
<th>Ordinal Extension</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Dummy Race A</td>
<td>Dummy Race B</td>
</tr>
<tr>
<td>White</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>Black</td>
<td>1</td>
<td>0</td>
</tr>
<tr>
<td>Other</td>
<td>0</td>
<td>1</td>
</tr>
</tbody>
</table>

Note. For dummy race A and dummy race B, white is the reference category. For dummy race C, black becomes the reference category because it is the first value of one in the ordinal sequence.

Logistic Regression

Given that the purpose of this study was to examine the relationships between sets of independent predictor variables ($X$) with dichotomous responses ($Y$), logistic regression was an appropriate technique to use for analysis (Harrell, 2001; Hosmer & Lemeshow, 2002, 2012; Mertler & Vannatta, 2005; Wright, 1995). Thirteen preliminary multivariate logistic regressions were executed to obtain Pearson standardized residuals using each of the dichotomous e-health survey questions separately as the dependent variable with all of the sociodemographic independent variables—dichotomous gender and ethnicity, interval-ratio-level age, and dummy-coded couplets of race, education, and income. This process allowed for all outlying and influential cases defined as $z = \pm 2.00$ to be eliminated. After the thirteen variables were collapsed
into the single dependent variable of social e-health, this new variable was used in one last preliminary multivariate logistic regression to obtain its standardized residuals and eliminate outliers at $z = \pm 4.00$.

With all influential and outlying cases eliminated, two final multivariate logistic regressions were executed using social e-health as the dependent variable with all of the sociodemographic independent variables. Two final regressions were needed to account for the ordinal extension. The first regression used the traditional dummy-coded couplets for race, education, and income, while the second exchanged one of the traditionally-coded variables with an ordinal-coded one. Still using race as an example from Table 2, the first regression included dummy race A and B. In the second regression, however, dummy race A was replaced with dummy race C. Menard (2002, p. 60) notes that, “the use of different contrasts for ordinal variables has no effect on the model fit or on the statistical significance of the categorical ordinal variable.” Thus, the removal of dummy race A and addition of dummy race C in the second regression did not change the previous data obtained from the first regression. Table 3 outlines the variables used for both final multivariate logistic regressions.

Both final multivariate logistic regressions were combined to test the six hypotheses of the current study and create a final model predicting the odds that social e-health behavior would occur based on sociodemographics. The final model with all statistics and parameters is presented in Table 5 in Chapter 4.
Table 3

Variables Used in the Final Two Logistic Regressions

<table>
<thead>
<tr>
<th>Final Logistic Regression 1</th>
<th>Final Logistic Regression 2</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Dependent Variable</strong></td>
<td><strong>Dependent Variable</strong></td>
</tr>
<tr>
<td>Social E-Health</td>
<td>Social E-Health</td>
</tr>
<tr>
<td><strong>Independent Variables</strong></td>
<td><strong>Independent Variables</strong></td>
</tr>
<tr>
<td>Gender</td>
<td>Gender</td>
</tr>
<tr>
<td>Dummy Race A</td>
<td>Dummy Race B</td>
</tr>
<tr>
<td>Dummy Race B</td>
<td>Dummy Race C</td>
</tr>
<tr>
<td>Ethnicity</td>
<td>Ethnicity</td>
</tr>
<tr>
<td>Age</td>
<td>Age</td>
</tr>
<tr>
<td>Dummy Education A</td>
<td>Dummy Education B</td>
</tr>
<tr>
<td>Dummy Education B</td>
<td>Dummy Education C</td>
</tr>
<tr>
<td>Dummy Income A</td>
<td>Dummy Income B</td>
</tr>
<tr>
<td>Dummy Income B</td>
<td>Dummy Income C</td>
</tr>
</tbody>
</table>

*Note. All variables are dichotomous except for age which is interval-ratio.*

For logistic regression, goodness-of-fit statistics are less important than in linear regression. In principle, goodness-of-fit measures the degree to which the observed model differs from the ideal, perfect model. However, Menard (2010, p. 58) noted that “there is less consensus on [the use of goodness-of-fit statistics] in logistic regression analysis, and if anything, there appears to be an emerging consensus that goodness-of-fit statistics need not be presented for logistic regression.” Cohen, Cohen, West, and Aiken (2002, p. 502) noted that “no single agreed upon index of goodness-of-fit exists in logistic regression.” Pedhazur (1997, p. 758) noted that one “should not put too much faith in any single fit index.” Agresti (2002, 2012) confirmed that a great deal of uncertainty exists in ascertaining how well a particular logistic regression model fits a set of data. One of the primary reasons why this is so is because “it is entirely possible
to have a model that fits well, but does a poor job predicting category membership” (Menard, 2002, p. 37). Nonetheless, as a matter of convention, each hypothesis test in the current study included goodness-of-fit statistics of the model as measured by the model chi-square ($\chi^2$), Hosmer-Lemeshow statistic (H-L), Nagelkerke $R^2$, -2 log likelihood index (-2LL), and the percentage of cases that were correctly classified (original %CC) with only the constant, or intercept, in the model as well as those correctly classified with all predictor variables in the model (improved %CC).

The model chi-square assessed if the model generated by the data was significantly different than the constant-only model (Mertler & Vannatta, 2005). Burns and Burns (2008, p. 579) define the model $\chi^2$ simply as “the likelihood of observing the actual data under the assumption that the model that has been fitted is accurate.” A model $\chi^2$ that is statistically significant suggests that chance alone cannot predict the outcome of the dependent variable (i.e., the independent variables have a predictive effect in the model).

The Hosmer-Lemeshow statistic is based on the Pearson chi-square (Cohen, Cohen, West, & Aiken, 2002) and works best with large sample sizes (Hosmer & Lemeshow, 2002, 2012). A good-fitting model has an H-L value that is not statistically significant at any $p$-value (Burns & Burns, 2008; Menard, 2002). However, the usefulness of the H-L statistic has been questioned (DeMaris, 1992).

The Nagelkerke $R_N^2$ described the statistical significance of the model (Field, 2009, 2013; Mertler & Vannatta, 2005). Nagelkerke $R_N^2$ is known as a pseudo-$R$ statistic, meaning that it is not a true equivalent to the $R^2$ used in ordinary least squares (OLS) regression. Even in statistically reliable models, Nagelkerke $R_N^2$ is often a small
value. Cohen, Cohen, West, and Aiken (2002) and DeMaris (1992) have written that Nagelkerke $R^2_N$ does not explain the amount of variance in the dependent variable that is represented in the model as in linear regression due to inherent heteroscedasticity in logistic regression, but can be used to explain null deviance. However, in many studies Nagelkerke $R^2_N$ is often interpreted to explain the amount of variance by convention (Field, 2009, 2013) and is done as such in the current study. In the end, Hosmer and Lemeshow (2000, 2012) and Menard (2002, 2010) question the usefulness of any $R^2$ pseudo-equivalent in logistic regression.

The -2 log likelihood calculated the sum of probabilities from both the observed and expected data and indicated how much unexplained information remains in the model (Field, 2009, 2013; Tabachnik & Fidell, 2006, 2012). Although smaller values of -2LL are preferred (Field, 2009, 2013; Menard, 2002; Mertler & Vannatta, 2005; Pedhazur, 1997), there is no best practices scenario indicating what range of values are ideal. Large -2LL values still may be present in a model that generally fits well.

The percentage of correctly classified cases compared expected data from the model with actual observed data (Mertler & Vannatta, 2005). A %CC value of 50% would indicate that the model results could equally occur by chance (Pampel, 2000). Thus, higher percentages of correctly classified cases were desired. Two different %CC values were provided in the current study. First, the original %CC gave the percent of classified cases before the predictor variables were put into the regression model—in SPSS, this is known as Block 0. Second, the improved %CC gave the percent of classified cases after the predictor variables were put into the regression model—SPSS
calls this Block 1. If the improved %CC value is higher than the original then the regression model has improved the percent of correctly classified cases.

Model coefficients included the unstandardized regression coefficient (b), the standard error of b (se), the Wald statistic, the odds ratio (Exp(B)), and the significance value (p). A confidence interval at 95% for the odds ratio also was provided.

The unstandardized regression coefficient indicated the effect of the independent variable on the dependent variable (Knoke, Bohrnstedt, & Mee, 2002; Mertler & Vannatta, 2005). The standard error of b as an estimate of standard deviation represented the amount that the coefficient varies across cases (Allison, 1999; Knoke et al., 2002; Shavelson, 1996).

The Wald statistic measured the statistical significance that b coefficients for variables in the model are different from zero and, therefore, predictive of the outcome (Field, 2009, 2013; Mertler & Vannatta, 2005). The Wald statistic is analogous to the t-test in linear regression and measured the contributions of independent variables to the model (Field, 2009, 2013; Menard, 2002).

