Title

Adoption and Use of Internet Technologies in Health Communication: Examining Disparities in Diffusion Patterns, Health Information Sources, and Patient-Provider Encounters

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Adoption and Use of Internet Technologies in Health Communication: Examining Disparities in Diffusion Patterns, Health Information Sources, and Patient-Provider Encounters

A dissertation submitted in partial satisfaction of the
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in Public Health

by

Philip Minter Massey

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ABSTRACT OF THE DISSERTATION

Adoption and Use of Internet Technologies in Health Communication: Examining Disparities in Diffusion Patterns, Health Information Sources, and Patient-Provider Encounters

by

Philip Minter Massey
Doctor of Philosophy in Public Health
University of California, Los Angeles, 2013
Professor Deborah Glik, Chair

This dissertation examines the impact of internet technologies on the field of health communication. Access and use of health communication technologies has and will continue to become increasingly important to manage and treat chronic conditions and other ailments, particularly in the context of health care reform that promotes improved quality of care along with cost-saving measures. Through examining internet adoption rates, its use as a source of health information, and its influence on the patient-provider encounter, findings highlight ways in which the internet can be leveraged to help health consumers, health providers, health care organizations, and health insurance companies transition into the digital age of health care and health promotion.

Data from the 2003 and 2008 Health Information National Trends Survey (HINTS) are used to examine online technologies for health communication among U.S. adults. HINTS, a nationally representative repeated cross-sectional survey, is developed and implemented by the National Cancer Institute (NCI) to measure knowledge, attitudes, and practices related to health information and media use, reflecting the growing reliance on internet sources for health and illness information. Three studies based on HINTS incorporating diffusion models and communication theories to describe the use of online technologies for health information and communication are presented.

The first study demonstrates that the largest growing disparity in internet use is among women and men, with women significantly outpacing men between 2003 and 2008. A proposed disparities diffusion model suggests that other disparities in internet use are neither growing nor shrinking – that is, vulnerable populations remain at a disadvantage. The second study shows that internet use for health information continues to grow among both internet users as well as non-users. This suggests that non-users get online health information through surrogates, supporting a "team" approach to health information seeking. The third study demonstrates that the first source an individual uses for health information can influence the patient-provider encounter. Specifically, compared with individuals who use a health provider as a first source, those who use the internet have on average a more negative experience with their provider.

Health consumers will continue to use online technologies for health information; thus, it is imperative for health care providers and organizations to implement policies and procedures that acknowledge and incorporate online health information into the care process to improve satisfaction, quality of care, and ultimately health outcomes. As new technologies expand throughout populations and are integrated more into decisions regarding health and wellbeing, findings from this dissertation can be used to support intervention and policy development.

The dissertation of Philip Minter Massey is approved.

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2013

DEDICATION

To my wife, Elise,
whose steadfast support, encouragement, and love was my rock,

my parents, Woody and Shirley Massey,
who have always believed in me,

my grandparents, Curtis and Louise Minter, and Elwood and Joanne Massey,
whose hard work and faith paved the way for many, and

the Wagner and Ditte families,
who have given me a home away from home.

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INTRODUCTION

There has never been a more exciting time for the field of health communication. The importance of health communication for the health and wellbeing of the U.S. population continues to grow, especially given the impending health care reform that places emphasis on an informed and activated health care consumer. Moreover, Healthy People 2020, a set of 10-year national objectives for improving the health of all Americans, lists health communication and health information technologies as a key area of focus for improving population health outcomes and achieving health equity [1].

Given the growing emphasis on health communication coupled with the expanding role of the health care consumer, this dissertation examines the impact of growing information sources on knowledge, attitudes, and practices related to health information seeking, and, ultimately the impact on the quality of the patient-provider encounter. Through the investigation of three studies, this dissertation examines the influence of the internet in shaping the way people look for and use health information.

Unprecedented levels of information access and exchange at both national and global levels have transformed the field of health communication, in large part due to the expansion of the internet. Often described as both an interpersonal and mediated communication channel, the internet's role as a hybrid channel has played a significant role in the field's evolution [2]. Even as internet use among the general U.S. population has steadily grown over the past decade and a half, disparities in access and use still exist based on socio-economic and demographic characteristics as well as structural factors. However, what is less clear is whether these disparities are perpetuated over time.

Moreover, despite nearly 80% of the U.S. population using the internet, only 60% use it to look for health information [3]. Again, using the internet as a source for health information has been shown to vary based on individual and structural factors [4]; however, there is a dearth of research examining these determinants over time. Additionally, with greater access and exchange of health information, there is increased emphasis placed on the role of communication and informed decision-making between the consumer and the health care provider [5]. Therefore, it becomes imperative to ask what influence using the internet as a source for health information may have on the patient-provider encounter.

To address these research gaps in the field of health communication, this dissertation examines secondary data from the Health Information National Trends Survey (HINTS). The HINTS provides data related to health information needs and practices of the American public [6]. Specifically, the survey provides information related to internet use, health information-seeking behaviors, and health care experiences. Two survey waves (HINTS 2003 & 2008) are examined to assess changes over time. This investigation explores, through three interlinked studies based on the HINTS data set, the impact of the internet in shaping the way people look for and use health information.

The first study applies the diffusion of innovations theory to recent trends in internet use, examining adoption rates between two points in time based on key characteristics. Although nearly ubiquitous in its use, the rate of internet adoption varies among sub-populations, leading to disparities in information access. Studies examining predictors of internet use often focus on one point in time, neglecting the rate of adoption when compared to previous time points. While examining one point in time provides useful information on current disparities in access or use, it does not provide a picture as to whether these differences or disparities have increased or decreased over time. This is important when evaluating the effectiveness of policies or programs that target the reduction of such disparities. Moreover, fewer studies have examined internet trends using the framework of the diffusion of innovations theory. Therefore, Study 1 assesses diffusion patterns and digital disparities in internet adoption by examining: *What factors are associated with differences in internet use between 2003 & 2008?*

The second study examines determinants for turning to the internet as the first source for cancer-related health information. The internet is a medium by which many gain access to vast amounts of health information. This becomes particularly relevant in an era marked by increased patient and health consumer participation in health care and health promotion. Building upon the first study's goal of examining differences in use and adoption of the internet, Study 2 describes changes in the first source for cancer-related health information between two points in time and explores differences in information-seeking behaviors among internet users and non-users. Specifically, Study 2 examines: *How has the first source for cancer-related health information changed over time?*

The final study looks at the impact of using the internet as an information source on the patient-provider encounter. As the American health care system continues to place more emphasis on managed care and an activated patient, coupled with an ever-increasing burden on patients to manage complex preventive, health maintenance, and curative regimens, the patient-provider encounter becomes a central focus for improving care and ultimately health outcomes. Therefore, Study 3 examines: *What role does the first source of consumer health information have on the quality of the health care experience?*

A notable contribution of this research will be the examination of determinants and diffusion patterns of health information access and use over time, particularly concerning the role of the internet. Whether determinants change over time, and if so, at what rate among which populations, provides meaningful information to health providers, educators, and policy makers regarding internet use for health information. Identifying trends in determinants will be key as the field moves forward, particularly for predicting future trends as well as anticipating future challenges. Moreover, as fewer individuals view themselves as patients, but rather health care consumers, the internet and health information will play a larger role in the informed decision-making process and ultimately must be considered as a factor affecting patient outcomes.

This dissertation first provides background on the framework and evolution of the field of health communication. To provide a context for its development and evolution, it is necessary to discuss changes in models of patient-provider interactions. Furthermore, a description of key theories in the field of health communication will provide a foundation for the reasoning behind the studies. Finally, three studies are presented that describe patterns of internet use, changes in sources of health information, and the impact of information technologies on the patient-provider encounter.

CHAPTER 1: HEALTH COMMUNICATION

Levels of Health Communication

The field of health communication is a broad and ever-changing area of inquiry. Fundamental to this field is the examination of the functions and effects of human and mediated communication in health care and health promotion that occur within diverse social contexts [5,7,8]. An often-used framework to describe various levels of health communication inquiry includes intrapersonal, interpersonal, group, organizational, and societal levels [8,9]. This interrelated, hierarchical framework illustrates how pervasive and ubiquitous the field of health communication is as an area of research in various social contexts. It also illustrates the complex nature of health communication that may breed friction or difference of opinions between scholars as well as practitioners in the field. Ultimately, the multi-level nature of health communication and research that it has engendered is both a strength and a challenge that underscores the need for an interdisciplinary approach and perspective. Moreover, as new communication technologies continue to emerge, the line between the varying levels are likely to blur and become superficial.

Intrapersonal: The intrapersonal level is the most basic level of health communication. This level is concerned with cognitive and psychological processes including beliefs, attitudes, and perceptions that influence health behaviors and decisions [10]. At this level, meanings of health, illness, and treatment are created and communicated, influencing health information and subsequently health-related choices [9,11]. Moreover, these meanings are formed through both physical conditions as well as symbolic understanding [12]. That is, definitions of health and illness are relative as opposed to absolute.

Decision-making is a critical process that occurs at the intrapersonal level, and is based on the beliefs, values, and attitudes held by an individual [13]. Many of the contemporary theories in health behavior predict behavior change based on the organization and weighing of such beliefs and attitudes [14,15]. The decision-making process can influence health in a variety of ways, including both physical as well as psychosomatic processes and responses [16,17].

One limitation of the intrapersonal level is that it relies heavily on a value-expectancy model. That is, there is an assumption that an individual values health and that specified information or actions will help fulfill the valued health state. Additionally, decision-making at this level assumes that clear and complete information will be followed by a rational process that will in turn maximize individual satisfaction. The concept of a rational process of decisions making, as it turns out, is difficult to predict due to its largely overlooked subjective nature [18]. Emerging literature on behavioral economics and its application on health communication and ultimately health outcomes supports the naïve and somewhat misinformed assumption of rational decision-making [19,20].

Interpersonal: The interpersonal level of health communication adds an important dimension of relational influences on health behaviors and outcomes, particularly when concerned with the health care interactions and health delivery issues [9]. The main focus at this level is the role and influence that interactions with others have on health information, decisions, and actions [8]. Most often interpersonal interaction is in the form of dyadic communication, where two individuals share information, beliefs, and attitudes related to health. In health communication, the most examined dyadic relationship is between health care provider and patient [21–24].

Roles play a key function in interpersonal communication, particularly in processing information and interpreting responses. Communication between health care provider and consumer generally has two features – a content-oriented characteristic and a relationship-oriented characteristic. Content-oriented communication focuses on question asking, information giving, treatment, and referral. Relationship-oriented communication pertains more to facial expressions, conveyed affect, social talk, and satisfaction. Interpreting the two features can sometimes be challenging depending on the nature of the information [25]. For example, for content-oriented communication the physician needs fundamental and correct information from the patient in order to diagnose and treat an illness, and the consumer needs relevant and easy-to-understand information from the physician regarding treatment. Features such as nonverbal cues, empathy or caring, and whether or not this process occurs in a satisfactory way relates to relationship-oriented communication.

