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Health Status and Health Behavior as Factors Predicting Online Health Seeking

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HEALTH STATUS AND HEALTH BEHAVIOR AS FACTORS
PREDICTING ONLINE HEALTH SEEKING

by

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A DISSERTATION

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MEDICAL SOCIOLOGY

ABSTRACT

The purpose of this dissertation is to examine why people use the Internet for

health-related purposes and whether this usage is part of larger pattern of health-

promoting behaviors, or health lifestyle. Pierre Bourdieu's concept of habitus provides

the key theoretical concept that links health lifestyle theory and the digital inequality

framework to explain how socioeconomic status and level of Internet access may

contribute to status-specific attitudes and behaviors, or lifestyles.

Two dependent variables are used to measure online health behavior: (1) online

health information seeking, and (2) an index constructed from six types of online health-

related activities. Path analysis is used to examine the effects of key endogenous

variables (socioeconomic status and level of Internet access) on attitudes, health

behavior, health status, and the two outcome variables while controlling for

demographics and other factors. Data comes from the mail mode sample of the National

Cancer Institute's 2007 Health Information National Trends Survey.

The findings show that people who were most likely to search online for health

information tended to have poorer health and participate in fewer offline

health-promoting behaviors. People who made greater use of online health-related

activities tended to be in better health and engaged in a greater number of offline health-

promoting behaviors that may represent a broader, collective pattern of status-specific

behaviors or a health lifestyle. For both outcomes, socioeconomic status and Internet

access influenced Internet-related attitudes and usage and suggests that social and structural conditions contribute to status-specific Internet use.

In conclusion, the results demonstrate that online health behaviors can be usefully conceptualized as a health lifestyle. The combination of health lifestyle theory and digital inequality provides a broader theoretical framework that highlights the importance of social and structural conditions to influence people's habitus and routine health-promoting behaviors. The combination of health lifestyle theory and digital inequality provides a useful theoretical framework for future research investigating persistent social disparities in health and new ways to leverage information and communication technology to narrow gaps in digital inequality and in health disparities.

DEDICATION

I dedicate this dissertation to my wife, Renicha 'Nish' McCree-Hale. Without her

love and encouragement this dissertation would not have been possible.

ACKNOWLEDGMENT

Completing a Ph.D. is most often celebrated as a significant individual accomplishment. However, it would not be possible without the support, guidance, and mentoring of established scholars and researchers. I owe many thanks to the entire UAB Department of Sociology faculty for their support and assistance. On numerous occasions I have turned to them for help and in every instance they have gone out of their way to be available to answer my questions. I also thank Dr. Patricia Drentea, Dr. Melinda Goldner, Dr. Nir Menachemi, and Dr. Belinda Needham for agreeing to serve on my committee and for their suggestions and comments that have helped me to improve this dissertation.

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Last, but not least, I also thank my fellow graduate students for their advice, support, and friendship. I am lucky to have been surrounded by such a bright, caring, and fun group of people.

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LIST OF ABBREVIATIONS

CMIS   Comprehensive Model of Information Seeking

HINTS   Health Information National Trends Survey

ICT   information and communication technology

NTIA   National Telecommunications and Information Administration

NCI   National Cancer Institute

OHB   online health behavior

OHIS   online health information seeking

OHRA   online health-related activity

OSP   online service provider

SES   socioeconomic status

WWW   World Wide Web

CHAPTER 1

INTRODUCTION

A key question that has not yet been resolved is whether individuals tend to use

the Internet for health-related purposes in response to poor health or to maintain good

health. The former can be described as *illness behavior* and defined as any activity

undertaken by a person who feels ill for the purpose of defining their illness and seeking

to get well (Kasl and Cobb 1966). The later can be described as *health behavior* and is

defined as any activity undertaken by a person to maintain or enhance their health, or to

prevent future health problems (Cockerham 2004). Thus, illness behavior is generally

reactive, initiated by poor health or a specific medical problem; whereas health behavior

is proactive, as people engage in behaviors to maintain health and prevent future illness.

Most research on health-related uses of the Internet have focused on health

information seeking and the assumption that poor health or medical problems are the

primary reasons people search for information (Lambert and Loiselle 2007). Previous

research, however, has produced conflicting results. Some researchers find that healthier

individuals are more likely to search for health information online (Cotten and Gupta

2004), supporting the health behavior model. Findings reported by other researchers,

however, support the illness behavior model, showing that individuals in poor health are

more likely to search for health information online (Baker et al. 2003; Goldner 2006b;

Houston and Allison 2002).

Another line of research has focused on the relative strength of health behaviors and health status to predict seeking health information online. Pandey, Hart, and Tiwary (2003) hypothesized that individuals who engage in healthy behaviors tend to have a proactive approach to health, which they called a *wellness model,* and would be more likely to seek health information online regardless of their current health status. In fact, they found that in multivariate models that an index measuring seven healthy behaviors was associated with a greater likelihood of seeking health information online. Health status, however, was not significant after controlling for differences in health behavior and sociodemographic variables. Other researchers have also found that individuals who engage in healthy behaviors are more likely to seek health information online (Dutta-Bergman 2004a; Ramanadhan and Viswanath 2006).

Each of the studies mentioned have made a valuable contribution to our knowledge of the factors that determine differences among individuals seeking health information online. However, each of these studies has important limitations. Several studies have focused on health status but have not included measures of health behavior (i.e., Baker et al. 2003; Cotten and Gupta 2004; Goldner 2006b; Houston and Allison 2002) while other studies have included health behaviors but not measures of health status (Dutta-Bergman 2004a). Others are too specific in their choice of health measures or samples to be generalizable to the general U.S. population. For example, Ramanadhan and Viswanath (2006) examine health status as a diagnosis of cancer; Pandey, Hart, and Tiwary's (2003) study is conducted using a sample of women from only three counties in the state of New Jersey.

This dissertation seeks to address the limitations of previous research in three important ways. First, while most research on online health seeking has focused on online health information seeking I also examine factors associated with a range of online health-related activities that include: buying medicine; participating in support groups; sending email to health care professionals; using a website to help with weight, diet, or exercise; looking for a health care provider; and keeping track of personal health information. With the increasing and widespread use of the Internet for health-related purposes, it's important to move beyond a narrow focus on a binary measure of information seeking to understand how social conditions contribute to collective patterns of health-related Internet uses.

Second, I build on existing theoretical frameworks to examine online health information seeking and online health-related activities as behaviors that represent a *health lifestyle,* To do so, I draw on Cockerham's (2005) conceptualization of health lifestyle, which he defines as "collective patterns of health-related behavior based on choices from options available to people according to their life chances" (p. 55). The concept of health lifestyle highlights the influence of social conditions to shape people's experiences that in turn, are internalized as status-specific attitudes and habits or behaviors (i.e., physical exercise, food choices, smoking tobacco). Using the Internet for health-related purposes may be more closely associated with health lifestyle choices today than in the past. Whereas Internet access was once considered a luxury, it has become a central to our social infrastructure and necessity to fully participate in society and interact effectively with public and private institutions (Hargittai 2008). In an era that places greater responsibility upon individuals to manage their health and be informed

medical consumers (Conrad 2005; Crawford 1980, 2006) – the Internet has become a key resource people may use to find health information, communicate with others, and garner social support (Drentea and Moren-Cross 2005; Fogel et al. 2002, 2003; Fox 2011a, b, c; Fox and Purcell 2010) and foster participation in health promoting behaviors (Ayers and Kronenfeld 2007; Webb et al. 2010).

To advance our understanding of health-related Internet use as a form of lifestyle, I draw on the *digital inequality* framework. Similar to the concept of health lifestyle, the digital inequality framework explains how social conditions influences people's experiences using the Internet and how this contributes to status-specific Internet attitudes and patterns of usage that tend to reproduce preexisting social inequalities (DiMaggio and Bonikowski 2008; DiMaggio et al. 2004; Hargittai and Hinnant 2008). Thus, I seek to bridge two bodies of research to examine online health behaviors, measured as online health information seeking (OHIS) and online health-related activities (OHRA), as lifestyle choices that may be associated with offline healthy behaviors and represent a health lifestyle.

Third, I seek to overcome limitations in the methodology used in previous studies. I include measures of both offline health behaviors and health status in my models to examine the independent relationship of each to online health information seeking and online health-related activities. In addition, to avoid confounding factors known to predict Internet users from non-users, I use sub-samples restricted to Internet users. This focuses the analysis on the factors associated with variations in Internet usage. Finally, I use a nationally representative sample of non-institutionalized adults collected in 2007. The Health Information National Trends Survey (HINTS) is sponsored by the National

Cancer Institute (NCI) to gather data on how people use a variety of health information resources, including the Internet. The survey also addresses a range of questions specific to cancer and cancer treatment, but the sample is not restricted to people with a diagnosis of cancer and is representative of the health status of adults living in the U.S.

Based on the theoretical framework derived from health lifestyle theory and the digital inequality framework, I seek to answer the following research questions: (1) Are online health behaviors better explained as illness behavior or health behavior? (2) Does online health behavior fit the conceptualization of lifestyles? (3) Is there a relationship between online health behavior and offline health behavior that might suggest a broader pattern of health-promoting behavior or health lifestyle?

CHAPTER 2

LITERATURE REVIEW

The purpose of this dissertation is to examine online health behaviors, why people use the Internet for health-related purposes, and whether these activities are related to offline health behaviors that may represent status-specific forms of health lifestyle. Much of the previous research has been based on the assumption that online health information seeking is motivated primarily by poor health or a concern about a medical problem. In this dissertation, I seek to examine online health information seeking as part of a larger set of health behaviors that represent a health lifestyle. Online health information seeking is thus understood to be not strictly in response to an acute health condition or need for information, but as part of a person's more general set of daily routine and habits related to maintaining health and avoiding illness and premature death.

In this section I first provide a brief overview of the history of the Internet and early online service providers (OSP). Second, I review the early literature on the individual and social impacts of the Internet and the two dominant perspectives that emphasized dystopian or utopian outcomes. Third, I discuss the development of the concept of the digital divide from a relatively simple binary conceptualization of "the haves" and the "have nots" to a more nuanced conceptualization of digital inequality consisting of multiple factors and dimensions of Internet usage, ending with a brief discussion of status-specific Internet skills, attitudes, and types of uses. Fourth, I review

descriptive findings regarding online health information seeking and other types of online health-related activities. Fifth, I review the research on health status and health behavior to predict online health information seeking and online health-related activities and the limitations of this research. Sixth, I review the literature on the many factors that previous research finds are significant predictors of online health information seeking and online health-related activities. I finish with a summary of the most relevant findings from previous research.

<div align="center">The Internet</div>

History of the Internet

Given that information and communication technologies (ICTs) have changed dramatically over the last 30 years, it is useful to review the rapid technological developments and changes in this area. This provides a better understanding of the way in which people viewed the early Internet and the health-related resources available online. Although the history of the Internet can be traced back to earlier computer network systems (for details, see Gillies and Cailliau 2000; Abbate 1999), I outline three developmental phases of online services and the Internet, and explain how these changes have influenced research on the Internet and online health activities. The first phase is dominated by a few online service providers operating as largely isolated, self-contained online services accessed through dedicated, direct dial-up modem connections. The second phase is the era of Web 1.0, marked by the emergence of the World Wide Web and freely available web browsers that heralded the birth of the Internet as we know it

today. The third phase is the era of Web 2.0 characterized by a focus on user participation, user generated content and data sharing, and social networking.

Most people's early experiences with the Internet during the 1980's and early 1990's was using one of several OSPs like CompuServe, America Online (AOL), and Prodigy. This is the first phase in the development of widespread use of online information and communication services. In fact, people who subscribed to one of the OSPs were not connecting to the Internet, but *intranets* – isolated computer networks that one accessed directly using a dial-up modem (Abbate 1999). Each OSP offered users a unique destination consisting of tightly controlled services and information content (Zittrain 2008). There was little or no connection or sharing of information between OSPs as each OSP used proprietary software that was largely incompatible with other systems (Abbate 1999; Zittrain 2008). CompuServe was one of the first online services widely available to the general public and provided customers with a way to exchange mail, read and write messages in discussion forums, and other services based on an hourly fee (Abbate 1999). By the mid-1990s AOL emerged as the dominant OSP and acquired CompuServe in 1998 (AOL 2010).

During 1989 and 1990 a new type of computer networking system was being developed by Timothy Berners-Lee at CERN (Conseil Européen pour la Recherche Nucléair – European Organization for Nuclear Research). He termed his invention the World Wide Web (WWW) and developed a method of presenting content as pages using an embedded set of coding (hypertext markup language, or HTML) that also enabled text in a page to link to pages across computer networks (Cantoni and Tardini 2006; Gillies and Cailliau 2000). Unlike the OSPs proprietary systems, HTML was a freely distributed

standard for sharing information across computer networks in the form of pages that were viewed as text, photographs, and other graphical elements that was more intuitive to navigate and use than previous computer networking systems. However, to view WWW pages required a special application, a web browser, that converted the HTML code into a page that could be viewed on a computer. The first web browsers were designed to run only on large mainframe computers. This limited the adoption of the WWW until a widely available web browser was developed that would operate on personal computers. The first of these freely distributed web browsers was Mosaic, released in 1993 and was soon followed by the more popular Netscape browser in 1994 (Abbate 1999).

The dominance of OSPs began to erode in the mid-1990s as people sought to connect to the WWW and explore the information and entertainment resources available outside of the closely managed content available on the OSP's systems (Cantoni and Tardini 2006). This change marks the second phase in the development of online information and communication services and the birth of the Internet that people are familiar with today. This development fostered much excitement over the potential of this new technology and also much uncertainty and speculation of negative effects. DiMaggio and colleagues (2001) note that early research on the social impacts of the Internet tended towards two distinct and opposing perspectives. First, there were those who speculated that the Internet would reduce inequality by making information more widely available, increase social capital, and foster a more equitable and engaged civic community (e.g., Anderson et al. 1995). The second is a dystopian perspective that emphasizes several potential negative impacts of the Internet. This includes a concern that Internet use might displace time spent with family and friends (e.g., Nie and Erbring 2000), increase

loneliness and depression (e.g., Kraut et al. 1998), and widen social inequalities due to the greater benefits that might accrue to people of high socioeconomic status (SES) who have greater access to the Internet (e.g., DiMaggio and Hargittai 2001; National Telecommunications and Information Administration 1995, 1998, 1999, 2000). In terms of OHRA, much of the concern centered on the questionable quality of health information available online and the potential harm caused to people who followed online information rather than that of a health care professional (Cline and Haynes 2001).

Many entrepreneurs greeted the decline of OSPs and the emergence of the WWW with great enthusiasm, reminiscent of the 1889 Oklahoma "land rush" that took place when the United States opened access to previously unsettled regions of the west. Between 1995 and 2000 a great number of new companies were established, all seeking to make a claim to some part of the new, largely unsettled landscape of the WWW. For the most part, the "dot-coms" as they were called, sought to duplicate brick and mortar business models online, with little or no consideration of how to adapt their business models to the make best use of the capabilities on the WWW. This initial phase of the WWW, called Web 1.0, came to an end in the fall of 2001 when many of the newly established dot-coms declared bankruptcy (O'Reilly 2005).

Whereas the start of the second developmental stage of the Internet is marked by the decline of the OSPs, the third developmental stage is marked by the collapse of the dot-coms and the beginning of a new era called Web 2.0. The phenomenon of Web 2.0 did not emerge all at once, but gradually as web-based technology was refined and functionality extended. Tim O'Reilly was particularly instrumental in establishing the concept of Web 2.0 in a series of conferences and workshops beginning in 2004, where

he argued that the companies that survived the dot-com collapse shared many

commonalities that illustrated a new way of thinking and using web-based technology

(O'Reilly 2005). Although there is no single definition of what constitutes Web 2.0,

O'Reilly (2005) describes Web 2.0 as a set of principles and practices based on: (1) user

control of data; (2) web-based services, not software; (3) fostering user participation; (4)

scalability; (5) mixable data sources and transformation; (6) software not tied to a single

device; and (7) harnessing collective intelligence.

In sum, Web 2.0 applications are designed to be user-centric, based on an implicit

"architecture of participation" (O'Reilly 2005), and clearly focused on ways to facilitate

users in finding, creating, and sharing data with other users. This emphasis on creating

web applications and systems that facilitate user participation is illustrated by the growth

in the popularity of web logs (i.e., blogs, and services like Blogger or WordPress), sites

that facilitate sharing photos and videos (e.g., Flickr, Picasa, and YouTube), social

networking sites (e.g., MySpace, LinkedIn, and Facebook), and micro-blogging or status

update services (e.g., Twitter). Interoperability means that information found or created

in one web application can be easily shared in another application. In addition, Web 2.0

applications are largely device independent and run on a variety of computer platforms

and even mobile phones.

The culmination of these developments is that Internet usage has become

ubiquitous and central to a range of daily activities (Fuchs 2008; Hargittai 2008). On a

daily basis people use the Internet to search for and share information, read the news,

check the weather, find directions, keep track of appointments, balance their checkbook

and pay bills, communicate with family and friends, and a variety of other things (Fuchs

2008). The Internet has also become an important source of information about health with about 59% of all adults, or 80% of adult Internet users, having ever searched for health information online (Fox 2011a:5). It is also an important way for people to connect with others with similar medical conditions for information and social support (Fox 2011b; Fox and Jones 2009). With the diffusion of high-speed or broadband connections (i.e., digital subscriber line (DSL), satellite, cable) and the increasing use of wireless devices to access the Internet, much of the debate has shifted from questions of computer ownership and access to a more nuanced examination of how social status influences early experiences with technology, the development of Internet skills, and the types of uses people make of the Internet (DiMaggio and Hargittai 2001; Zillien and Hargittai 2009).

Dystopian Perspective

Initial research proposed that Internet use would displace traditional, offline social interaction with friends and family and have negative impacts on psychological well-being. Kraut and colleagues (1998) conducted the seminal research on this topic in 1998. They found that among new Internet users in 1995-1996, that greater use of the Internet was associated with a decline in their communication with friends and family, a decrease in the size of their social network, and increased feelings of loneliness and depression. They described this phenomenon as the "Internet paradox" to highlight the fact that Internet use was not associated with the expected gains in social involvement and psychological well-being. Several early studies found similar declines in social involvement and psychological well-being associated with Internet use (Mesch 2001; Nie

and Erbring 2000; Nie, Hillygus, and Erbring 2002; Sanders et al. 2000) and many recent studies continue to find a small, but negative association between Internet use and psychological well-being (Huang 2010; Stepanikova, Nie, and He 2010).

Despite the studies that find a negative relationship between Internet use and psychological well-being, other studies find a positive association between Internet use and social involvement and psychological well-being (Boase et al. 2006; Cotten et al. 2011; Fogel et al. 2002, 2003; Quan-Haase et al. 2002) and that any potential negative impacts are short-lived (Kraut et al. 2002). For example, in a follow-up study to the one conducted in 1998, Kraut et al. (2002) found no significant relationship between Internet use and frequency of communication, social network size, or feelings of loneliness. In addition, the positive relationship between Internet use and depression found in the 1998 survey had reversed, and now indicated that increased use of the Internet was associated with lower levels of depression.

Just as many scholars were investigating the possible negative effects of Internet use on social involvement and psychological well-being, scholars and medical professionals raised concerns about the potential negative health outcomes that might result from people using information they found online to self-diagnose and treat a medical condition rather than seeking diagnosis and treatment from a physician (Cline and Haynes 2001). A 1997 editorial by Silberg and Lundberg in the Journal of the American Medical Association (JAMA) outlines the key points raised by those concerned. First, there is the problem of too much information of which "vast chunks are incomplete, misleading, and inaccurate" (Silberg and Lundberg 1997:1244). Second, "science and snake oil may not always look all that different on the Net," due to the lack

of proper identification of authorship and information sources (Silberg and Lundberg 1997:1244). And third, people may place more value on the health information they find online than if it was obtained from other sources. In response to these concerns, in 2000 a new focus objective was added to *Healthy People 2010,* recommending that health-related web sites provide visitors with details about the information presented so that visitors can better evaluate information quality (Cline and Haynes 2001). The American Medical Association (AMA) recommended a more conservative approach. In a 2001 press release the AMA warned people that using the Internet "to self-diagnose and to self-medicate may be putting their lives at risk" and advised people to "trust your physician, not a chat room" (American Medical Association 2001:2).

Despite the concerns scholars and medical professionals raised over the quality of health information on the Internet, early studies found little evidence to warrant these concerns. In a Pew Internet & American Life Project 2001 survey of adults who looked online for health or medical information, 2% reported knowing someone who has ever been seriously harmed by following the health information they found online (Fox and Rainie 2002:6). Sixty-one percent said the Internet improved the way they take care of their health either "some" or "a lot" and 16% said the health information they found online had a major impact on how they take care of their health or that of a loved one (Fox and Rainie 2002:6). A Pew survey conducted in 2010 asked similar questions of all adults and found that just 1% report knowing someone who has been seriously harmed due to following health information found online and 21% said that following the medical advice or health information they found online was a major or moderate help (Fox 2011c:12)..

There is also very little evidence from case studies of harm associated with treatment based on health information people find on the Internet. Eysenbach and Kohler (2002) established the Database of Adverse Events Related to Internet (DAERI) use to document case studies of harm to patients caused by information found online. After four years only one case had been reported and the project was discontinued in September 2004 (Ferguson 2007:29). Crocco, Villasis-Keever, and Jadad (2002) conducted a review of peer-reviewed literature published up to March 2001, and found only one case of physical harm involving a man who died from liver failure after using hydrazine sulphate to treat cancer. The authors point out that cases of harm are likely to be underreported in the literature. However, they conclude that the "Internet's capacity for harm is likely to be equal to or exceeded by its capacity for providing good and useful health information to users in a relatively inexpensive and timely manner" (Crocco et al. 2002:2870).

In summary, there is little empirical evidence that large numbers of people are experiencing physical harm associated with using health information found online. The findings regarding Internet use and psychological well-being are inconclusive and several possible explanations for the conflicting findings have been proposed. First, early studies consisted of new Internet users, or "newbies," who may tend to experience greater negative outcomes associated with Internet use and related changes in their daily routines whereas later studies are comprised of a larger proportion of long-time Internet users (Wellman 2001). Another possibility is that the nature of the Internet has changed significantly during the span of only a few years. According to Kraut et al. (2002), the Internet may have become "a more hospitable place" (p. 68) with more people online making it easier for people to successfully connect with friends and family online. There

is a growing recognition that the impact of Internet use on a variety of psychological well-being outcomes is more complex than a simple positive or negative relationship, but varies by people's social resources and how they choose to use the Internet (Selwyn 2004). Most research shows that using the Internet enables people to maintain or strengthen their existing social connections and to forge new connections (Boase et al. 2006). The Internet is also an important means to strengthen neighborhood ties (Hampton and Wellman 2003). A 2009 Pew survey shows that 20% of all adults, or 27% of Internet users, use online tools to communicate with their neighbors and keep informed of community issues (Smith 2010c).

Utopian Perspective

In contrast to the dystopian views of the negative impacts of the Internet on society and people's lives, there emerged a great deal of "techno-utopian" proposals that highlight the potential for using computer technology and the Internet to overcome existing social divisions and inequalities (Bell 1973; Castells 1996; Turner 2006). Many scholars have noted that technological innovations in ICTs have contributed to the transformation and reorganization of American society from one based on manufacturing to one based on the delivery of services and information (Bell 1973). This social change has been conceptualized as a "post-industrial society" (Drucker 1969), the "information society" (Castells 1996), and the "network society" (Castells 1996, 2000; van Dijk 2006).