The odds ratio identified the increase or decrease in odds of classification into a category or the predicted probability of an occurring event (Field, 2009, 2013; Mertler & Vannatta, 2005; Pampel, 2000). The direction of the change in odds—an increase or decrease—depended on whether or not the b coefficient was negative or positive. Direction also was assessed by whether or not the odds ratio (OR) was less than or greater than 1; an OR >1 indicated that the odds of occurrence increased when the independent variable increased, while an OR <1 indicated that the odds of occurrence decreased when the independent variable increased (Burns & Burns, 2008; Cohen,
The further away odds ratios were from the value of one, the stronger was the association between the independent and dependent variables (Menard, 2010; O’Connell, 2006). The value of an odds ratio was interpreted in terms of the odds that something will or will not happen (e.g., the odds of Y occurring was 1.675 times greater for females than males). In this example, 1.675 could not be interpreted as a probability unless transformed into a percentage (e.g., females were 68% more likely than males to engage in Y behavior) (Pedhazur, 1997).

The significance value noted the probability at which the null hypothesis ($H_0$)—that there was no statistical relationship between the variables—could be safely rejected in favor of the alternative hypothesis ($H_a$) (Knoke et al., 2002). Standard $p$-values of .001, .01, and .05 were used and those that fell outside of these parameters led to a failure to reject the null hypothesis (i.e., acceptance that there was no evidence of a statistically significant relationship).

The 95% confidence interval provided a lower and upper limit within which there was a 95% chance that the odds ratio fell (Knoke et al., 2002). Many studies commonly use the 95% confidence interval.

The coefficients obtained via logistic regression do not predict values of dependent variables as in linear regression, but instead predict the probability of the occurrence of dependent variables (Field, 2009, 2013; Mertler & Vannatta, 2005; Wright, 1995). In the current study, the odds ratios were used to determine when social e-health behavior did or did not occur based on sociodemographic predictors.
CHAPTER IV
RESEARCH RESULTS

This chapter presents the results of the current study. Brief univariate analyses introduce descriptive data for all six sociodemographic variables and the dependent variable of social e-health behavior. Univariate tables in Appendix A were constructed to illustrate the distribution of variables preceding multivariate logistic regression. Hypothesis testing was conducted by creating one model using two logistic regression analyses. Two regressions were required to complete the data needed for comparisons of all possible categories. The single, final logistic regression model is provided in this chapter along with a short narrative for all six hypotheses.

Univariate Analyses

Univariate results of each of the thirteen individual survey questions showed that the majority of respondents reported not engaging in any of the behaviors. Valid percentages of respondents who did report social e-health engagement behaviors ranged from as low as 3.0% (Q29e: Have you ever posted a review online of a hospital?) to as high as 22.8% (Q26c: Have you ever used a social networking site to follow your friends’ personal health experiences or health updates?) Tables A.2 through A.14 in Appendix A provides all univariate raw frequencies, valid percentages, and total sample sizes for each of the thirteen social e-health survey questions.

Once the survey questions were collapsed, univariate results of the social e-health behavior variable showed that the majority of respondents did report engagement of at least some form of behavior. Table A.1 in Appendix A provides the
univariate results for the social e-health variable. Also in Appendix A, Tables A.15 through A.20 provides all univariate information for each of the six independent variables.

For all Tables, the total N reflects the sample size noted in each Table heading minus any missing-coded cases (i.e., don’t know, refused, and system missing). Frequency analyses were performed on all dummy variables to check categorical distribution and sample sizes but those univariate results are not reported.

As noted, Tables for complete univariate data are in Appendix A, but the following Table is provided here to show only the highest frequencies for all variables at the univariate level.

Table 4

*Highest Frequencies for All Seven Variables at the Univariate Level (N = 2,065)*

<table>
<thead>
<tr>
<th>Variable</th>
<th>Frequency</th>
</tr>
</thead>
<tbody>
<tr>
<td>Social E-Health Behavior</td>
<td>60.1% Yes</td>
</tr>
<tr>
<td>Sex</td>
<td>58% Female</td>
</tr>
<tr>
<td>Race</td>
<td>71.7% White</td>
</tr>
<tr>
<td>Ethnicity</td>
<td>86.1% Non-Hispanic</td>
</tr>
<tr>
<td>Age</td>
<td>3.6% 18 Years Old</td>
</tr>
<tr>
<td>Education</td>
<td>39.7% College Graduate</td>
</tr>
<tr>
<td>Income</td>
<td>40.7% &lt;$40,000</td>
</tr>
</tbody>
</table>
Logistic Regression Analysis

Multivariate logistic regression was conducted to determine if gender, race, ethnicity, age, education, or income accounted for the odds of engaging in social e-health behavior. Six hypotheses were tested, one for each of the sociodemographic variables. Results indicated the overall model was statistically reliable, $\chi^2 (9, N = 583) = 213.654, p \leq .001$. The model was a good fit for the data based on the non-significant Hosmer-Lemeshow statistic of .128, though the -2 log likelihood value was high. The $R^2_N$ value of .368 indicated that 37% of the variance in whether or not a person engages in social e-health behavior based on their social demography was accounted for by the model. In regression with the constant only, 67% of the cases were correctly classified. In regression with all predictor variables added, the model correctly classified an improved three-fourths of the cases (76%).

Hypothesis 1 stated that women are more likely than men to engage in social e-health behavior. Results of logistic regression analysis rejected the null hypotheses for gender by showing the odds that women engaged in social e-health behavior was nearly four-and-a-half times greater than men ($b = 1.496, p \leq .001, OR = 4.465, CI 2.970-6.713$) when controlling for the other sociodemographic variables. Support for the alternative hypothesis was found.

Hypothesis 2 stated that non-whites are less likely than whites to engage in social e-health behavior. In addition, the hypothesis stated that people in the racial category of other—Asians, Native Americans, mixed race, and other—would be less likely than blacks to engage in social e-health behavior. Results of logistic regression analysis rejected the null hypothesis for all three categorical comparisons of race.
Blacks were 50% less likely ($b = -0.701, p \leq .05, OR = 0.496, CI 0.266-0.923$) and those in the racial category of other were 86% less likely ($b = -1.962, p \leq .001, OR = 0.141, CI 0.059-0.335$) than whites to engage in social e-health behavior when controlling for the other sociodemographic variables. In addition, those in the other category of race were 72% less likely ($b = -1.261, p \leq .05, OR = 0.283, CI 0.102-0.786$) than blacks to engage in social e-health behavior. Support for the alternative hypothesis was found.

Hypothesis 3 stated that non-Hispanics are more likely than Hispanics to engage in social e-health behavior. Results of logistic regression analysis failed to reject the null hypothesis ($b = 0.381, p = .262, OR = 1.464, CI 0.752-2.849$). No support for the alternative hypothesis was found.

Hypothesis 4 stated that as age increases people are less likely to engage in social e-health behavior. Results of logistic regression analysis rejected the null hypothesis by showing that the odds ratio for age estimated that the odds of engaging in social e-health behavior decreased by a factor of 0.936 for each one-unit increase in age ($b = -0.038, p \leq .001, OR = 0.963, CI 0.948-0.978$) when controlling for the other sociodemographic variables. In other words, for every year of increase in age social e-health behavior was 4% less likely than not to occur when holding the other variables constant. Support for the alternative hypothesis was found.

Hypothesis 5 stated that people with at least some college education are more likely than those without any college education to engage in social e-health behavior. In addition, the hypothesis stated that college graduates are more likely than those with only some college to engage in social e-health behavior. Results of logistic regression analysis rejected the null hypothesis for two of the three categorical comparisons of
education. The odds that college graduates ($b = 2.035, p \leq .001, OR = 7.652, CI 4.289-13.652$) and those with only some college education ($b = 1.768, p \leq .001, OR = 5.861, CI 3.360-10.226$) engaged in social e-health behavior was just over seven-and-a-half and nearly six times greater, respectively, than those with a high school or less-than-high school education when controlling for the other sociodemographic variables. Support for the alternative hypothesis was found for these two comparisons. The null hypothesis was not rejected for the comparison between college graduates and those with only some college education ($b = 0.267, p = .230, OR = 1.305, CI 0.844-2.018$).