Traditionally, the interaction between the health care provider and patient has exemplified interpersonal health communication, and rightfully so, as this is the most traditional and accepted dyadic interaction related to health information and communication. However, more examination is needed to understand other interpersonal influences and channels of health communication. In particular, the role of power in influencing interpersonal communication seems to be generally understated in its influence on communication and interaction. Additionally, an emerging area of inquiry that blends interpersonal and mediated health communication is the role of new media and technologies on interpersonal interactions and relationships. This becomes particularly interesting as online interpersonal interactions continue to grow through support groups and other informational resources.

Group: The group level of health communication is concerned with the role of communication in interactions between members of collectives, such as health care teams, support groups, or families [9]. In the health care setting, groups are often necessary in working through complex problems; thus effective communication can facilitate the sharing of expertise as well as practical, moral, and legal responsibility [26].

Communication in a group can vary depending on the structure of the group. For example, hierarchical groups have very different channels of communication compared with egalitarian groups [27]. Thus, power is an important consideration when examining group-level health communication. Moreover, in the health care setting, the effectiveness of group-level communication is often dependent on the ability to overcome inter-professional status barriers [28].

Like interpersonal relationships, groups are capable of providing social support through acceptance, validation, and insight into personal problems [8,26]. Furthermore, families and support groups can provide a broader perspective in that multiple members share experiences and relevant information that they have gathered over time. Thus, the group is able to share a cache of knowledge and information [8]. Group-level influence on health communication is a particularly interesting when considering online health-information seeking. Namely, as sources of health information continue to emerge and become more complex (i.e., the internet), information seeking will likely become a “team sport” as greater emphasis and requirements are placed on technical skills and navigation abilities [29].

Organizational: Organizational health communication is concerned with the role of communication in managing and coordinating interdependent groups as well as in sharing relevant health information within complex health systems, such as hospitals, medical centers, nursing homes, clinics [9]. This level of communication becomes even more relevant in a health care system that is shifting towards a managed care model, where financial concerns and cost-saving measures must be introduced into the decision-making process. Moreover, with the advent and implementation of electronic medical records along with other electronic methods of health care management, the role of health communication at the organizational level becomes even more critical.

With a greater emphasis placed on managed care, there is a growing concern among health consumers about the quality of care and the consumer role in the decision-making process [30]. Communication will be necessary in facilitating the transition into managed care and making it more amenable to consumer concerns. Additionally, along with the increasing complexity of health information and knowledge especially regarding chronic disease management, navigating the health care system has also become more involved and elaborate, for both consumer and health provider. Thus, communication technologies will continue to be necessary to manage complex health situations [31].

Societal: The societal level of health communication, the broadest level, examines how health education, promotion, and health care practices are created, communicated, and utilized via diverse media to a range of audiences [8]. Media communication scholars have examined how media can be used to communicate messages of health promotion and risk prevention to targeted audiences [32,33]. Traditional forms of mediated communication include print media (newspapers, books, magazines, journals, pamphlets, etc.), telephone (hotlines for AIDS and depression, call centers for abuse, etc.), and radio and television (health news shows such as 60 minutes, Oprah, Law and Order) [34].

Media provide an extremely important forum from which to coordinate resources and activities in response to the environment, to learn about culturally relevant phenomena, and to pass on cultural information to future societies [32]. For example, societal health communication plays a role in changing social and cultural norms, especially associated with stigma [8].

Moreover, societal health communication can influence ethical considerations in health and health care. In this way, this level has an enormous impact on health decisions and health behaviors given its use of mass media.

Perspectives in Health Communication

Two perspectives have traditionally been used to described health communication: human communication and mediated communication. Each branch offers an array of strengths and challenges when communicating information and messages to a target audience. There are multiple ways in which to distinguish the two interdependent branches, and scholars have tried for the past 60 years to define and maintain branch uniqueness. However, many scholars argue that the only driving force behind branch distinction is history and politics [35–37].

Human communication is thought of in terms of interpersonal communication, and is mostly applied in the context of health care delivery. The health care delivery branch is concerned with how communication influences health care utilization and services, such as through patient-provider interactions, use of emergency room services, and other settings of health care treatment [9,38]. Group and organizational levels also play integral roles in this perspective given its use in health care delivery [39]. These forms of communication are particularly relevant to patients and their families and caregivers.

Mediated communication, on the other hand, is thought of in terms of mass or societal level communication, and is most often applied to a health promotion context. This branch communicates messages through media directed at the masses, promoting health education programs, health promotion campaigns, and risk prevention efforts often to individuals, families, and households [9,33,40].

Traditionally the two branches have been in direct competition with one another, in terms of both resource allocation and research spotlight [35]. However, each branch offers strengths in effectively delivering information and messages. Mass media channels are capable of reaching and informing large audiences, whereas interpersonal channels are effective in influencing attitudes and motivating behavior change [2,41,42]. In this sense, mass media are appropriate channels for creating and maintaining awareness as well as setting an agenda, whereas interpersonal channels may be better equipped in influencing or persuading individuals to adopt health-promoting or health maintenance behaviors.

Recently, scholars from each branch are finding reasons to shift their research towards an inter-branch approach. For example, scholars working in health care delivery have begun using broader communication channels for health care marketing and health education. Similarly, scholars of health promotion have begun using interpersonal and micro-social strategies of health promotion, such as support groups, family involvement programs, and neighborhood and workplace interventions [9].

Emergence of a hybrid channel

Newer forms of media, namely the internet, are reshaping the traditional, interdependent dichotomy of health communication inquiry [7]. New media have mass, interpersonal, and organizational dimensions that are often difficult to differentiate. New media has helped bridge communication contexts by blurring the boundaries between the two factions of health communication [33]. However, some scholars still argue that the internet and other forms of new media are best situated within their branch of health communication [43,44]. Despite some controversy over which perspective the internet is better suited for, it is more likely that the internet functions as a hybrid channel with both interpersonal and mass communication characteristics.

A hybrid channel such as the internet is equipped to function simultaneously as both mass communication as well as interpersonal communication. For example, through the use of algorithms, internet programs are able to customize feedback of an interaction based on a participant's characteristics. By tailoring the interaction to meet the participant's needs, the internet is mimicking an interpersonal form of communication [2]. Moreover, communication with other individuals through chat, email, or messaging demonstrates the internet's interpersonal characteristics.

On the other hand, the internet acts as mass media through its ability to reach vast audiences for little to no economic cost. Moreover, as technologies continue to advance, internet-based resources continue to expand to mediums other than computers, including cell phones, television, and other handheld devices, further increasing its reach and expanding its audience [2]. The internet's hybrid nature is able to make both mass and interpersonal communication more persuasive and interactive [2]. Thus, the message is better equipped to influence attitudinal change that will in turn facilitate behavioral change [2,45].

Furthermore, the increasing use of the internet to look for health information has a direct impact on health communication. As the internet becomes the preferred first source for health information for more individuals, studies are emerging that examine the impact of looking online for health information on the patient-provider encounter [4,46]. Findings suggest that online health information may contribute to professional blurring of the traditional patient-provider relationship [47]. That is, online information may serve to lessen the knowledge gap and ultimately reduce the asymmetrical care relationship.

In response to growing health-related internet resources, health care professionals and organizations must update their trainings and protocols to accommodate internet-informed health consumers [48]. Kreps [9] states “communication is a primary social process that can help equalize power between providers and consumers of health care by promoting wide dissemination of relevant health information.” Paul Arntson refers to this increasing role of health consumers in the decision process as health care “citizenship” – becoming a participating citizen of the modern health care system [49].

The traditional medical model placed low importance on patient communication as health issues were conceptualized as strictly biological. The emergence of chronic disease (as well as emphasis on health promotion and wellness care) has ignited a rethinking of this model [5]. In particular, health promotion and disease management require ongoing communication between patient and physician, as there is no clear “victory” line. A reductionist perspective in medical and health care that supports an asymmetrical relationship between provider and patient no longer meets the needs of the chronic care or disease management enterprise; rather, a “systems biology” or collaborative care approach is more suited for chronic disease in primary care [50,51]. Most importantly, performance measures focusing on quality of care outcomes, patient satisfaction, and the patient decision-making process are becoming important determinants of health outcomes.

To provide a context for recent development in health communication, it is also important to examine the field juxtaposed with changes in the broader health care system, particularly with structural changes that occurred in patient-provider models during the 20th century.

Shifting Patterns in Disease and Medical Care

The U.S. has witnessed a marked shift in mortality and disease patterns over the last 100 years [52]. The early 20th century was characterized by an infectious disease burden and germ theory paradigm. However, during the second half of the century a shift occurred towards a chronic disease burden described by a risk factor paradigm [52]. The epidemiologic transition, characterized by a drop in mortality rates and a rise in infant and child survival rates [53], resulted in an aging population and thus a rise in chronic disease.

Mirroring the changes in mortality and disease patterns, the patient-provider interaction shifted from a heavy focus on acute often hospital-based care to incorporating treatment plans for the management of chronic illness often in ambulatory care settings [54]. For the first half of the 20th century, individuals mostly sought a physician's care to treat acute illness. From this, physicians developed an asymmetrical approach to treatment, rarely asking the patient for their opinion or their understanding of the treatment regimen [55]. Thus paternalism emerged as the dominant model for medical practice from the early 20th century to post World War II [56].

Paternalism in medical care

Paternalism is defined as interference with a person's liberty of action with the explicit purpose of doing good for, or avoiding harm to, that person, ostensibly by reason of their limited autonomy or diminished capacity [56,57]. The medical profession was able to justify this behavior based on theories of professionalism [58]. Features of professionalism that reinforced the asymmetrical model included autonomy, protection from encroachment, control of production and application of knowledge, and a code of ethics [59]. Most importantly, physicians controlled a monopoly on technical knowledge related to the etiologies of infectious disease.

According to Parsons, illness is a form of social deviance that must be restored by seeking care from a physician; this is manifested through the sick role [60]. This belief is rooted in Parsons' deeper conviction of functionalism, asserting that society survives through shared values and interrelated functions, with various accepted instruments of social control maintaining equilibrium within the system [60]. The "competence gap" is another functionalist justification for paternalism [61]. Proponents argue that the gap in expert and technical knowledge between the patient and provider is necessary for asymmetrical care. From a Parsonian perspective, narrowing the competence gap will blur the line between patient and provider functions. Thus the maintenance of the gap strengthens a functionalist approach by maintaining order and functions in the health care system, and reaffirms the social control function of medicine.

One critique of the paternalism model is the assumption that knowledge and decisions of the health care provider are considered objective and rational. Moreover, information is assumed correct, accurate, and relevant to the patient, taking a positivist perspective that truth exists and is most easily identified through science-based inquiry, eliminating the role of patient preference. Another critique of the model is the assumption that information is both necessary and sufficient for treatment adherence and behavior change for health maintenance.

Communication skills needed for dialogue and participation between patient and provider are not supported in the paternalistic medical model. Apart from divulging necessary information to form a diagnosis, the patient is not expected to contribute to the health interaction with health information from outside sources, supporting a unidirectional communication approach.