These concepts have in common the assumption that information is a *primary good* – goods that are essential for individuals' basic survival in an information-based society (van Dijk 2006). Not surprisingly, much of the enthusiasm regarding the potential

benefits derived from Internet usage has centered around the enhanced ability for people

to quickly and inexpensively find information online and to redistribute information

among their social networks (DiMaggio et al. 2001). Despite inequalities in Internet

access and use, the Internet is understood to be the primary means of accessing and

controlling information that is crucial to people's educational attainment, opportunities to

find jobs and develop businesses, political and civic participation, and accrue social

capital (Anderson et al. 1995; DiMaggio et al. 2004; DiMaggio et al. 2001; Hargittai

2008; Mossberger, Tolbert, and McNeal 2008; van Dijk 2006).

Empirical evidence tends to support these techno-utopian claims. Despite

evidence of a historical trend in which the size of Americans core discussion networks

has decreased (McPherson, Smith-Lovin, and Brashears 2006) and that Americans have

become less involved in their local communities and civic organizations (Putnam 2000),

other studies find that Internet use is positively associated with social interaction and

civic involvement (Boase et al. 2006; Hampton and Wellman 2001, 2003; Katz, Rice, and

Aspden 2001; Mossberger et al. 2008) and economic gains (DiMaggio and Bonikowski

2008; Mossberger et al. 2008).

A survey conducted in 2008 highlights the potential positive impacts of Internet

use. Hampton and colleagues (2009; 2011) designed a study to assess the impact of the

Internet and cell phone use on Americans social networks and participation in their local

community. Their findings supported previous research showing that the average size and

diversity of core discussion networks has declined since 1985. However, in contrast to

the large increase in the number of people who are truly isolated (i.e., with no one they

can discuss important matters) as found by McPherson, Smith-Lovin, and Brashers

(2006), Hampton and colleagues found only a small to modest increase – 12.0% in 2008 compared to 8.1% in 1985. In addition, they found no evidence that Internet or mobile phone usage were contributing to people's social isolation. Instead, they found that Internet and mobile phone users were less likely to report having no one they can discuss important matters with, and have larger and more diverse discussion networks. Finally, they found that most uses of the Internet and mobile phones are positively associated with participation in local communities and in voluntary associations. Hampton and colleagues (2009) conclude that Internet and mobile phone usage are not the cause for the changes in people's social networks, and suggest "that people's lives are likely to be enhanced by participation with new communication technologies, rather than by fearing that their use of new technology will send them into a spiral of isolation" (p. 56).

Internet use is also likely to have a significant impact on the health care system and individual health outcomes – improving people's access to health information, ability to share information and build social support networks, and to empower individuals in the management of their health and medical treatment (Cotten 2001; Goldsmith 2000). Some have gone so far as to argue that "we are witnessing the most important technocultural medical revolution of the past century" and noted that Internet empowered patients are capable of "managing much of their own care, providing care for others, helping professionals improve the quality of their services, and participating in the collaboration between patients and professionals" (Ferguson and Frydman 2004:1149). Similarly, Eysenberg (2008) describes how new types of social media, or Web 2.0 applications, and other new information technologies enable the development of a new era of "Medicine

2.0" to connect patients, health professionals, and biomedical researchers in an open exchange of information and collaboration to achieve optimal health outcomes.

Although the most optimistic assessments of the impact of the Internet on the health care system may never be realized, there is empirical evidence showing that health-related Internet use is associated with increased social support (Drentea and Moren-Cross 2005; Fogel et al. 2002, 2003; Fox 2011b), behavioral change beneficial to health (Ayers and Kronenfeld 2007; Webb et al. 2010), and access to information that is helpful to make decisions about health or medical treatments (Fox and Jones 2009). Finally, in contrast to dystopian fears that people will use health information found online as a substitute to seeking professional health care, most studies find that people use the Internet to supplement professional health care and to better inform themselves about medical problems and treatment options (Fox 2011b; Fox and Jones 2009; Nettleton et al. 2004; Pandey, Hart, and Tiwary 2003).

To summarize, despite persistent fears among some scholars and in the popular press, the Internet does not appear to be replacing traditional forms of communication and interaction, but supplements and strengthens existing social ties and is positively associated with civic engagement and political participation (Bargh and McKenna 2004; Boase et al. 2006; Hampton et al. 2009; Hampton and Wellman 2001, 2003; Katz et al. 2001). On the other hand, the utopian projections of a radical transformation of the health care system may be exaggerated. However, there is a good deal of empirical evidence that the Internet has become an important resource for health information, gaining social support, and participating in decisions about one's health and medical treatment (Ayers

and Kronenfeld 2007; Drentea and Moren-Cross 2005; Fogel et al. 2002, 2003; Fox 2011b; Fox and Jones 2009).

Despite the fact that the Internet affords greater access to information, modes of communication, and participation in social networks – not everyone uses the Internet in the same way. Van Dijk (2005, 2006) points out that it is important to consider the relative differences between social groups in access to and control of information. Castells (1996, 2000) goes further to argue that the potential power and benefits derived from the use of the Internet and electronic communication networks is determined by a person's position within the information network. Therefore, it is important to understand how people's access and use of the Internet vary.

Digital Divides

In contrast to the scholarly and popular debate concerning the possible negative and positive impacts of the Internet there is widespread agreement that a range of socio-demographic factors are related to differences in Internet access and usage (DiMaggio et al. 2004; Selwyn 2004). This concern came to the foreground in 1995 when the National Telecommunications and Information Administration (NTIA) published the first in a series of reports examining socio-demographic differences in Internet access using the U.S. Census Bureau Current Population Survey (CPS). The first report, titled "Falling Through the Net: A Survey of the Have Nots in Rural and Urban America," highlighted the development of a "nascent Information Age" where "individuals' economic and social well-being increasingly depends on their ability to access, accumulate, and assimilate information" (National Telecommunications and Information Administration

1995: section 1, paragraph 3). The report points out inequalities in computer ownership and Internet access between the "haves" and the "have nots" that was later termed the "digital divide" in a 1998 NTIA report titled, "Falling Through the Net II: New Data on the Digital Divide" (National Telecommunications and Information Administration 1998). The following year, the NTIA report described the digital divide as "one of America's leading economic and civil rights issues" (National Telecommunications and Information Administration 1999:xiii).

This formative research by the NTIA was useful in highlighting persistent differences in computer ownership and Internet access by a variety of socio-demographic or digital divide factors, including place of residence, income and educational attainment, employment status, age, gender, race/ethnicity, and family structure (DiMaggio et al. 2004; National Telecommunications and Information Administration 1995, 1998, 1999, 2000, 2002). DiMaggio and colleagues (2004:360-61) summarize the NTIA findings as showing that (1) suburbanites are more likely to use the Internet than those people living in rural or urban areas, (2) income and education are positively associated with Internet use, (3) older adults are less likely to use the Internet, (4) men were more likely than women to use the Internet prior to 2001 and are now equally likely to be online, (5) non-Hispanic whites and Asians are more likely to use the Internet than non-Hispanic blacks and Hispanics, and (6) families with children are more likely to use the Internet than families without children.

The NTIA reports also document the rapid diffusion of computer ownership and Internet access. Between 1998 and 2001, households with computers increased from 36.6% to 56.5% and households with an Internet connection increased from 18.6% to

50.5% (National Telecommunications and Information Administration 2002:3). By 2003 computer ownership and household Internet access were reaching high levels of penetration in U.S. households, with 61.8% of households with a computer and 54.6% of households reporting Internet access (National Telecommunications and Information Administration 2004:4). As disparities in computer ownership and Internet access narrowed, a focus on other factors emerged. The 2004 NTIA report, "A Nation Online: Entering the Broadband Age," focused on the use of high speed broadband connections versus slower dial-up modems. The report found that in 2003, most people accessed the Internet through relatively slow dial-up modems and only 19.9% of households had a broadband Internet connection, or 33.9% of households with Internet access (National Telecommunications and Information Administration 2004:7). Questions regarding computer ownership were dropped from the CPS after 2003, a fact that further highlights changes in the conceptualization of the digital divide beyond a simple binary classification of the "haves" versus the "have nots" to focus on differences in quality of Internet connection. Reflecting this change the 2007 NTIA report was titled, "A Networked Nation: Broadband in America" contains only one mention of the digital divide (see page 27, National Telecommunications and Information Administration 2007) and highlights the Bush Administration's goal of achieving "universal, affordable access to broadband technology" (p. i).

The most recent estimates show that Internet access and broadband connections have diffused to a large proportion of the U.S. population. The October 2010 Current Population Survey (CPS) estimates show that of all U.S. households, 71.1% have an Internet connection and 68.2% have a broadband connection (National

Telecommunications and Information Administration 2011:7). The most recent survey

data collected by the Pew Research Center's Internet and American Life Project during

April and May 2010 finds that 79% of the population are Internet users and 66% have a

home broadband connection (Smith 2010a:5). A recent 2009 survey of 5,005 adults

conducted by the Federal Communications Commission (FCC) found similar estimates of

people who are Internet users (78%) and have home broadband access (65%) (Horrigan

2010:3). In addition to the diffusion of high speed broadband Internet connections, people

are making greater use of portable devices and wireless Internet access. A Pew 2010

survey finds that 55% of adults own a laptop computer with 61% connecting wirelessly at

more than one location, including at home (86%), work (37%), and some other place

(54%) (Smith 2010b:19-22). Mobile phones have also become important tools to access

the Internet; 82% of adults own a mobile phone and 38% of mobile phone owners have

accessed the Internet using their mobile phone (Smith 2010b:4). Over-all, 59% of adults

now access the Internet wirelessly using laptops or cell phones, up from 51% just one

year earlier (Smith 2010b:7).

Digital Inequality and Status-Specific Internet Use

Although there has been a steady increase in the percentage of people who access

and use the Internet (National Telecommunications and Information Administration

2011), this does not necessarily mean that people are using the Internet in similar ways

(Hargittai and Hinnant 2008). Recognizing this fact, scholars have argued that research

should move beyond a binary classification of Internet "haves" and "have nots," to a

more nuanced conceptualization of how people *use* technology and the Internet (Barzilai-

Nahon 2006; DiMaggio and Hargittai 2001; DiMaggio et al. 2004; van Dijk 2005, 2006; Warschauer 2003), or what DiMaggio and colleagues (2001, 2004) term *digital inequality.* Although many factors contribute to digital inequality, DiMaggio and colleagues (2001, 2004) classify factors as belonging to one of five dimensions:[1] (1) the *technical means* to access the Internet, (2) individual's degree of *autonomy* to access and use the Internet, (3) level of *skill* and proficiency at using the Internet effectively, (4) the *social context* and level of *social support* that individuals can draw upon to enable and sustain their use of the Internet, and (5) variation in the *purposes* that people use the Internet.

Most recently, researchers have focused on what Hargittai has termed the "second level digital divide" defined as "differences in how people use the Web for information retrieval" (Hargittai 2002: second paragraph). This research examines differences in people's Internet skills or "the ability to efficiently and effectively find information on the Web" (Hargittai 2002: second paragraph) and how Internet skills contribute to differences in Internet use and the implications for the reproduction of social inequality (Hargittai 2008; Hargittai and Hinnant 2008; Hargittai and Walejko 2008; Zillien and Hargittai 2009). A central assumption is that the Internet is no longer a luxury, but has become deeply ingrained in our social infrastructure making it increasingly difficult or impossible for a person to access essential information and services (Hargittai 2008). Therefore, "differential uses of digital media have the potential to lead to increasing inequalities benefiting those who are already advantaged and denying access to better resources for the underprivileged" (Hargittai 2008:943).

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[1] For other classificatory schemes see Warschauer (2003), Barzukau-Nahon (2006), and van Dijk (2006).

What is important about this research is that it demonstrates the linkage between a person's social status position, level of Internet skills, and how they use the Internet as part of their daily routine. In terms of digital inequality, the focus is on Internet activities that enhance life chances or *capital-enhancing* uses of the Internet (Hargittai and Hinnant 2008). For example, Hargittai and Hinnant (2008) found social status, measured as level of education, was positively associated with self-reported Internet skills and number of capital-enhancing Internet uses during the past 30 days. Similarly, Zillen and Hargittai (2009) found that higher social status predicted greater use of capital-enhancing Internet use among a representative sample of German youth and adults collected in 2004. In discussing their findings, Zillien and Hargittai (2009) explain that "Internet users' position on the social ladder has a significant influence on the uses toward which they put the medium, even after controlling for the quality of their technical equipment, their digital experience, and topic-specific interests related to various activities" (p. 288). Zillien and Hargittai (2009) conclude by stating:

> …we find that differences in Internet use cannot be attributed simply to individual variation in motivation, interest, or will; rather… forms of Internet use are determined by age, gender, the quality of technical access, digital experience, topic-specific interest, *and* something status related that we—following Bourdieu (1984)—can perhaps call *habitus*. [italics in original] (p. 288)

In sum, initial research on the Internet tended to focus on two perspectives of possible outcomes (dystopian and utopian) using a binary classification of Internet users versus non-users (the haves versus the have nots). The result was rather general statements of negative or positive impacts depending on whether an individual did or did not use the Internet. With the diffusion of the Internet across population segments, the focus of research shifted from a simple binary conceptualization of a digital divide to a

more nuanced conceptualization of multiple factors and dimensions of digital inequality and how different types of Internet use contribute to reproducing existing patterns of social inequality. Rather than a luxury, the Internet is now widely understood to be a key means by which people carry out a variety of daily tasks (Fuchs 2008; Hargittai 2008). In doing so, some researchers have found that social status is a strong determinant of types of Internet use and suggest that status-specific patterns of Internet use can be usefully conceptualized as habitus.

Briefly, the concept of habitus demonstrates how social status position influences a person's life chances and experiences that subsequently shape the development of technology skills and preferences in how they use technology, in this case the Internet (North, Snyder, and Bulfin 2008; Sterne 2003). The concept of habitus has been used to explain social class differences in young people's technology use (North et al. 2008), leisure Internet activities (Roderick 2008), and seeking health information online (Lewis 2006a, b). Of particular relevance to this study are social status differences in patterns of online health seeking and the association with offline health behaviors that represent status-specific health behaviors or health lifestyle. In the following section I review the literature on online health seeking.

<div align="center">Online Health Seeking</div>

Online Health Information Seeking

Although people may use the Internet for a variety of health-related purposes (Eysenbach 2003), most studies find that information seeking is the most common (Atkinson, Saperstein, and Pleis 2009; Beckjord et al. 2007; Fox 2006, 2011a; Fox and

Jones 2009; Fox and Rainie 2000; Hale et al. 2010; Hesse et al. 2005; McMullan 2006; Rutten et al. 2007). One widely cited source of estimates comes from the Pew Research Center's Internet and American Life Project, which has conducted surveys at regular intervals to track trends in Internet usage using nationally representative samples of U.S. adults. These surveys often include two questions asking adult Internet users whether they have *ever* used the Internet to search for health or medical information, and how frequently they did so. In 2000, the first survey year, 55% of Internet users reported having ever searched for health information online and 29% doing so about once a week (Fox and Rainie 2000:9). In more recent surveys, conducted between 2002-2010, this percentage varied between 75%-83% of Internet users reporting they have ever looked for health or medical information on the Internet (Fox 2008, 2011a) with 19% doing so once a week or more often (Fox and Jones 2009:21). These estimates are consistent with findings from the Harris Poll, which has conducted annual surveys of U.S. adults starting in 1998 to measure the number of people going online for health-related information (Harris Poll 2010). Between 2003-2008, the Harris Poll found between 72%-84% of Internet users had ever searched for health information online. The most recent Harris Poll surveys conducted find 78% (July 2009) and 88% (July 2010) of adult Internet users have ever searched for health information online.

Although about 80% of Internet users report having ever looked for health-related information online (Fox 2006, 2008, 2011a; Fox and Jones 2009; Harris Poll 2010), about half of all searches are conducted for someone else (Fox 2006, 2011a). A 2010 Pew survey found that during their most recent search for health-related information online,

48% looked for someone else, 36% looked for themselves, and 11% said they looked for both someone else and themselves (Fox 2011a:8).

The most recent Pew survey conducted in August-September 2010 finds that among those who searched online for health information, the greatest percentage searched for information about: (1) a specific disease or medical problem (66%); (2) a certain medical treatment or procedure (56%); (3) doctors or other health professionals (44%); (4) hospitals or other medical facilities (36%); (5) health insurance (33%); (6) food safety or recalls (29%); (7) drug safety or recalls (24%); (8) environmental health hazards (22%); (9) pregnancy and childbirth (19%); and (10) memory loss, dementia, or Alzheimer's (Fox 2011a:22). A similar survey conducted two years earlier in December 2008 included additional items about exercise and fitness and weight control. The top ten types of health information people searched for online were for: (1) a specific disease or medical problem (66%); (2) a certain medical treatment or procedure (55%); (3) exercise or fitness (52%); (4) doctors or other health professionals (47%); (5) prescription or over-the-counter drugs (45%); (6) hospitals or other medical facilities (38%); (7) health insurance (37%); (8) alternative treatments or medicine (35%); (9) how to lose weight or how to control your weight (33%); or (10) depression, anxiety, stress or mental health issues (28%) (Fox and Jones 2009:11).

Between 2002 and 2010 the two most common health topics people have searched for online have been (1) seeking information about a specific disease or medical problem, and (2) certain medical treatment or procedure (Fox 2011a). These findings suggest that a large percentage of online health information seeking is reactive – in response to concerns about a specific medical condition and a desire to learn more about the medical

problem and appropriate medical treatment. In fact, people are more likely to search for health information if they or someone close to them has recently experienced a serious medical emergency. Pew survey data from 2010 finds that 85% of people who experienced a serious medical emergency during the past year looked for health information online compared to 77% of people who have not experienced a medical crisis (Fox 2011a:12). Other studies find that poor health, measured as the number of chronic conditions, is associated with a greater likelihood of seeking health information online (Ayers and Kronenfeld 2007) and searching for information about a specific disease or medical problem, a certain medical treatment, and prescription or over-the-counter drugs (Fox 2007). However, more recent Pew survey data from 2008 finds that people with one or more chronic conditions do not differ significant from people with no chronic conditions in searching for information about a specific disease or medical problem, or a certain medical treatment; but they are more likely to search for information about prescription or over-the-counter drugs (Fox 2011a:11).

There is evidence that people are making greater usage of the Internet for seeking health information for a variety of topics other than about a specific medical problem or health condition. For example, Pew survey data gathered between 2002 and 2008 show that the percentage of adult Internet users seeking information about a specific disease or medical problem has not significantly changed (63% to 66%) (Fox and Jones 2009). However, there has been a significant increase in the percentage of Internet users who have searched online for information about exercise or fitness (36% to 52%), prescription or over-the-counter drugs (34% to 45%), certain medical treatments or procedures (47% to 55%), and alternative treatments or medicine (28% to 35%) (Fox and Jones 2009).

Between 2006 and 2008 there was a significant increase in the percentage of adult

Internet users who looked online for information about health insurance (33% to 37%)

(Fox and Jones 2009).

These findings suggest that people are becoming more proactive in their use of

the Internet to seek out information on a variety of health-related topics that may be

important to maintaining their health and preventing future illness and premature death.

In this case, current health status might be a less important factor explaining seeking

information about exercise or fitness, how to lose or control weight, and alternative

treatments or medicines as this information appears related to preventative practices

rather than to a specific health condition or medical problem. In fact, Fox (2007) found

no significant difference between adults with a chronic condition and those without in the

percentage who searched online for information about diet, nutrition, vitamins or

nutritional supplements and exercise or fitness using data from a Pew 2006 survey.

Although many adult Internet users report having sought health-related

information online, only a small proportion do so frequently. Estimates using 2008 Pew

data find that among online health seekers, about 9% do so once a week, 6% every few

days, and 4% once a day or more (Fox and Jones 2009:21). The frequency of online

health searches has been relatively stable since at least 2002. Using similar Pew survey

data, Goldner (2006a:699) found that 21% of adults sought health information online

once a week or more often. To my knowledge only one other set of surveys, the Harris

Poll, has repeatedly included questions about the frequency of online health searches.

Although not directly comparable to the Pew estimates due to differences in the wording

of the question and response categories, the most recent 2008 estimates are similar to the

Pew estimates. The Harris Poll (2008) found that among online health seekers 33%

looked 3 or more times a month and 14% did so more than once a week. However, in

contrast to the Pew findings of little change in the frequency of health searches during the

last several years, the Harris Poll data finds that people searched about half as often in

2001 as in 2008. In 2001 only 17% reported looking 3 or more times a month and about

7% did so more than once a week.

Online Health-Related Activities

      Other types of health-related use of the Internet are far less common than

information seeking. Estimates from the 2005 HINTS show that 4% of Internet users

have participated in online support groups, 13% have purchased medicine or vitamins,

and 10% have used email to communicate with health care providers (Rutten et al.

2007:13). Consistent with the findings from the 2005 HINTS showing that a low

percentage of people participate in support groups, Fox (2011a:6-9) found that few online

health seekers participate in discussions about health by creating or adding to online

health content. For example, only a small percentage of online health seekers have done

the following: posted comments, questions, or information on a health or news website

(6%), on a listserv or discussion group forum (5%), on a blog (4%), or posted a review

about a doctor (4%), hospital (3%), or their experiences with a particular drug or medical

treatment (4%).

      In summary, Americans are increasingly turning to the Internet for health

information or to participate in other health-related activities. The most common online

health seeking behavior is seeking health information, and most often people are looking

for information about a specific disease or medical problem. This suggests that a large proportion of online health activities may be reactive, in response to concerns about their poor health and to seek specific medical information. Much of the research literature has focused on health status as the primary determinant of online health information seeking. However, people may be proactive in managing their health and seek health information online or engage in other online health-related activities to help them maintain their health and prevent future illness and disease. In fact, Pew survey data finds no increase between 2002-2008 in the percentage of people searching online for information about a specific disease or medical problem, but a large increase in the percentage of people seeking health information about exercise and fitness (Fox and Jones 2009) that is important to living a healthy lifestyle. In the next section I review the research literature that examines health status and/or health behaviors as factors predicting online health seeking.

Determinants of Online Health Seeking

    Health Status

Many studies find that poor health status is associated with a greater likelihood of using the Internet to search for health-related information. However, there are conflicting findings when health status is measured by self-rated health. Some research finds that people who rate their health status as poor or fair are more likely to search for health-related information on the Internet (Baker et al. 2003; Houston and Allison 2002) while other researchers report the opposite relationship (Cotten and Gupta 2004) or no significant relationship (Atkinson et al. 2009; Goldner 2006a). For example, Baker et al.

(2003) found that those who rated their health status as fair or poor had almost twice the odds (OR 1.8) of searching for health information on the Internet, compared to those who rated their health as excellent, after controlling for differences in age, gender, household income, education, and urban residency. Cotten and Gupta (2004) conducted bivariate analysis comparing the self-rated health of offline and online health information seekers. They found that 86% of online health seekers reported their health as "excellent or good" compared to 60% of the offline health seekers. Using canonical discriminant analysis people with better self-rated health were found to be significantly more likely to search online for health information than exclusively offline.