Hypothesis 6 stated that persons with income greater than $40,000 are more likely than those with income less than $40,000 to engage in social e-health behavior. In addition, the hypothesis stated that persons in the $40,000 to under $75,000 income range would be less likely than those with income of at least $75,000. Results of logistic regression analysis rejected the null hypothesis for two of the three categorical comparisons of income. The odds that those with income of at least $75,000 ($b = 0.540, p \leq .05, OR = 1.715, CI 1.048-2.807$) and those with income between $40,000 and under $75,000 ($b = 0.919, p \leq .001, OR = 2.506, CI 1.497-4.194$) engaged in social e-health behavior was just over one-and-a-half and two-and-a-half times greater, respectively, than those with income under $40,000 when controlling for the other sociodemographic variables. Support for the alternative hypothesis was found for these two comparisons. The null hypothesis was not rejected for the comparison between those with income of at least $75,000 and those with income between $40,000 and under $75,000 ($b = -0.379, p = .124, OR = 0.685, CI 0.423-1.109$).
Table 5

*Multivariate Logistic Regression Effects of Predictor Variables on Social E-health Behavior (N = 583)*

<table>
<thead>
<tr>
<th>Predictor Variable</th>
<th>$b$</th>
<th>(se)</th>
<th>Wald</th>
<th>df</th>
<th>$p$</th>
<th>Exp($B$)</th>
<th>Lower</th>
<th>Upper</th>
</tr>
</thead>
<tbody>
<tr>
<td>Gender</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>(Male) Female</td>
<td>1.496***</td>
<td>.208</td>
<td>51.750</td>
<td>1</td>
<td>.000</td>
<td>4.465</td>
<td>2.970</td>
<td>6.713</td>
</tr>
<tr>
<td>Race</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>(White) Black</td>
<td>-0.701*</td>
<td>.317</td>
<td>4.890</td>
<td>1</td>
<td>.027</td>
<td>0.496</td>
<td>0.266</td>
<td>0.923</td>
</tr>
<tr>
<td>(White) Other</td>
<td>-1.962***</td>
<td>.443</td>
<td>19.629</td>
<td>1</td>
<td>.000</td>
<td>0.141</td>
<td>0.059</td>
<td>0.335</td>
</tr>
<tr>
<td>(Black) Other</td>
<td>-1.261*</td>
<td>.520</td>
<td>5.869</td>
<td>1</td>
<td>.015</td>
<td>0.283</td>
<td>0.102</td>
<td>0.786</td>
</tr>
<tr>
<td>Ethnicity</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>(Non-Hispanic) Hispanic</td>
<td>0.381</td>
<td>.340</td>
<td>1.259</td>
<td>1</td>
<td>.262</td>
<td>1.464</td>
<td>0.752</td>
<td>2.849</td>
</tr>
<tr>
<td>Age</td>
<td>-0.038***</td>
<td>.008</td>
<td>21.427</td>
<td>1</td>
<td>.000</td>
<td>0.963</td>
<td>0.948</td>
<td>0.978</td>
</tr>
<tr>
<td>Education</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>(≤High School) Some College</td>
<td>1.768***</td>
<td>.284</td>
<td>38.789</td>
<td>1</td>
<td>.000</td>
<td>5.861</td>
<td>3.360</td>
<td>10.226</td>
</tr>
<tr>
<td>(≤High School) College Graduate</td>
<td>2.035***</td>
<td>.295</td>
<td>47.455</td>
<td>1</td>
<td>.000</td>
<td>7.652</td>
<td>4.289</td>
<td>13.652</td>
</tr>
<tr>
<td>(Some College) College Graduate</td>
<td>0.267</td>
<td>.222</td>
<td>1.439</td>
<td>1</td>
<td>.230</td>
<td>1.305</td>
<td>0.844</td>
<td>2.018</td>
</tr>
<tr>
<td>Income</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>(&lt;$40,000) $40,000-&lt;$75,000</td>
<td>0.919***</td>
<td>.263</td>
<td>12.214</td>
<td>1</td>
<td>.000</td>
<td>2.506</td>
<td>1.497</td>
<td>4.194</td>
</tr>
<tr>
<td>(&lt;$40,000) ≥$75,000</td>
<td>0.540*</td>
<td>.251</td>
<td>4.611</td>
<td>1</td>
<td>.032</td>
<td>1.715</td>
<td>1.048</td>
<td>2.807</td>
</tr>
<tr>
<td>($40,000-&lt;$75,000) ≥$75,000</td>
<td>-0.379</td>
<td>.246</td>
<td>2.372</td>
<td>1</td>
<td>.124</td>
<td>0.685</td>
<td>0.423</td>
<td>1.109</td>
</tr>
<tr>
<td>Constant</td>
<td>-1.963***</td>
<td>.371</td>
<td>28.033</td>
<td>1</td>
<td>.000</td>
<td>n/a</td>
<td>n/a</td>
<td>n/a</td>
</tr>
</tbody>
</table>

$\chi^2 = 213.654$

H-L = .128

df = 9

$R^2_{\text{lr}} = .368$

-2LL = 669.584

Original %CC = 66.5%

Improved %CC = 75.5%

$p \leq .05, \; \; \; p \leq .01, \; \; \; p \leq .001$

Note. Reference categories for the categorical variables are in parentheses.
CHAPTER V
SUMMARY AND CONCLUSION

In this final chapter, the results of the current study are discussed. As noted in Chapter 4, gender, race, and age influenced the occurrence of social e-health behavior, and two categories of education and income each did the same. Several limitations of the study are mentioned in this chapter and some ideas for future study in social e-health are posited.

Discussion

Overview

The current study is exploratory, designed to shed light on the sociodemography of the social e-health phenomenon. The study of relationships between online interactive and creative e-health behaviors with sociodemographics represents a foray into a new area of medical sociology where internet technology, social media networks, social demographics, and human health come together.

The current study adds to the extant sociological literature by isolating the interaction and creation elements of e-health behaviors apart from mere information seeking. Interactive and creative online health behaviors are conceptually different than seeking behaviors; the former rely on participation between and actions of individuals in technological and social interaction with others, while the latter does not. The conceptualization of the term social e-health introduced here allows for a new way of thinking about participative health-related behaviors online.

Within the larger social e-health dialogue, this study focuses on the sociodemographic considerations of social e-health. Sociodemographic exploration of
social e-health behavior is important because only by knowing who is and is not engaging in this behavior can researchers begin to understand why and how some sociodemographic groups engage while others do not. Approaching social e-health from a sociodemographic perspective draws attention to the patterns of use distributed by gender, race, ethnicity, age, education, and income. Knowing the social demography of social e-health behavior exposes the demographic gaps in use and non-use and leads to greater understanding of why patterns might exist, what they mean, and why they matter.

The social determinants of health and digital divide frameworks provide a backdrop against which the distribution of social e-health may be studied. These frameworks separately allow for analysis of the ways in which health and technology individually are distributed. When combined, they create an ideal approach for examination and explanation of health and internet technology together.

On the whole, results of the current study as detailed in Chapter 4 show that sociodemographic patterns are evident in social e-health behavior when gender, race, and age are taken into consideration. Education and income also dictate social e-health behavior in two of three categories each.

In fact, the two highest odds of social e-health behavior occurrence are found in the education variable when comparing the college graduates (OR = 7.652) and some college categories (OR = 5.861) with the high school and less-than-high school education category. There is no difference between the college graduates and some college categories. This finding suggests that having at least some exposure to college education—completed or not—is sufficient enough for there to be a marked difference
in the occurrence of social e-health behavior. College graduates are more likely than those with only some college to engage in this behavior when compared to high school, but not when compared with each other. A strong association is evident between college education and engagement in social e-health behavior. This finding may be due to two factors. First, having at least some college education versus no college education is likely to lead to better employment and hence larger salaries with greater potential to access both technology and health resources. Second, persons with at least some college experience may possess also the skills to more quickly adapt and assimilate technology for health purposes, interpret the health-related information they receive, and believe that online health information is pertinent for them.

The next highest odds of social e-health behavior occurs with the variable gender (OR = 4.465). Simply put, women are significantly more likely than men to engage in social e-health. This finding is not surprising given that, according to the previous literature, gender seems to be the most reliable socioeconomic predictor of blog and online support group activity. At the same time, the finding may seem counterintuitive based on what might be predicted by digital divide—that men, as the more socially advantaged group, would use social e-health with more frequency. However, as noted in Chapter 2 the higher occurrence of social e-health behavior among women is likely due to two factors. One, within social systems women are more likely than men to take on caregiving roles, and, two, men habitually do not reach out and actively seek health care or health information.

Statistically significant odds ratios for two categories of income show that breaking the $40,000 barrier is crucial to social e-health behavior when compared with
the next highest income bracket of $40,000 to under $75,000 (OR = 2.506), as well as
the highest income bracket of at least $75,000 (OR = 1.715). As with education, the
comparison between the second and third categories failed to reveal any difference.
This finding suggests that being a part of lower economic class is linked with non-
engagement of social e-health. Such a finding is sensible because lower income often
restricts access to myriad resources. As economic poverty is eclipsed, people often
have greater access to resources, including technology and health services. Thus,
people on the lowest end of the income spectrum would be the least likely to use social
e-health, while those in the middle and higher end would be the most likely.

A pattern exists, too, in social e-health behavior along the sociodemographic
dimension of age. As age increases, people are less likely to engage in social e-health
activity. Such a finding is unsurprising for two possible reasons. First, younger age
groups become accustomed to health technology more swiftly and are more
comfortable at using it than older groups—this occurs in part because of generation
gaps; younger age groups have grown up with accelerating and frequently-changing
complex technology, whereas older age groups have not. Second, the vast majority of
older people may have less disposable income than younger people, especially if they
have retired from work or become disabled. Younger people, typically those between 35
and 65, on the other hand are less likely to be ill and are still generating employment-
based income to spend on technology and health services compared to those older
than 65.