Consumerism in medical care

The traditional relationship between patient and provider is rooted in power and manifested through the sick role [62]. Physicians have a monopoly on knowledge as well as the claim of public service. However, as infectious disease and other acute illnesses begin to decline and the prevalence of chronic illnesses increases, physicians are forced (rather reluctantly) to alter their approach in treating their patient's illness – curative treatments are now being replaced by disease management plans [21]. This has a direct effect on health communication, at both the interpersonal and societal levels, as patients are now being asked to follow complex instructions and understand health materials [63]. As patient participation and responsibility increases (i.e., patient activation), the need for improved communication skills becomes more apparent as well as improvements in how providers interact with health consumers [24,64].

Consumerism in medicine and health care challenges the physician's ability to make unilateral decisions and places an emphasis on shared and informed decision making between the patient and provider [24,64,65]. The consumerist model rejects the asymmetrical relationship between patient and provider and asserts that power and decision making is at minimum shared by the two agents. Simply put, dialogue and justification encouraged by the consumerist model replaces faith and trust expected by the paternalistic model [59].

Informed decision making is a key concept in consumerism and can be viewed as a mechanism to decrease the asymmetrical relationship between patient and provider. Based on this model, informed decision making is likely to enhance the patient-provider relationship by: 1) diminishing the tendency of the physician to view the patient as an object; 2) providing more satisfactory care as evaluated by both patient and providers; 3) narrowing the gap between patient expectations and provider capabilities; and 4) increasing the quality of care, inferred through health outcomes. A crux of the informed decision-making model is that the technical knowledge resides within the purview of the physician while preferences reside with the purview of the patient [66]. Striking a balance with necessary information as well as reaching consensus is paramount to the success of this model [23,67].

As the passive patient transitions into an active one, the health consumer is able to develop and exercise greater skills and abilities related to finding and using health care information, so that they can participate more fully in the medical encounter as well as preventive measures to promote and maintain health [68]. Thus the need arises for the field of health communication to examine how patients actively participate in their health care decisions, including accessing and navigating health care resources – particularly resources available through online technologies [69].

The consumerism movement liberates patients from submitting to a sick role, and empowers them to use information to exert greater control over their health care and life situations [70]. This belief takes an agency approach to health, namely that individuals are not merely products of their environments, but rather intentionally influence their life circumstances. This perspective is most notably developed by Bandura in the Social Cognitive Theory [71]. Social cognitive theory acknowledges the interplay and influence between individual and environment, but ultimately contends that it is the individual that creates the system, which is then used to direct and manage human activities [71]. Moving forward, the field of health communication must acknowledge the existence of social structure as well as the role agency plays within that structure.

Quality of care

As consumerism in health care continues to gain ground and prevention and management of chronic disease becomes a focus in health care, quality of care becomes a critical determinant of health outcomes and health status. Chronic disease management has no “victory” line; that is, there is no cure or clear-cut treatment plan to recovery and health. Thus, traditionally objective health outcomes (objective in the biomedical sense of lacking disease or illness) are supplemented with quality of care measures – the health care experience becomes equal parts process and outcome.

Donabedian is considered a pioneer in the field of quality of care, both in his conceptualization as well as his measurement of the concept [72]. Importantly, Donabedian's research embraces the subjective nature and social construction of quality of care and helps identify key areas to operationalize the construct for health services and social science research. Key issues that Donabedian raises in terms of defining and measuring quality of care include: 1) quality is best measured using both patient and provider perspectives; 2) quality depends on how broadly health and responsibility for health are defined; 3) quality varies based on whether maximize effectiveness or optimal effectiveness is sought; and 4) optimal care can be defined by the individual or society and can vary accordingly.

Based on this research, quality of care can be described using two dimensions: access and effectiveness. Access is described in terms of affordability, availability, and other geographic or physical determinants. Effectiveness is concerned with both the clinical care aspect as well as the interpersonal aspect of care [73]. Thus, from an individual perspective, quality of care is described as the ability to "access effective care with the aim of maximizing health benefit in relation to need" [73]. The population perspective emphasizes accessing effective care on an efficient and equitable basis for optimizing health and wellbeing among the whole population.

Communication is a critical determinant of quality of care along the continuum of care, from health care access, to treatment of an illness, to health management. In a quasi-experimental study by Roter [24], quality of care measures were compared between a group of patients who received training on asking questions during the health care encounter with a group of patients who did not receive the training. Findings show that the experimental group (trained in asking questions related to their health) reported on average lower scores on quality of care measures. These finding suggests that communication during the health care experience can lead to not only positive outcomes, but can actually have negative consequences or add stress to the encounter. This in turn may inhibit future attempts at communication and may ultimately prevent optimal health outcomes. Thus, health communication plays a critical role in quality of care and ultimately health outcomes.

Quality is not an object, but rather the process to achieve an object or goal (in many cases the goal is effective health maintenance and management) [74]. Communication is critical in identifying and determining patient and provider goals during the health care encounter [74]. Importantly, patient values and expectations shape goals and outcomes in health care – these values are not always assessed or recorded prior to, during, or after the health care encounter. Moreover, understanding communication behaviors prior to the encounter is important in terms of forming and evaluating health goals based on health information received from outside sources (i.e., the internet, family members, etc.). Finally, communication also plays a role after the encounter – adherence, maintenance, and support will ultimately sustain healthful behaviors and lead to improved health outcomes [74].

The chronic illness care model along with the impending health care reform both place great emphasis on the measurement of quality of care as an indicator of effective and successful health care and health promotion. Given the changing landscape of the health care system, an emerging health promotion model and an evolving medical model will rely heavily on information and communication technologies used by health consumers, health providers, health care organizations, and health insurance companies to provide a high quality of care and ultimately better health outcomes. With quality of care becoming a more relied upon construct, accessibility and effectiveness of health care and health promotion will be influenced by health communication strategies that will play a pivotal role along the health care continuum.

CHAPTER 2: THEORIES

As changes in the health care model place greater emphasis on the health consumer, coupled with the expanding role of new media and technologies in health promotion and health maintenance, the need arises for health communication theory to help understand, guide, and inform developments in the field. This is particularly relevant when examining the role of the informed health consumer (i.e., activated patients) and changes in the patient-provider relationship.

Both interpersonal and mediated perspectives in health communication provide a framework for discussing theories in the field. Two communication theories, both taking a mediated perspective, that are particularly relevant when examining the impact of new technologies on the health consumer and patient-provider communication are discussed in depth to provide an understanding of how they can be applied to this area of inquiry. The theories include: 1) Diffusion of Innovations, and 2) Uses and Gratifications Theory. While interpersonal health communication theories are only discussed briefly, it is important to provide a short survey so as to give a perspective on the different approaches and frameworks that are possible.

Interpersonal Communication Theories

Interpersonal communication theory can take a psychological as well as sociological perspective. The psychological perspective focuses on increasing control of the environment (the interaction, the message, etc.) so that individuals can gain access to needed resources and maximize rewards [75]. Dominant theories include the Uncertainty Reduction Theory and the Goal-Plan-Action model.

The Uncertainty Reduction Theory (URT) posits that individuals engage in behaviors intended to reduce uncertainty of a target (i.e., other people), so as to increase accuracy of predicted behaviors [75]. It is based upon the principle that interactions with strangers or unknown entities present complex predictive and explanatory problems for the interactant [76]. According to Roloff, both quantity of interactions as well as the quality of interactions helps reduce uncertainty [38].

The Goal-Plan-Action model asserts that when individuals sense that some discrepancy exists between current state and some ideal (i.e., illness), they will take actions to eliminate the deviation. If the deviation (illness) is of sufficient magnitude, individuals will develop an influence goal that motivates action by facilitating planning and persistent attempts to achieve the goal (i.e., looking for health information or going to the doctor). The content of the influence goal (whether a doctors visit or looking for health information) characterizes the influence attempt (calling to make appointment or looking on internet) [77].

The sociological perspective, on the other hand, views interpersonal communication as a symbolic process involving the presentation and validation of self [78]. This orientation asserts that the fundamental function of communication is to regulate consensus. At the interpersonal level, consensus is most often sought between a dyad (two people). Politeness and face sensitivity are common models used by the sociological perspective. Politeness asserts that the norm of politeness exists across cultures, thus communication is dictated and influenced by this norm. Face sensitivity is concerned with the degree to which individuals vary in their sensitivity to face issues, such as the role of verbal aggressiveness and the wish to avoid confrontation.

Mediated Communication Theories

Mediated communication theories include agenda setting, framing, diffusion of innovations, cognitive dissonance, third-person effects, priming, and uses and gratifications [33]. Many of these theories examine 'media effects', or the degree to which media makes a difference in people's behaviors and perceptions [32].

Agenda setting is concerned with how the media can set and influence the public's agenda [79]. Lippman first examined agenda setting and posited that news media is a window into the world beyond individuals' direct experiences [33]. Moreover, this window helps shape our "cognitive maps" (i.e., opinions) of the world. This theory allows scholars to predict public opinion and public agenda based on media coverage. Additionally, framing is an important aspect of agenda setting, and concerns how the audience will react differently (either positively or negatively) based on how the message/event is framed by the media [80].

Other theories in media communications include third-person effects, priming, and cognitive dissonance. Third-person effects theorize that individuals tend to overestimate media impact on others and underestimate media impact on themselves [81]. The priming theory suggests that media exposure can activate ideas, feelings, or values. Lastly, cognitive dissonance theory posits that individuals seek consistency in their cognitions. For example, if an individual trusts one source over others, then they are more likely to use that source [32].

Diffusion of Innovations

The diffusion of innovations theory attempts to understand why members of a society or social group adopt innovations at different rates over time [82]. Diffusion theory is a sub-specialty of communication research. Whereas communication research examines both new and old messages, attitudes, and behaviors, diffusion research is concerned with the communication and spread of *new* ideas. Moreover, Rogers [82] states that communication research in general focuses on knowledge and attitudinal change, whereas diffusion research focuses on an overt behavior change (i.e., an adoption of some innovation) – knowledge and attitudes are considered intermediate steps towards behavior change.

Diffusion theory is founded on the principle that adoption does not occur at random, but rather certain characteristics predict and influence adoption patterns. The diffusion process occurs when an innovation is communicated through channels over time among members of a society or social group, leading to adoption or rejection of that innovation. An underlying driving force of innovation adoption is that individuals or groups seek security; that is, given environmental constraints, adoption of an innovation must maximize a subjective state of wellbeing that minimizes tension [82]. Major components of the diffusion process include: 1) characteristics of the innovation, 2) characteristics of the innovator, 3) characteristics of the channel, 4) environmental context, 5) adoption result, and 6) time [82–84].