Studies that use measures of health status other than self-rated health have produced more consistent findings of a positive relationship between health and seeking health information online. For example, Goldner (2006a) found that self-rated health, reported by participants as 'excellent or good' versus 'only fair or poor' was not a significant predictor of seeking health-related information online or the frequency of searching. However, participants who reported having a 'disability, handicap or chronic disease' that prevented them from full participation in their daily activities were about two times more likely to search for health-related information online (OR 2.17) and to do so more frequently (OR 2.11) even after controlling for self-rated health status.

Other research suggests that the total burden of poor health, rather than any specific health or medical problem, is a better predictor of the likelihood of seeking health information online (Ayers and Kronenfeld 2007; Fox 2007) and the frequency of searches (Rice 2006). Wagner et al. (2004) found that individuals with diabetes, cancer, heart problems, or depression were at no greater odds of having used the Internet to

search for health-related information during the past year compared to those with hypertension. However, those with three or more chronic conditions were at greater odds of searching the Internet for health-related information (OR 1.66), after controlling for differences in age, gender, and education.

Flynn et al. (2006) report similar findings using data from the 2004 Wisconsin Longitudinal Survey. They found that physical health, measured as health-related quality of life (the physical component summary from the SF-12) was not a significant predictor of having ever sought health information online. However, the number of health conditions (measured as the total number of eight health conditions common to older adults) was associated with a small, but significant increase in the odds of having ever sought health information on the Internet (OR 1.10), seeking information after a doctor visit (OR 1.09), and seeking information instead of or unrelated to a doctor's visit (OR 1.18). In addition, Flynn et al. (2006) found that having cancer was the only one of the eight health conditions to have an independent relationship to seeking health information online. Controlling for health-related quality of life, other health conditions, and sociodemographic factors, having cancer was associated with a 51% (OR 1.51) greater odds of seeking health information online after a doctor visit compared to having never sought health information online.

In summary, most studies find that people in poor health are more likely to look online for health information. Although there are some contradictory findings in studies that measure health status using self-rated health – studies that measure health as disability or number of chronic conditions have consistently found that people in poorer health are more likely to search for health information online.

Health Behavior

Although people often turn to the Internet for information for a specific health or medical problem, there is evidence that online health activities are associated with healthy behaviors that make up a healthy lifestyle. As noted previously, Fox and Jones (2009) in their analysis of Pew survey data found that the largest increases in online health activities between 2002-2008 have been for seeking information on exercise or fitness (36 to 52%), while seeking information about a specific disease or medical problem has not significantly changed (63 to 66%) (Fox and Jones 2009:22). Using other Pew survey data from 2006, Fox (2007) found that the number of chronic conditions was associated with an increased likelihood of seeking information related to a health problem, but was not related to seeking information about healthy behaviors (information about diet, nutrition, vitamins or nutritional supplements, and exercise or fitness).

Despite evidence showing that online health activities are becoming more common, very little empirical research has been conducted investigating the relationship between online health-related activities and information seeking to offline health behaviors. The only research on this topic that I am aware is Dutta-Bergman's (2004a, b) research examining the relationship between a person's health-orientation, choice of communication channel, and the type of health information sought. He focused on four types of health-orientation that may motivate people to seek health information: (1) health behaviors, the number of healthy activities in which a person regularly participates; (2) health consciousness, an attitude that preventative behaviors are important to one's health; (3) health-oriented beliefs, measuring the belief that specific health behaviors are important for overall health; and (4) health information orientation, a

willingness to actively seek health information. In each of these studies he used the 1999

Porter Novelli HealthStyles survey data, consisting of a stratified random sample of 2,636

respondents drawn from a research panel of 500,000 households.

In the first of these studies, Dutta-Bergman (2004b) conceptualized

communication channels as two types, active and passive. Active channels require the

person to initiate a search for health information, such as via the Internet, interpersonal

communication, and reading print materials. Passive channels transmit information to a

broad audience who may or may not be in need of health information, such as television

and radio. Dutta-Bergman (2004b) hypothesized that people who are more

health-oriented would be more likely to use active channels of communication, such as

the Internet, for health information whereas less health-oriented people would be more

likely to use passive channels. This hypothesis was largely supported. The findings show

that people who used the Internet as their primary source of health information engaged

in a greater number of healthy behaviors, held greater health-oriented beliefs, and were

more health information oriented. Dutta-Bergman (2004b) concluded that seeking health

information online is an active process that is more likely to be undertaken by individuals

who are more proactive about their health and are more likely to engage in healthy

behaviors than people who use other health information sources.

In the second study, Dutta-Bergman (2004a) examined how health-orientations

differ by type of health information participants usually seek online. The findings show

that people who searched online for information on medical news, specific diseases, and

living a healthy lifestyle engaged in a greater number of healthy behaviors than

non-seekers. There was no significant difference in the number of health behaviors

between non-seekers and seekers of information about medical services, in health-based discussion groups. Over-all, three of the four health-orientations (health information, health-oriented beliefs, and health behaviors) tended to be greater among online health information seekers than non-seekers. Health consciousness (an attitude that preventative behaviors are important to one's health), however, was significantly greater only among seekers of health lifestyle information compared to non-seekers.

Unfortunately, Dutta-Bergman did not use inferential statistical models and therefore did not control for health status in his analyses. However, Flynn et al. (2006) found that participants who reported they have to "work hard to stay healthy" were more likely to have ever sought health information online even after controlling for eight chronic health conditions, physical and mental component scores from the SF-12, total number of common health problems, and sociodemographic factors. Although Flynn et al. (2006) did not include measures of health behavior, their finding provides additional evidence that proactive health beliefs and attitudes, such as the belief that one has to work hard to stay healthy, are associated with a greater likelihood of using the Internet to seek health information.

In summary, the findings from previous research indicate that using the Internet as a primary source of health information is associated with proactive health-orientations, including engaging in a greater number of healthy behaviors, placing a greater value on preventative practices to maintain health, and willingness to find health information to educate oneself about health topics. Unfortunately, these studies use cross-sectional data and are not able to determine the causal ordering between health orientations and communication channels. Therefore, it is unknown to what extent a person's health

orientations determine online health-information seeking. Despite this limitation, these studies suggest that online health information seeking is positively associated with healthy behaviors, attitudes, and beliefs consistent with a healthy lifestyle.

Studies Examining Both Health Status and Health Behavior

Another line of research has focused on the relative strength of health status and health behaviors to predict seeking health information online. The only study that I know of that has examined the relative strength of health status and health behaviors was conducted by Pandey, Hart, and Tiwary (2003). They proposed three, exploratory models to explain online health information seeking: (1) health and wellness model, (2) health needs model, and (3) a search cost model. Using the health and wellness model, they hypothesized that the Internet had become "such an integrated part of daily life that health-conscious women use the Internet in a pro-active manner for health promotion" (p. 179). In contrast, using the health needs model they hypothesize that women with greater health needs or concerns are more likely to seek online health information. Finally, using the search cost model they hypothesize that the Internet is a low-cost alternative to traditional sources of health information that might explain likelihood of use over other sources. To measure a health-conscious orientation they created a health and wellness index of seven health behaviors that include incidence of eating out, eating a balanced diet, intensity of physical exercise, frequency of physical exercise, smoking, and annual screening examinations. Health status was measured by participants' self-rated health. Search costs were measured by employment status, time pressures at work, and time to travel to health care professionals and facilities.

To test these hypotheses they conducted a random digit dial telephone survey of 1,016 adult women living in one of three counties in New Jersey. Bivariate models demonstrated some support for all three models. However, using multivariate logit models, they found that the health and wellness index, measuring seven health behaviors, was associated with a greater likelihood of seeking health information online, controlling for health status, employment status, and sociodemographics. Health status and employment status were not significant after controlling for the health and wellness index and sociodemographics. Overall, the authors conclude that although health needs and search costs motivate seeking health information online, the results provide greater support for the health and wellness model.

This suggests that a general health-consciousness on the part of individuals is a stronger predictor of seeking health information online than health status. This may be due to several factors. First, as Pandey et al. (2003) point out in their discussion, people use the Internet as a supplemental source of health information, a finding supported by Pew survey data (Fox and Jones 2009). Specific to Pandey et al. (2003), the dependent variable measured if women had "ever" searched online for health information. Thus, the response did not directly contrast the use of the Internet to other sources of health information, such as doctors or other forms of media. The analysis merely suggests that health consciousness is positively associated with seeking health information online and therefore supports the conclusion that people who have a more proactive attitude towards their health will tend to seek out health information, even after controlling for health status and other factors.

Trust of the Internet

People's level of trust of the Internet, versus other information sources, is an important factor related to seeking health information online (Lemire et al. 2008; Rains 2007; Zulman et al. 2011). Zulman et al. (2011) found trust to be significantly related to a variety health information topics and purchasing prescription drugs, even after controlling for sociodemographic and health status. Among adults aged 50 years and older, participants who reported they trusted the Internet "a lot" or "somewhat" versus "not too much" or "not at all" were more likely to have ever used the Internet for health information (OR 4.84, $p < .001$) (Zulman et al. 2011:6). Participants who trusted the Internet as a source of health information were also more likely to have searched for information on a specific medical topic (OR 4.43, $p < .001$), health care providers (OR 2.24, $p < .050$), health policy news (OR 3.37, $p < .010$), and prescription drug prices (OR 4.93, $p < .001$), purchase prescription drugs online (OR 2.61, $p < .050$) (Zulman et al. 2011:6).

Earlier concerns that the Internet may replace the expertise of physicians appears to be unfounded. Professional health care providers and physicians are the most highly trusted source of health information for specific medical problems (i.e., cancer) and this level of trust has increased between 2002 to 2008, while trust in the Internet as an information source has decreased (Hesse, Moser, and Rutten 2010; National Cancer Institute 2010). Adults who said they trust professional health care providers and physicians "a lot" increased from 61% to 68%, whereas adults who said they trust the Internet "a lot" decreased from 23% to 19% (National Cancer Institute 2010). However, despite the decline in trust of the Internet, a larger percentage of participants turned first

to the Internet first for cancer information (55%) than to health care providers (25%) (National Cancer Institute 2010).

Several factors contribute to people's evaluation of the credibility of the health information they find online, including the characteristics of the web site, people's previous experiences using the Internet, and sociodemographics. Using 2001 Pew survey data, Fox and Rainie (2002:17) found that health information was rejected when it appeared the Internet site was too commercial (47%), did not clearly indicate the source of the information (42%), when the information was last updated (37%), lacked the endorsement of a trusted organization (30%), or appeared sloppy or unprofessional (29%). Lemire et al. (2008) identified five factors related to the frequency people use a health web site: (1) trust in the information available, (2) the perceived usefulness of the site, (3) the relative importance given to print media, (4) the level of concern for his/her health, and (5) the relative importance give to professional health care providers. Given the high level of trust placed in professional health care providers versus the Internet as a source of information (Hesse et al. 2010; National Cancer Institute 2010), it is not surprising that a doctor's website is the most trusted source of health information, followed by a medical university and federal government sites (Dutta-Bergman 2003).

Previous experience using the Internet is another factor related to people's trust of online health information. Zulman et al. (2011:7) found that years of Internet experience was associated with a greater odds (OR 1.78, $p < .050$) of trusting the Internet "a lot" or "somewhat" versus "not too much" or "not at all" after controlling for sociodemographics and health status. Socidemographic factors are also important predictors of trust in the Internet as a source of health information. Adults who are younger, female, and with

higher levels of education are more likely to report they trust the Internet as a source for

health information (Zulman et al. 2011). Adults who are younger, with higher levels of

education and income are more likely to report "a lot" of trust in the Internet as a source

of cancer information, versus other information channels (National Cancer Institute

2010).

Limitations of Previous Research

Each of the studies mentioned has made a valuable contribution to our knowledge

of the factors that determine differences among individuals seeking health information

online. However, each of these studies has important limitations. Several have focused on

health status but have not included measures of health behavior (i.e., Baker et al. 2003;

Cotten and Gupta 2004; Flynn et al. 2006; Goldner 2006b; Houston and Allison 2002)

while other studies have included health behaviors but not measures of health status

(Dutta-Bergman 2004a, b). In addition, other studies use samples that are not

generalizable to the U.S. adult population. For example, Pandey, Hart, and Tiwary (2003)

use a sample of women from only three counties in the state of New Jersey. Flynn et al.

(2006) use data from the Wisconsin Longitudinal Study – a cohort based study of

Wisconsin high school graduates in 1957. The sample is not representative of the U.S.

adult population, consisting of older, predominantly White men and women living in the

Mid-West. Finally, Dutta-Bergman (2004a; 2004b) uses data collected in 1999. Given the

rapid diffusion and adoption of the Internet as well as the many technological changes

that have taken place during the last ten years, use of data that is more recent is

warranted.

Traditional Digital Divide Factors

Although information gathering online is now a "habit for many" (Fox 2008:1) there remains significant differences in people's use of the Internet for health information seeking due to demographic and social status factors. Of particular relevance to this study is the relationship of socioeconomic status, measured by education and income. In general, people who have higher levels of education and income make greater use of the Internet to access health information (Ayers and Kronenfeld 2007; Baker et al. 2003; Cotten and Gupta 2004; Fox 2011a; Rice 2006). Education and income are key measures of social status which have been found to be significant predictors of specific capital-enhancing types of Internet use (Zillien and Hargittai 2009) and are also strong predictors of health behaviors and health lifestyles (Cockerham 2005). In the section that follows I review the literature for each of these factors as well as others that have been found to be significant predictors of online health information seeking.

Socioeconomic Status

Education. Higher levels of education are consistently found to be associated with a greater likelihood of health-related Internet use, even after controlling for other factors (Andreassen et al. 2007; Atkinson et al. 2009; Baker et al. 2003; Bundorf et al. 2006; Cotten and Gupta 2004; Dickerson et al. 2004; Flynn et al. 2006; Goldner 2006a; Hesse et al. 2005; Lorence and Heeyoung 2007; Miller, West, and Wasserman 2007; Ramanadhan and Viswanath 2006; Wagner et al. 2004; Ybarra and Suman 2006), more types of online health activities (Hale et al. 2010), and more frequent information searches (Ayers and Kronenfeld 2007). Pew survey data collected in 2010 shows that

among Internet users, 81% of people with a college degree have searched for health information online versus 45% of high school graduates and 24% of people who did not graduate from high school (Fox 2011a:6).

The increased likelihood of health-related Internet use associated with higher levels of education appears to be strong, even after controlling for other factors. For example, Bundorf et al. (2006) found that people with more than 12 years of education were about 1.8 times more likely to have searched at least once for health-related information on the Internet, compared to those with less education, even after controlling for differences in income, gender, age, type of insurance, and chronic health conditions. The increased odds of searching for health-related information on the Internet associated with more than 12 years of education appears to be greater for non-whites than whites. Miller, West, and Wasserman (2007) found that 12 or more years of education was associated with a 1.65 greater odds of accessing information on a health website during the past year among whites. However, the increased odds of having accessed health information increased to 2.99 among African-Americans and 4.22 among Hispanics.

Household Income. Although the research literature has consistently found a positive relationship between education and online health seeking, the literature regarding the relationship between household income and online health seeking is less clear. After controlling for sociodemographic factors, many early studies find a positive relationship between household income and online health seeking, while studies using data collected in the past few years find no significant relationship.

Studies using data collected between 1999-2002, and inferential statistics that controlled for other sociodemographic factors, find that higher income is associated with

a greater likelihood of searching for health-related information on the Internet (Cotten and Gupta 2004; Goldner 2006b; Pandey et al. 2003) and more frequent searches (Ayers and Kronenfeld 2007; Goldner 2006b). However, other studies using more recent data collected between 2005-2007 find that that after controlling for other sociodemographic factors, household income is not a significant predictor of online health seeking (Atkinson et al. 2009; Hale et al. 2010; Miller et al. 2007; Weaver et al. 2009).

The most recent bivariate statistics from the 2010 Pew survey finds that among Internet users, people with higher household income are more likely to have ever looked online for health information (Fox 2011a). People with household incomes of $75,000 or more (83%) and $50,000-$74,999 (71%) are significantly more likely to have searched for health information online than people with household incomes of $30,000-$49,999 (66%) and less than $30,000 (41%). Even moderate increases in household income increase the likelihood of seeking health information online. People living in households with incomes of $30,000-$49,999 are significantly more likely to seek health information online than people living in households with less than $30,000 total income (Fox 2011a:6).

The changing relationship across years might in part be due to the decreasing importance of traditional digital divide factors and the increasing importance of other, newly emerging factors. For example, Davison and Cotten (2003, 2009) have found that speed of Internet connection, measured as broadband versus dial-up modem, is a more important factor that explains differences in online activities than traditional digital divide factors such as income, education, race and gender.

Age

Studies using age as a continuous variable generally find that after controlling for sociodemographic and other factors that older adults are less likely to search for health information online (Ayers and Kronenfeld 2007; Cotten and Gupta 2004; Goldner 2006b; Pandey et al. 2003). Interpretation of results from studies using categorical measures of age are complicated by the choice of age categories and reference group. A few studies find no significant age-related differences in online health information seeking (Atkinson et al. 2009; Brodie and Flournoy 2000; Dickerson et al. 2004). However, most studies find that older adults, aged 65 and older, are less likely than middle-aged or younger adults to search for health information online (Bundorf et al. 2006; Fox 2011a; Fox and Jones 2009; Miller et al. 2007; Wagner et al. 2004; Weaver et al. 2009; Ybarra and Suman 2006).

Gender

Although there is little or no difference in the proportion of men and women who use the Internet (Rainie 2010), most studies find that women are more likely to use the Internet for a variety of health-related purposes (Andreassen et al. 2007; Flynn et al. 2006; Ybarra and Suman 2006). The most recent figures from the 2010 Pew survey show that 65% of women and 53% of men report having ever looked online for information about health or medical issues (Fox 2011a:6). Women were also found to be significantly more likely than men to have ever looked for 6 of 14 health topics online (Fox 2011a:6). Other studies using different data sets find that women are about twice as likely as men to seek health information online, after controlling for sociodemographic and health status

(Atkinson et al. 2009; Baker et al. 2003; Goldner 2006b; Hesse et al. 2005; Ybarra and Suman 2006). For example, Atkinson, Saperstein, and Pleis (2009) found that among adult Internet users in the 2005 HINTS, females were 2.23 times more likely to search the Internet for health-related information than males after controlling for age, race, education, household income, marital status, health status, and type and place of Internet access.

Race/Ethnicity

Use of the Internet for health purposes also varies by race/ethnicity. On average, ethnic minorities are less likely to search for health-related information on the Internet than whites (Dickerson et al. 2004; Fox and Jones 2009; Goldner 2006a; Lorence, Park, and Fox 2006; Miller et al. 2007; Ybarra and Suman 2006). Bivariate statistics from the most recent 2010 Pew survey show that among Internet users, 63% of whites have looked online for health information versus 47% of African Americans and 45% of Hispanics (Fox 2011a:6). Studies using inferential statistics find that after controlling for sociodemographic factors and health status, African-Americans are 40-60% less likely than whites to search online for health information (Dickerson et al. 2004; Ybarra and Suman 2006).

Marital Status and Parenting

About half (48%) of all online health information seeking is conducted for someone else, rather than the person doing the search (Fox 2011a:8). Given this fact, it is reasonable to assume that health conditions of other household members may contribute

to the likelihood of a spouse or parent to seek health information online. Unfortunately, many studies of online health information seeking do not include measures of marital status or number of children in the household (e.g., Ayers and Kronenfeld 2007; Miller et al. 2007; Pandey et al. 2003; Wagner et al. 2004; Ybarra and Suman 2006) or include these measures only as control variables (e.g. marital status for example, Atkinson et al. 2009; Hale et al. 2010; Lorence and Heeyoung 2008).

For marital status, few empirical studies have been published that examine these relationships, and those that have been published generally find no significant relationship. For example, studies using survey data collected between 2005 and 2007 find that people who are married are no more likely to search for health information online than people who are not married, after controlling for sociodemographic factors (Atkinson et al. 2009; Flynn et al. 2006; Hale et al. 2010; Weaver et al. 2009). However, some studies using 2002 Pew survey data find that married people are more likely to report having ever sought health information online (Goldner 2006b) and to have searched online for specific types of health-related information (i.e., medical treatments or procedures, experimental treatments, alternative treatments, prescription or over-the-counter drugs, and immunizations) than people who are not married (Goldner 2006a).

Even fewer studies have been published that specifically examine the relationship between parenting and online health activities. Studies that have included a measure of the number of children in the household find that it is not a significant predictor of online health information seeking (Flynn et al. 2006) or using the Internet versus another source of health information (Goldner et al. 2011). However, parental status (defined as having one or more children in the household) was found to be associated with a greater odds of

seeking health information online for others versus for self after controlling for sociodemographic factors (Stern, Cotten, and Drentea 2011).

Broadband

A broadband Internet connection can also influence how people use the Internet. The convenience of a high speed, always-on connection expands people's range and frequency of online activities (Horrigan 2008; Horrigan and Rainie 2002). Davison and Cotten (2003, 2009) argue that broadband is a new digital divide factor that is more important in explaining differences in a variety of online activities than traditional digital divide factors, including income, education, race and gender. People who access the Internet using broadband versus a dial-up modem connection are more likely to have ever looked online for health information (Fox and Jones 2009; Rains 2008a) and engage in more types of online health activities (Hale et al. 2010). Not having home broadband access is understood by many people as a "major disadvantage" to people trying to find a job and improve career skills (43%), learn new things (31%), and access government services (29%) (Smith 2010a:14). Home broadband access is also important for getting health information; 34% of adults said they thought that not having home broadband access was a "major disadvantage" and 28% said it was a "minor disadvantage" (Smith 2010a:14).

Medical Insurance

Barriers to accessing medical care may be an important factor prompting individuals to seek health-related information from other, more readily available sources,

including the Internet. Studies, however, report conflicting findings. While some studies find that the uninsured are more likely to search online for health information (Bundorf et al. 2006) others find the uninsured to be less likely to search online (Ayers and Kronenfeld 2007) or that health insurance is not a significant predictor of online health seeking (Flynn et al. 2006; Hale et al. 2010). Among Internet users, Bundorf et al. (2006) found that the uninsured and publicly insured were more likely to search for health information online than those with private insurance. They compared the odds of searching for health-related information between groups with and without chronic conditions and by type of insurance among a sample of 8,378 Internet users collected during 2000-2001. Compared to those with private insurance and no chronic conditions, having a chronic condition was associated with a 36% increase in the odds (OR 1.36) of having searched every 2-3 months or more for health information on the Internet. For the uninsured the odds increased by 94% (OR 1.94) and for the publicly insured by 160% (OR 2.60). Using data from the Wisconsin Longitudinal Survey, a relatively homogenous sample of white adults ages 63-66 years surveyed in 2004, Flynn et al. (2006) found that compared to private health insurance, there was no significant difference in the likelihood of having ever sought health-related information on the Internet by types of health insurance.