Race, as a whole, is an important factor for social e-health activity as all three
comparisons of racial categories showed a statistically significant difference. Blacks
(OR = 0.496) and other (OR = 0.141) were less likely than whites to engage in social e-health behavior. Moreover, those in the other racial category were less likely than blacks to do the same (OR = 0.283). Compared to whites, these results show that blacks and other are the more socially disadvantaged groups when it comes to social e-health behavior as the likelihood of them engaging in these behaviors is much lower than whites. However, blacks become a socially advantaged group when compared with the other category—this other group comprised of Asians, Native Americans, mixed races, etc. is far less likely than blacks to partake in social e-health activity. These findings concur with what would be expected using social determinants of health and digital divide frameworks—whites, as the most privileged group, are more likely than non-whites to engage in social e-health.

One overall reason for some of the sociodemographic differences is likely technological in nature. As noted in Chapter 2, people are beginning to use their mobile devices to engage in social e-health behaviors. For behaviors where being younger, having more income, and having higher levels of education are predictive, use of smartphones—compared to standard cell phones—may be making it easier overall to perform social e-health behaviors. Younger people have a preference for using the internet as a means of obtaining health information (Berger et al., 2005) and are more likely to do so using mobile phones (Fox & Duggan, 2013b). Indeed, people of younger ages, higher incomes, and higher education are more likely to be smartphone owners (Fox & Duggan, 2012). Thus, in situations where these factors are predictors of social e-health behavior, one facilitator may be the smartphone.
Another overall reason that may account for some socioeconomic differences is likely related to skill. For those groups not engaging in social e-health behaviors, it is reasonable that they may not know how to do social e-health. Social e-health behavior may be more straightforward for people who are, for example, younger and more educated than those who are older and less educated. Moreover, finding social e-health outlets such as blogs, online support groups, and so on require some technological literacy in terms of using search engines and developing accurate searching strategies to hone in on the most desired social e-health resources. Plus, other activities—such as creating a blog or website, making an online profile, downloading and using software to track health data—require some level of technological proficiency. Not everyone knows how to find a high-quality health blog nor does everyone know how to create their own. Not everyone knows how to locate a mobile health app, and learning how to use the app may not be intuitive at first. The point here is that disadvantaged populations—whether they be non-whites, the economically poor, the uneducated, or the elderly—may not be engaging in social e-health behaviors not only because they lack the resources to do so, but also because they do not know how to get started (e.g., they lack the necessary skills and appropriate type of literacy).

The overall findings of the current study support the six tested hypotheses and, in general, sociodemographics are found to play a key role in the distribution of social e-health activity. The social determinants of health and digital divide frameworks work well together to explain, first, the reality that social e-health behavior is distributed along sociodemographic dimensions and, second, how and why the distributions occur. On the whole, the findings of the current study are not surprising given what is known about
the population patterns of health resources via the social determinants of health framework and the population patterns of technology access and use via the digital divide framework. Nonetheless, the current study is important because it confirms that the use of social e-health—an emerging blend of interaction and creation technologies—is sociodemographically distributed in very similar ways to health resources and technological resources. Moreover, this confirmation is based on statistically generalizable results that are applicable to the greater U.S. population.

Why Does It Matter?

The current study is important for demonstrating that engagement of social e-health behavior is determined by sociodemographic factors in ways that are mostly consistent with extant literature on internet technology and health, as well as both the social determinants of health and digital divide frameworks. But, now that statistically generalizable evidence has been established showing differentially distributed social e-health behavior according to gender, race, age, education, and income, the question must be asked: Why does it matter?

Unclear is whether or not all sociodemographic groups who engage in social e-health are using the same technologies, getting good information, and reaping the same potential benefits. As discussed in Chapter 2, there is some evidence of correlation between social e-health and favorable health outcomes. However, the actual pathways through which social e-health might result in better health outcomes are not fully understood. Based on the application of the social determinants of health and digital divide frameworks, I argue that sociodemographic factors—in this study, the
statistically significant variables of gender, race, age, education, and income—are pathways that connect social e-health with health outcomes. Although measurement of health outcomes vis-à-vis social e-health falls outside the scope of this study, I suggest that sociodemography provides opportunities for social e-health behavior through which better or worse health outcomes may occur. Thus, to understand any relationship between the technologies used in, information received from, and benefits attributed to social e-health, the social demography within which these occur must be considered.

Like health outcomes, social e-health does not occur in a social vacuum—both are influenced by gender, race, age, education, income, and their associated social structures. Only when sociodemographic factors are considered does social e-health technology, information, and benefits matter because it is those factors that control which technologies are available, what information is received, how that information is interpreted, and what benefits—if any—are gained. Although research outlined in Chapter 2 does show that social e-health behavior can lead to favorable health outcomes, this is not equivalent to concluding that social e-health leads to better health outcomes universally for all sociodemographic groups nor that these groups equally use the same technologies to get favorable information.

The revelation that social e-health behavior occurs according to gendered, racial, age-based, educational, and income-related patterns is a key finding because it opens a discussion on why and under what conditions sociodemographic groups engage in this behavior. Just because people are white, female, or college educated does not mean they will engage in social e-health. Similarly, just because a person is black, an elder, or economically poor does not mean these are automatic antecedents of not engaging in
social e-health behavior. Rather, these sociodemographics provide a platform upon which to pursue a discovery of the reasons and conditions within social and cultural contexts that lead to the engagement of social e-health for particular populations. It is within these sociocultural contexts that social e-health does or does not have meaning for its users, and these contexts provide the conditions under which social e-health may be engaged.

Indeed, social e-health may be understood and employed differently by different sociodemographic groups. Sociodemography, then, can provide a window into the unique social and cultural implications of social e-health behavior for groups varying along sociodemographic dimensions. Groups may embrace or refuse to use social e-health technology for reasons that may be related to their sociodemographic background but not necessarily because of it. Gender, race, age, education, and income may be considered proxy variables representing underlying shared beliefs and/or entrenched social structures that are dictatorial of the reasons, desires, conditions, and agency for social e-health behavior.

Moreover, many underlying aspects of social e-health such as interactivity, creativity, personalization, and empowerment play a role in dictating health outcomes. However, these aspects may differ according to population group norms, beliefs, and social rules. In this way, knowledge about sociodemography can lead to the exploration of questions about the sociocultural conditions behind engagement or non-engagement of social e-health, as well as determine how effective or non-effective is social e-health behavior and its underlying mechanisms (e.g., self-esteem, coping, group solidarity, etc.) for specific populations.
Limitations

This study relied on a secondary data analysis of an existing dataset that I did not create, resulting in no control over how the data were collected. Moreover, a large amount of data preparation was necessary before any analyses could be performed and careful decision making as outlined in Chapter 3 was necessary throughout the entire methodological and statistical process.

The Internet and American Life Project (IALP) dataset used in the current analyses was collected by telephone surveys where respondents were asked questions whose answers were subsequently recorded by a representative of the research agency. Two problems are possible. First, errors in validity may have been increased by self-report bias; this drawback has been noted in previous e-health survey literature (Hargittai, 2005; Hsu et al., 2005; van Deursen & van Dijk, 2010). Second, the recorder could have made errors when documenting the respondents’ answers. Notwithstanding the potential methodological issues, self-report survey research is common.

All but one variable (age) in this study is categorical and all categorical variables were re-coded as dummy variables. The dichotomy inherent in dummy variables sometimes fails to capture the full breadth of possible outcomes. Most notably, the social e-health variable is dichotomized simply as yes, the behavior occurred and no, the behavior did not occur. This approach ignores the nuances that might be found between respondents if social e-health behavior had been measured by the actual number of times respondents affirmed that they did engage in one of the thirteen survey question behaviors. In such a methodology, the number of times every respondent engaged in a behavior would be tallied, creating a distribution scale of social e-health...
engagement from zero (i.e., no behaviors) to thirteen (i.e., all behaviors) with every respondent falling somewhere on that scale. If this had been done, differences could have been analyzed between people who fell on the low end of the scale and engaged in very few social e-health behaviors versus those who fell on the high end of the scale and engaged in many social e-health behaviors.

The final sample size of the multivariate logistic regression model ($N = 583$) is drastically less than the sample size of the raw dataset ($N = 3,001$). Reasons why this is so were explained in Chapter 3—reduction is due to a combination of filtering, removal of outlying cases, and the presence of missing cases. Filtering was necessary to exclude from analysis those respondents who reported not using the internet at all. Exclusion of outlying cases was necessary to remove the undesired effects of those influential cases. Missing cases were especially problematic for several of the e-health behavior survey questions (see Tables A.8, A.10, and A.11), but these questions were too central to the current study to be removed altogether.