First, innovations can be described as an idea, practice, or object perceived as new by an individual or group. The newness of an innovation is subjective rather than objective; that is, exposure to the innovation is a critical component, regardless of the time lapse between invention and adoption. Importantly, innovations can have both public and private consequences that ultimately influence the diffusion process [84]. Whether or not an innovation's adoption will impact other individuals or groups (public consequence) versus only the adopter (private consequence) is an important characteristic of the innovation. Additionally, costs associated with an innovation (complexity, monetary, deviance) as well as its benefits (utility, productivity) weigh heavily on the decision to adopt or reject an innovation [85].

Second, characteristics of innovators are important determinants of adoption in the diffusion process. Behavior takes place within a social system, and thus memberships in social systems influence individual behavior. Behavior in this sense is normatively regulated through comparing one's self with other members of the group or society. Thus, the manner in which an individual identifies themselves relative to other members in the group influences adoption behavior [83]. This can be based on socio-economic status, sense of security, conceptual skills, relative position in social networks, and propensity to take risks, among other factors [82,84,85]. Rogers provides a general framework to describe adopter characteristics, including: innovators, early adopters, early majority, late majority, and laggards. Each adopter category is described by dominant values that are employed to reach security, i.e., to maximize subjective wellbeing [82].

Innovators are venturesome and reach a sense of security by being deviant from the social system's norms. They often bypass change agents and are themselves sources of new ideas. *Early adopters* are marked by a respect from their peers. They rate higher in opinion leadership in the social system than other adopter categories. They are critical in enhancing or slowing adoption. Deliberation is the dominant value of the *early majority*. Their sense of security is enhanced through deliberating on their adoption decision. They often wait for other respected individuals in their social system to adopt innovations and see how successful they are.

The dominant value among *late majority* adopters is skepticism. They are most secure and comfortable in following traditional values and behaviors rather than adopting an innovation. It often takes quite a few peers to convince the late majority to adopt an innovation. *Laggards* are best characterized by valuing tradition above all other things. In terms of the entire social system, laggards may be viewed as socially deviant, not in the same sense as innovators, but rather in the sense of unwillingness to accept new ideas. They find security in resisting innovations.

Third, channel characteristics are important in the diffusion process. The channel is the means by which the message or innovation is communicated as well as the means by which information is exchanged. An individual or group uses information provided over a channel to become aware of the innovation, evaluate it, and ultimately adopt or reject it. During the awareness period, impersonal or “cosmopolite” sources are most influential [83]. For example, if the source wants to raise awareness of a message, mass media is appropriate channel. On the other hand, during evaluation and adoption periods, interpersonal communication channels are most influential. During the evaluation phase, the adopter identifies the innovation’s relative advantage, compatibility, and complexity to help decide on adoption [82]. During this period, interpersonal communication is effective in persuading or influencing attitude or action [82]. Importantly, diffusion theory incorporates interpersonal level communication, showing that interpersonal and mass communication can work in tandem to stimulate adoption or change [85].

Fourth, the environmental context in which diffusion occurs is a critical factor influencing adoption. Adoption of an innovation is not independent of societal, geographical, and political factors. From a societal perspective, diffusion occurs among members of a social system that may be individuals, groups, complex organizations, or other subsystems. The social system constitutes a set of boundaries within which innovations diffuse that include social norms, traditions and modern norms, opinion leaders, and change agents [83].

Importantly, incorporating an environmental context into diffusion theory balances out the often narrowly focused adopter categories that emphasize individual characteristics. Values described in adopter categories lean heavily on an agency perspective; that is, these values assume that individuals are able to make decisions and take actions that maximize their security, neglecting environmental or structural factors that may influence or limit adoption. Incorporating such structural components of adoption integrates a disparities perspective to diffusion. Regardless of how certain individuals or groups are “prone” to adopt an innovation, structures and environments influence diffusion rates.

Fifth, acceptance or rejection of the innovation characterizes the results stage. This is not a static stage or decision, but rather a dynamic one that may fluctuate with time [85]. For instance, once an innovation is adopted, it can be discontinued at any point. Similarly, if an innovation is rejected, it can be adopted at a later time or continually rejected. This is a major strength in that the theory recognizes that adoption or rejection is not static. Rather than occurring at a single time point, the theory recognizes that adoption is dynamic and may fluctuate with time.

Finally, time is a critical element of the diffusion process that differentiates this theory from other communication theories [83]. Time is involved in three process: 1) the innovation-decision process by which the individual passes from initial knowledge to adoption; 2) the innovativeness of the individual compared to other members (early vs. late adopter); and 3) the rate of adoption of the innovation in the entire social system. The influence and importance of time permeates throughout many of the diffusion theory stages and is important when examining disparities in access and use of innovations (i.e., internet use).

Diffusion models

Drawing from the major components of diffusion theory, Figure 2.1 provides a traditional model for the diffusion process. The adopter categories described by Rogers [83] inform the breakdown of the bell-shaped curve and approach normality over time. The S-shaped curve represents the overall adoption rate, whereas the bell-shaped curve represents the population for which the adoption rate occurs. The figure shows that early adoption is characterized by a relatively small number of adopters but increases in size as the diffusion process continues. The largest segment of the population belongs to the early majority and late majority adopters.

The S-shaped curve, or sigmoid curve, shows that early adoption occurs slowly in a positive acceleration phase, then increases rapidly approaching exponential adoption, and finally declines in a negative acceleration phase [86]. Key to the S-shaped curve is the inflection point, marking the 50% point in population adoption as well as where acceleration changes from positive to negative (from growth to decline). The maximum rate of adoption is found at the inflection, and also represents the point where late majority adopters begin adopting the innovation.

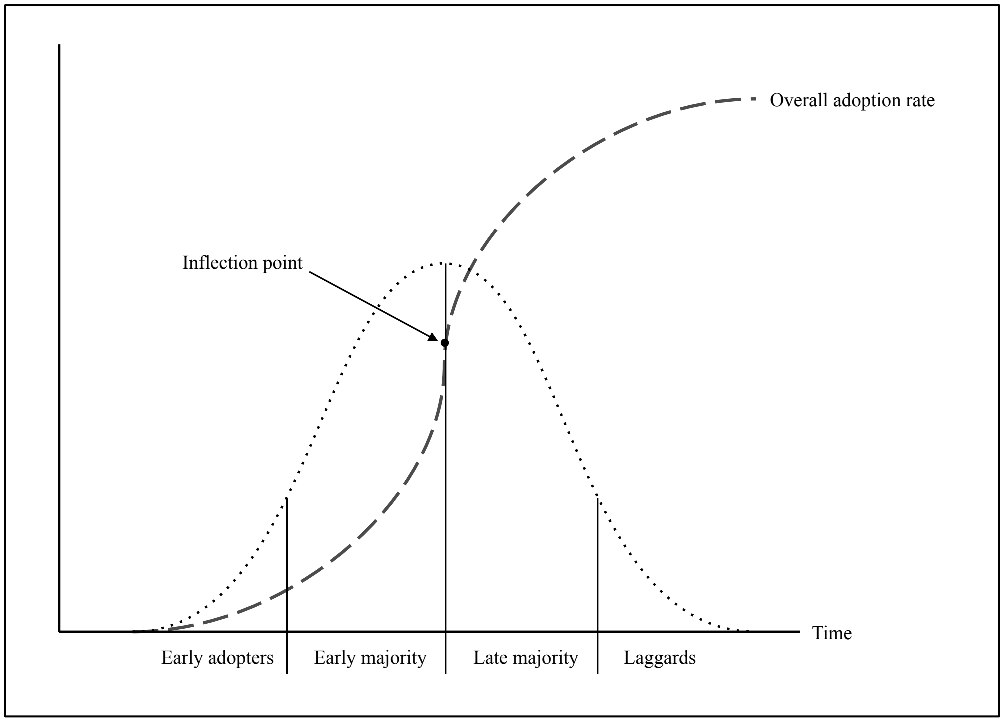

Figure 2.1 Traditional diffusion model with adopter categories

The point at which the S-shaped curve begins to level off represents the saturation point (or carrying capacity in biological terms) [86]. The saturation point signifies full adoption of the innovation – or at least all members of a particular group who have the opportunity to adopt the innovation have already done so.

Based on innovation and innovator characteristics, along with structural components that enable or impede adoption, both adoption rates and the saturation points may vary. Figure 2.2

displays various diffusion examples that highlight potential variations between two groups. These variations in diffusion patterns can be described as disparities experienced by sub-groups, based on individual or group characteristics, structural factors, or other pertinent issues related to innovation adoption.

Example A demonstrates delayed adoption between a reference group (solid line) and a disadvantaged group (dotted line). Once the diffusion process is complete, both groups reach the same saturation level, albeit the disadvantage group is delayed to saturation. Thus, the delayed adoption represents the disparity. Example B shows that adoption begins at the same time for both groups; however, the disadvantaged group experiences a saturation level below that of the reference group. Here the disparity is observed by the differences in the saturation level.

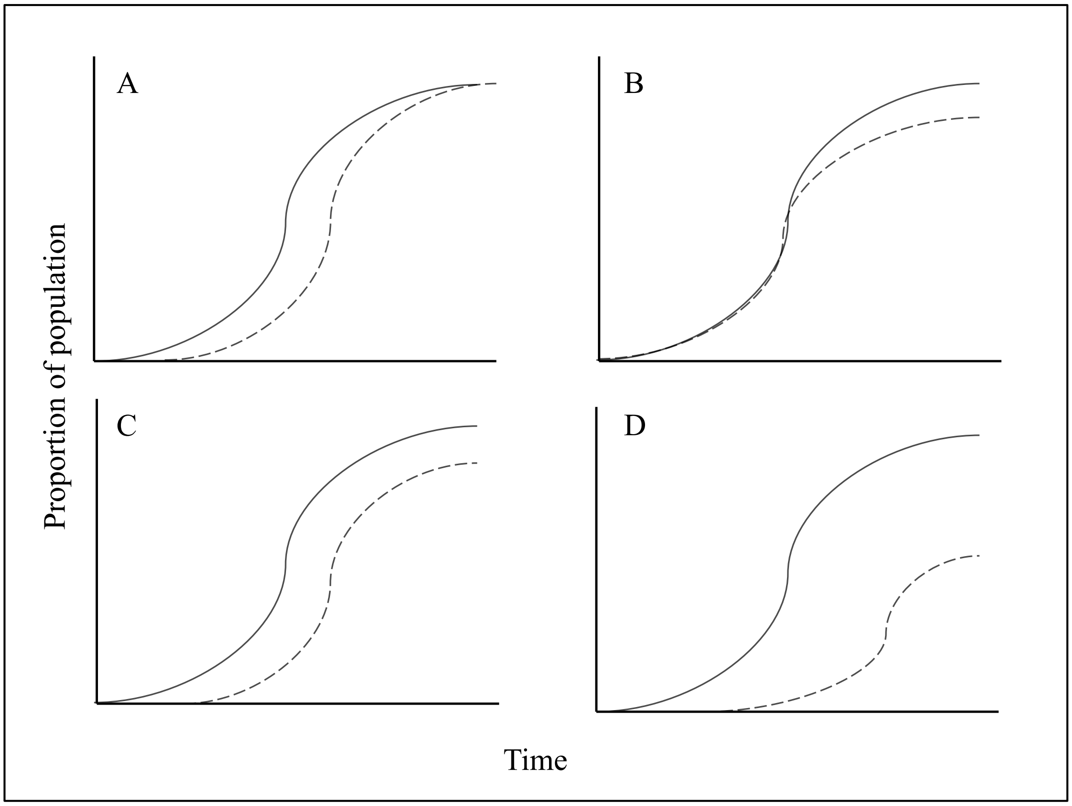

Figure 2.2 Varying diffusion patterns between reference group (solid line) and disadvantaged group (dotted line) based on different adoption rates and saturation levels

Example C shows a delayed adoption as well as a lower saturation level among members of the disadvantaged group. Thus, disparities occur both with a delayed adoption as well as with a lower saturation level. Finally, Example D highlights that the disadvantaged group experiences both a delayed adoption as well as a slower adoption rate. Moreover its saturation level is lower than the reference group. This example represents the greatest disparity in adoption of an innovation compared with the other examples, where not only adoption is delayed and occurs at a slower rate, but the saturation level is also lower.