Summary

The research literature on the Internet illustrates the shifts in research questions as the technology matured and Internet access diffused across segments of the U.S. population. Early research focused on a variety of relatively simple conceptualizations of

online services and the Internet as "good versus bad" on many dimensions including quality of health information, social support and civic participation, loneliness and depression. Similarly, early models focused on various digital divide factors to understand the Internet 'haves' from the 'have nots.' With the diffusion of the Internet to wider segments of the U.S. population and the ubiquitous presence of Internet usage in many aspects of people's daily activities, research questions have moved beyond classifying outcomes as a series of binary oppositions to examine differences in how people use the Internet and how these differences contribute to persistent social inequalities. This has shifted the most commonly used conceptualization of Internet use from one based on the idea of 'digital divides' to 'digital inequalities.'

Research on online health seeking, however, has largely focused on demographic and digital divide factors to generate a profile of the characteristics of online health information seekers versus non-seekers (i.e., Atkinson et al. 2009; Brodie and Flournoy 2000; Flynn et al. 2006; Hesse et al. 2005; Houston and Allison 2002; Hsu et al. 2005; Lorence and Heeyoung 2007, 2008; Lorence and Heeyoung 2006; Lorence et al. 2006; Miller et al. 2007; Rice 2006; Wagner et al. 2004; Warner and Procaccino 2007; Weaver et al. 2009; Ybarra and Suman 2006; Ybarra and Suman 2008). This research has been useful in constructing a basic understanding of how these factors contribute to a person's likelihood of seeking health information online. However, the conceptualization of online health information could benefit from moving beyond a focus on digital divide factors to one based on digital inequality and how differences in a person's social status background contribute to the development of status-specific skills and preferences in technology and Internet use that can be understood more broadly as a form of lifestyle. In

the theory section that follows, I outline a theoretical model of health information seeking

and online health-related activities as a set of status-specific cognitions and behaviors that

may be part of a larger set of health behaviors or health lifestyle.

CHAPTER 3

THEORETICAL FRAMEWORK AND HYPOTHESES

Online health seeking, including online health information seeking and online

health-related activities, can be conceptualized as fitting into one of two broad,

classifications of behavior: illness behavior or health behavior. Kasl and Cobb (1966)

define *illness behavior* as any activity undertaken by a person who feels ill for the

purpose of defining their illness and discovering a suitable remedy (p. 246). Symptoms of

illness that interfere with a person's ability to function in their daily activities and social

roles are the primary determinants of seeking medical care (Mechanic 1995:1208).

However, an individual's interpretation of symptoms varies by social, cultural, and

psychological factors that ultimately determine whether individuals engage in self-care or

seek professional medical care (Mechanic 1980, 1995).

Online health seeking can also be conceptualized as one of many types of health

behavior. *Health behavior* is defined as "the activity undertaken by individuals for the

purpose of maintaining or enhancing their health, preventing health problems, or

achieving a positive body image" (Cockerham 2004:94). More specifically, Gochman's

(1988) definition of health behavior includes a range of cognitive factors, "those personal

attributes such as beliefs, expectations, motives, values, perceptions, and other cognitive

elements; personality characteristics, including affective and emotional states and traits;

and overt behavior patterns, actions and habits that relate to health maintenance, to health

restoration, and to health improvement" (p. 3). These definitions do not limit health behavior to healthy people, but includes people with health problems and medical conditions who seek to maintain or improve their health through diet, exercise, and other forms of behavior. Although health behavior may include contact with health care professionals for checkups and preventative care, most health-related activities take place outside of the health care delivery system (Cockerham 2004). Therefore, the conceptualization of health behavior is focused on primary and secondary preventative behaviors to maintain health, whereas illness behavior is focused on actions people take in response to symptoms of changes in bodily functioning or poor health status (Gochman 1988).

Conceptualizing online health seeking as either health behavior OHB or as illness behavior yields very different explanations of factors that may predict people's use of the Internet. As a form of online health behavior (OHB), people's use of Internet would tend to be associated with people's participation in offline health-promoting behaviors. On average health status would be expected to be positively related to OHB or not be significant predictor. As illness behavior, poor health would be the primary factor predicting OHB and offline health-promoting behaviors are not likely to be positively associated with OHB.

OHB is a relatively new topic of research and to date most research has focused on binary measures of non-specific health information seeking (e.g., have you ever sought health information online) or for specific types of health information (e.g., information on medications, a specific medical condition or illness) based on the assumption that health information seeking is a form of illness behavior and is initiated

by a specific health concern or medical problem (Lambert and Loiselle 2007). This body of research has been useful in advancing our understanding of online health information seeking by illustrating the many digital divide factors (i.e., age, gender, education, income, and place) that characterize online health information seekers versus non-seekers. However, most research cited in the previous literature review lacks a well-developed theoretical model and does not test formal hypotheses (e.g., Atkinson et al. 2009; Brodie and Flournoy 2000; Flynn et al. 2006; Hesse et al. 2005; Houston and Allison 2002; Hsu et al. 2005; Lorence and Heeyoung 2007, 2008; Lorence and Heeyoung 2006; Lorence et al. 2006; Miller et al. 2007; Rice 2006; Wagner et al. 2004; Warner and Procaccino 2007; Weaver et al. 2009; Ybarra and Suman 2006, 2008).

The focus of this dissertation is examining OHB, measured as online health information seeking and online health-related activities, as one of many health behaviors that represent a *health lifestyle.* To do so, I draw on Cockerham's (2005) conceptualization of health lifestyle, which he defines as "collective patterns of health-related behavior based on choices from options available to people according to their life chances" (p. 55). Although OHB is not generally conceptualized as a behavioral component of health lifestyle, changes in the health care system has weakened the professional dominance of physicians and the monopoly over medical knowledge (Light 2008) and placed greater responsibility on individuals as consumers who must make choices on how to best maintain their health and manage their health care if they become ill (Conrad 2005; Crawford 1980, 2006).

The development of a new theoretical framework for understanding OHB is needed to move beyond a focus on digital divide factors as predictors of Internet 'haves'

versus 'have-nots' (e.g., Barzilai-Nahon 2006; DiMaggio and Hargittai 2001; DiMaggio et al. 2004; van Dijk 2006; Warschauer 2003) and the focus on information seeking to understand gradations in the many types of health-related uses people make of the Internet. The digital inequality framework illustrates that a person's social status background is a strong predictor of Internet use and participation in a variety of Internet activities that contribute to the reproduction of social inequality (DiMaggio and Bonikowski 2008; North et al. 2008; Roderick 2008; Zillien and Hargittai 2009). However, a theoretical model that explains status-based differences in OHB has not been fully developed.

I seek to develop a theoretical framework that links health lifestyle theory and the digital inequality framework and Boudieu's concept of habitus. I use this new framework to explain how social and structural conditions (i.e., social status and Internet access) influence attitudes and behaviors. Thus, I seek to bridge previously disparate lines of research and theory to conceptualize OHB as status-specific health behaviors consistent with the concept of health lifestyles. In the following section I will briefly outline: (1) the main elements of health lifestyle theory and Bourdieu's concept of habitus, (2) social conditions that influence habitus and health lifestyles, (3) the concept of Internet habitus, and (4) how structural conditions (i.e., Internet access) contribute to an Internet habitus and status-specific attitudes and behaviors.

Health Lifestyles

Cockerham (2005) defines health lifestyles as "collective patterns of health-related behavior based on choices from options available to people according to their life

chances" (p. 55). Rather than strictly individual choices, health behavior is conceptualized as distinctive health lifestyles associated with a person's social class background. Therefore, health lifestyles "are not the uncoordinated behaviors of disconnected individuals, but are personal routines that merge into an aggregate form representative of specific groups and classes" (p. 56). Health lifestyles consist of socially patterned health behaviors that contribute to good health or poor health (Cockerham 2004). This may include contact with health care professionals for preventative care, but the majority of health-related behaviors take place outside the health care system as part of people's routine activities (Cockerham 2004). The most commonly measured health behaviors are smoking, diet, physical activity, and alcohol use (Cockerham 2005:62). Citing examples from the United States, the United Kingdom, and Russia, Cockerham (2005) notes that virtually every study confirms that "the lifestyles of the upper and upper-middle classes are the healthiest" (p. 58) and that more disadvantaged social groups tend to engage in fewer positive health behaviors.

While some researchers highlight how dimensions of social status increase individual agency (choice) in health behaviors (e.g., Mirowsky and Ross 2003), health lifestyle theory highlights the effect of social conditions (structure) to generate status-specific patterns of behavioral choices that are relatively durable and that are reproduced over time (Cockerham 2005). Cockerham (2005:56) identifies four categories of structural conditions which influence lifestyle choices: (1) class circumstances, (2) demographic factors, (3) collectivities, and (4) living conditions. Class circumstances are most often conceptualized as socioeconomic status (SES) using three variables that measure level of income, education, and occupational prestige (Cockerham 2004:98).

Demographic factors include age, gender, and race/ethnicity. Collectivities are defined as groups of individuals who are linked together through social networks and share norms, values, and ideals that constitute a particular worldview (Cockerham 2005:59). Living conditions can also enable or constrain peoples' choices and include factors such as differences in neighborhoods, housing, and basic utilities (e.g., electricity, gas, water supplies).

As described by Cockerham (2005) health lifestyle theory is primarily derived from the work of two social theorists, Max Weber and Pierre Bourdieu. Weber provides the key formulation of the modern sociological concept of lifestyle as the dialectical interplay between life choices and life chances. Bourdieu contributes the concept of habitus to illustrate how social conditions are internalized as differences in socially stratified cultural "tastes" as attitudes, values, and preferences that contribute to habitual patterns of behavior and are reproduced across generations.

Weber: Lifestyles

Weber contributes to the understanding of health lifestyles in two ways (Cockerham, Rütten, and Abel 1997). First, he provides a sociological framework of human action as the dialectical interplay between life choices (agency) and life chances (social conditions or structure). Second, he links the concepts of lifestyle and status groups by pointing out that a particular lifestyle is expected of people who wish to belong to a specific status group.

Weber provides a key theoretical contribution to the understanding of lifestyles as the dialectical relationship between life choices and life chances (Cockerham, Abel, and

Lüschen 1993:418). Abel and Cockerham (1993) make a clear distinction between the three terms Weber uses to express his concept of lifestyles. *Lebensstil* or *Stilisierung des Lebens* that means lifestyles, *Lebensführung* meaning life conduct, and *Lebenschancen* meaning life chances. Current English editions translate *Lebensführung* as lifestyle, instead of life conduct or choice. This blurs the distinction in Weber's conceptualization of lifestyle as the dialectical interplay of life choices and life chances. Life choices refers to individual agency in the selection of behavior, whereas life chances refers to social conditions (structure) that determine the probability the individual will realize their choices (Abel and Cockerham 1993; Cockerham 2005; Cockerham et al. 1993; Cockerham et al. 1997). Therefore, people's lifestyle choices are largely constrained or enabled by their social status and their access to economic and material resources. People are not likely to engage in activities when economic and material resources present barriers to access or participation.

Weber points out that other social factors contribute to determining lifestyle choices. As economic and material constraints are reduced, Weber proposed that people's lifestyle choices reflect their membership in social groups stratified by levels of social prestige and esteem. These 'status groups' consist of patterns of consumption which represent 'styles of life' that are expected of group members (Weber [1922] 1978). Thus, lifestyle choices are not strictly determined by a person's economic and material resources, but also by people's efforts to participate in particular social groups. Thus, lifestyle choices also serve as meaningful markers of differences between status groups. In fact, status plays a more important role than class in Weber's theorizing, with class primarily indicative of position in the economic structure represented by level of income

and property, whereas status groups are aggregates of people who share similarities in education, interests, and/or occupational prestige (Weber [1922] 1978:936).

Although Weber provides the key conceptualization of lifestyle as the exercise of individual choice bounded by the opportunities and constraints associated with social conditions and resources, he does not provide a detailed explanation of how social status-related differences in behavioral patterns develop and persist across time. To explain health behaviors as socially patterned health lifestyles, Cockerham (2005) draws on Bourdieu's concept of *habitus* as the "centerpiece in the health lifestyle paradigm" (p. 63).

Bourdieu: Habitus

The problem of social reproduction was a primary theoretical concern of Bourdieu, who sought to understand the relations between social structural conditions, culture, and behavior (Swartz 1997:6). Whereas Weber emphasized status and social prestige as markers of boundaries between groups, Bourdieu's emphasis is on the struggle for power between social classes in the legitimation of one set of symbolic, cultural tastes as signs of social status position that are differentially rewarded and thus maintain and reproduce social inequalities. Bourdieu does this by developing a cultural framework that links class-based differences in socialization experiences that are incorporated into a person's attitudes, beliefs, preferences, and behavioral routines as *habitus* (Bourdieu [1980] 1990; Bourdieu and Wacquant 1992).

Bourdieu ([1980] 1990) defines habitus as "a system of durable, transposable dispositions, structured structures predisposed to function as structuring structures, that

is, as principles which generate and organize practices and representations that can be objectively adapted to their outcomes without presupposing a conscious aiming at ends or an express mastery of the operations necessary to attain them" (p. 53). What Bourdieu is saying, is that habitus is set of embodied ways of perceiving, thinking, and acting that once established, are relatively durable and not easily changed. Once established, these "structuring structures" tend to guide future behavior in ways that are largely routine and habitual. Behaviors often closely reproduce the social conditions experienced during socialization of the individual due to the close correspondence between external social conditions; internalized cognitive structures, and behavior. Therefore, the habitus provides enduring dispositions to act in ways that are consistent with the opportunities of the individual's social class background. Bourdieu's concept of habitus expands on Weber's concept of lifestyle as the interplay of life choices and life chances – to explain why people from similar class backgrounds will have similar socialization experiences and are likely to develop a similar habitus and engage in similar health behaviors (Cockerham 2005).

To explain how class conditions contribute to differences in habitus, Bourdieu (1984) developed the concept of "distance from necessity" which he describes in the book *Distinctions.* In this book, Bourdieu examines French lifestyles to illustrate that a person's habitus reflects a set of cultural tastes. Differences in cultural taste vary according to one's social class position and "distance from necessity" or ability to exercise choice given the constraints of one's resources (Bourdieu 1984) or what Weber calls, life chances. Privileged classes have greater flexibility in their choices and develop cultural tastes that are less constrained by economic or material necessity, whereas

members of the working class are more limited in their choices. As a result, privileged

classes have greater freedom to make choices that reflect high-status, cultural values that

serve as symbolic markers of their privileged social class position. The working class

must make more pragmatic choices, given the constraints of their social class position

and resource, and internalize and attitudes and values that makes a virtue out of the

necessity of their choices (Bourdieu 1984). As a result, different social classes develop

different sets of habitus and different attitudes, preferences, and justifications for the

cultural tastes they acquire. Cultural tastes are imbued with power, as one set of tastes is

more highly regarded and confers greater prestige, status, and power; while other tastes

are considered more common.

An example that is often cited (e.g., Cockerham 2000, 2005) of the relationship

between social class and cultural tastes relevant to health lifestyles comes from

Bourdieu's discussion in *Distinctions*. Bourdieu (1984:177-200) argues that the French

working class developed a preference for foods that are cheap, nourishing, fatty, and

hearty that is consistent with working class attitudes related to male strength. In contrast,

the French professional class prefers food that is light, low in calories, and with more

refined or delicate flavor. A contemporary example in the U.S might find that working-

class individuals are more likely to shop at "big-box" stores where they purchase large

quantities of prepared foods that are relatively inexpensive, have long shelf lives, and are

convenient to prepare; whereas the more privileged classes tend to shop at specialty

stores that sell foods that emphasize flavor, freshness, nutrition, and are organic. Working

class shoppers make a virtue of necessity and develop a preference for the taste of canned

and frozen foods while shoppers from more privileged classes develop a taste for fresh,

organic foods. Thus, 'distance of necessity' is a useful concept to understand how a person's social class background contributes to distinct class-related differences in habitus and cultural tastes that are markers of differences between social groups and contributes to the maintenance and reproduction of social group boundaries and social stratification.

Although habitus is most often measured by behavioral choices, it also is understood to be a "subjective style of thinking and perceiving that is characteristic of particular people and social classes" (Cockerham and Hinote 2009:202). Thus, the relationship between structural conditions (i.e., SES and Internet access) and behavior (i.e., health behavior and health-related Internet use) is related with status-specific attitudes, beliefs, and preferences. Although status-specific attitudes are less studied than behavioral outcomes as elements of habitus, there has been a good deal of theory and empirical research that demonstrates the relationship between social status, attitudes, and health behavior.

In terms of health behavior, perhaps the most important cognitive factor is sense of control or mastery. Individuals who perceive themselves as having a high degree of personal control believe they can "master, control, and effectively alter the environment" to direct the course of their own life (Mirowsky and Ross 2003:60). The opposite of sense of control is perceived powerlessness—the belief that outcomes are beyond one's personal control or efforts, and are determined by external forces such as powerful others, luck, fate, or chance (Mirowsky and Ross 2003). A strong sense of control serves as a protective factor that enables individuals to deal more effectively with the challenges and stressors of daily living (Pearlin et al. 1981).

Findings focus on the relationship between level of education, sense of control, and health behaviors. This body of research demonstrates that the better educated develop a greater sense of control over their lives (Mirowsky and Ross 1998) and have a greater sense of control for their health (Cockerham et al. 1986). For example, Mirowsky and Ross (1998) found that level of education was positively associated with a sense of control or mastery over one's life that was in turn, associated with health-promoting behaviors including physical exercise, not smoking tobacco, and moderate consumption of alcoholic beverages. .

Summary of Health Lifestyle Theory

The health lifestyle theory proposed by Cockerham (2005) seeks to give appropriate theoretical weight to both individual-level factors and social conditions that influence health behavior choices. Rather than strictly individual choices, health behaviors are conceptualized as a *health lifestyle,* defined as "collective patterns of health-related behavior based on choices from options available to people according to their life chances" (Cockerham 2005:55). This definition highlights the dialectical interplay of life choices (agency) and life chances (structural conditions) central to Weber's concept of lifestyle. Bourdieu's concept of habitus provides the key concept linking social class conditions to the development of enduring patterns of health behavior or health lifestyles. Habitus can be understood as a cognitive map of social conditions that produces enduring and routine patterns of thought and perception that when acted upon tends to reproduce the social conditions from which they are derived (Cockerham 2000:164).

Internet Habitus

Digital inequality scholars have also used Bourdieu's concept of habitus to explain how structural conditions influence peoples' attitudes and Internet usage (Hargittai 2010; Kvasny 2006; Kvasny and Truex 2000; North et al. 2008; Robinson 2009; Zillien and Hargittai 2009) that can be described as representing an 'Internet habitus.' For example, Zillien and Hargittai (2009) found that among adults, social status (measured using a composite of educational degree, income, occupation, and interviewer rating) was positively associated with using the Internet for information gathering activities and personal financial transactions, even after controlling for differences in equipment, access, technology experience, and general interest in technology. They conclude that "differences in Internet use cannot be attributed simply to individual variation in motivation, interest, or will" and that scholars must take into account "something status related that we—following Bourdieu (1984)—can perhaps call habitus" to explain the independent relationship of social status and types of Internet use (Zillien and Hargittai 2009:288-289). In a similar study using a sample of U.S. college students, Hargittai (2010) found that students from higher social status backgrounds (measured by parents' highest level of education and race/ethnicity) engaged in more information seeking activities online and a greater diversity of activities online than their counterparts.

North, Snyder, and Scott (2008) draw on Bourdieu's concepts of habitus to propose that young people's social status background (measured by parents' level of education and income) influences their exposure to and experiences using ICT that shape distinct forms of status-based 'digital tastes' in their preferences for technology use.

Similar to Bourdieu's finding of distinct differences in habitus and tastes in food and leisure activities among the French working and middle class, North and colleagues found that although study participants had similar levels of ICT access and knowledge, they developed distinct status-based differences in 'digital tastes' and preferences for ICT use (North et al. 2008:908). Thus, what might appear as strictly individual preferences for ICT use are in fact determined in part by the habitus, which s the internalization of a person's experiences within the opportunities and constraints of their structural conditions. New forms of technology are "accepted as valuable or rejected depending on how well they fit with already existing thoughts and processes incorporated into the habitus" (North et al. 2008:899).

In addition to social conditions (e.g., SES measured as level of education, income), structural conditions specific to Internet access can influence Internet habitus. Perhaps the two most fundamental factors of Internet access are (1) the technical means people have to access the Internet, and (2) a person's degree of autonomy or freedom to access and use the Internet when and where they want (Hargittai 2008). Inequalities in Internet access influences people's experience using the Internet, their development of online skills, and what they do online (Hargittai 2008).

Robinson (2009) used Bourdieu's concept of 'distance from necessity' to examine how Internet access is related to an 'informational habitus' that reveals how constrained access influences attitudes and Internet usage. Compared to the high access group, the low access group had no home Internet access or slower dial-up modem access, less time available to use the Internet, and in general experienced less autonomy in their ability to access and use the Internet. Robinson (2009) found that the low access group experienced

greater constraints and developed a task-oriented approach to Internet use that

emphasized accomplishing Internet tasks as quickly as possible. In contrast, people in the

high access group had more time to leisurely explore the Internet and developed better

information seeking skills. High access users conducted more searches on a topic, were

more likely to compare the information found from multiple sources, and reported

finding information online to be relatively easy. The low access group is less effective or

efficient searching for information online, and report more frustration and confusion

about the results of their searches.

Communication scholars have also developed theoretical models that illustrate

how prior experiences using the Internet contribute to differences in attitudes and health

information seeking behavior consistent with the concept of an Internet habitus. The

Comprehensive Model of Information Seeking (CMIS) was proposed by Johnson and

Meischke (1993) to explain usage of particular channels for information versus other

possible sources (Johnson 2003). The basic model consists of three primary types of

variables: antecedent, information channel, and information seeking behavior.

Antecedents include sociodemographic factors (e.g., age, gender, race/ethnicity, and

socioeconomic status), experiences (including health status and wider social

experiences), salience (perceived utility of the information channel), and beliefs (e.g.,

perception of lack of knowledge, self-efficacy). Information channel factors relate to

characteristics of various types of information channels (e.g., family and friends, health

care providers, print media, TV, radio media) objective measures of the channel's

usefulness to the specific needs of the information seeker. Finally, the last set of variables

are information seeking behaviors, that may be active seeking or passive exposure to information.

Although the CMIS is not specific to Internet use, Rains (2007, 2008b) adapts this model to identify specific attitudes and beliefs (i.e., self-efficacy and trust of online health information) that might mediate the relationship between previous experiences and health-related Internet use. Drawing on Bandura's (1986) concept of self-efficacy, Rains (2008b) argues that people's experience using the Internet contributes to the knowledge and skills required to successfully find health information online, and a greater sense of self-efficacy. Results from an empirical study found that online health information seeking self-efficacy completely mediates the relationship between Internet experiences and perception of successful online health information seeking (Rains 2008b). Trust of online information sources may also be related to previous experiences and perception of the salience, or utility of a particular channel to find needed information. In a similar study using the CMIS framework, Rains (2007) found that trust or online health information sources was positively related to seeking health information online and with the perceived usefulness of the information found.

Summary and Conceptual Model

Figure 1 presents the full conceptual model. The primary independent variables are measures of social conditions that measure social status (SES as education and income) and structural conditions that measure Internet access (i.e., broadband Internet connection, number of Internet access places). Habitus is measured as a cognitive dimension (health and Internet related attitudes) and a behavioral dimension (i.e. offline

health-related behaviors and online health-related behaviors). The dependent variables are measures of OHB, specifically online health information seeking and online health-related activities. Due to the many causal relationships predicted by the conceptual model, it is useful to first summarize the main conceptual components and the general hypothesized relationships.