The intention of my study was not necessarily to build the best-fitting statistical model. If model building had been the goal, backwards likelihood-ratio logistic regression would have been used. The model, however, is the best fitting when the data are setup and processed according to the details laid out in Chapter 3. Overall model fitting would have been better had backwards likelihood-ratio logistic regression been used, but that would have necessitated removing categories of variables, and in some cases variables altogether, to get the best fit. Pursuant to the sociodemographic emphasis of my study, all categories were left in every model to serve as controls rather than remove them just to obtain better model parameters.
The overall model parameters were reported for the multivariate logistic regression analysis in Chapter 4. The difficulties with these parameters were discussed in Chapter 3. The Hosmer-Lemeshow statistic, Nagelkerke $R_N^2$, and -2 log likelihood cannot be used to make authoritative decisions on any model. They can be used as rough guides when evaluating a model, but much caution is warranted when interpreting them to make claims about association and goodness-of-fit. Notwithstanding their limitations, these parameters have been reported because their inclusion is conventional procedure.

My study did not statistically examine any independent-variable interaction effects. It is possible that combinations of predictors together are indicative of social e-health behavior. For example, gender and race could have been combined into a two-way interaction variable, or gender, race, and education into a three-way interaction variable. In fact, all possible permutations of interactions of all variables and categories could have been included in varying permutations of models. Doing so, however, would have resulted in a long list of interaction categories. That in itself is not prohibitive, but because the individual e-health behavior survey questions used to create the dependent variable contained so few yes answers relative to no, adding more variables would have created additional strain on the statistical power of the model and compounded the potential for statistical error.

Finally, the data used in the analyses of the current study are representative of and applicable to the U.S. population only. With representative samples from other countries or a fully international sample, results of sociodemographic factors on social e-health behaviors may have differed.
Future Study

Adams (2010b, p. 89) noted that “within the specific area of health care, little attention has been devoted to understanding what applications are available to the lay public and how these are being used.” A number of topics within social e-health are ripe for future studies that may address Adams’ concern. A few of these areas are addressing the conditions under which and reasons why groups engage or do not engage in social e-health; more qualitative analyses of health blogs and share-your-experience websites; inquiry on how video blogs, YouTube, Skype®, and other audiovisual content creation media are used to produce and share personal health experiences; examination of how social discovery mobile apps may be used to locate other people in real time within one’s vicinity; sociodemographic analyses that examine differences and similarities within single identified groups, rather than comparisons across multiple groups; and development of health and technological literacy initiatives.

Conditions and Reasons for Social-Health Behavior

My study is a step forward in addressing the conditions and reasons why sociodemographic groups engage differentially in social e-health behavior because it identifies sociodemographic patterns of use. However, the statistical evidence shown in my study is limited to whether or not social e-health was engaged; it does not offer concrete statistical evidence of how or why it is engaged. Future investigations will extend my study to understand the specific reasons why persons in sociodemographic groups engage in social e-health behavior or not, including the specific type(s) of
technology used; the type(s) of information obtained; the meaning of this information; 
and the measurable health outcomes attributed as a result of this behavior.

**Blogs and Share-Your-Experience Websites**

Although blogs have been around for a while, Adams (2010b) is aware that:

The literature specifically on health-related blogs has been quite limited … Little 
attention has been devoted to understanding different types of blogs as they are 
being used by the lay public for health-related purposes. There is a need for 
more research devoted to patients’ use of these alternative avenues for 
managing both information and experiences with respect to health. (p. 89)

Chapter 2 discussed some studies that examined health blogs. Minimal research on 
health blogging exists and more is needed to determine the motivations of why people 
read blogs, post comments on them, and create their own. Does the impetus to interact 
with and create blogs differ according to type or severity of illness? How does the 
effectiveness of interacting and creating blogs differ from interacting with or creating 
online support groups? How might blogs and support groups be used most effectively in 
conjunction? These are just some of the questions waiting to be answered.

In addition, content analyses of health blogs and the comments posted on them 
by readers would be useful in identifying key themes in the lived experiences of people 
suffering from illnesses and/or who have an interest in particular illnesses. The 
narratives of these bloggers and posters are essential to understand more about the 
everyday lives of people with illness, how they experience that illness, how they 
communicate their experiences with others, and how others respond to their 
experiences. Only through content analyses can researchers begin to get a sense of the
daily struggles and triumphs of people going through an illness journey, as well as an understanding of how others view and respond to this journey in virtual space.

Future health blog studies should steer away from those created by physicians and other health workers. These types of blogs are written predominately for professional reasons; assert a typical top-down, medical dominance approach; and are sometimes sponsored by the pharmaceutical industry or other commercial health services via advertisements (Lagu, Kaufman, Asch, & Armstrong, 2008; Miller & Pole, 2010). Instead, social and behavioral scientists should concentrate on analysis of blogs created by consumers and patients, everyday people living extraordinary lives experiencing life-altering disease and illness. Also, blogs written by caregivers (e.g., friends and family who know and/or are taking care of someone) are likely to provide rich information about the day-to-day experiences of knowing and caring for a person facing health difficulties.

In the same way, health forums and share-your-experience websites such as PatientsLikeMe, Inspire, and CureTogether could be content analyzed for the same purpose. However, these sites are password protected meaning that users must create basic profiles and agree to terms of service conditions. As such, researchers may need to obtain permission from the sites and consider the ethical implications of collecting data from a membership only website. Though blogs have been around for a long time, share-your-experience health websites represent a new vehicle people are using to share their own health narratives and personal health data. Also, these websites act as support groups where people with illnesses meet others with the same or similar illnesses to share stories and offer informational and emotional support. Along with
content analyses, quantitative examinations of sociodemographic and health data entered by users into their profiles can be analyzed independently and alongside the conversational content they are creating and sharing. Thus, researchers could see what patterns in postings might exist based on gender, race, age, or any other self-identified variable including actual health data such as blood pressure, weight, diagnosed illnesses, and medications taken. For individuals who have used a share-your-experience website for a while, health data is tracked over time in the users' profiles, allowing a unique opportunity for researchers to examine patterns of health discourses and data longitudinally.

Vlogs and Audiovisual Content Creation

A vastly overlooked area within social e-health is the interactive and creative content behaviors associated with audiovisual media. Via platforms such as YouTube, Vimeo®, Vine®, DailyMotion®, Keek® and other sites used for recording and storing videos, users are creating and uploading video blogs, or vlogs as they are called, describing their personal health experiences. For all practical purposes, a vlog is an often self-recorded video where the user talks to the camera—and vicariously the viewing audience—about any topic(s) the user desires. Traditionally, vlogs have been used for entertainment, news, and education (Burgess & Green, 2009; Crawford, 2007; Gao, Tian, Huang, & Yang, 2010). However, a whole world of vlogs exists where health content is regularly created by users and watched by interested viewers. Viewers can leave text or video responses, creating ongoing threads of dialogue on vlogs. The
creator of the vlog and the viewers are all eligible to engage in a discourse around the vlogs’ topics by subsequent posts.

A simple search in July 2013 on YouTube for “cancer vlog” (in quotes) resulted in over 4,000 video results. Clearly, consumers and patients are using YouTube and related media as a place to publish online unique audiovisual content regarding their own health experiences. Like blogs, the qualitative study of vlogs would serve as an essential key to unlocking enhanced understandings of illness from the patients’ point of view. Plus, vlogs by their audiovisual definition would allow researchers to analyze additional qualitative features such as facial expressions, body language, voice tones, and physical displays of emotion (e.g., sadness, anger, etc.) along with sociodemographic visual indicators such as sex, race, age, and more.

Along similar lines of interactive and creative audiovisual social tools, some programs such as Skype, Hangouts®, and FaceTime® may be used by consumers and patients to share health information with others in real time. Using these synchronous programs, an immediate audiovisual interactive element is added because users can see and speak with each other with immediate results, much like instantaneous chat sessions, telephone communication, and face-to-face encounters. In fact, Skype, Hangouts, and FaceTime transform traditional in-person face-to-face communication into virtual face-to-face communication. Google Hangouts is a popular program for multiple users to join in on online conversations. The implications of this could be extended to online support groups where users can see and hear each other as they discuss their health experiences in the moment.
As of July 2013, I am unaware of any existing studies that have examined health-related interaction among consumers and patients through Skype, Hangouts, or FaceTime. Similar technologies, however, have been used between physicians and other health workers with patients in telemedical contexts that, again, mostly reify top-down, medical dominance (Agha, Roter, & Schapira, 2009). Instead, emphases should be repositioned to explore these technologies between consumers and patients seeking outreach and support from other consumers and patients rather than from those with allegiance to the medical industrial complex.