While diffusion theory acknowledges that individual decisions and behaviors occur within a social system, greater emphasis and research on structural enablers or barriers to adoption is needed. Despite an individual's desire to adopt an innovation, they may be unable to due to economic constraints or other structural factors, such as limitations related to geography or infrastructure. This is important to recognize and evaluate as social and cultural norms may have greater influence on decisions or behaviors, regardless of the individual's willingness to change.

As information and communication technologies related to health information and health care continue to develop and expand, examining patterns in adoption and utilization among health consumers, health care providers, and health care organizations will likely lead to better understandings of an innovation's utility and potential impact. In particular, highlighting early or late adopter groups can help with marketing and disseminating materials that may help in the adoption phase. It can also be used to identify social disparities during the innovation and adoption processes.

Uses and Gratifications Theory

The Uses and Gratifications Theory (UGT) attempts to understand why people choose certain media to gratify their needs, given that a variety of media and communication alternatives exist [87]. Katz [88] outlined the underlying justification of UGT as the following: to explain how people use media to gratify their needs, to understand motives for media behavior, and to identify functions or consequences that follow from needs, motives, and behaviors [88]. In other words, rather than being random, media use is selective and motivated, based on an individual's rational identification of needs, and an expectation that particular actions (or types of media) will satisfy those needs.

UGT is grounded in five assumptions: 1) The selection and use of media (i.e., communication behavior) is goal-directed, purposive, and motivated; 2) Individuals select and use media to satisfy their needs; therefore, activity is variable; 3) Social and psychological factors guide and influence communication behavior; 4) Media compete with other functional alternatives; and 5) Individuals' influence is dominant throughout this process [89–91].

Essential to this theory is the understanding that a medium or message is only a single source of influence in the social and psychological environment [87]; that is, a medium is but one source of influence within the context of other possible influences. Rosengren [91] underscored the importance of psychological and social influence in UGT by asserting that the theory does not only incorporate a mediated view of communication influence, but also acknowledges that individual differences influence media effects in different ways – i.e., mediated communication is a two-way street. Therefore, to examine the influence of media effects, one must understand the characteristics, motivation, and involvement of media users [87].

Central to UGT is defining the audience as an “active” participant as opposed to passive receiver [87]. However, one must be cautious in defining the audience as active and passive, as this creates a false sense of dichotomy. Rather, the audience is viewed as variably active as opposed to universally active (or passive for that matter) [92]. Media consumers participate and are involved in the communication process at varying levels depending on consumer characteristics. The “active” label received pushback and criticism from traditional media researchers, who fervently argued for the study of media effects as opposed to media uses [88,93]. Nevertheless, UGT shifted the focus from only analyzing what media do to people, to also examining what people do with media [87].

Another central tenet to UGT is the functional role the media play in fulfilling some need of media users. This functionalist perspective asserts that every media serves a particular function, and use of a medium fulfills some specific gratification need; thus, functionalism plays an important role in UGT [92].

UGT emerged out of a sub-tradition of media effects to examine motivations (or gratifications) that attract people to use certain types of media [90,91]. Lazarsfeld [94], a pioneer in the field of communication, was one of the first researchers to examine why people were interested in certain radio programs as opposed to others. The field continued to evolve in the 1950s and 1960s in an attempt to understand audience involvement in mass media campaigns [95]. Rosengren [91] tried to provide stronger theoretical underpinnings by asserting that certain basic needs interact with personal characteristics and the social environment, producing perceived problems and perceived solutions. Further validating a niche in the field for UGT, Palmgreen found that the theory complemented other types of media use determinants, including media availability, work schedules, and social constraints [90].

UGT is not without its critics. First, there is a general lack of defined (or operationalized) constructs [87]. Second, the nature of the audience may be treated as too active or too rational [95]. That is, assuming the people understand their needs and motives and act upon them accordingly (and to some extent, rationally) may be a detrimental bias. Third, there is a reliance on self-report data; however, this is a challenge for many disciplines in the social sciences [95].

Some researchers argue for the integration of UGT with other social and behavioral theories. LaRose [96] situates UGT within the framework of the Social Cognitive Theory by describing 'expected' gratifications [96]. LaRose further argues that concepts such as self-efficacy and self-regulation may strengthen the UGT model by describing enabling and reinforcing factors that influence use and ultimately gratification. In examining an array of studies that apply UGT to Internet use, LaRose found that most of the studies upheld the model's basic proposition in that gratifications sought (i.e., motivation) explained individual media exposure (i.e., internet use). However, he asserts that self-efficacy is relevant to novice internet users, as they may lack the confidence or skills in using the media effectively [96].

The UGT is particularly relevant in an era marked by more interactive media, including online and digital technologies. In addition to their traditional properties, these media have interpersonal properties that may influence use and gratification [93,95]. For instance, motivations for internet use may include information, convenience, and entertainment, but also social interaction [97]. Current research studying the effect of the internet on gratification focuses on its ability to span multiple types of gratification uses [97,98].

There is general consensus as to the two paths that computer- and internet-mediated communication may take. First, it is a medium that will empower individuals, allowing them not only the chance to find information, but also giving them the ability to create information [95].

Conversely, others see it as a medium that may lead to loneliness and isolation, manifested through excessive use and ultimately dependency (i.e., internet addiction) [95]. Thus, it is not only important to understand and measure media use, but also the consequences of that use [99].

Expanding technologies have brought UGT to the forefront of communications research. Ruggiero discusses three critical aspects that will help shape UGT in the future, particularly concerning the expansion of new media and internet technologies. This dissertation draws from these concepts of the UGT and applies them to health communication research. The concepts include: interactivity, demassification, and asynchroneity.

First, interactivity highlights the role of the active participant. Five dimensions describe interactivity, including: playfulness, choice, connectedness, information collection, and reciprocal communication [95]. In health communication research, activated health consumers can use digital and online technologies to look for health information, interact with other health consumers, or even interact with health care providers. Based on their needs and uses, consumer responses to media use are likely to vary based on the gratification of needs and behaviors.

Second, demassification is described as the breaking down of the media industry into smaller titles, so that certain products appeal to targeted audiences [95]. This is particularly relevant in the new media market. Specifically, as more internet users transition from consumers to producers, the process and targeting of demassification is limitless. In health communication research, traditional consumers of online health information have the potential to become producers, and are thus able to target similar populations and others with internet technologies

Finally, asynchroneity of new media allows for consumers to interact at their convenience, without sacrificing the sense of ‘participation’ [95]. This is particularly relevant in health communication research as information exchange and communication between patient and provider begins to leverage online technologies. Such tools include email, secure electronic messaging, or accessing and updating electronic health records. Because of internet technologies, these behaviors can be done in an asynchronous manner and thus are more likely to meet the needs of potential users.

The application of both the diffusion on innovations theory along with the uses and gratification theory will allow health communication researchers and practitioners to better understand current patterns and use of online health information resources. Additionally, this area of inquiry can inform interventions and policies aimed at reducing disparities in health information access and use based on population characteristics or structural factors.

CHAPTER 3: METHODS

Health Information National Trends Survey (HINTS)

Secondary data from the Health Information National Trends Survey (HINTS) is used in this dissertation to examine increasing accessibility and use of health information via the internet as well as from other forms of media. The overall purpose of the HINTS is to provide information related to health information needs and practices of the American public [6]. The National Cancer Institute (NCI) created the HINTS as a national survey in response to a dearth of population level data measuring attitudes and behaviors related to health communication. There are three successive survey waves called the HINTS 2003, 2005, and 2008.

HINTS enables communication scholars and researchers to assess the impact of intervening process variables (i.e., beliefs, attitudes, and affect) along with changes in the health communication environment on health behaviors and outcomes [100]. Data from HINTS not only provide a picture of how U.S. populations are using health information from different sources (both passively and actively), but also provide information on how variations in use and efficacy occur, based on theoretical considerations such as beliefs, attitudes, and self-efficacy.

Examining the impact and influence of health communication is critical in today's health environment, particularly as more health consumers use health information at nearly every stage of health and illness, including health promotion, disease prevention, diagnosis, treatment, and palliative care. The following discussion details the conceptual framework of the HINTS as well as survey design, instrument development, and analysis procedures. Additional detail is provided elsewhere [6,100].

Survey rationale

Because of its institutional mandate, HINTS focuses both on cancer-related information beliefs, attitudes, and practices, as well as general health information and communication practices. Beginning in 2003, HINTS is administered every two to three years so that researchers, practitioners, and the general public can gain better understanding of trends in health information over time [6]. For HINTS 2003, data were collected from October 2002 to April 2003. HINTS 2005 data were collected from February through August 2005. For HINTS 2008, data collection occurred from January through April 2008.

The field of cancer research provides a natural home for the HINTS, as data are collected on health promotion-related behaviors relevant to health consumers as well as chronic health-related behaviors relevant to patients. However, many of the constructs are general and examine how consumers and patients use new information tools regardless of health issue. This becomes relevant in a society that has witnessed an explosion in information exchange and accessibility, most notably associated with internet use.

Survey design

The HINTS 2003 and HINTS 2005 sample design uses a list-assisted random digit dialing (RDD) sample from all telephone exchanges in the U.S. The RDD method is a random sample of telephone numbers from all "working banks" in the U.S. Working banks are described as a set of 100 telephone numbers with at least one residential number listed. Oversampling of minority populations, including African Americans and Hispanics, helps ensure that the final sample is a nationally representative sample of households. Computer-assisted telephone interviewing (CATI) is used to conduct respondent interviews.

In each sampled household, one member is chosen to participate in the survey based on probability sampling. Within household sampling for HINTS 2003 and HINTS 2005 uses a combination of a respondent-selection algorithm based on the number of adults in the household, as well as the “last birthday method” [101]. If there are three or fewer respondents in the household, an algorithm is run with the sampling probability of 1/N, with N being the number of adults in the household. For one-adult households, the screener respondent is always selected. For two-adult households, if the screener respondent is not selected based on the algorithm, then the second adult is chosen for the sample. For three person households, if the screener respondent is not chosen, the younger or older housemate is sampled based on the algorithm. However, for households with more than three adults, if the screener respondent is not chosen, then the housemate with the “more recent birthday” is included in the sample. The use of the algorithm and “most recent birthday” is used to minimize the number of screener questions necessary to obtain a probability sample, thus minimizing response burden.