Figure 1. Conceptual Model
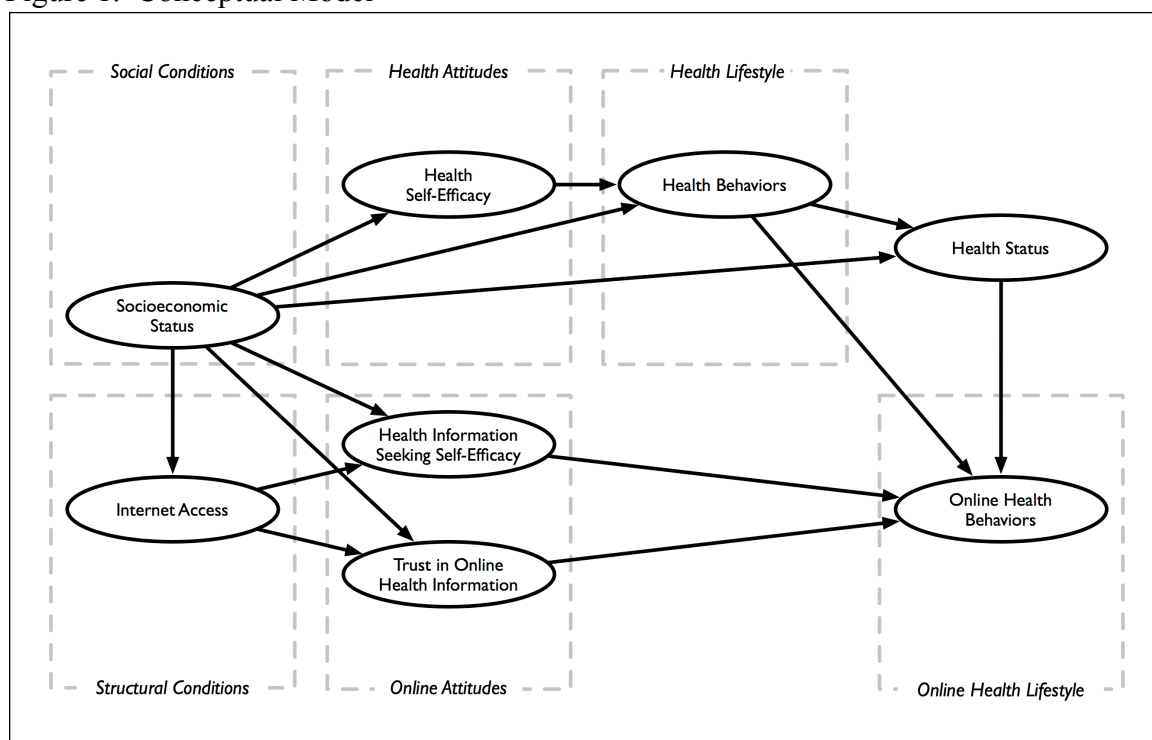
The upper half of the model illustrates the hypothesized causal relationships predicted by health lifestyle theory. The causal order follows a path from social conditions (SES) → health habitus (cognitions or attitudes) → health habitus (health

behaviors) → health status → Internet habitus (online health behaviors). Social conditions are measured by SES, that are hypothesized to be positively associated with a health habitus consisting of a cognitive dimension measured by health-related attitudes (health self-efficacy), and offline health-related behaviors. Health-related attitudes and behaviors are positively associated with health status. OHB, conceptualized as health behaviors that are collectively patterned as an OHB lifestyle, are positively associated with SES. Additionally, SES will have a positive, indirect effect on OHB via health attitudes and health behaviors (health lifestyle). Based on the premise that OHB is a form of health behavior, health status should have a positive, direct effect on OHB or no statistically significant effect.

The lower half of the conceptual model is similar to health lifestyle theory, but draws on the digital inequality framework to add measures of Internet access as important elements of structural conditions that influence Internet habitus. The hypothesized causal relationships follow the path of social conditions (SES) → structural conditions (Internet access) → Internet habitus (attitudes) → Internet habitus (online health behavior). The general hypothesis is that OHB represents an Internet health lifestyle and that social conditions (SES) will have positive, significant direct effects as well as positive indirect effects via Internet access and Internet attitudes. Additionally, since Internet access is an important element of structural conditions that influence Internet habitus, it may have a positive direct effect on OHB and indirect effect via Internet attitudes.

Research Questions and Hypotheses

The goal of this dissertation is to answer three research questions: (1) Are online health behaviors better explained as illness behavior or health behavior? (2) Does online health behavior fit the conceptualization of lifestyles? (3) Is there a relationship between online health behavior and offline health behavior that might suggest a broader pattern of health-promoting behavior or health lifestyle? In the section that follows, I state hypotheses derived from the proposed theoretical framework to answer each of the three research questions.

Research Question 1

At the most fundamental level, OHB can be conceptualized as either illness behavior or health behavior. Illness behavior is largely driven by a person's perception of changes in body functioning as symptoms of illness. In response, people engage in behaviors that may include searching for health information to make sense of their symptoms and to determine the type of medical care they need to get well (Kasl and Cobb 1966; Mechanic 1980, 1995). Thus, OHB will be largely a reactive behavior, in response to a person's perception of poor health status, and is hypothesized to be negatively associated with health status. In contrast, the concept of health behavior emphasizes preventative and proactive behaviors to maintain health and avoid illness (Cockerham 2004; Gochman 1988). As a form of health behavior, OHB will have a positive or no relationship to health status, but is expected to be more strongly related to a range of offline health behaviors that people practice to maintain their health and prevent illness and premature death.

Given the focus of this dissertation on the conceptualization of OHB as status-based patterns of health behavior or a health lifestyle, I hypothesize:

H1:   Health status has either a positive or no direct effect on OHB.

H2:   Health behavior has a positive direct effect on OHB.

Research Question 2

Health lifestyle theory adds to our understanding of health behaviors by illustrating that people's choices are not random, but depend on their social conditions that enable or constrain their choices of health behavior. The most important component of social conditions related to health lifestyles is social class, most often measured as SES (Cockerham 2005). Bourdieu's (1984, [1980] 1990) concept of habitus is a key element of health lifestyle theory and is used to explain how a person's experiences within the opportunities and constraints of their social conditions become embodied as habitus and status-specific tastes. The habitus is a cognitive map that tends to reproduce behavior in consistent, status-specific patterns or lifestyles (Cockerham 2005). Habitus can be conceptualized as consisting of cognitive factors (i.e., attitudes, values, and preferences) and as observed behaviors that represent a lifestyle (Cockerham and Hinote 2009).

Thus, social status should have a positive relationship to health behavior and positive indirect effect via habitus-related cognitions or attitudes. Based on the above, I propose the following hypotheses:

H3   SES has a positive, direct effect on health behavior.

H4   SES has a positive direct effect on health self-efficacy.

H5   Health self-efficacy has a positive direct effect on health behavior.

H6   SES has a positive indirect effect on health behavior via health self-efficacy.

Similar to health lifestyle theory, the digital inequality framework has drawn on the concept of habitus to explain how social status is related to Internet use (Hargittai 2010; Kvasny 2006; Kvasny and Truex 2000; North et al. 2008; Robinson 2009; Zillien and Hargittai 2009). Rather than focusing on whether people use or don't use the Internet, the digital inequality framework focuses on social conditions that influence the development of Internet-related attitudes, skills, and behaviors (DiMaggio et al. 2004; Hargittai 2008). Additionally, the digital inequality framework highlights structural conditions, such as level of Internet access, as important factors that influence the development of distinct 'digital tastes' and an 'Internet habitus' (North et al. 2008; Robinson 2009; Zillien and Hargittai 2009). Social status and level of Internet access influence people's experience using the Internet and contributes to the development of distinct forms of 'informational habitus' (Robinson 2009) and that may consist of increased sense of self-efficacy to find health information online and greater trust of online information sources that predicts health-related Internet usage (Rains 2007, 2008b).

Thus, social status and structural conditions specific to the Internet (i.e., Internet access) should have a positive direct effect on OHB and an indirect effect via habitus-related attitudes (i.e., health information seeking self-efficacy and trust of online information sources). Based on the above, I propose the following hypotheses:

H7   SES has a positive direct effect on OHB.

H8   SES has a positive direct effect on Internet access.

H9   SES has a positive direct effect on health information seeking self-efficacy and trust of online health information.

H10   Internet access has a positive direct effect on OHB.

H11   Internet access has a positive direct effect on health information seeking self-efficacy and trust of online health information.

H12   Health information seeking self-efficacy and trust of online information sources have a positive direct effect on OHB.

H13   SES has a positive indirect effect on OHB via Internet access or via health information seeking self-efficacy and trust of online health information have a direct positive effect on OHB.

H14   Internet access has a positive indirect effect on OHB via health information seeking self efficacy and trust of online health information.

Research Question 3

Research Question 3 is answered by reviewing the findings from the previously stated hypotheses. For OHB, measured either as online health information seeking or online health-related activities, to be considered a lifestyle H7-H14 should generally be supported. In addition, as evidence that OHB is part of a more general set of health-promoting behaviors that represent a health lifestyle (i.e., diet, physical activity, and non-smoking), H2 should be supported. Finally, as a form of health behavior OHB should not be significantly related to health status, thus H1 should be supported.

CHAPTER 4

METHODS

Data

Data comes from the National Cancer Institute's 2007 Health Information

National Trends Survey (HINTS). HINTS is a cross-sectional survey that collects

nationally representative data about cancer-related health communication. The survey

also includes a wide variety of questions about health communication and

communication channels, including the Internet and specific types of online health

activities that are not cancer-specific. HINTS is administered every 2-3 years and has

been conducted in 2003, 2005, and 2007. The 2007 HINTS data was collected between

December, 2007 and April 2008. The data set and documentation about the design and

administration of the survey instrument are available online.[2]

The 2007 HINTS uses a dual-frame, mixed mode design that is based on

experiments conducted with the Behavioral Risk Factor Surveillance System (BRFSS)

data collection and is intended to counteract the trend of declining response rates to

random digit dialing (RDD) administered surveys (Cantor et al. 2009). One frame used a

list-assisted RDD to randomly sample telephone numbers from sets of 100 telephone

numbers where at least one is a residential number. One adult is randomly selected from

the sampled household to respond to the computer-assisted telephone interview (CATI).

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[2] See the Health Information and National Trends Survey website, located at:
http://hints.cancer.gov.

The screener response rate was 42.4%, the extended interview response rate 57.2%, and the over-all response rate was 24.2% (N = 4,092). The second frame used a mail survey and a stratified sample that oversampled minorities. The sample was selected from a listing of addresses provided by the United States Postal Service. This listing included households with and without a landline telephone. All adults at a sampled household were asked to complete the mail survey. The household response rate was 40%, the within household response rate was 77.4%, and the over-all response rate was 31% (N = 3,582).

Sample and Replicate Weights

The data set contains two types of weights: sample weights and replicate weights. Three sets of sample weights are computed, one for the mail mode sample, one for the RDD mode sample, and a combined sample weight for analysis using both survey modes. The sample weights are designed to adjust for non-response and coverage bias in the sample and include adjustments for demographics, ever having cancer, and health insurance status (Cantor et al. 2009). Use of the weights is recommended to achieve point estimates that are representative of the national population.

Replicate weights are also computed for each mode and for analysis using the combined survey modes. Replicate weights are needed to adjust the computation of the standard errors needed for inferential statistical tests that involves the calculation of p-values and confidence intervals. This is necessary because the 2007 HINTS data collection is not a simple random sample, but is comprised of a stratified random sample (the RDD mode), and a stratified sample clustered by households (the mail mode).

Therefore, participants are drawn from clusters that tend to be similar in a variety of ways. Because of the similarities among participants, conventionally computed standard errors will be incorrect, and most often underestimated (Kalton 1983). To compensate for this design effect requires information about how sampled participants are clustered, typically using geographic identifiers that can compromise the anonymity of participants. Replicate weights allow statisticians with access to this confidential data to construct a series of replicates weights that can be used to make adjustments to the computation of standard errors.

Details regarding the computation of the sample and replicate weights can be found in the *2007 HINTS Final Report* by Cantor et al. (2009). Recommendations about the use of weights and the syntax appropriate to specify the weights using a variety of statistical packages are provided with the data set. Unless specifically noted, all analysis presented in this dissertation are conducted using the sample and replicate weights as recommended in the 2007 HINTS documentation.

Analytic Sample

Despite the use of weights, estimates may vary significantly by mode of survey administration due to differences in non-response, coverage, and measurement differences related to the mail instrument versus CATI. Preliminary analyses by Cantor and McBride (2009) found that there are significant mode effects for questions related to use of the Internet and looking for health information. Cantor and McBride suggest that the mail mode data is the best choice when analysis will focus on questions related to

Internet use and looking for health information. Following this advice, I use only the mail mode sample ($N = 3,582$) in this study.

The analytic sample is restricted to participants who are Internet users ($N = 2,526$), defined as participants who responded 'yes' to the question, "Do you ever go on-line to access the Internet, World Wide Web, or to send and receive e-mail?" Analysis using the Internet user sub-sample focuses on differences in key variables among Internet users rather than digital divide factors related to Internet use and non-use. The analytic sample is further restricted to participants who have home Internet access ($N = 2,191$). This excludes 335 participants who do not have home Internet access or are missing data on this variable. Excluding participants who do not have home Internet access focuses the analysis on the difference between dial-up modem access and high-speed broadband access. This yields the *Internet User* sub-sample which is used to model factors related to the number of online health-related activities participants have engaged during the past year. To examine factors that predict the use of the Internet as a health information source versus other information sources, a second *Health Seeker* sub-sample is used. This sub-sample is further restricted to participants who responded 'yes' to the question, "Have you ever looked for information about health or medical topics from any source?" This is necessary because only health seekers were asked the follow-up question about the source of their last health information search. This reduces the *Internet User* sub-sample by 204 participants to $N = 1,987$.

Missing Data

The size of the two subsamples was further reduced due to cases with missing data on variables common to both sets of statistical models. Only two variables were missing data on more than 2.1% of cases: the health lifestyle index (136 cases, 6.2%) and household income (156 cases, 7.1%). Household income was imputed using a regression modeling technique in Stata 10.1 using the 'uvis' command (Royston 2004). Because household income is an ordinal level measurement, an ordered logit model was specified using 3 predictor variables found to be significantly correlated with household income: (1) education level, (2) a binary variable indicating the participant is unemployed, and (3) self-rated health. Household income was not imputed for cases missing data on one of the three predictor variables. Thus, missing data was imputed for 104 observations in the *Internet User* subsample and 99 observations in the *Health Seeker* subsample. The final size for the *Health Seeker* subsample is 1,887 and for the *Internet User* subsample is 1,734.

Measures

Dependent Variables

The focus of this study is two set of variables that measure the concept online health behavior (OHB). The first dependent variable, *online health information seeking (OHIS),* is derived from the question, "The most recent time you looked for information about health or medical topics, where did you go first?" Participants may select one of 12 listed sources or specify another source. Possible sources included: (1) books, (2) brochures, pamphlets, etc., (3) cancer organization, (4) family, (5) friend/co-worker, (6)

doctor or health care provider, (7) Internet, (8) library, (9) magazines, (10) newspapers, (11) telephone information number, (12) complementary, alternative, or unconventional practitioner. The variable is coded 1 = online health information seeking and 0 = all other health information sources. This question is asked of all participants and enables the analysis to focus on the factors that predict online HIS versus other sources of health information between Internet users and non-users.

The second dependent variable, *online health-related activities (OHRA),* in a summated index intended to measure the participant's engagement in a range of online health behaviors during the past 12 months. The index is constructed from six items that assess whether participants have: (1) bought medicine or vitamins online; (2) participated in an online support group for people with a similar health or medical issue; (3) used email or the Internet to communicate with a doctor or a doctor's office; (4) used a website to help you with your diet, weight, or physical activity; (5) looked for a healthcare provider; (6) kept track of personal health information, such as care received, test results, or upcoming medical appointments. Responses for each item are coded 0 = no and 1 = yes.

The OHRA index was created only for cases with no missing data on any of the six items. The OHRA index has a range of 0-6, with a higher score represents engaging in a greater number of online health-related activities. Cross-tabulation tables with other key variables indicated few or no observations at the high end of the OHRA index. To ensure there were no cells with few or no observation, the OHRA index was collapsed, recoding cases with a score of 6 as 5 and yielding a range of 0-5 on the variable used in the statistical analyses. Since the items that comprise the index are binary, factor analysis

was conducted in Stata 10.1 using the 'tetrachroic' command to produce a tetrachoric

correlation matrix, and the 'factormat' command to estimate the number of factors and

variance. The results show the four items load on a single factor that explains 49.2% of

the variance. Chronbach's alpha is .572.

Independent Variables

    Health Behavior

    Health behavior (HB) is measured using a summated index created from four

items that assess the frequency participants engage in four health behaviors: (1) daily

fruit servings, (2) daily vegetable servings, (3) physical activity during the past week, and

(4) tobacco use. Items were recoded to create dichotomous variables that indicate 1 =

meeting healthy behavior recommendations and 0 = less healthy behavior. In previous

research using the HINTS 2003 data, researchers used these four items to create a health

behavior or lifestyle index by summing the number of healthy behaviors reported by

participants (Shim, Kelly, and Hornik 2006). I follow this same method and construct a

health behavior index with a higher score indicating participants engage in a greater

number of recommended health behaviors. Although few individuals engage in entirely

positive or negative health lifestyles (Blaxter 1990; Reeves and Rafferty 2005), the use of

an index comprised of healthy behaviors provides a more parsimonious overall measure

of healthy lifestyle choices. Studies have used similar indexes of health behavior to

identify groups at greater risk of chronic diseases (Ford et al. 2009; Jiao et al. 2009;

Kurth et al. 2006).

The HB index was created only for cases with no missing data on any of the four items. The HB index has a range of 0-4, with a higher score representing engaging in a greater number of healthy behaviors or a healthier lifestyle. Since the items that comprise the index are binary, factor analysis was conducted in Stata 10.1 using the 'tetrachroic' command to produce a tetrachoric correlation matrix, and the 'factormat' command to estimate the number of factors and variance. The results show the four items load on a single factor that explains 47.6% of the variance. Chronbach's alpha is .432. Details of the recoding used to create each of the binary measures of meeting recommended healthy behaviors is explained below.

Fruit and vegetable servings. Participants were asked two questions regarding their daily consumption of fruit and vegetables. Responses were coded as 7 ordinal levels, ranging from $0 =$ none to $6 = 4$ cups or more. Current recommendations are for adults' daily diet are determined based on an individual's age, gender, and level of physical activity (for example, see http://www.fruitsandveggiesmatter.gov/index.html). However, it is generally recommended that adults should consume each day ≥ 2 cups of fruit and ≥ 2.5 cups of vegetables (U.S. Department of Health and Human Services 2000). Daily consumption of fruit and vegetables are both recoded to $0 =$ less than 2 cups per day and $1 = 2$ cups or more per day. About 21% of participants in the full mail sample consume the recommended daily servings of fruit and 27% the recommended daily servings of vegetables.

Physical activity. Participants were asked three questions to determine their level of physical activity. First, participants were asked, "During the past month, did you participate in any physical activities or exercises such as running, yoga, golf, gardening,

or walking for exercise?" Responses were coded 0 = no and 1 = yes. Participants who responded "yes" were asked the following question, "In a typical week, how many days do you do any physical activity of at least moderate intensity, such as brisk walking, bicycling at a regular pace, swimming at a regular pace, or heavy gardening? Moderate-intensity activities make you breathe somewhat harder than normal." Responses were coded 0 to 7 corresponding to the number of days per week participants engaged in moderate-intensity activity. Participants who responded they engaged in moderate-intensity activities 1 or more days were asked "…how long are you typically doing these activities?" Responses were open-ended and recorded as either hours or minutes and recoded to minutes.

Using these three variables, a dichotomous variable of physical activity was created coded 1 = meets recommended levels of physical activity and 0 = does not meet recommended levels of physical activity. Current recommendations are for adults to engage in at least 150 minutes of moderate physical activity each week (U.S. Department of Health and Human Services 2000). Participants who answer "no" to participating in any physical activities during the past month are coded 0. Participants who answer "yes" and who engage in 0 to 149 minutes a week do not meet the minimum recommended level of physical activity and are coded 0. Participants who engage in 150 minutes or more per week meet the recommended level of physical activity and are coded as 1. About 35% of the mail sample meets the recommended level of moderate intensity exercise each week.

Tobacco use. Non-smoker is created from a single item included in the HINTS data set that indicates current smoking status as 1 = current smoker, 2 = former smoker,

and 3 = never smoked. This variable is recoded as a binary variable, 1 = never smoked or former smoker and 0 = current smoker. About 78% of the mail sample are non-smokers.

Status-Specific Attitudes

The lifestyle concept posits that a person's social status background is related to status-specific habitus that consists of attitudes, beliefs, and preferences that subsequently influence behavior or lifestyle choices (Cockerham 2000, 2005). Two sets of status-related attitudes are included to model this relationship: health-related attitudes and online health information seeking attitudes.

Health-related attitudes are measured using one item. *Health self-efficacy (HSE)* assesses participants' sense of confidence to take good care of their health. Participants were asked, "Overall, how confident are you about your ability to take good care of your health?" HSE is coded as one of five Likert-type options ranging from 1 = not confident at all to 5 = completely confident.

Online health information seeking attitudes are measured using two items. The first, *health information seeking self-efficacy (HISSE)* measures participants' general feeling of confidence that they can find health information. This is measured by a single question asking participants, "Overall, how confident are you that you could get health-related information advice or information if you needed it?" HISSE is coded as one of five Likert-type options ranging from 1 = not confident at all to 5 = completely confident. The second item is *trust in online health information (TRUST)*. TRUST is measured by a single item that asks participants, "In general, how much would you trust information

about health or medical topics from each of the following… the Internet?" Responses are coded as one of four Likert-type options ranging from 1 = not at all to 4 = a lot.

Other Key Independent Variables

Socioeconomic Status

Two variables are used to measure socioeconomic status. *Education (EDU)* is measured by asking participants, "What is the highest grade or level of schooling you completed?" Responses are coded as one of five ordinal-level options: 1 = "less than high school," 2 = "12 years or completed high school," 3 = "some college," 4 = "college graduate, bachelor's degree," and 5 = "postgraduate, post-baccalaureate degree." *Household income (HHINC)* is measured by a single item asking participants, "Thinking about members of your family living in this household, what is your combined annual income, meaning the total pre-tax income from all sources earned in the past year?" Responses were coded as one of five ordinal-level options: 1 = "less than $20,000," 2 = $20,000 to less than $35,000," 3 = "$35,000 to less than $50,000," 4 = $50,000 to less than $75,000," and 5 = "$75,000 or more."

Internet Access

Internet access is measured by two variables, home Internet access and number of places a participant accesses the Internet. *Broadband (ACCESSBB)* measures the speed of home Internet access and is coded 1 = high speed (i.e., digital subscriber line (DSL), satellite, or cable) home connection and 0 = telephone dial-up modem or other.. *Internet access places (PLACES)* is the total number of places participants use the Internet,

selected from a list of seven locations: (1) home, (2) work, (3) school, (4) public library, (5) community center, (6) someone else's house, and (7) some other place. Cross-tabulation tables with other key variables indicated few or no observations at the high end of the PLACES index. To ensure there were no cells with few or no observation, PLACES was collapsed, recoding cases with a score of 6 and 7 to 5. The analytic subsamples are restricted to participants who have home Internet access. Thus, all participants report using the Internet at home and PLACES ranges from 1-5 as used in the statistical analyses.