*Mobile Social Discovery Apps*

Smartphone geosocial networking apps are controversial. These apps also may be known as social discovery apps, proximity-based apps, and location-based apps. The idea behind these apps is straightforward. Using their mobile devices, people can locate other people in real time that are nearby in their vicinity. This form of technology has been used mainly for friendship seeking, dating, and casual sexual encounters (Quiroz, 2013; Weiss & Samenow, 2010). When a person signs up with one of these social discovery apps such as Skout®, Tingle®, Swoon® or Grindr®, if any other people using the same app are nearby the app will notify them and the two people can begin to text message each other and meet face-to-face spontaneously within minutes to talk in person. Of course, any situation where strangers meet for casual or intimate encounters involve serious concerns for privacy and safety. Of immediate interest to my study, however, is that social discovery apps could be developed to bring together people with similar health issues.
For example, if there existed a social discovery app for people with diabetes who wanted to make real life friends with others suffering from the same condition, the app could bring them together quickly by identifying the users of the app in close proximity. Thus, person A with diabetes might be one block away from person B with diabetes. The app would pick up on this and connect them through their mobile devices so that they could begin chatting and meet up in person should they so desire. Doing so would allow each of them to meet someone suffering from the same condition, possibly develop a friendship, and share their diabetic experiences. As of July 2013, I am unaware of any social discovery apps currently available that are designed to bring health-minded people in close vicinities together. However, with use of apps on the rise in general and specifically for health purposes (Fox, 2011b; Fox & Duggan, 2012, 2013a; Purcell, Entner, & Henderson, 2010) it is likely that health-related varieties of geosocial networking apps will soon appear.

Within-Group Analyses

Because research traditionally focuses on differences between gender, race, ethnicity, age, education, and income, often overlooked have been differences and similarities among these variables. For example, all too often studies seek to determine how women differ from men and vice versa that questions about how men differ from men and women from women remain unanswered (Mo et al., 2009). Research has suggested that differential communication, behavioral, and health patterns between women and men do seem to exist (Tannen, 1991; Greaves, 2012), except they materialize not simply on the axis of gender but also on other multiple social axes such
as age, occupation, income, education, social networks, power structures, institutionalized hierarchies, and more (Bradley, 1996; Gerson, 1993; Johnson, 1994; Kollok, Blumstein, & Schwartz, 1985; Smith-Lovin & Brody, 1989). Masculine and feminine communication and behavioral patterns may be less dictated by the biology of being male or female, per se, and more related to one’s social position, background, life experiences, and socialization influences. Research has suggested also that under certain circumstances and situations men and women when compared may think, communicate, and behave more similarly than differently (Fairweather, 1976; Halpern & LaMay, 2000; Hogrebe, Nist, & Newman, 1985; Jaffee & Hyde, 2000; Kanter, 1977; Maccoby, & Jacklin, 1975; Risman, 1998), supporting the proposition that gender differences are not universally evident and that sex itself and alone is not solely responsible for gendered communication, behavior, and health outcomes. As Connell (1987, p. 170) wrote, the “main finding from 80 years of research is a massive psychological similarity [not difference] between men and women.”

The same argument can be said about differences among people in racial, ethnic, educational, income, and age groups; less is known about the similarities and dissimilarities of people within same categories than those compared across different categories. Gender, race, ethnicity, age, education, and income are not universal and do not carry the same meaning for all people. So too, these variables do not occur in isolation; instead, they influence and are influenced by each other. Whether directly or indirectly, plenty of studies often want to know, for instance, how whites differ from blacks and how the poor differ from the rich. Much new knowledge, however, could be gained by asking questions directed at within-group analyses. How do black people only
differ along social e-health behavior? How do economically poor people engage in social e-health compared with other poor people?

In any event, the current study suffers exactly from the aforementioned within-group criticism—how do whites compare to blacks, how do educated persons compare to uneducated ones, and so on. The current study itself then serves as an implicit call for increased within-group research designs so that researchers can begin to learn, for example, how poor people use social e-health if they are, and why they do not if they are not. What are the barriers, motivations, and reasons among poor people that allow or disallow them to use social e-health, not compared to rich people, but compared to other economically disadvantaged groups? How do those with only a high school education differ in their social e-health use, not compared to those with college education, but relative to other educationally disadvantaged groups? At the other end of the spectrum, questions could be asked about how wealthy patients differentially use social e-health technologies, or how social e-health is being used by patients with doctoral education. In sum, it is possible that new knowledge about how e-health generally and social e-health specifically is used among people grouped along similar sociodemographic variables rather than following the tradition of making comparisons between sociodemographic gradients.

Particular within-group sociodemographic variables that are less prevalent in the social e-health literature are sexual orientation and gender identity. Certainly, studies could examine how straight, gay, bisexual, and gender-variant people use interactive online health technologies differently. Research shows, for example, that gay and lesbian couples are more likely than straight couples to experience a large range of
barriers and difficulties in health care settings (e.g., limited or no hospital visitation rights, lack of health insurance coverage, and discrimination by medical staff) (Rolland, 1994). What types of barriers might exist in the social e-health environment for lesbian/gay/bisexual/transgender (LGBT) populations?

Research using only LGBT populations could yield intriguing results. More research is needed to examine the potential social and psychological reasons why social e-health behaviors may hold extra benefit or detriment for LGBT patients. If social e-health engagement decreases sense of stigma and discrimination relative to face-to-face encounters, for example, LGBT populations may be more willing to use those avenues to get health information and participate more actively in achieving their own health goals and outcomes.

Health and Technological Literacy

Finally, a short note about health literacy and sociodemography is needed. Research has shown that people who are on the negative side of the digital divide lack the health literacy skills required to make sense of online medical information (Norman & Skinner, 2006; Sarkar et al., 2010; van Deursen & van Dijk, 2011). Underserved groups—including women, the poor, the elderly, LGBT communities, the disabled, the uneducated, and the rural—could greatly benefit from adequate around-the-clock access to socially and culturally appropriate online health information (Gustafson & Wyatt, 2004; Neuhauser & Kreps, 2003) at accommodating reading and comprehension levels. Some research has been successful in reaching underserved populations with online health information (Brodie et al., 2000; Cotten, 2001; Zarcadoolas, Blanco,
Boyer, & Pleasant, 2002). Future research aimed at specific demographics that seek to measure and improve health and technological literacy is needed especially toward the use of social e-health as a potential means of self-care (e.g., tracking one's own health data and obtaining social support from others online).

Final Remarks

In 2001, Hardey (p. 395) wrote that “little attention has been paid to consumer or lay production of health information on the internet.” Surprisingly, in 2013 still not much is known about how people create and produce online health information via social e-health technologies. The current study has added to the academic sociological literature by considering e-health interaction and creation behaviors as conceptually different from information seeking behaviors. In doing so, the term social e-health was introduced in Chapter 1 to describe the engagement of interactive and creative activities of internet users for health purposes where interaction with technology and other people occur in online space. The focus in social e-health is on the behaviors of consumers and patients interacting with each other through social technologies for purposes of social, emotional, and informational support. Also, social e-health is concerned with how consumers and patients rely on e-health technologies to track, monitor, record, and share their own health data.

Also in Chapter 1, the argument was made that generalizable data analyses were needed regarding social e-health and that such analyses could be examined through a combination of the social determinants of health and digital divide frameworks. As discussed in Chapter 2, much research has been conducted on online
To conclude, the current study addressed the problem that social e-health literature is lacking in the discipline of sociology and that generalizable analyses pertaining to social e-health behaviors are few. By separating the conceptual differences between general e-health and social e-health and by conducting secondary data analysis via multivariate logistic regression, my study has helped fill this gap. Moreover, by drawing parallels between the social determinants of health and digital divide frameworks and illustrating how they together might describe the sociodemographic distribution of social e-health, this study has helped advanced social e-health research particularly in terms of social demography.
APPENDIX A
UNIVARIATE TABLES
Social E-Health Behavior Dependent Variable

Table A.1

Frequency Distribution of Social E-Health Behavior Obtained by Combining Thirteen E-Health Survey Questions (N = 2,065)

<table>
<thead>
<tr>
<th>Response</th>
<th>Frequency</th>
<th>Valid Percent</th>
</tr>
</thead>
<tbody>
<tr>
<td>0 = No</td>
<td>473</td>
<td>39.9%</td>
</tr>
<tr>
<td>1 = Yes</td>
<td>713</td>
<td>60.1%</td>
</tr>
<tr>
<td>Total N</td>
<td>1,186</td>
<td>100.0%</td>
</tr>
</tbody>
</table>

Note. The total N value of 1,186 represents the elimination of 879 don’t know, refused, and missing responses.