In addition to the RDD-based sampling strategy used in HINTS 2003, the HINTS 2005 introduces a pilot experiment to examine how data collected over the internet influence response rates. Data collected in this experiment are not included in the final dataset, but rather are used to investigate the effectiveness of additional data collection methods. The pilot study includes three designs: a RDD screener followed by RDD interview; a RDD screener followed by an internet-based interview; and an internet screener followed by an internet interview. Preliminary results show that the RDD-RDD method is the most effective (response rates could not be calculated for the internet-internet condition because of non-probability sampling). However, despite the added efforts, response rates for HINTS 2005 are lower than anticipated.

Dual frame methodology

Based on declining RDD response rates and poor results from the HINTS 2005 pilot study, HINTS 2008 uses a mixed mode data collection (mail and telephone). This method is adapted from the Behavioral Risk Factor Surveillance Survey (BRFSS) implemented by the

Centers for Disease Control and Prevention (CDC). Additionally, research shows that a mail survey, with appropriate follow-up, can achieve higher response rates than both RDD and web-based surveys [102]. Because of these findings, HINTS 2008 uses a dual-frame design that mixes modes in a complementary way. The rationale behind implementing a dual frame survey is to use the results to inform future survey designs.

The first frame in HINTS 2008 is RDD-based and uses the same methodology as in HINTS 2003 and HINTS 2005. The second frame is a mail survey based off of the national listing of addresses available from the United States Postal Service, stratified by high-minority stratum and low-minority stratum. High-minority strata are defined by census data where census block groups are at least 24% minority. Unlike the RDD frame, all adults in the household are asked to complete a mailed questionnaire; responses are weighted accordingly. Thus, the mail sample is a stratified cluster sample, where the household is the cluster. This decision is made after comparing respondent-selection methods, that show that 1) any adult in household, 2) adult in household with next birthday, or 3) all adults in household yield similar results [103].

A strength of the mixed mode design is that a USPS sampling frame includes households with landlines as well as households without landlines or mobile-only households. In addition to improving response rate and reaching households that do not have landlines, the mail survey is also thought to provide improved measurement for questions that are subject to social desirability bias.

A general limitation of address-based surveys is that respondents have been shown to have higher SES, be from the majority race, and have a higher education [104]. Moreover, the dual frame introduces bias in sampling mode, including bias related to social desirability and having a reference for response categories.

Response rates

Response rates vary for each HINTS iteration, with the highest response rate occurring in 2003. Response rates are calculated at the screener level, the extended interview level, and the overall level. Response rates for HINTS 2008 are provided for both the RDD mode as well as address mode. Total number of respondents for each year are as follows: HINTS 2003 n=6,369; HINTS 2005 n=5,586; HINTS 2008 n=7,674 (RDD=4,081 and mail=3,593). Table 3.1 provides details on response rates and total number of respondents by year.

Table 3.1 Response rate and total number of respondent by HINTS iteration, 2003-2008

	Overall response	Screener response	Interview response	Total number of respondents
HINTS 2003	33%	55%	60%	6,369
HINTS 2005	21%	34%	61%	5,586
HINTS 2008				
RDD	24%	42%	57%	4,081
Address	31%	40%	77%	3,593

Response rates for HINTS 2003 and HINTS 2008 are comparable to other national telephone surveys [105]. However, the rates reflect a trend in survey research that suggests that response rates for telephone-based surveys are declining [106].

Response rates for HINTS 2005, however, are particularly low. Furthermore, HINTS 2005 weighted proportions (that include non-response weights) have elevated standard errors when compared with HINTS 2003 and 2008 data. Table 3.2 provides examples of variables with elevated standard errors in HINTS 2005. The shaded cells represent the largest standard errors when comparing row categories across years – all but two are in HINTS 2005. Due to increased standard errors along with low response rates, HINTS 2005 data are excluded from this dissertation.

While the inclusion of three time points increases the ability to exam trends over time, if a certain time point has unreliable data, the entire analysis comes into question. Thus, the decision to exclude HINTS 2005 data and focus on data from HINTS 2003 and HINTS 2008 is justified and support by potentially biased and unreliable data present in HINTS 2005.

Table 3.2 Comparison of standard errors between HINTS 2003, 2005, and 2008

	HINTS 2003		HINTS 2005		HINTS 2008	
	Weighted %	SE (%)	Weighted %	SE (%)	Weighted %	SE (%)
Race/ethnicity						
Non-Hispanic white	71.740	0.434	69.855	0.673	69.465	0.231
Non-Hispanic black	10.496	0.191	10.002	0.500	11.342	0.157
Hispanic	11.717	0.138	12.994	0.494	12.852	0.236
Non-Hispanic other	6.048	0.381	7.150	0.580	6.341	0.164
Gender						
Male	47.862	0.193	47.795	0.291	48.259	0.203
Female	52.138	0.193	52.205	0.291	51.741	0.203
Age						
18-34	30.876	0.276	31.135	0.313	30.774	0.250
35-49	31.480	0.226	30.191	0.353	29.372	0.283
50-64	21.645	0.227	23.024	0.205	23.565	0.150
65-74	9.613	0.270	9.177	0.271	8.293	0.079
75+	6.386	0.279	6.474	0.253	7.995	0.087
Internet use						
Yes	63.149	0.652	61.080	0.783	68.536	0.650

Non-response is also an issue in HINTS 2003 and 2008, however less so when compared with HINTS 2005. Nevertheless, to examine potential bias as a result of non-response, it is necessary to compare respondents with non-respondents using whatever information is available – preferably information that speaks to demographic and socioeconomic characteristics so that analysis will identify any bias associated with the decision to respond to the survey. Unfortunately, HINTS staff has indicated that data are not yet available on non-respondents; thus, comparing differences in gender, age, education, income, or other important characteristics between respondents and non-respondents is not possible at this time.

Another strategy to examine potential bias due to non-response is comparing demographic and socioeconomic data from HINTS to larger, more reliable survey findings. To do this, the U.S. Census [107,108] and the National Health Interview Survey (NHIS) [109,110] are used to compare similarities and differences between key variables. Table 3.3 shows the comparison of variables stratified by year (2003 & 2008).

In 2003, both unweighted and weighted HINTS data have larger percentages of non-Hispanic white respondents (70.5 and 72.6, respectively) compared with the Census (69.0) and the NHIS (68.7). Despite oversampling of minority populations, both non-Hispanic black and Hispanic respondents are underrepresented in HINTS 2003 data. Similar trends are observed when comparing HINTS 2008 data with the Census and NHIS.

Table 3.3 Comparisons between HINTS, Census, and NHIS data among key socio-demographic variables

	2003 data				2008 data			
	Unweighted HINTS	Weighted HINTS	Census	NHIS	Unweighted HINTS	Weighted HINTS	Census	NHIS
Gender								
Male	40.4	48.3	48.3	48.8	39.7	49.5	48.6	49.0
Female	59.6	51.7	51.7	51.2	60.3	50.5	51.4	51.0
Age								
18-34	26.3	31.2	28.7	---	15.7	31.0	28.0	---
35-49	32.4	31.1	31.6	---	25.5	29.5	29.5	---
50-64	23.4	21.5	22.4	---	33.3	23.0	24.9	---
65-74	10.1	9.7	8.8	6.4	14.3	8.3	9.1	6.6
75+	7.7	6.6	8.4	5.6	11.3	8.1	8.5	5.8
Race/ethnicity								
White	70.5	72.6	69.0	68.7	75.3	68.9	66.9	65.5
Black	11.9	10.2	12.7	12.0	9.7	11.7	12.8	12.4
Other	5.1	5.7	6.0	5.5	6.0	5.8	6.5	6.6
Hispanic	12.6	11.5	13.7	13.9	9.1	13.5	15.4	15.5
Educational attainment								
Less than HS	11.4	15.8	21.0	16.2	8.8	13.2	18.9	15.1
HS graduate	29.2	31.4	30.0	30.4	23.7	30.0	29.3	29.0
Some college	27.2	27.6	25.6	26.8	30.3	31.1	26.4	27.0
College grad	32.1	25.2	23.4	26.6	37.2	25.7	25.4	28.8
Health insurance								
Uninsured	12.7	14.5	15.1	14.7	11.5	17.0	15.3	14.8
Annual income								
> $20K	20.5	19.6	22.6	18.6	17.5	15.9	19.0	---
$20K-$34,999	23.2	22.3	19.0	14.0	16.7	17.3	16.5	---
$35K-$49,999	17.3	17.4	15.1	---	13.9	13.6	14.1	15.3
$50K-$74,999	17.2	17.7	18.3	---	19.2	21.3	18.2	18.7
$75K or more	21.9	23.0	25.1	21.6	32.7	31.9	32.1	34.4
Use internet	64.6	64.8	59.0	63.0 (Pew)	69.7	68.2	73.0	73.0 (Pew)

Additionally, the HINTS 2003 sample has a lower percentage of respondents with less than a high school education (unweighted: 11.4; weighted: 15.8) compared with the Census

(21.0) and NHIS (16.2), and slightly more respondents with some college education (unweighted: 27.2; weighted: 27.6) compared with the Census (25.6) and NHIS (26.8). The same patterns are present in HINTS 2008 data. Other demographic variables, as well as internet use, are comparable between surveys. Thus, analyses and findings must be interpreted knowing that, in general, the HINTS sample represents slightly more non-Hispanic white respondents and respondents with a slightly higher educational attainment.

Instrument development

In each HINTS iteration (2003, 2005, and 2008), five key topics are identified by National Cancer Institute investigators and HINTS stakeholders: 1) Health communication; 2) Health services; 3) Behaviors and risk factors; 4) Cancer; and 5) Health status and demographics.

The communication sections of the questionnaire are developed using a framework that captures both “passive” mass media exposure as well as “active” processes associated with information-seeking behaviors. The framework is described by two stages of consumer-oriented health communication, an awareness stage and an information-seeking stage [111]. The awareness stage focuses on media effects in which messages are *pushed* onto target audiences, influencing both awareness and contemplation. The information-seeking stage of the model examines how consumers *pull* information from both human and mediated sources of information. Due to this multistage framework, the application of theories and models of behavior change that accommodate impact of information along a continuum of influence is feasible and appropriate [6].

Examination of prior questionnaires helps identify gaps in current research as well as inform the development of the HINTS instrument. In general, current communication surveys lack an examination of health beliefs, attitudes, and behaviors [112–114]. Similarly, surveys from Nielsen and Harris Interactive collect information on mass media and internet use, but lack health data. Moreover, many of the health-related surveys collect excellent data on health behaviors and preventive service utilization, but contain little to no questions on health communication [115,116]. HINTS fills this gap by assessing health beliefs, attitudes, and practices within a communication context.