Health Status

Health status is measured as *self-rated health (SRH),* using a single question that asks, "In general, would you say your health is...?" Responses are coded 1 = "poor," 2 = "fair," 3 = "good," 4 = "very good," and 5 = excellent. Self-rated health is a strong predictor or morbidity and mortality and is correlated with objective measures of health status (Idler and Benyamini 1997).

Control Variables

Demographics

Several demographic variables are included as controls. *Age (AGE)* is measured in years. Race/ethnicity is measured by the variable *non-white (NONWHITE)* coded as 1 = African American, Hispanic, Asian, or other race/ethnicity" and 0 = "non-Hispanic white." Sex is measured by the variable *female (FEMALE),* coded 1 = "female" and 0 = "male." Marital status is measured by the variable *married (MARRIED),* coded 1 =

"married" and 0 = "single, divorced, widowed, or other marital status." A binary

variable, CHILD, is coded 1= "child in household" and 0 = "no children in household."

Health Care Access

Access to health care may be an important factor related to people's use of

alternative sources of health information, advice, and services. Health insurance is

recoded as *uninsured (UNINS),* a dichotomous variable coded 1 = "does not have health

insurance" and 0 = "does have health insurance." *Regular health care provider*

(REGHCP) is coded 1 = "have a regular health care provider" and 0 = "does not have a

regular health care provider." Access to care may be more difficult for people living in

rural areas. *Rural (RURAL)* is measured using the 2003 Rural-Urban Continuum (RUC)

codes created by the U.S. Department of Agriculture's Economic Research Service

(USDA-ERS). The RUC is created using 2000 Census data to classify counties as one of

nine types, ranging from 1 = "counties in metro areas of 1 million population or more" to

9 = "completely rural or less than 2,500 urban population, not adjacent to a metro area"

(U.S. Department of Agriculture 2007). RUC codes 4-9 are recoded as 1 = "rural" and

RUC codes 1-3 as 0 "urban".

Seeking Health Information for Yourself or Others

About half of all online health information searches are conducted for someone

else, rather than the person doing the searching. To control for differences in the

relationship between key factors in each model, I include a series of dummy variables

that indicate for whom the most recent health information search was conducted. This

includes indicators for *looking for self (LOOKSELF)*, *looking for someone else (LOOKELSE)*, and *looking for both myself and someone else (LOOKBOTH)*.

<div style="text-align:center">Analytic Strategy</div>

Data recoding, descriptive analyses, and tests of differences between subsamples is conducted using Stata 10.1 (StataCorp 2009). The statistical program Mplus Version 6.1 (Muthén and Muthén 2010a) is used to conduct path analysis. All analyses use the sample and replicate weights in the HINTS 2007 to adjust for the complex sample design. Because the variables used in the structural models include categorical variables (binary and ordinal) the weighted least squares mean variance (WLSMV) estimator is used in Mplus (Muthén and Muthén 2010b).

The first phase of analysis consists of generating descriptive statistics and testing for significant differences between the full mail sample, the health seeker subsample, and the Internet user subsample. This is useful in providing a general overview of each sub-sample, identifying significant differences between subsamples, and facilitate comparisons to samples used in similar research projects.

The second phase of analysis examines a structural model of the relationships between endogenous variables (e.g., independent variables, intervening variables, and the two dependent variables) while controlling for exogenous variables (e.g., demographics, health care access, and other factors). Using path analysis and Mplus has two advantages over other statistical techniques, such as entering variables as blocks using multivariate logit regression. First, indirect and direct effects can be computed more easily using path analysis and Mplus, which enables the testing of complex relationships between

independent, intervening, and dependent variables (Allison 1999). Second, the results can be illustrated as a path diagram showing the direction and strength of statistically significant relationships between variables.

For each of the dependent variables measuring OHB (OHIS and OHRA), results will be presented as path diagrams with standardized probit coefficients to facilitate comparison of the relative strength of the effect of each variable in the model. Although logit regression is more commonly used than probit (Pampel 2000:54), Mplus is limited to calculating probit estimates when the path model includes categorical variables. The use of categorical intervening variables necessitates the use of the WLSMV estimator, which is not compatible with logit regression methods. Despite this limitation, analyses using logit and probit regression produce results that are essentially equivalent (Pampel 2000:54).

For each dependent variable, tables will list the unstandardized and standardized coefficient estimates, standard errors, and p-values for all direct paths in the structural model. Model fit will be assessed using commonly used thresholds of acceptable model fit on root-mean-squared error of approximation (RMSEA $\leq$ .08) and the comparative fit index (CFI $\geq$ .90) (Kline 2005). Because RMSEA and CFI can not be calculated using Mplus when using replicate weights, model fit is examined using estimates without use of sample and replicate weights. Using the survey weights, the weighted root-mean-square residual (WRMSR < 1.0) is examined (Yu 2002).

CHAPTER 5

RESULTS

Sample Characteristics

Sample characteristics for the full sample and the two analytical sub-samples are

presented in Table 1. The mean and standard deviation were estimated using the survey

weights included in the HINTS 2007 data set. Use of the survey weights should provide

estimates that are representative of the adult, non-institutionalized, U.S. population. Table

1 is divided into two sets of variables: exogenous variables (e.g., SES, demographics,

health care access, and controls) and endogenous variables that comprise the observed

variables in the path models.

Three variables are used to identify participants in the two sub-samples: (1)

having ever used the Internet, (2) having home Internet access, and (3) having ever

sought health information. In the full mail sample, about 77% have ever looked for health

information, 71% use the Internet, and 62% have home Internet access. Therefore, the

means for variables measuring health information seeking, online health-related

activities, and Internet access are significantly lower among the full mail sample

compared to the sub-samples. Additionally, Internet access and use are strongly related to

numerous sociodemographic factors, including age, race/ethnicity, education, household

income, and rural versus urban location. This results in sub-samples that are significantly

Table 1. Sample Characteristics HINTS 2007 Mail Sample and Analytical Sub-Samples
of Health Seekers and Internet Users.

Variable Name	Mail Sample N = 3,582		Health Seekers N = 1,734		Internet Users N = 1,887	
	M	*SD*	*M*	*SD*	*M*	*SD*
Exogenous Variables						
Education: 5 levels	2.817	1.369	3.266	1.041	3.173	1.034
Household Income: 5 levels	3.215	1.539	3.736	1.426	3.688	1.395
Household Income: 5 levels, imputed	3.208	1.536	3.725	1.431	3.685	1.397
Gender: female	.515	.500	.550	.509	.518	.498
Age	45.929	17.834	42.792	15.292	41.698	15.231
Race/ethnicity: nonwhite	.306	.461	.239	.436	.248	.430
Marital status: married	.565	.496	.633	.493	.609	.486
Child in household	.373	.484	.416	.504	.418	.491
Occupational status: employed	.598	.490	.676	.479	.677	.466
Location: rural	.165	.372	.110	.320	.109	.310
Health insurance: uninsured	.172	.378	.122	.334	.133	.338
Regular health care provider	.672	.470	.726	.456	.696	.458
Who look for						
Look for yourself	.429	.495	.542	.510	.471	.497
Look for someone else	.150	.357	.215	.420	.187	.388
Look for both	.195	.396	.243	.439	.211	.406
Has never looked for health info.	.226	.418	.000	.000	.132	.337
Endogenous Variables						
Online health information seeking	.570	.495	.717	.461	.717	.454
Online health-related activities: 0-6	.864	1.152	1.394	1.255	1.283	1.207
Online health-related activities: 0-5	.853	1.115	1.373	1.195	1.265	1.154
Buy medicine	.109	.312	.173	.387	.162	.367
Support group	.035	.185	.059	.241	.054	.226
Talk with doctor	.086	.280	.137	.352	.123	.327
Diet, weight, physical activity	.283	.451	.459	.510	.420	.491
Provider	.266	.442	.439	.508	.405	.489
Personal health record	.084	.278	.124	.337	.118	.322
Self-rated health	3.401	.910	3.522	.895	3.256	.876
Health behavior: 0-4	1.614	1.057	1.736	1.252	1.708	1.055
Meet fruit recommendation	.213	.410	.227	.428	.223	.415
Meet vegetable recommendation	.267	.443	.313	.475	.292	.453
Meet weekly recommended exercise	.352	.478	.391	.499	.394	.487
Non-smoker	.781	.414	.804	.406	.798	.399
Health self-efficacy	3.772	.877	3.838	.808	3.819	.810
Health information seeking self-efficacy	3.717	.979	3.871	.904	3.833	.903
Trust online health information	2.838	.835	3.088	.637	3.019	.669
Places where access Internet: 0-7	1.246	1.130	1.860	1.024	1.827	.978
Places where access Internet: 0-4	1.201	1.086	1.827	.916	1.798	.884
Home Internet connection						
No home connection	.380	.485	.000	.000	.000	.000
Modem or other	.155	.362	.243	.439	.251	.438
Broadband	.465	.499	.757	.439	.749	.432

Weighted means.

different from the full sample on most sociodemographic factors and measures of Internet use, access, and online health activities. Thus, in the section below I will only briefly describe the sociodemographic characteristics of the full mail sample, then describe in greater detail the characteristics and significant differences between the two analytic subsamples.

Characteristics of the Full Mail Sample

The full mail sample is 52% female, mean age 46 years old, and 31% non-white race/ethnicity (see Table 1). Fifty-seven percent of participants are married and 37% have at least one child in the household. Sixty percent are employed and 17% live in a rural county. Eighty-three percent have medical insurance and 67% have a regular health care provider. The mean education is 2.8 which represents a level of education higher than a high school degree, but a little lower than some college (category 2 = high school degree, 3 = some college). The mean, imputed household income is 3.2 which represents a level of income of about $35,000 to less than $50,000 (category 3).

Due to the criteria used to select the two analytic sub-samples, participants in the full mail sample are markedly different on most sociodemographic measures. Participants are older, and a greater proportion are non-white and live in rural areas. A smaller proportion of participants in the full mail sample are married, have a child in the household, or employed. Mean education and household income are lower among participants in the full mail sample than either of the two analytical sub-samples.

Characteristics of the Health Seeker Sub-Sample

The health seeker sample is 55% female, mean age 43 years old, and 24%

non-white race/ethnicity (see Table 1). Sixty-three percent of participants are married and

42% have at least one child in the household. Sixty-eight percent are employed and 11%

live in a rural county. Eighty-eight percent have medical insurance and 73% have a

regular health care provider. The mean education is 3.3 which represents a little higher,

on average, than attending some college (category 3 = some college, 4 = college degree).

The mean, imputed household income is 3.7 which represents a level of income of about

$50,000 to less than $75,000 (category 4). During the last search for health information,

54% looked for themselves, 22% for someone else, and 24% for both themselves and

someone else.

The outcome variable used with this sub-sample is health information source.

Seventy-two percent searched online for health information, versus all other sources,

during their most recent search. The mean self-rated health is 3.5, which indicates that on

average, participants report very good to excellent health (category 3 = very good, 4 =

excellent). The mean on the summated index of health lifestyle items (range 0-4) is 1.7.

About 23% meet the recommended daily consumption of fruits and 31% vegetables.

Thirty-nine percent participate in the recommended weekly minutes of physical exercise.

Eighty percent of participants do not currently smoke cigarettes. Mean health self-

efficacy is 3.8, which indicates that on average, participants are "very confident" in their

ability to take care of their health (category 4 = very confident).

Mean health information seeking self-efficacy is 3.9, which indicates participants

are, on average, "very confident" they can find health information if they need it

(category 4 = very confident). The mean trust level in online health information is 3.1

which indicates participants have "some" trust of online health information (category 3 =

some). The mean number of places where participants can access the Internet is about 1.9

in the full, 0-7 summated index. With high values collapsed to a high value of 4, the

mean is 1.827. The sample is restricted to participants who have home Internet access.

Twenty-four percent have a modem or slower type of home Internet access and 76% have

broadband.

Characteristics of the Internet User Sub-Sample

The Internet user sample is about 52% female, 42 years old, and 25% non-white

race/ethnicity (see Table 5.1). Sixty-one percent of participants are married and 42% have

at least one child in the household. Sixty-seven percent are employed and 11% live in a

rural county. Eighty-seven percent have medical insurance and 70% have a regular health

care provider. The mean education is 3.2 which represents a little higher, on average, than

attending some college (category 3 = some college). The mean, imputed household

income is 3.7 which represents a level of income of about $50,000 to less than $75,000

(category 4). Unlike the health seeker sample, the Internet user sample is not restricted to

health seekers, and 13% have never looked for health information from any source.

During the last search for health information, 47% looked for themselves, 19% for

someone else, and 21% for both themselves and someone else.

The outcome variable used with this sub-sample is a summated index of online

health-related activities. The mean of the full-range index (range 0-6) and for the index

that collapses scores to a high value of 5 (range 0-5) is 1.3. On the six items are used to

measure online health-related activities during the past year, 16% buy medicine online, 5% used support groups, 12% have talked to their doctors, 42% have looked for diet information, 41% have looked for information about a health care provider, and 12% have used online personal health records. The mean self-rated health is 3.3, which indicates that on average, participants report "very good" health (category 3 = very good). The mean on the summated index of health lifestyle items (range 0-4) is 1.7. About 22% meet the recommended daily consumption of fruits and 29% vegetables. Thirty-nine percent participate in the recommended weekly minutes of physical exercise. Eighty percent of participants do not currently smoke cigarettes. Mean health self-efficacy is 3.8, which indicates that on average, participants are "very confident" in their ability to take care of their health (category 4 = very confident).

Mean health information seeking self-efficacy is 3.8, which indicates participants are, on average, "very confident" they can find health information if they need it (category 4 = very confident). The mean trust level in online health information is 3.0 which indicates participants have "some" trust of online health information (category 3 = some). The mean number of places where participants can access the Internet is about 1.8 in the full, 0-7 summated index. In the places variable with upper levels collapsed to a high end of 4, the mean is 1.8. Like the health seeker sample, the Internet user sample is restricted to participants who have home Internet access. Twenty-five percent have a modem or slower type of home Internet access and 75% have broadband.

Comparing the Characteristics of the Analytic Sub-Samples

Compared to the Internet user sub-sample, the health seeker sub-sample is significantly older and consists of a greater proportion of females. Participants in the health seeker sub-sample are also more likely to be married and to have a regular health care provider. The health seeker sub-sample also has significantly higher levels of education and higher household income, although there is no significant difference between sub-samples on imputed household income. There is no significant difference between sub-samples on race/ethnicity, having a child in the household, employed, or health insurance.

Comparing common endogenous variables between sub-samples, the health seeker sub-sample is more likely to meet recommended daily consumption of vegetables than the Internet user sub-sample. However, there is no significant difference between sub-samples on the health lifestyle index or other items used to create the index. The health seeker sub-sample is significant higher in health information seeking self-efficacy and trust of online health information. The health seeker sub-sample has significantly more places where they can access the Internet, but there is no difference between the health seeker and the Internet user sub-samples in type of home Internet access. There was no significant difference between the two sub-samples on measures of self-rated health or health self-efficacy.

Online Health Information Seeking – Outcome Variable OHIS

Figure 2 depicts the path model and the coefficients for all direct effects that are statistically significant at the $p \leq .05$ level, while controlling for all exogenous variables

(e.g., demographics, health care access, place). Solid lines represent paths among key variables included in the hypotheses and dotted lines represent paths that were not part of the tested hypotheses. Table 2 shows the unstandardized and standardized probit coefficients, standard errors, and *p*-value for all direct relationships between variables in the model. The statistically significant ($p \leq .05$ level) relationships are in bold to highlight the direct effects depicted in Figure 2. Hypothesized relationships and results are summarized in Table 3. A complete list of the total, direct, and indirect effects for all

Figure 2. Path Model and Probit Coefficients of the Direct Effects Between Socioeconomic Status, Internet Access, Health and Information Seeking Attitudes, Health Behavior, and Self-Rated Health on Online Health Information Seeking (OHIS) HINTS 2007 (*N* = 1,734).
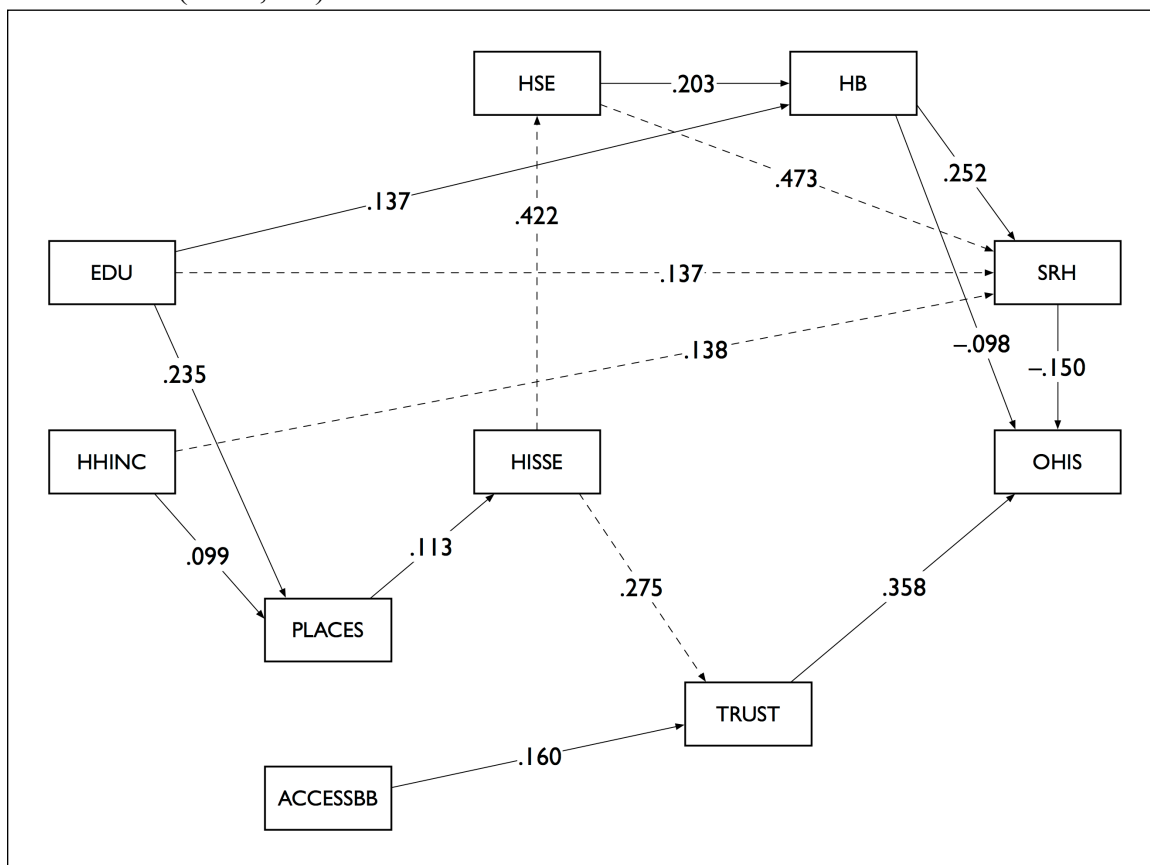
Table 2. Direct Effects, Online Health Information Seeking (OHIS) HINTS 2007 Mail Sample ($N = 1,734$).

Dependent Variable and Path	b	S.E.	β	p-value
ACCESSBB				
EDU → ACCESSBB	0.103	0.053	0.097	0.054
HHINC → ACCESSBB	0.018	0.038	0.023	0.636
PLACES				
EDU → PLACES	**0.235*****	**0.046**	**0.200**	**0.000**
HHINC → PLACES	**0.099***	**0.040**	**0.117**	**0.012**
HISSE				
PLACES → HISSE	**0.113***	**0.055**	**0.129**	**0.041**
ACCESSBB → HISSE	-0.026	0.056	-0.027	0.640
EDU → HISSE	0.061	0.039	0.060	0.122
HHINC → HISSE	0.056	0.033	0.075	0.090
TRUST				
HISSE → TRUST	**0.275*****	**0.047**	**0.268**	**0.000**
PLACES → TRUST	-0.079	0.060	-0.089	0.186
ACCESSBB → TRUST	**0.160****	**0.058**	**0.161**	**0.006**
EDU → TRUST	-0.036	0.045	-0.035	0.417
HHINC → TRUST	-0.014	0.035	-0.018	0.691
HSE				
HISSE → HSE	**0.422*****	**0.052**	**0.395**	**0.000**
EDU → HSE	0.030	0.046	0.027	0.516
HHINC → HSE	-0.030	0.037	-0.038	0.420
HB				
HSE → HB	**0.203*****	**0.045**	**0.215**	**0.000**
HISSE → HB	-0.014	0.049	-0.013	0.782
EDU → HB	**0.137*****	**0.037**	**0.132**	**0.000**
HHINC → HB	0.035	0.036	0.046	0.342
SRH				
HB → SRH	**0.252*****	**0.039**	**0.217**	**0.000**
HSE → SRH	**0.473*****	**0.041**	**0.431**	**0.000**
HISSE → SRH	-0.050	0.040	-0.043	0.216
EDU → SRH	**0.121****	**0.042**	**0.101**	**0.004**
HHINC → SRH	**0.121****	**0.037**	**0.138**	**0.001**
OHIS				
SRH → OHIS	**-0.150****	**0.053**	**-0.163**	**0.004**
HB → OHIS	**-0.098***	**0.042**	**-0.092**	**0.019**
HSE → OHIS	0.003	0.062	0.003	0.956
TRUST → OHIS	**0.358*****	**0.061**	**0.340**	**0.000**
HISSE → OHIS	-0.063	0.070	-0.058	0.369
PLACES → OHIS	0.078	0.068	0.083	0.248
ACCESSBB → OHIS	0.041	0.062	0.039	0.516
EDU → OHIS	0.081	0.058	0.073	0.162
HHINC → OHIS	0.028	0.042	0.035	0.501

* $p < .05$; ** $p < .01$; *** $p < .001$

Table 3. Summary of Hypotheses, Online Health Information Seeking (OHIS).