Individual Social E-Health Survey Questions Used to Create the Social E-Health Behavior Dependent Variable

Table A.2

Frequency Distribution of Social E-Health Survey Question Q24a: Have you ever signed up to receive e-mail updates or alerts about health or medical issues? (N = 2,065)

<table>
<thead>
<tr>
<th>Response</th>
<th>Frequency</th>
<th>Valid Percent</th>
</tr>
</thead>
<tbody>
<tr>
<td>0 = No</td>
<td>1,735</td>
<td>84.2%</td>
</tr>
<tr>
<td>1 = Yes</td>
<td>326</td>
<td>15.8%</td>
</tr>
<tr>
<td>Total N</td>
<td>2,061</td>
<td>100.0%</td>
</tr>
</tbody>
</table>

Note. The total N value of 2,061 represents the elimination of four don’t know, refused, and/or missing responses.
Table A.3

*Frequency Distribution of Social E-Health Survey Question Q24d: Have you ever gone online to find others who might have health concerns similar to yours? (N = 2,065)*

<table>
<thead>
<tr>
<th>Response</th>
<th>Frequency</th>
<th>Valid Percent</th>
</tr>
</thead>
<tbody>
<tr>
<td>0 = No</td>
<td>1,698</td>
<td>82.3%</td>
</tr>
<tr>
<td>1 = Yes</td>
<td>365</td>
<td>17.7%</td>
</tr>
<tr>
<td>Total N</td>
<td>2,063</td>
<td>100.0%</td>
</tr>
</tbody>
</table>

*Note.* The total *N* value of 2,063 represents the elimination of two don't know, refused, and/or missing responses.

Table A.4

*Frequency Distribution of Social E-Health Survey Question Q24e: Have you ever tracked your weight, diet, or exercise routine online? (N = 2,065)*

<table>
<thead>
<tr>
<th>Response</th>
<th>Frequency</th>
<th>Valid Percent</th>
</tr>
</thead>
<tbody>
<tr>
<td>0 = No</td>
<td>1,728</td>
<td>83.8%</td>
</tr>
<tr>
<td>1 = Yes</td>
<td>334</td>
<td>16.2%</td>
</tr>
<tr>
<td>Total N</td>
<td>2,062</td>
<td>100.0%</td>
</tr>
</tbody>
</table>

*Note.* The total *N* value of 2,062 represents the elimination of three don't know, refused, and/or missing responses.
Table A.5

*Frequency Distribution of Social E-Health Survey Question Q24f: Have you ever tracked any other health indicators or symptoms [besides weight, diet, or exercise routine] online? (N = 2,065)*

<table>
<thead>
<tr>
<th>Response</th>
<th>Frequency</th>
<th>Valid Percent</th>
</tr>
</thead>
<tbody>
<tr>
<td>0 = No</td>
<td>1,701</td>
<td>82.6%</td>
</tr>
<tr>
<td>1 = Yes</td>
<td>358</td>
<td>17.4%</td>
</tr>
<tr>
<td><strong>Total N</strong></td>
<td><strong>2,059</strong></td>
<td><strong>100.0%</strong></td>
</tr>
</tbody>
</table>

*Note.* The total N value of 2,059 represents the elimination of six don’t know, refused, and/or missing responses.

Table A.6

*Frequency Distribution of Social E-Health Survey Question Q25a: Have you ever posted comments, questions, or information about health or medical issues in an online discussion, a listserv, or other online group forum? (N = 2,065)*

<table>
<thead>
<tr>
<th>Response</th>
<th>Frequency</th>
<th>Valid Percent</th>
</tr>
</thead>
<tbody>
<tr>
<td>0 = No</td>
<td>1,971</td>
<td>95.5%</td>
</tr>
<tr>
<td>1 = Yes</td>
<td>92</td>
<td>4.5%</td>
</tr>
<tr>
<td><strong>Total N</strong></td>
<td><strong>2,063</strong></td>
<td><strong>100.0%</strong></td>
</tr>
</tbody>
</table>

*Note.* The total N value of 2,063 represents the elimination of two don’t know, refused, and/or missing responses.
Table A.7

*Frequency Distribution of Social E-Health Survey Question Q25b: Have you ever posted comments, questions, or information about health or medical issues on a blog? (N = 2,065)*

<table>
<thead>
<tr>
<th>Response</th>
<th>Frequency</th>
<th>Valid Percent</th>
</tr>
</thead>
<tbody>
<tr>
<td>0 = No</td>
<td>1,991</td>
<td>96.6%</td>
</tr>
<tr>
<td>1 = Yes</td>
<td>70</td>
<td>3.4%</td>
</tr>
<tr>
<td>Total N</td>
<td>2,061</td>
<td>100.0%</td>
</tr>
</tbody>
</table>

*Note.* The total N value of 2,061 represents the elimination of four don’t know, refused, and/or missing responses.

Table A.8

*Frequency Distribution of Social E-Health Survey Question Q25c: Have you ever posted comments, questions, or information about health or medical issues on a social networking site such as Facebook, MySpace, or LinkedIn? (N = 1,228)*

<table>
<thead>
<tr>
<th>Response</th>
<th>Frequency</th>
<th>Valid Percent</th>
</tr>
</thead>
<tbody>
<tr>
<td>0 = No</td>
<td>1,070</td>
<td>89.2%</td>
</tr>
<tr>
<td>1 = Yes</td>
<td>130</td>
<td>10.8%</td>
</tr>
<tr>
<td>Total N</td>
<td>1,200</td>
<td>100.0%</td>
</tr>
</tbody>
</table>

*Note.* The total N value of 1,200 represents the elimination of 28 don’t know, refused, and/or missing responses.
Table A.9

*Frequency Distribution of Social E-Health Survey Question Q25e: Have you ever posted comments, questions, or information about health or medical issues on a website of any kind, such as a health site or news site that allows comments and discussion? (N = 2,065)*

<table>
<thead>
<tr>
<th>Response</th>
<th>Frequency</th>
<th>Valid Percent</th>
</tr>
</thead>
<tbody>
<tr>
<td>0 = No</td>
<td>1,944</td>
<td>94.1%</td>
</tr>
<tr>
<td>1 = Yes</td>
<td>116</td>
<td>5.6%</td>
</tr>
</tbody>
</table>

Total N   2,060  100.0%

*Note. The total N value of 2,060 represents the elimination of five don’t know, refused, and/or missing responses.*

Table A.10

*Frequency Distribution of Social E-Health Survey Question Q26b: Have you ever used a social networking site to start or join a health-related group? (N = 1,228)*

<table>
<thead>
<tr>
<th>Response</th>
<th>Frequency</th>
<th>Valid Percent</th>
</tr>
</thead>
<tbody>
<tr>
<td>0 = No</td>
<td>1,100</td>
<td>91.6%</td>
</tr>
<tr>
<td>1 = Yes</td>
<td>101</td>
<td>8.4%</td>
</tr>
</tbody>
</table>

Total N   1,201  100.0%

*Note. The total N value of 1,201 represents the elimination of 27 don’t know, refused, and/or missing responses.*
Table A.11

*Frequency Distribution of Social E-Health Survey Question Q26c: Have you ever used a social networking site to follow your friends’ personal health experiences or health updates? (N = 1,228)*

<table>
<thead>
<tr>
<th>Response</th>
<th>Frequency</th>
<th>Valid Percent</th>
</tr>
</thead>
<tbody>
<tr>
<td>0 = No</td>
<td>926</td>
<td>77.2%</td>
</tr>
<tr>
<td>1 = Yes</td>
<td>274</td>
<td>22.8%</td>
</tr>
<tr>
<td>Total N</td>
<td>1,200</td>
<td>100.0%</td>
</tr>
</tbody>
</table>

*Note.* The total N value of 1,200 represents the elimination of 28 don’t know, refused, and/or missing responses.

Table A.12

*Frequency Distribution of Social E-Health Survey Question Q29d: Have you ever posted a review online of a doctor? (N = 2,065)*

<table>
<thead>
<tr>
<th>Response</th>
<th>Frequency</th>
<th>Valid Percent</th>
</tr>
</thead>
<tbody>
<tr>
<td>0 = No</td>
<td>1,973</td>
<td>95.6%</td>
</tr>
<tr>
<td>1 = Yes</td>
<td>91</td>
<td>4.4%</td>
</tr>
<tr>
<td>Total N</td>
<td>2,064</td>
<td>100.0%</td>
</tr>
</tbody>
</table>

*Note.* The total N value of 2,064 represents the elimination of one don’t know, refused, and/or missing response.
Table A.13

*Frequency Distribution of Social E-Health Survey Question Q29e: Have you ever posted a review online of a hospital? (N = 2,065)*

<table>
<thead>
<tr>
<th>Response</th>
<th>Frequency</th>
<th>Valid Percent</th>
</tr>
</thead>
<tbody>
<tr>
<td>0 = No</td>
<td>2,002</td>
<td>97.0%</td>
</tr>
<tr>
<td>1 = Yes</td>
<td>62</td>
<td>3.0%</td>
</tr>
<tr>
<td><strong>Total N</strong></td>
<td><strong>2,064</strong></td>
<td><strong>100.0%</strong></td>
</tr>
</tbody>
</table>

*Note.* The total N value of 2,064 represents the elimination of one don’t know, refused, and/or missing response.