The structure of the HINTS questionnaire is designed to allow respondents to easily progress through questions, starting with general questions related to communication and media use, and then move into more sensitive questions, such cancer-related questions. Respondents are also asked questions regarding demographics, knowledge and attitudes of health promotion and risk prevention, as well as prior experience with health-related problems (i.e., cancer experience).

The CATI method of interviewing is developed and refined through cognitive interviewing in both English and Spanish. For HINTS 2008, the mail instrument included the same questions as the CATI, although some questions are reworded to reflect self-administration. The Dillman double-column approach is used for formatting mail survey [117]. Importantly, the mailed questionnaire is only available in English. Therefore, a telephone number is provided in each mailed packet for Spanish-speaking respondents to call to take the survey over the telephone. This is important information if examining specific questions related to Spanish-speaking respondents, as only telephone-based data are collected. Based on the pretesting process, mode-specific cuts are made to mail instrument based on analysis of skip patterns and problematic formatting. Thus, the HINTS 2008 CATI instrument includes 201 items compared to 189 items on the mailed instrument.

Sample weights

For HINTS 2003 every respondent receives one final sampling weight and a set of 50 replicate weights. Because of the dual frame methodology used in HINTS 2008, three final sampling weights, each with a set of 50 replicate-sample weights (for a total of 150), are calculated. Two of the three weights correspond to mode of sample (RDD vs. mail). The third weight is a composite weight based on data from both samples. All respondents receive a composite weight. Therefore, respondents in the 2008 survey receive a weight corresponding to their mode of sample and another based on the composite of the full sample [118].

Each sampling weight consists of three components: a base weight, a weight to adjust for non-response, and a calibration weight. The base weight is the reciprocal of the probability that the respondent had of being sampled. Base weights include both the probability of selection at the household level as well as at the respondents level. Similarly, the adjustment for non-response weight includes adjustments for both the household as well as the sampled respondent.

The calibration adjustment weight is used to reduce sampling variance of estimators through comparing HINTS data to reliable auxiliary information. This weight is applied after adjusting for non-response and applying base weights. The purpose of calibration weights is to adjust the data based on key variables (often demographics, such as gender) to better match other larger, nationally representative surveys [101,118]. In the case of the HINTS, data are calibrated to the Current Population Survey and the American Community Survey, both of which are implemented by the U.S. Bureau of the Census. Calibrated variables include: gender, race/ethnicity, age, educational level, health insurance status, and ever having cancer.

The jackknife technique is used to produce replicate weights that provide statistically valid standard errors for the parameter estimates [118]. This method selects a subset of the data, producing a “replicate subset”. Then, each respondent in the replicate subset is given a sampling weight, as if the replicate subset was in fact the full sample. This is done 50 times to produce 50 replicate weights. The standard error for a nationally representative estimate can then be computed by aggregating sampling weights of all respondents for a particular variable of interest. Table 3.4 displays sample weights used for merged data on telephone-only analysis of HINTS 2003 and 2008 (HINTS 2008 RDD sample only).

Table 3.4 Weights used for merging two iterations of the HINTS dataset, 2003 & 2008

	Final sample weight (nfwgt)	Replicate weights 1-50 (nfwgt1-nfwgt50)	Replicate weights 51-100 (nfwgt51-nfwgt100)
HINTS 2003	2003 final weight (fwgt)	2003 replicate weights (fwgt1-fwgt50)	2003 final weight (fwgt)
HINTS 2008	2008 final weight (rwgt0)	2008 RDD final weight (rwgt0)	2008 RDD replicate weights (rwgt1-rwgt50)

Mode comparison

In reaction to decreasing response rates from telephone-based surveys using the random digit dialing technique, HINTS 2008 introduces a second methodology using address-based sampling. Due to this difference in sampling methodology, it is necessary to compare potential mode differences among variables of interest. Cantor details that this is necessary both when examining data across HINTS iterations (i.e., 2003 and 2008 iterations) as well as when comparing telephone and mail responses in HINTS 2008 [119].

Internet use is a main outcome of interest for this dissertation. Significant differences based on sampling mode are examined to determine if combined HINTS 2008 data (i.e., data from both telephone and mail surveys) can be used when comparing internet use changes over time. If significant differences in mode are observed, only questionnaires completed over the telephone from HINTS 2008 will be used, thus matching the HINTS 2003 data collection method.

Table 3.5 displays the mode comparisons of internet use. Three comparisons are examined: 1) using the combined survey weights; 2) using the mode-specific survey weights; and 3) using mode-specific survey weights among the sub-population examined in Study 1 and Study 2. For each comparison, the difference in internet use between respondents who answered the questionnaire over the phone versus through the mail is significantly different. Thus, in order to limit bias and match the data collection method in HINTS 2003, only respondents who completed the questionnaire over the telephone in HINTS 2008 are included in analyses in Paper 1 and Paper 2.

Table 3.5 Sampling mode comparison for internet use, HINTS 2008

	Internet use (%)	**SE (%)**	**95% CI**	
Combined weight				
Mail	71.91	0.79	*70.32*	*73.51*
Telephone	64.59	1.11	*62.35*	*66.83*
Mode-specific weight				
Mail	71.13	0.88	*69.36*	*72.90*
Telephone	66.28	1.07	*64.13*	*68.44*
Paper 1 & 2 weighted sub-population				
Mail	74.09	0.97	*72.14*	*76.04*
Telephone	69.24	1.20	*66.84*	*71.65*

Table 3.6 displays mode comparisons among key variables in Paper 3. The main outcome (the patient-provider encounter score), the main predictor (first source of health information), and potential mediating variables (gratification score and trust measures) are examined using mode-specific weights. No difference is observed for the main outcome variable. Only one significant difference based on sampling mode is observed for the mediating variable – responses related to somewhat trusting a health provide is significantly different based on mode.

The greatest significant difference is observed with the main predictor, first source of health information. However, despite this significant difference, Paper 3 uses the combined respondent sample. This is done because no significant differences are observed in the main outcome variable and also to increase the N of the sample to provide more robust analysis and results. Furthermore, the sampling mode is included as a covariate in the model-building process so as to control for differences that may arise based on the mode.

Table 3.6 Mode comparisons for key variables in Paper 3, HINTS 2008

Variable	**Mode comparison**						
	Mail	**95% CI**		**Telephone**	**95% CI**		**95% Overlap**
Patient-provider encounter	-22.92	*-38.89*	*-6.95*	-2.57	*-19.10*	*13.97*	Yes
First source of health information							
Health provider	11.42	*9.31*	*13.52*	5.72	*4.04*	*7.41*	No
Internet	75.95	*73.56*	*78.34*	86.24	*83.97*	*88.52*	No
Print material	12.63	*10.34*	*14.93*	8.03	*6.62*	*9.44*	No
Gratification score	2.47	*-9.34*	*14.29*	18.33	*5.04*	*31.63*	Yes
Trust information from internet							
A lot	23.08	*19.80*	*26.37*	26.12	*22.84*	*29.40*	Yes
Somewhat	61.86	*57.68*	*66.05*	59.08	*55.37*	*62.79*	Yes
A little	13.78	*11.05*	*16.52*	13.75	*10.64*	*16.86*	Yes
Not at all	1.27	*0.01*	*2.53*	1.06	*0.45*	*1.66*	Yes
Trust information from health provider							
A lot	71.32	*67.78*	*74.86*	77.23	*74.59*	*79.87*	Yes
Somewhat	26.28	*23.15*	*29.41*	19.93	*17.27*	*22.60*	No
A little	1.91	*0.91*	*2.91*	2.66	*1.57*	*3.75*	Yes
Not at all	0.49	*-0.36*	*1.33*	0.18	*-0.01*	*0.37*	Yes

HINTS limitations

HINTS is a cross-sectional survey, and thus, longitudinal analysis is not possible. This limits the ability to describe change at the individual level as well as the certainty in describing the true nature of a variable (i.e., independent vs. dependent). However, because multiple iterations of HINTS is administered over time, researchers are able to describe changes over time or trends at the population level. Additionally, analytical approaches that apply rigorous methods based on theoretical underpinnings help to strengthen findings.

One of the greatest limitations to HINTS data is the low response rate. This can lead to systematic differences between respondents and non-respondents. That is, individuals who choose not to participate in the survey may be inherently different from those who do complete the survey (i.e., non-respondents members may disproportionately represent lower income populations or greater minority populations). However, when comparing HINTS iterations, large differences in response rates, for example between HINTS 2003 and HINTS 2008, are not always a deterministic indicator of bias [120].

Despite survey weights, estimates from HINTS data will have larger standard errors associated with parameter estimates compared with other national surveys such as the National Health Interview Survey (NHIS) [115] or the Behavioral Risk Factor Surveillance Survey (BRFSS) [116]. This is due to the difference in sample sizes between the HINTS, NHIS, and BRFSS. The NHIS and BRFSS are much larger surveys and will thus generate population estimates with much smaller sampling errors. HINTS data are weighted in order to provider nationally representative findings; however, based on the comparison between key variables in Table 3.3, HINTS findings may represent a slightly larger non-Hispanic white and education sample.

Decomposition Analysis

Significant demographic changes between HINTS 2003 and 2008 in sample composition can have an effect on findings. For example, if a significant change in racial/ethnic composition occurs between the two survey years, it is necessary to asses whether changes observed in the outcome variable (internet use) are a result of the change in sample composition or a result of actual changes in the outcome variable. Thus, decomposition analysis [121] is used to examine whether demographic changes, specifically related to racial/ethnic composition, influence changes in internet use in the U.S.

Four racial/ethnic categories are used in the analysis: non-Hispanic white, non-Hispanic black, Hispanic, and non-Hispanic other. The non-Hispanic other category includes respondents identifying as multi-racial, Asian, American Indian, and Pacific Islander. Figure 3.1 displays changes in racial/ethnic sample composition between HINTS 2003 and 2008. The non-Hispanic white population declines by 2.5%, from 72.5% in 2003 to 69.0% in 2008, while all racial/ethnic minorities groups increase. The largest increase is observed among Hispanic respondents, increasing from 11.6% in 2003 to 13.5% in 2008.