Hypothesis	Dependent Variable and Path	Hypothesized Relationship	b	S.E.	β	p-value	Conclusion
H1	SRH → OHIS	Positive or n/s direct effect	-0.150**	0.053	-0.163	0.004	Not supported
H2	HB → OHIS	Positive direct effect	-0.098*	0.042	-0.092	0.019	Not supported
H3	**EDU → HB**	**Positive direct effect**	**0.137*****	**0.037**	**0.132**	**0.000**	**Supported**
H3	HHINC → HB	Positive direct effect	0.035	0.036	0.046	0.342	Not supported
H4	EDU → HSE	Positive direct effect	0.030	0.046	0.027	0.515	Not supported
H4	HHINC → HSE	Positive direct effect	-0.030	0.037	-0.038	0.420	Not supported
H5	**HSE → HB**	**Positive direct effect**	**0.203*****	**0.045**	**0.215**	**0.000**	**Supported**
H6	EDU → HSE → HB	Positive indirect effect	0.006	0.010	0.006	0.525	Not supported
H6	HHINC → HSE → HB	Positive indirect effect	-0.006	0.008	-0.008	0.422	Not supported
H7	EDU → OHIS	Positive direct effect	0.081	0.058	0.073	0.162	Not supported
H7	HHINC → OHIS	Positive direct effect	0.028	0.042	0.035	0.501	Not supported
H8	EDU → ACCESSBB	Positive direct effect	0.103	0.053	0.097	0.054	Not supported
H8	HHINC → ACCESSBB	Positive direct effect	0.018	0.038	0.023	0.636	Not supported
H8	**EDU→ PLACES**	**Positive direct effect**	**0.235*****	**0.046**	**0.200**	**0.000**	**Supported**
H8	**HHINC → PLACES**	**Positive direct effect**	**0.099***	**0.040**	**0.117**	**0.012**	**Supported**
H9	EDU → HISSE	Positive direct effect	0.061	0.039	0.060	0.122	Not supported
H9	HHINC → HISSE	Positive direct effect	0.056	0.033	0.075	0.090	Not supported
H9	EDU → TRUST	Positive direct effect	-0.036	0.045	-0.035	0.417	Not supported
H9	HHINC → TRUST	Positive direct effect	-0.014	0.035	-0.018	0.691	Not supported

$^*p < .05$; $^{**}p < .01$; $^{***}p < .001$

Table 3. (Continued).

Hypothesis	Dependent Variable and Path	Hypothesized Relationship	b	S.E.	β	p-value	Conclusion
H10	ACCESSBB → OHIS	Positive direct effect	0.041	0.062	0.039	0.516	Not supported
H10	PLACES → OHIS	Positive direct effect	0.078	0.068	0.083	0.248	Not supported
H11	ACCESSBB → HISSE	Positive direct effect	-0.026	0.056	-0.027	0.640	Not supported
H11	**PLACES → HISSE**	**Positive direct effect**	**0.113***	**0.055**	**0.129**	**0.041**	**Supported**
H11	**ACCESSBB → TRUST**	**Positive direct effect**	**0.160****	**0.058**	**0.161**	**0.006**	**Supported**
H11	PLACES → TRUST	Positive direct effect	-0.079	0.060	-0.089	0.186	Not supported
H12	HISSE → OHIS	Positive direct effect	-0.063	0.070	-0.058	0.369	Not supported
H12	**TRUST → OHIS**	**Positive direct effect**	**0.358*****	**0.061**	**0.340**	**0.000**	**Supported**
H13	EDU → ACCESSBB → OHIS	Positive indirect effect	0.004	0.006	0.004	0.518	Not supported
H13	HHINC → ACCESSBB → OHIS	Positive indirect effect	0.001	0.002	0.001	0.669	Not supported
H13	EDU → PLACES → OHIS	Positive indirect effect	0.018	0.016	0.017	0.245	Not supported
H13	HHINC → PLACES → OHIS	Positive indirect effect	0.008	0.007	0.010	0.295	Not supported
H13	EDU → HISSE → OHIS	Positive indirect effect	-0.004	0.005	-0.003	0.435	Not supported
H13	HHINC → HISSE → OHIS	Positive indirect effect	-0.004	0.004	-0.004	0.427	Not supported
H13	EDU → TRUST → OHIS	Positive indirect effect	-0.013	0.016	-0.012	0.422	Not supported
H13	HHINC → TRUST → OHIS	Positive indirect effect	-0.005	0.013	-0.006	0.694	Not supported
H14	ACCESSBB → HISSE → OHIS	Positive indirect effect	0.002	0.003	0.002	0.624	Not supported
H14	PLACES → HISSE → OHIS	Positive indirect effect	-0.007	0.008	-0.008	0.375	Not supported
H14	**ACCESSBB → TRUST → OHIS**	**Positive indirect effect**	**0.057***	**0.023**	**0.055**	**0.015**	**Supported**
H14	PLACES → TRUST → OHIS	Positive indirect effect	-0.028	0.023	-0.030	0.219	Not supported

$^{*}p < .05;\ ^{**}p < .01;\ ^{***}p < .001$

variables (endogenous and exogenous control variables) is available from the author.

Model fit indices indicate an acceptable fit between the path model and the data. Without

survey weights, RMSEA = .038, CFI = .986, and WRMR = .457. Using survey weights

WRMR = .420.

The first general hypothesis is that OHB can be usefully conceptualized as health

behavior, rather than illness behavior. Thus, H1 states that OHIS is positively or not

significantly related to health status and H2 states that health behavior (HB) is positively

associated with OHIS. The results do not support either hypotheses. In fact, both self-

rated health (SRH) ($b = -.150$, $p < .010$) and health behavior (HB) ($b = -.098$, $p <. 050$)

are negatively associated with OHIS (see Figure 2). Health behavior (HB) also has a very

small negative indirect relationship to OHIS through self-rated health (SRH) (indirect

effect $b = -.038$, $p < .010$; results available from author). The total effect of health

behavior (HB) to OHIS is negative and significant ($b = -.136$, $p < .001$). The results show

that among Internet users who have searched for health information, participants in better

health and/or who engage in a greater number of healthy behaviors are less likely to seek

health information online versus other information sources. This is the opposite of the

hypothesized relationship and suggests that OHIS is not a form of heath behavior, but can

be better understood as illness behavior.

The second set of hypotheses (H3-H6) are based on the premise that health

behaviors represent distinct status-specific patterns of behaviors or a health lifestyle. As

such, measures of social status (SES) are hypothesized to have positive direct effects to

health behavior and positive indirect effects via habitus-related attitudes measured as

health self-efficacy (HSE). There is partial support for H3, showing that education (EDU)

is positively associated with health behavior (HB) (b = .137, p < .001), but household income (HHINC) is not a significant predictor of health behavior (HB) (see Table 3). The hypothesis (H4) that social status is directly related to health-specific attitudes is not supported. Education (EDU) and household income (HHINC) are not significantly related to health self-efficacy (HSE) (see Table 3). However, health self-efficacy (HSE) is positively associated with health behavior (HB) (b = .203, p < .001) supporting H5. Since there is no direct effect between SES and health self-efficacy (HSE) there can be no significant indirect effects between SES and health behavior (HB) via health attitudes and H6 is not supported.

The third set of hypotheses (H7-H14) are based on the premise that in addition to SES, Internet access is an important structural factor that influences Internet attitudes and use. Therefore, SES and Internet access are hypothesized to have direct effects to OHIS and indirect effects via Internet-related attitudes. There is only partial support for these hypotheses. SES (i.e., education (EDU) and household income (HHINC)) and Internet access (i.e., broadband (ACCESSBB) and the number of places where a person uses the Internet (PLACES)) do not have a significant direct effect to OHIS (see Table 3, H7 and H10 respectively). SES has no significant indirect effect to OHIS via either Internet access or to Internet-related attitudes (see Table 3, H13). There is partial support for the hypothesis that SES is directly related to Internet access (H8). Although SES is not significantly related to broadband access (ACCESSBB) (see Table 3), both education (EDU) and household income (HHINC) are positively associated with the number of places a person uses the Internet (PLACES), (EDU b = .235, p < .001; HHINC b = .099, p < .050).

Internet access factors appear to be stronger predictors of Internet-related attitudes and Internet usage than social status, consistent with theory derived from the digital inequality framework and research investigating the influence of Internet access to shape an informational and Internet habitus. SES is not significantly related to either measure of Internet related attitudes (health information seeking self-efficacy (HISSE) and trust of online health information (TRUST)) or to OHIS. Broadband access (ACCESSBB) is positively associated with trust of online health information (TRUST) ($b = .160, p <. 010$) and the number of places a person uses the Internet (PLACES) is positively associated with health information seeking self-efficacy (HISEE) ($b = .113, p < 050$) providing partial support for H11. Broadband access (ACCESSBB) also has a very small, but significant indirect effect to OHIS via trust of online health information (TRUST) ($b = .057, p <. 050$), providing partial support for H13. Although not one of the stated hypotheses, health information seeking self-efficacy (HISSE) was found to be positively associated with trust of online health information (TRUST) ($b = .275, p < 001$; see Table 2) providing additional support for the general hypothesis that Internet access is an important structural factor that shapes Internet-related attitudes. Surprisingly, health information seeking self-efficacy (HISSE) was found to be strongly related to health self-efficacy (HSE) ($b = .422, p < .001$) but is not significantly related to health behavior (HB) or OHIS (see Table 3).

Of the exogenous control variables not depicted in the path model (results available from the author), only age, and searching for health information for someone else (LOOKELSE) are significant, after controlling for all covariates. Age is negatively associated with OHIS ($b = -.212, p < .001$). Compared to participants who search for

health information for themselves, looking for someone else (LOOKELSE) was positively associated with OHIS ($b = .110$, $p < .050$).

To summarize, the results do not support the hypothesis that OHIS is a form of health behavior or that OHIS is strongly associated with SES and status-related attitudes consistent with the lifestyle concept. In fact, OHIS is negatively associated with self-rated health (SRH) and with health behavior (HB), suggesting that people chose to seek health information online over other sources in response to poor health and not as part of engaging in health-enhancing behaviors that represent a health lifestyle.

Online Health-Related Activities – Outcome Variable OHRA

Figure 3 depicts the path model and the probit coefficients for all direct effects that are statistically significant at the $p \leq .05$ level, while controlling for all exogenous variables (e.g., demographics, health care access, and place). Solid lines represent paths among key variables included in the hypotheses and dotted lines represent paths that were not part of the tested hypotheses. Table 4 shows the unstandardized and standardized coefficients, standard errors, and p-value for all direct relationships between variables in the model. Relationships statistically significant ($p \leq .05$ level) are in bold to highlight the direct effects depicted in Figure 3. Hypothesized relationships and results are summarized in Table 5. A complete list of the total, direct, and indirect effects for all variables (endogenous and exogenous control variables) is available from the author. Model fit indices indicate an acceptable fit between the structural model and the data. Without survey weights, RMSEA = .036, CFI = .988, and WRMR = .436. With survey weights the WRMR = .371.

In contrast to the results for the outcome OHIS, the results support the hypothesis that OHRA is a form of health behavior, rather than illness behavior. Self-rated health (SRH) is not a significant predictor of OHRA ($b = .013, p > .050$), supporting H1 (see Figure 3 and Table 5). Health behavior (HB) has a small, but statistically significant positive relationship to OHRA ($b = .093, p < .010$) supporting H2 (see Figure 3 and Table 5). Additionally, education (EDU) has a very small, but significant indirect relationship to OHRA via health behavior (HB, $b = .012, p < .050$), providing additional evidence of the positive effects between social status, health behaviors, and OHRA.

Figure 3. Path Model and Probit Coefficients of the Direct Effects Between Socioeconomic Status, Internet Access, Health and Information Seeking Attitudes, Health Behavior, and Self-Rated Health on Online Health-Related Activities (OHRA) HINTS 2007 ($N = 1,887$)
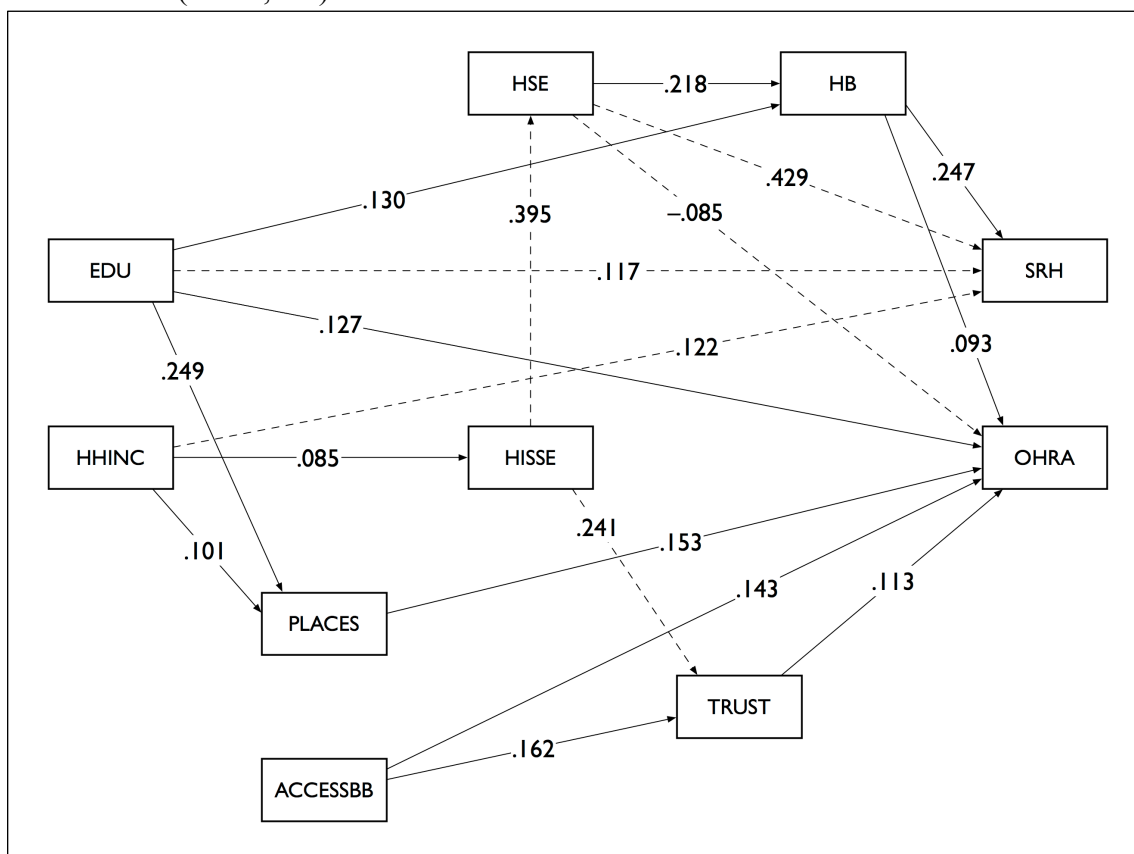
Table 4. Direct Effects, Online Health-Related Activities
(OHRA) HINTS 2007 Mail Sample (N = 1,887).

Dependent Variable and Path	b	S.E.	B	p-value
ACCESSBB				
EDU → ACCESSBB	0.101	0.057	0.099	0.076
HHINC → ACCESSBB	0.001	0.037	0.001	0.987
PLACES				
EDU → PLACES	**0.249*****	**0.044**	**0.218**	**0.000**
HHINC → PLACES	**0.101****	**0.039**	**0.119**	**0.009**
HISSE				
PLACES → HISSE	0.101	0.054	0.115	0.061
ACCESSBB → HISSE	-0.012	0.052	-0.012	0.817
EDU → HISSE	0.061	0.037	0.060	0.101
HHINC → HISSE	**0.085***	**0.033**	**0.114**	**0.010**
TRUST				
HISSE → TRUST	**0.241*****	**0.052**	**0.229**	**0.000**
PLACES → TRUST	-0.087	0.054	-0.094	0.109
ACCESSBB → TRUST	**0.162****	**0.060**	**0.156**	**0.007**
EDU → TRUST	-0.020	0.042	-0.019	0.640
HHINC → TRUST	-0.012	0.034	-0.016	0.711
HSE				
HISSE → HSE	**0.395*****	**0.046**	**0.375**	**0.000**
EDU → HSE	0.007	0.043	0.007	0.871
HHINC → HSE	-0.020	0.036	-0.025	0.583
HB				
HSE → HB	**0.218*****	**0.043**	**0.228**	**0.000**
HISSE → HB	-0.039	0.044	-0.039	0.376
EDU → HB	**0.130****	**0.037**	**0.129**	**0.001**
HHINC → HB	0.031	0.036	0.042	0.389
SRH				
HB → SRH	**0.247*****	**0.040**	**0.216**	**0.000**
HSE → SRH	**0.429*****	**0.055**	**0.394**	**0.000**
HISSE → SRH	-0.030	0.037	-0.026	0.422
EDU → SRH	**0.117***	**0.052**	**0.101**	**0.023**
HHINC → SRH	**0.122*****	**0.034**	**0.143**	**0.000**
OHRA				
SRH → OHRA	0.013	0.041	0.014	0.746
HB → OHRA	**0.093****	**0.030**	**0.086**	**0.002**
HSE → OHRA	**-0.085***	**0.039**	**-0.082**	**0.031**
TRUST → OHRA	0.113**	0.041	0.110	0.006
HISSE → OHRA	-0.032	0.041	-0.029	0.435
PLACES → OHRA	**0.153*****	**0.036**	**0.161**	**0.000**
ACCESSBB → OHRA	**0.143****	**0.052**	**0.134**	**0.005**
EDU → OHRA	**0.127****	**0.043**	**0.116**	**0.003**
HHINC → OHRA	-0.007	0.037	-0.008	0.855

* $p < .05$; ** $p < .01$; *** $p < .001$

Table 5. Summary of Hypotheses, Online Health-Related Activities (OHRA).

Hypothesis	Dependent Variable and Path	Hypothesized Relationship	b	S.E.	β	p-value	Conclusion
H1	**SRH → OHRA**	**Positive or n/s direct effect**	**0.013**	**0.041**	**0.014**	**0.746**	**Supported**
H2	**HB → OHRA**	**Positive direct effect**	**0.093**[**]	**0.030**	**0.086**	**0.002**	**Supported**
H3	**EDU → HB**	**Positive direct effect**	**0.130**[**]	**0.037**	**0.129**	**0.001**	**Supported**
H3	HHINC → HB	Positive direct effect	0.031	0.036	0.042	0.389	Not supported
H4	EDU → HSE	Positive direct effect	0.007	0.043	0.007	0.871	Not supported
H4	HHINC → HSE	Positive direct effect	-0.020	0.036	-0.025	0.583	Not supported
H5	**HSE → HB**	**Positive direct effect**	**0.218**[***]	**0.043**	**0.228**	**0.000**	**Supported**
H6	EDU → HSE → HB	Positive indirect effect	0.002	0.009	0.002	0.871	Not supported
H6	HHINC → HSE → HB	Positive indirect effect	-0.004	0.008	-0.006	0.584	Not supported
H7	**EDU → OHRA**	**Positive direct effect**	**0.127**[**]	**0.043**	**0.116**	**0.003**	**Supported**
H7	HHINC → OHRA	Positive direct effect	-0.007	0.037	-0.008	0.855	Not supported
H8	EDU → ACCESSBB	Positive direct effect	0.101	0.057	0.099	0.076	Not supported
H8	HHINC → ACCESSBB	Positive direct effect	0.001	0.037	0.001	0.987	Not supported
H8	**EDU→ PLACES**	**Positive direct effect**	**0.249**[***]	**0.044**	**0.218**	**0.000**	**Supported**
H8	**HHINC → PLACES**	**Positive direct effect**	**0.101**[**]	**0.039**	**0.119**	**0.009**	**Supported**
H9	EDU → HISSE	Positive direct effect	0.061	0.037	0.060	0.101	Not supported
H9	**HHINC → HISSE**	**Positive direct effect**	**0.085**[*]	**0.033**	**0.114**	**0.010**	**Supported**
H9	EDU → TRUST	Positive direct effect	-0.012	0.042	-0.019	0.640	Not supported
H9	HHINC → TRUST	Positive direct effect	-0.012	0.034	-0.016	0.711	Not supported

[*] $p < .05$; [**] $p < .01$; [***] $p < .001$

Table 5. (Continued).

Hypothesis	Dependent Variable and Path	Hypothesized Relationship	b	S.E.	β	p-value	Conclusion
H10	**ACCESSBB → OHRA**	**Positive direct effect**	**0.142****	**0.052**	**0.134**	**0.005**	**Supported**
H10	**PLACES → OHRA**	**Positive direct effect**	**0.153*****	**0.036**	**0.161**	**0.000**	**Supported**
H11	ACCESSBB → HISSE	Positive direct effect	-0.012	0.052	-0.012	0.817	Not supported
H11	PLACES → HISSE	Positive direct effect	0.101	0.054	0.115	0.061	Not supported
H11	**ACCESSBB → TRUST**	**Positive direct effect**	**0.162****	**0.060**	**0.156**	**0.007**	**Supported**
H11	PLACES → TRUST	Positive direct effect	-0.020	0.042	-0.019	0.640	Not supported
H12	HISSE → OHRA	Positive direct effect	-0.032	0.041	-0.029	0.435	Not supported
H12	**TRUST → OHRA**	**Positive direct effect**	**0.113****	**0.041**	**0.110**	**0.006**	**Supported**
H13	EDU → ACCESSBB → OHRA	Positive indirect effect	0.014	0.009	0.013	0.129	Not supported
H13	HHINC → ACCESSBB → OHRA	Positive indirect effect	0.000	0.005	0.000	0.987	Not supported
H13	**EDU → PLACES → OHRA**	**Positive indirect effect**	**0.038****	**0.011**	**0.035**	**0.001**	**Supported**
H13	**HHINC → PLACES → OHRA**	**Positive indirect effect**	**0.015***	**0.008**	**0.019**	**0.041**	**Supported**
H13	EDU → HISSE → OHRA	Positive indirect effect	-0.002	0.005	-0.002	0.749	Not supported
H13	HHINC → HISSE → OHRA	Positive indirect effect	-0.003	0.004	-0.003	0.459	Not supported
H13	EDU → TRUST → OHRA	Positive indirect effect	-0.002	0.005	-0.002	0.631	Not supported
H13	HHINC → TRUST → OHRA	Positive indirect effect	-0.001	0.004	-0.002	0.725	Not supported
H14	ACCESSBB → HISSE → OHRA	Positive indirect effect	0.000	0.002	0.000	0.810	Not supported
H14	PLACES → HISSE → OHRA	Positive indirect effect	-0.003	0.004	-0.010	0.422	Not supported
H14	**ACCESSBB → TRUST → OHRA**	**Positive indirect effect**	**0.018***	**0.008**	**0.017**	**0.015**	**Supported**
H14	PLACES → TRUST → OHRA	Positive indirect effect	-0.010	0.007	-0.010	0.147	Not supported

* $p < .05$; ** $p < .01$; *** $p < .001$

There is partial support for the second set of hypotheses that focus on health behaviors as health lifestyle. Education (EDU) has a positive direct effect on health behavior (HB) ($b = .130$, $p < .010$) providing partial support for H3. Health self-efficacy (HSE) is positively associated with health behavior (HB) ($b = .218$, $p < .001$) supporting H5. However, neither measure of SES (i.e., education (EDU) or household income (HHINC)) has a significant relationship to health self-efficacy (HSE). Thus, there is no support for H4 stating that SES has a positive direct effect on health self-efficacy (HSE) or H6 stating that SES will have a significant indirect effect on health behavior (HB) via health self-efficacy (HSE) (see Table 5). Although not one of the hypothesized effects, household income (HHINC) has a very small positive indirect effect on health behavior (HB) via health information seeking self-efficacy (HISSE) and health self-efficacy (HSE) ($b = .007$; $p < .05$; results available from author).