Table A.14

*Frequency Distribution of Social E-Health Survey Question Q29f: Have you ever posted your experiences with a particular drug or medical treatment online? (N = 2,065)*

<table>
<thead>
<tr>
<th>Response</th>
<th>Frequency</th>
<th>Valid Percent</th>
</tr>
</thead>
<tbody>
<tr>
<td>0 = No</td>
<td>1,996</td>
<td>96.7%</td>
</tr>
<tr>
<td>1 = Yes</td>
<td>68</td>
<td>3.3%</td>
</tr>
<tr>
<td><strong>Total N</strong></td>
<td><strong>2,064</strong></td>
<td><strong>100.0%</strong></td>
</tr>
</tbody>
</table>

*Note.* The total N value of 2,064 represents the elimination of one don’t know, refused, and/or missing response.

**Categorical Independent Variables**

Table A.15

*Frequency Distribution of the Categorical Independent Variable of Sex (N = 2,065)*

<table>
<thead>
<tr>
<th>Response</th>
<th>Frequency</th>
<th>Valid Percent</th>
</tr>
</thead>
<tbody>
<tr>
<td>0 = Male</td>
<td>867</td>
<td>42.0%</td>
</tr>
<tr>
<td>1 = Female</td>
<td>1,198</td>
<td>58.0%</td>
</tr>
<tr>
<td><strong>Total N</strong></td>
<td><strong>2,065</strong></td>
<td><strong>100.0%</strong></td>
</tr>
</tbody>
</table>
Table A.16

*Frequency Distribution of the Categorical Independent Variable of Race (N = 2,065)*

<table>
<thead>
<tr>
<th>Response</th>
<th>Frequency</th>
<th>Valid Percent</th>
</tr>
</thead>
<tbody>
<tr>
<td>1 = White</td>
<td>1,436</td>
<td>71.8%</td>
</tr>
<tr>
<td>2 = Black</td>
<td>395</td>
<td>19.7%</td>
</tr>
<tr>
<td>3 = Other</td>
<td>170</td>
<td>8.5%</td>
</tr>
<tr>
<td><strong>Total N</strong></td>
<td><strong>2,001</strong></td>
<td><strong>100.0%</strong></td>
</tr>
</tbody>
</table>

*Note.* The total N value of 2,001 represents the elimination of 64 don’t know, refused, and/or missing responses.

Table A.17

*Frequency Distribution of the Categorical Independent Variable of Ethnicity (N = 2,065)*

<table>
<thead>
<tr>
<th>Response</th>
<th>Frequency</th>
<th>Valid Percent</th>
</tr>
</thead>
<tbody>
<tr>
<td>0 = Non-Hispanic</td>
<td>1,760</td>
<td>86.1%</td>
</tr>
<tr>
<td>1 = Hispanic</td>
<td>285</td>
<td>13.9%</td>
</tr>
<tr>
<td><strong>Total N</strong></td>
<td><strong>2,045</strong></td>
<td><strong>100.0%</strong></td>
</tr>
</tbody>
</table>

*Note.* The total N value of 2,045 represents the elimination of 20 don’t know, refused, and/or missing responses.

Table A.18

*Frequency Distribution of the Categorical Independent Variable of Education (N = 2,065)*

<table>
<thead>
<tr>
<th>Response</th>
<th>Frequency</th>
<th>Valid Percent</th>
</tr>
</thead>
<tbody>
<tr>
<td>1 = ≤High school graduate</td>
<td>674</td>
<td>32.9%</td>
</tr>
<tr>
<td>2 = Some college</td>
<td>563</td>
<td>27.5%</td>
</tr>
<tr>
<td>3 = College graduate</td>
<td>813</td>
<td>39.7%</td>
</tr>
<tr>
<td><strong>Total N</strong></td>
<td><strong>2,050</strong></td>
<td><strong>100.0%</strong></td>
</tr>
</tbody>
</table>

*Note.* The total N value of 2,050 represents the elimination of 15 don’t know, refused, and/or missing responses.
Table A.19

*Frequency Distribution of the Categorical Independent Variable of Income (N = 2,065)*

<table>
<thead>
<tr>
<th>Response</th>
<th>Frequency</th>
<th>Valid Percent</th>
</tr>
</thead>
<tbody>
<tr>
<td>1 = &lt;$40,000</td>
<td>712</td>
<td>40.7%</td>
</tr>
<tr>
<td>2 = $40,000 to &lt;$75,000</td>
<td>497</td>
<td>28.4%</td>
</tr>
<tr>
<td>3 = ≥$75,000</td>
<td>541</td>
<td>30.9%</td>
</tr>
</tbody>
</table>

Total N          | 1,750     | 100.0%        |

*Note.* The total N value of 1,750 represents the elimination of 315 don't know, refused, and/or missing responses.

Continuous Independent Variable

Table A.20

*Descriptive Statistics for the Continuous Independent Variable of Age (N = 2,065)*

<table>
<thead>
<tr>
<th>Measure</th>
<th>Value</th>
<th>Valid Percent</th>
</tr>
</thead>
<tbody>
<tr>
<td>Mean</td>
<td>44.75</td>
<td></td>
</tr>
<tr>
<td>Standard deviation</td>
<td>17.147</td>
<td></td>
</tr>
<tr>
<td>Median</td>
<td>45</td>
<td></td>
</tr>
<tr>
<td>Mode</td>
<td>18</td>
<td>3.6%</td>
</tr>
<tr>
<td>Minimum value</td>
<td>18</td>
<td></td>
</tr>
<tr>
<td>Maximum value</td>
<td>91</td>
<td></td>
</tr>
<tr>
<td>Range</td>
<td>73</td>
<td></td>
</tr>
<tr>
<td>Skewness</td>
<td>.161</td>
<td></td>
</tr>
<tr>
<td>Kurtosis</td>
<td>-.900</td>
<td></td>
</tr>
</tbody>
</table>

Frequency

| Total N            | 2,020 | 100.0%         |

*Note.* The total N value of 2,020 represents the elimination of 45 don’t know, refused, and/or missing responses.
APPENDIX B

LIST OF TRADEMARKS
<table>
<thead>
<tr>
<th>Name of Trademark</th>
<th>Owner of Trademark</th>
<th>Website</th>
</tr>
</thead>
<tbody>
<tr>
<td>CureTogether®</td>
<td>23andMe, Inc.</td>
<td><a href="http://www.curetogether.com">http://www.curetogether.com</a></td>
</tr>
<tr>
<td>DailyMotion®</td>
<td>DailyMotion Société Anonyme (SA) France</td>
<td><a href="http://www.dailymotion.com">http://www.dailymotion.com</a></td>
</tr>
<tr>
<td>Facebook®</td>
<td>Facebook, Inc.</td>
<td><a href="http://www.facebook.com">http://www.facebook.com</a></td>
</tr>
<tr>
<td>Grindr®</td>
<td>Grindr, LLC</td>
<td><a href="http://www.grindr.com">http://www.grindr.com</a></td>
</tr>
<tr>
<td>Instagram®</td>
<td>Instagram, Inc.</td>
<td><a href="http://www.instagram.com">http://www.instagram.com</a></td>
</tr>
<tr>
<td>Keek®</td>
<td>Keek, Inc.</td>
<td><a href="https://www.keek.com/">https://www.keek.com/</a></td>
</tr>
<tr>
<td>LinkedIn®</td>
<td>LinkedIn, Ltd.</td>
<td><a href="http://www.linkedin.com">http://www.linkedin.com</a></td>
</tr>
<tr>
<td>MySpace®</td>
<td>MySpace, LLC</td>
<td><a href="http://www.myspace.com">http://www.myspace.com</a></td>
</tr>
<tr>
<td>PatientsLikeMe®</td>
<td>PatientsLikeMe, Inc.</td>
<td><a href="http://www.patientslikeme.com">http://www.patientslikeme.com</a></td>
</tr>
<tr>
<td>Pinterest®</td>
<td>Pinterest, Inc.</td>
<td><a href="https://www.pinterest.com">https://www.pinterest.com</a></td>
</tr>
<tr>
<td>Skype®</td>
<td>Microsoft Corp.</td>
<td><a href="http://www.skype.com">http://www.skype.com</a></td>
</tr>
<tr>
<td>Tingle®</td>
<td>AppSocial Media, Inc.</td>
<td><a href="https://www.tingle.com">https://www.tingle.com</a></td>
</tr>
<tr>
<td>Twitter®</td>
<td>Twitter, Inc.</td>
<td><a href="https://www.twitter.com">https://www.twitter.com</a></td>
</tr>
<tr>
<td>Vimeo®</td>
<td>Connected Ventures, LLC</td>
<td><a href="https://www.vimeo.com">https://www.vimeo.com</a></td>
</tr>
</tbody>
</table>
Vine® Vine Labs, Inc. https://www.vine.co
WebMD® WebMD, Inc. http://www.webmd.com
YouTube® Google, Inc. http://www.youtube.com

*Note. Trademark information was obtained using the products’ individual websites and the Trademark Electronic Search System (TESS) database from the U.S. Patent and Trademark Office (http://www.uspto.gov/trademarks).*
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