The third set of hypotheses (H7-H14) focus on factors related to OHRA and is based on the premise that in addition to SES, Internet access is an important structural factor that influences Internet attitudes and use. There is partial support for these hypotheses. Although household income (HHINC) is not significantly related to OHRA, education (EDU) is positively associated with OHRA ($b = .127$, $p < .010$) providing partial support for H7. Both measures of SES are positively associated with the number of places a person uses the Internet (PLACES) (EDU $b = .249$, $p < .001$; HHINC $b = .101$, $p < .010$; see Table 4 and 5) providing partial support for H8 stating that SES is positively associated with Internet access. In addition to the direct effect between education (EDU) and OHRA, both education (EDU) and household income (HHINC) have a significant indirect effect through the number of places a person uses the Internet

(PLACES) (EDU b = .035, p < .010; HHINC b = .015, p < .050) providing partial

support for H13. Household income (HHINC) has a positive direct effect on health

information seeking self-efficacy (HISSE) (b = .085, p < 050) providing partial support

for H9 stating that SES has a significant direct effect on Internet-related attitudes (i.e.,

health information self-efficacy (HISSE) and trust of online health information

(TRUST)). Although not one of the hypothesized effects, additional evidence that

supports the general hypothesis that SES is positively related to Internet-related attitudes

comes from the small, but significant positive indirect effect between household income

(HHINC) on trust of online health information (TRUST) via health information seeking

self-efficacy (HISSE) (b = .026, p < .050; results available from the author).

As predicted by the digital inequality framework, Internet access is a relatively

strong predictor of trust of online health information (TRUST) and OHRA. Broadband

access (ACCESSBB) is positively related to trust of online health information (TRUST, b

= .162, p < .010) providing partial support for H11. Both measures of Internet access

have a positive, direct relationship to OHRA (ACCESSBB b = .143, p < .010; PLACES b

= .153, p < .001) supporting H10. In addition, broadband access (ACCESSBB) has a very

small, but significant positive indirect effect on OHRA through trust on online health

information (TRUST) (b = .018, p < .050; see Table 5) for a total positive effect of b =

.161 (p < .050; results available from author). Although the strength of this indirect effect

is small, the direct effects along the path are in the hypothesized direction and provide

general support that Internet access is related to more positive attitudes and to greater use

of the Internet for health-related activities.

Of the exogenous control variables not depicted in the path model, only age, having a regular health care provider (REGHCP), and indicators of who one last looked for health information for (LOOKSELF, LOOKELSE, LOOKBOTH) are significant, after controlling for all covariates (results available from author). Age is negatively associated with OHRA ($b = -.081$, $p < .050$) and having a regular health care provider (REGHCP) is positively associated with OHRA ($b = .093$, $p < .050$). Compared to participants who have never searched for health information from any source, looking for health information for yourself (LOOKSELF) ($b = .258$, $p < .001$), someone else (LOOKELSE) ($b = .211$, $p < .001$), and for both yourself and someone else (LOOKBOTH) ($b = .310$, $p < .001$) were significant and positive predictors of OHRA.

CHAPTER 6

DISCUSSION AND CONCLUSION

In this dissertation I sought to clarify why people engage in online health seeking and whether such activities are related to offline health behaviors that might represent a broader, collective pattern of behaviors as a health lifestyle. In this section, I review several of the key findings from this dissertation and discuss some implications derived from these findings. I then discuss some of the limitations of this dissertation and suggest possible topics for future research. Finally, I end with a short conclusion that summarizes key questions and what this dissertation contributes to the research literature.

The first important finding demonstrates more clearly than previous studies that online health information seeking is related to poor health status and is not associated with a broader set of health-promoting behaviors. Although the relationship between health status and health promoting behaviors is relatively weak, it remains significant after controlling for demographics, SES, and measures of Internet access. Therefore, seeking health information online, versus other sources, is better explained as a form of illness behavior than health behavior. In addition, there is no evidence to suggest that online health information seeking is part a broader set of health-promoting behaviors that represent a health lifestyle, since there is not a significant relationship between SES, health-related attitudes, and online health information seeking..

Direct comparisons to previous studies is problematic due to differences in analytic samples and measurement of the dependent variable. Previous studies of Internet users have found a negative association between self-rated health and online health information seeking (Baker et al. 2003; Houston and Allison 2002), but other studies find no significant relationship (Atkinson et al. 2009; Goldner 2006a). Cotten and Gupta (2004) found that among participants who had sought health information during the past 12 months, self-rated health was positively associated with the use of online health information sources versus other sources. One possible reason for the conflicting findings is that the analytic sample used by Cotten and Gupta (2004) included both Internet users and non-users and used analytic methods that did not control for Internet use. Internet users, as a group, tend to be healthier than non-users (Fox and Jones 2009) and this may have contributed to the positive relationship between health status and use of online health information sources.

In contrast to the current findings, previous studies have found a positive relationship between the number of health-promoting behaviors and seeking health information online (Dutta-Bergman 2004a; Pandey et al. 2003; Ramanadhan and Viswanath 2006). However, the results are not directly comparable as these studies did not specifically examine use of online versus other sources of health information (e.g., Dutta-Bergman 2004a), focused on cancer-related information (e.g., Ramanadhan and Viswanath 2006), did not restrict the analysis to Internet users and health seekers (e.g., Dutta-Bergman 2004a; Pandey et al. 2003), or used a sample that is not representative of the U.S. adult population (Pandey et al. 2003).

This finding highlights the increasing significance of the Internet as a source of health information (Cotten 2001; Fox 2008; Fox and Jones 2009; Fox and Purcell 2010; Hesse et al. 2005; Viswanath 2006; Viswanath and Kreuter 2007). Although previous studies have often found that digital divide factors (i.e., income, education, occupation, age, gender, race/ethnicity, and location) are significant factors related to online health information seeking (e.g., Andreassen et al. 2007; Atkinson et al. 2009; Baker et al. 2003; Bundorf et al. 2006; Cotten and Gupta 2004; Dickerson et al. 2004; Flynn et al. 2006; Fox and Jones 2009; Goldner 2006a; Hale et al. 2010; Hesse et al. 2005; Miller et al. 2007; Pandey et al. 2003; Ramanadhan and Viswanath 2006; Wagner et al. 2004; Ybarra and Suman 2006), only age is significant in these models. This is likely due to the fact that the sample is restricted to Internet users and suggests that once differences between Internet users and non-users is taken into account, poor health status emerges as a significant predictor of online health information seeking.

Scholars have raised concerns about the quality of health information online and the possibility of harm that might result to people who use the information they find to self-diagnose and treat a medical problem, rather than seeking professional medical care (Cline and Haynes 2001; Silberg and Lundberg 1997). However, doctors continue to be the preferred choice of health information (Fox 2011b, c; Fox and Jones 2009) and are a more trusted source of information than other sources even though people often turn to the Internet first for health information (Hesse et al. 2010; Hesse et al. 2005; National Cancer Institute 2010). Most research finds that people seek health information online to supplement other health care services rather than as a replacement (Fox 2011a, b; Fox and Jones 2009; Fox and Purcell 2010; Lee 2008; Pandey et al. 2003). Using the Internet

to find health information is not associated with self-diagnosis and self-care (Campbell 2009), but empowers people with medical problems, providing them with the information needed to communicate more effectively with health care providers and participate in decisions regarding medical treatments (Broom 2005; Campbell 2009; McMullan 2006). Rather than replacing health care professionals, one study found that using the Internet to find health information was associated with an increase in the frequency of contact with health care professionals, even after controlling for health status (Lee 2008).

A second important finding is that social conditions (i.e., SES) and structural conditions (i.e., Internet access) influence Internet-related attitudes and behaviors consistent with the concept of an Internet habitus and lifestyle. SES had a positive, direct effect to online health-related activities, the number of places a person can access the Internet, and to health information seeking self-efficacy. Both measures of Internet access had direct effects to online health-related activities. Home broadband access had a positive direct effect on online health-related activities and an indirect effect via trust of online health information. A similar pattern of relationships was found in the online health information seeking models. Although SES and Internet access factors were not directly related to online health information seeking, there were positive associations between SES, Internet access, and Internet-related attitudes.

This finding highlights the importance of examining how social conditions shape people's experiences using ICT and the development of distinct, status-based differences in Internet usage – an Internet habitus. The finding that SES is significantly related to online health-related activities, even after controlling for differences in Internet access, health status, and demographics, is consistent with findings using the digital inequality

framework showing that SES is associated with greater use of the Internet for information gathering activities (Hargittai 2010; Zillien and Hargittai 2009).

Quality of Internet access is another important part of structural conditions, or to use Weber's concept 'life chances,' that enable and constrain people's choices that contribute to habitus (Robinson 2009). These findings demonstrate that differences in the quality of Internet access clearly influence a person's sense of information seeking self-efficacy and trust of online information sources that in turn, predict health-related Internet use. Perhaps the two most fundamental factors of Internet access are (1) the technical means people have to access the Internet, and (2) a person's degree of autonomy or freedom to access and use the Internet when and where they want (Hargittai 2008). Robinson (2009) found that youth developed distinct differences in their "information habitus" (p. 491) related to their level of Internet access. Youth with greater Internet access experienced more freedom and less frustration in their use of the Internet, and developed better information seeking skills than youth with more constrained access. The findings also add to our knowledge of how social inequalities shape the distribution of health information and knowledge that may contribute to persistent health disparities – a topic of research that is currently underdeveloped (Link 2008). Inequalities in SES are understood to be a 'fundamental cause' of persistent, status-based health disparities (Link and Phelan 1995, 2000, 2005). Link and Phelan (1995) argue that in "a dynamic system with changes in diseases, risks, and knowledge of risks" (p. 87) the persistent relationship between disadvantaged socioeconomic status groups and poor health outcomes is not due to any one specific mechanism, but due to status-related differences in the ability to access and effectively use a range of resources that benefit health and improve longevity.

Health information is a crucial resource that is not equally distributed but varies by socioeconomic status. Link and Phelan (2000) note that "when innovations beneficial to health are developed, their implementation necessarily occurs within the social context of existing inequalities in knowledge, money, power, prestige, and social connections" (p. 40).

Although the Internet has the potential to alleviate social disparities in health by providing greater access to health information and other health-related resources (Cotten 2001; Korp 2006; Viswanath and Kreuter 2007), social inequalities may contribute to persistent differences in how people use the Internet and incorporate it into their daily routines (DiMaggio et al. 2004; DiMaggio et al. 2001; Hargittai 2008). Inequalities in Internet access, skills, and use may contribute to communication inequalities (Viswanath and Kreuter 2007), knowledge gaps (DiMaggio et al. 2004; Viswanath 2005, 2006) and differences in health literacy (Abel 2007). Thus, people who have limited access to the Internet are less likely to develop a range of health-related values, skills, and knowledge that are important to maintaining their health and participating in decisions regarding their medical treatment if they become ill (Abel 2007, 2008).

A third important finding is that there is some evidence to suggest that online health-related activities are part of a broader set of status-based health behaviors that represent a health lifestyle. Three findings help to support this conclusion. First, in contrast to online health information seeking, online health-related activities was not significantly related to health status. Second, people who engage in a variety of routine, health behaviors (e.g., physical activity, fruit and vegetable consumption, and not smoking) also used the Internet for a greater number of health-related activities. Third, as

hypothesized using Bourdieu's concept of habitus, social status and Internet-specific structural conditions (i.e., Internet access) were significant factors predicting online health-related activities and intervening Internet-related attitudes (i.e., health information seeking self-efficacy and trust of online health information sources). Taken all together, these three findings provide evidence to suggest that online health-related activities are part of a broader set of status-based health behaviors that represent a health lifestyle.

This finding is important because it extends the conceptualization of health behaviors that comprise health lifestyles to include using the Internet for a variety of health-related purposes. Most research examining health lifestyles has focused on diet, physical activity, tobacco use, and alcohol consumption (Cockerham 2005). The concept of health lifestyle is not limited to these four behaviors, and may include preventative behaviors, medical screenings, and risk-taking or protective behaviors (Cockerham 2000). However, very little research has been conducted that examines health-related Internet use as a lifestyle choice (one exception, discussed below, is the research conducted by Lewis 2006a; 2006b).

The Internet is increasingly understood to be a regular part of many people's everyday lives and a necessity in order to access a variety of services and to participate fully in society (Hargittai 2008). Therefore it is important to understand how new forms of technology-mediated health behaviors are being incorporated into people's daily lives. The concept of health lifestyle highlights that these choices are not strictly individual choices, but are collectively patterned due to the close linkage between a person's social status background and the internalization of structural conditions as habitus; attitudes, beliefs, and preferences to act in routine and habitual ways (Cockerham 2005).

Additionally, the Internet and related communication technology is widely understood to be transforming the culture of medicine – a new era of eHealth. Viswanath and Kreuter (2007) note that, "Advances in communication and computer technologies have revolutionized the way health information is gathered, disseminated, and used by healthcare providers, patients, citizens, and mass media, leading to the emergence of a new field and new language captured in the term 'eHealth'" (p. S131). Although there is no single definition of eHealth, Oh et al. (2005) found that Eysenbach's definition is the one most often cited. Eysenbach (2001) defined eHealth as:

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

What is important about this definition is that it highlights that the Internet is instrumental in generating a new "state-of-mind, a way of thinking, an attitude" (Eysenbach 2001:1), a new culture of health and health care. Health lifestyles are embedded in larger social and cultural contexts (Cockerham 2005) and provide a sense of social identity and status (Giddens 1991) to individuals. The utopian discourse surrounding ICT and the Internet is derived from a broader set of cultural values of individualization, personal empowerment and actualization, egalitarianism, and the emphasis on freedom of speech and access to information (Turner 2006). Thus, the findings from this dissertation are an important step towards understanding how technology-enabled health behaviors influence more traditionally studied health behaviors and how they combine as a person's lifestyle and contribute to sense of social identity.

These issues are at the core of Lewis' (2006a, b) research on youth's use of the Internet to find health information. Using the concept of lifestyle, Lewis (2006a) describes youth's use of the Internet as a 'do it yourself' attitude that reflects a broader set of cultural values that emphasize personal responsibility and a proactive attitude to maintain one's health and forge a sense of individual identity. In contrast to a view of the Internet and changes in contemporary society as contributing to freeing people from the constraints of their class conditions to forge new identities, Lewis (2006a) found that social status was important in shaping youth's health habitus as "structured by an individual's life biography, material circumstances, cultural values, habits and practices as well as broader institutional and social contexts" (p. 476). Thus, although youth in her study showed a general proactive attitude towards managing their health and that the Internet empowered them to do so, "the kinds of health information they access, how they perceive that information, and how they make use of it in their everyday lives" (Lewis 2006b:536) was influenced by their social status backgrounds.

<div align="center">Policy Implications and Future Research</div>

The findings in this dissertation highlight the importance of social conditions and structural factors to influence an Internet habitus or status-specific patterns of Internet use. This has important policy implications, as the Internet has now become a central feature in many people's lives and is quickly becoming less of a luxury and more of a necessity for people to access a range of public and private sector services (Hargittai 2008). Health care is one sector of society that is undergoing a rapid transformation due

to changes in information and communication technologies (Viswanath and Kreuter 2007).

Internet-based services may help to alleviate social inequalities in health by reducing barriers that limit access for disadvantaged groups. The Internet can be accessed anywhere there is an Internet connection; is available 24 hours a day, 7 days a week; provides greater anonymity that may be important for people with sensitive health care needs; and enables people to locate and connect with other people with similar medical problems (Cotten 2001). Thus, the Internet has the potential to reduce social disparities in health by empowering people with knowledge and services to better manage their health, change unhealthy behaviors, and participate in medical decisions.

However, as demonstrated by the findings in this dissertation, social status and structural conditions contribute to distinct differences in how people use the Internet and as part of a health lifestyle, are embedded in other everyday health behaviors. Attitudes towards and use of the Internet to accomplish a variety of tasks are not simply choices, but are embedded within a larger cultural framework of values and meaning, that is stratified by a person's social status background and their efforts to forge a social identity (Lewis 2006a, b). As habitus, attitudes, beliefs, preferences, and behaviors are relatively durable and resistant to change and contribute to the reproduction of differences between social groups. Thus, social conditions continue to be a 'fundamental cause' of persistent health disparities, despite advances in technology and medical knowledge (Link 2008). To narrow gaps and promote greater public health, it is necessary to look at how social conditions shape differences in knowledge, skills, and values that contribute to

differences in health behaviors and uses of information to improve health (Abel 2007, 2008).

In this dissertation, level of Internet access was found to be a strong determinant of Internet-related attitudes and health-related Internet usage. A high-speed broadband Internet connection influences how people use the Internet (Davison and Cotten 2009). The speed and convenience of an always on and fast broadband connection expands people's range and frequency of online activities (Horrigan 2008; Horrigan and Rainie 2002) and might be especially important for people's health-related Internet usage (Kolko 2010). Governmental efforts to make high speed broadband Internet access available and affordable is an important step towards reducing digital inequalities in Internet skills, attitudes, and use. The Federal Communications Commission has conducted an extensive investigation to develop a comprehensive plan to ensure the development of a robust broadband Internet infrastructure as a foundation needed "for economic growth, job creation, global competitiveness and a better way of life" (Federal Communications Commission 2010:xi). One of the stated goals of this plan is to ensure that all Americans have access to affordable broadband Internet connections (Federal Communications Commission 2010:xiv).

Despite these efforts, 32% of households in 2010 still do not have broadband Internet connection (National Telecommunications and Information Administration 2011:5). The most often cited reasons being, don't need or not interested (46%), too expensive (25%), and lacking a computer (14%) (National Telecommunications and Information Administration 2011:20). Recognizing the persistent barriers people may face in adopting broadband, President Obama announced a National Wireless Initiative

with the stated goal of ensuring 98% of the U.S. population has access to high speed wireless Internet (4G) within five years (National Telecommunications and Information Administration 2011). This initiative is a move in the right direction, as recent surveys have shown that people from minority groups make greater use of mobile devices to connect to the Internet wirelessly (Smith 2010b) and to seek health information and to use health applications (Fox 2010).

Limitations and Future Research

This dissertation has contributed to a clearer understanding of the factors associated with online health information seeking and online health-related activities using a nationally representative sample of adults collected in 2007. However, there are limitations to this research that should be noted. I briefly describe each of these limitations below.

First, the over-all survey response rate is relatively low (31%), compared to surveys conducted in the past. This raises the possibility of nonresponse bias in estimates to the extent that key variables of interest are correlated with the likelihood of persons not responding to the survey (Groves 2006). Although higher response rates reduce the risk of nonresponse bias, studies have not found that response rate alone is a good predictor of nonresponse bias (Groves 2006). The problem of low response rates is not unique to data used in this dissertation, but is a growing problem that is common to surveys conducted in richer countries (de Leeuw and de Heer 2002). Although a response rate of 31% is relatively low compared to surveys conducted in the past, it is similar to the overall response rate of other nationally representative surveys such as the 2007 Behavior Risk

Factor Surveillance System (33.5%) (Centers for Disease Control and Prevention 2008),

and considerably higher than data frequently used in studies examining Internet use

collected by the Pew Internet & American Life Project in 2006 (27.1%) and 2008

(21.0%) (Fox 2006; Fox and Jones 2009).

Second, unfortunately the variables measuring online health-related activities do

not account for frequency or duration of uses, but only having participated in an activity

during the past 12 months. This provides a rather limited measure of people's online

activities. Variables that take into account frequency and duration of time spent

participating in online health-related activities would capture to a greater extent behaviors

that are routine and habitual choices.

Third, analysis was limited to the use of many single, observed variables to

measure concepts such as trust of online information sources and health information

seeking self-efficacy. Data that used multiple observed variables to construct latent

variables would enable the use of more sophisticated statistical analysis such as structural

equation modeling.

Fourth, the data is relatively old for studying emerging trends in Internet usage

and does not contain information on the use of mobile devices to wirelessly connect to

the Internet or the use of mobile health applications. To some extent, this is

understandable, as the devices of the time had few features and were slow in accessing

the Internet. More powerful and user friendly devices were just beginning to become

available. For example, Apple's iPhone was announced in January 2007 and was not

released until June 2007. This marked the beginning of widespread popularity and rapid

growth in the use of 'smartphones' that are capable of wireless Internet browsing and

running a variety of health-related applications. As discussed previously, wireless devices may provide a technical means to narrow the digital divide making Internet access relatively affordable, available, and convenient than previous methods of access.

Future research should focus on the health-related uses of mobile devices and applications, as the convenience and portability of this technology is likely to contribute to people's incorporation of these devices in their everyday routines. Mobile devices also offer the potential for new means of data collection using applications that passively collect data on the activity of study participants and could be used to prompt participants at interval to record their current activities to provide a fine grained sample of routine behaviors.

Conclusion

In this dissertation I sought to explore three research questions: (1) Are online health behaviors better explained as illness behavior or health behavior? (2) Does online health behaviors fit the conceptualization of lifestyles? (3) Is there a relationship between online health behaviors and offline health behaviors that might suggest a broader pattern of health-promoting behaviors or health lifestyle? I examined two different measures of online health behavior: a single item measuring if people searched for health information online, versus other health information sources; and a summated index of 6 types of online health-related activities that people may have used during the past 12 months.

The findings from this dissertation advance our understanding of online health behaviors by more clearly highlighting the differences between a single measure of online health information seeking and the number of online health-related activities.

Whereas previous research has largely focused on health information seeking and produced at times conflicting findings as to the relationship with health status, the findings from this dissertation clearly suggest that online health information seeking appears to be better explained as illness behavior than health behavior. People who were most likely to search online for health information tended to have poorer health and participate in fewer health-promoting behaviors. Seeking health information online did not appear to be a lifestyle choice, as there was no significant relationship to either level of education or household income.

The findings for number of online health-related activities were quite different. There was no relationship between health status and number of online health-related activities and people in better health tended to make greater use of online health-related activities. Combined with the fact that level of education was associated with number of online health-related activities, the findings suggest that offline and online health behaviors may represent a broader, collective pattern of status-specific behaviors or a health lifestyle.

For both outcomes, it was found that social and structural conditions influenced Internet-related attitudes and use of the Internet. These findings support previous research using a digital inequality framework that finds social status background and level of Internet access are important determinants of an Internet and informational habitus (i.e., attitudes, beliefs, preferences, and behavioral routines). This pattern of relationships was more clearly supported in the online health-related activity models and suggests that social and structural conditions may contribute to distinct forms of Internet use and lifestyle.

Perhaps the most important contribution of this dissertation is to demonstrate that online health behaviors can be usefully conceptualized as part of much broader set of health behaviors that represent a health lifestyle. The combination of health lifestyle theory and digital inequality provides a broader theoretical framework that highlights the importance of social and structural conditions to influence people's habitus and routine, everyday behaviors that contribute to maintaining their health and the effective use of health care services if they become ill. Thus, it provides a useful tool for future research investigating persistent social disparities in health and ways to leverage new technology to potentially narrow gaps in digital inequality and in health disparities.

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APPENDIX A

IRB APPROVAL FORM

UAB THE UNIVERSITY OF
ALABAMA AT BIRMINGHAM

Institutional Review Board for Human Use

DATE: 10/18/10

MEMORANDUM

TO: Timothy Hale
           Principal Investigator

FROM: *Sheila Moore, CIP*
           Sheila Moore, CIP
           Director, UAB OIRB

RE: Request for Determination—Human Subjects Research
           IRB Protocol #N101012011 – Health Status and Health Behavior as Factors
           Predicting Online Health Information Seeking

An IRB Member has reviewed your application for Designation of Not Human Subjects
Research for above referenced proposal.

The reviewer has determined that this proposal is **not** subject to FDA regulations and is
not Human Subjects Research. Note that any changes to the project should be resubmitted to the
Office of the IRB for determination.

SM/cro

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