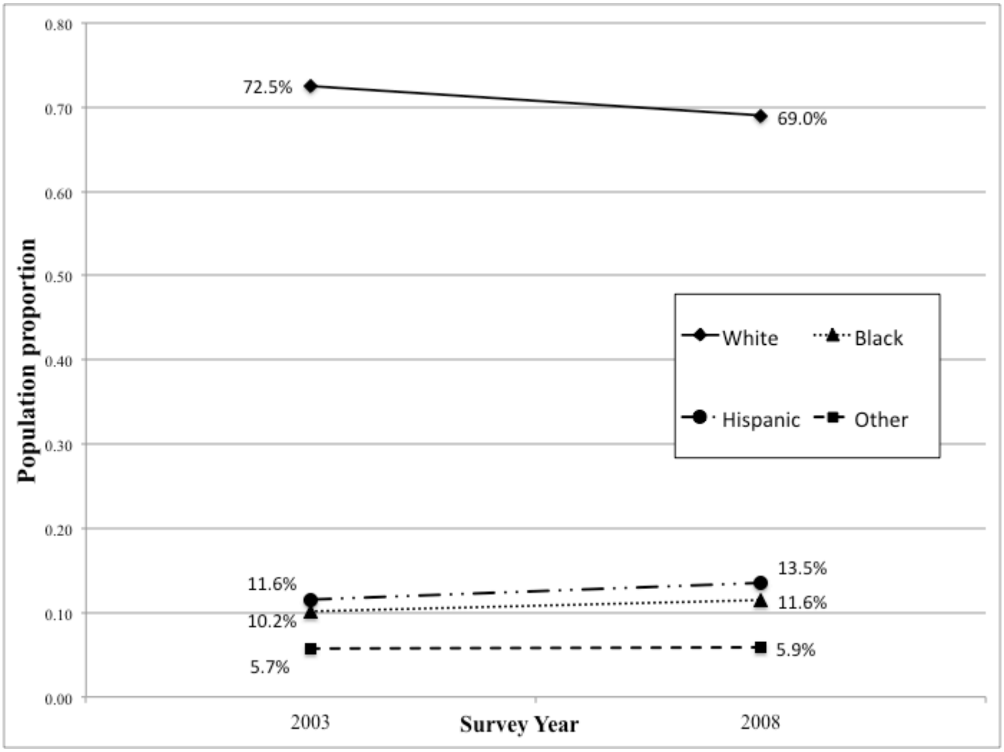

Figure 3.1 Population proportion by race/ethnic category, HINTS 2003 & 2008

Figure 3.2 displays another important factor when conducting decomposition analysis – the race-specific proportions in the outcome of interest (in this case, internet use). The overall proportion of internet users increases from 64.8% in 2003 to 68.4% in 2008 (a 3.6% increase).

Increases are observed among non-Hispanic white, non-Hispanic black, and non-Hispanic other respondents. The only decrease in internet use is seen among Hispanic respondents, dropping from 39.6% in 2003 to 38.3% in 2008.

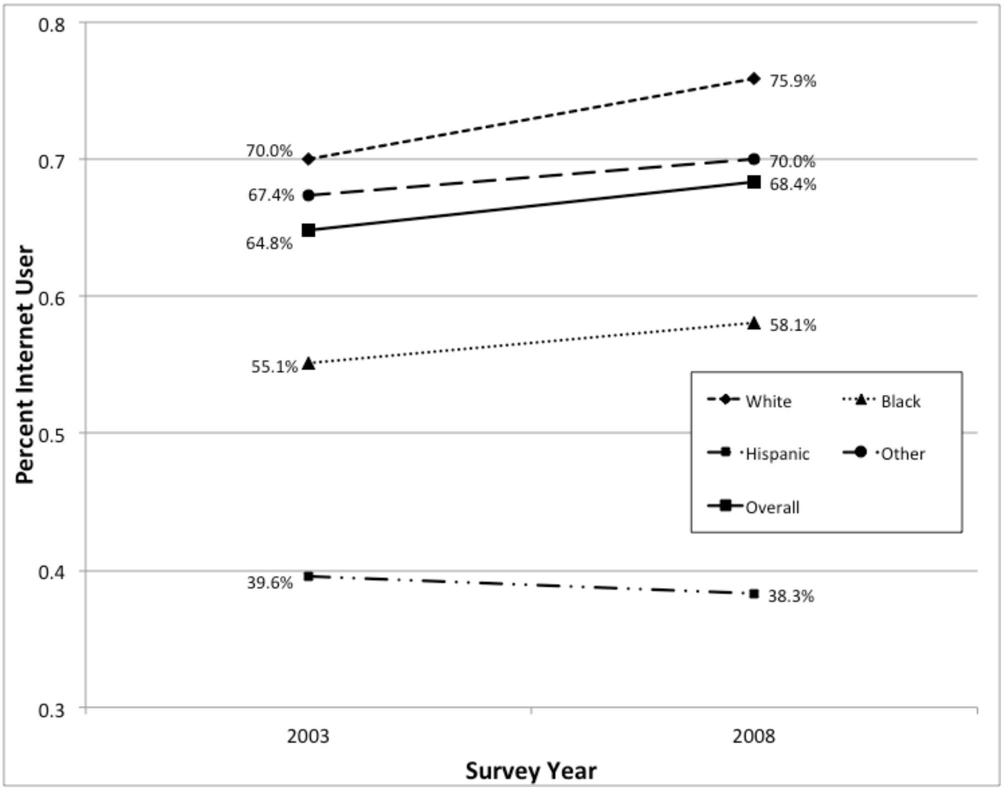

Figure 3.2 Percent internet users by race/ethnic category, HINTS 2003 & 2008

This initial analysis supports the need for decomposition analysis. Specifically, the proportion of Hispanic respondents increases from 2003 to 2008, and in this same period, Hispanic respondent use of the internet decreases, potentially impacting the overall internet use proportion. Thus, a bivariate analysis is conducted to examine the effect of racial/ethnic changes and race-specific propensities to use the internet.

Changes in racial/ethnic distributions along with changes in each racial/ethnic group's proportion of internet use are examined, adjusting for the distribution of race/ethnicity between HINTS 2003 and 2008 data. Equation 1 in Figure 3.3 is used to calculate the difference in normalized proportion of internet use between HINTS 2003 and 2008 where P is the percentage of a racial/ethnic group in the U.S. population in the given year [121]. U represents the weighted proportion of internet users specific to the racial/ethnic group. i represents a particular racial/ethnic group ($n = 4$).

Equation 1:

$$\Delta = \sum_{i=1}^{4} \left(Pi^{2008} Ui^{2008} - Pi^{2003} Ui^{2003}\right)$$

Figure 3.3 Difference between crude internet use rates in population i

Next, contributions to internet use resulting from changes in racial/ethnic distributions along with changes in each racial/ethnic group's proportion of internet use are examined using Equation 2. In Figure 3.4, the first part of the equation represents the contribution of race/ethnic composition difference to Δ and the second part represents the contribution of race-specific proportion differences to Δ [121].

Equation 2:

$$\Delta = \sum_{i=1}^{4} \left(Pi^{2008} - Pi^{2003}\right) \cdot \left[\frac{Ui^{2008} + Ui^{2003}}{2}\right] + \sum_{i=1}^{4} \left(Ui^{2008} - Ui^{2003}\right) \cdot \left[\frac{Pi^{2008} + Pi^{2003}}{2}\right]$$

$$= \begin{array}{l}\text{difference in racial}\\ \text{composition}\end{array} \cdot \left[\begin{array}{c}\text{weighted by average}\\ \text{race specific internet use}\end{array}\right] + \begin{array}{l}\text{difference in}\\ \text{internet use}\end{array} \cdot \left[\begin{array}{c}\text{weighted by average}\\ \text{racial composition}\end{array}\right]$$

Figure 3.4 Decomposition of differences between rates in population i

Based on findings in Table 3.7, after adjusting for the distribution of race/ethnicity, the percentage of internet users in 2008 is higher than 2003 by 3.45%. Rising populations of racial/ethnic minorities lowers the normalized proportion of internet users by 0.9% – this accounts for -26.1% (-0.009/0.0345) of the difference between the crude internet rates. The differences in race-specific internet use accounted for a 4.35% increase between 2003 and 2008 – this accounts for 126.1% (0.0435/0.0345) of the difference between crude internet rates. The two factors work in opposite directions, which is not uncommon in decomposition analysis [121]. Theses findings suggest that racial/ethnic compositional changes in the sample do not significantly contribute to or alter overall changes in internet use.

Table 3.7 Bivariate decomposition analysis of internet use and racial/ethnic composition, HINTS 2003 & 2008

Race	P^{2003}	P^{2008}	U^{2003}	U^{2008}	$P^{2003} * U^{2003}$	$P^{2008} * U^{2008}$	$(P^{2008}-P^{2003}) * [(U^{2008}+U^{2003})/2]$	$(U^{2008}-U^{2003}) * [(P^{2008}+P^{2003})/2]$
White	0.7254	0.6903	0.6997	0.7566	0.5076	0.5223	-0.0255	0.0403
Black	0.1016	0.1158	0.5509	0.5794	0.0560	0.0671	0.0080	0.0031
Hispanic	0.1156	0.1351	0.3955	0.3827	0.0457	0.0517	0.0076	-0.0016
Other	0.0574	0.0587	0.6711	0.7003	0.0385	0.0411	0.0009	0.0017
Total	1.00	1.00			0.6478	0.6823	-0.0090	0.0435

Percent of internet users adjusting for the distribution of race/ethnicity = 0.6823 - 0.6478 = 0.0345

Contribution of race/ethnicity compositional differences = -0.009

Contribution of differences in racial/ethnic-specific internet use = 0.0435

Proportion of difference attributed to differences in racial/ethnic composition = -0.009 / 0.0345 = -0.2609 or -26.1%

Proportion of difference attributed to racial/ethnic specific propensities for using the internet = 0.0435/0.0345 = 1.2609, or 126.1%

Spatial Analysis

Geographic Information Systems (GIS) is used to examine geographic variation in adult internet users between 2003 and 2008. In the HINTS dataset, the designated market area (DMA) in which the respondents resides is collected to serve as a geographic indicator. Nielsen media developed the DMA to serve as a unit of analysis when collecting and examining data related to media exposure and consumption. Importantly, counties within the same DMA may reside in different states; that is, DMAs extend beyond state boundaries to capture the television market area. An example of this is in southwestern Virginia, where cities in Pittsylvania County that border the North Carolina state line are in the Greensboro, North Carolina market area. Furthermore, HINTS incorporates the DMA size into the sampling methodology so that larger DMA are sampled at rates proportionate to its size.

Nielsen defines the DMA as: "an exclusive geographic area of counties in which the home market television stations hold a dominance of total hours viewed" [122]. According to 2011-2012 Nielsen data, the three largest market areas are: New York, Los Angeles, and Chicago; and the three smallest market areas are: Alpena, SD, North Platte, NE and Glendive, MT. A full list of 2011-2012 DMAs and their corresponding sizes can be found on the Nielsen website [123]. Using 210 DMAs as a unit of analysis throughout the U.S. may provide a more nuanced understanding of media use (originally developed for television use but now extending to internet use) compared with state-level data. DMA shapefiles are provided by geocommons and TVB research central [124]. All shapefiles are projected on WGS_1984_Web_Mercator. The world shapefile as well as the U.S. states layer is provided by UCLA mapshare [125].

Spatial smoothing: the head-banging method

With 210 designated market areas (DMAs) as the unit of analysis, coupled with an imperfect sampling methodology, general geographic trends as well as regional variations can be difficult to identify or understand. To better identify general trends, a spatial smoothing methodology is implemented. The "head-banging" method helps to identify geographic trends by removing background noise due to unreliable data or measurement error [126]. The head-banging method is utilized by the National Cancer Institute to display regional patterns in health information seeking [106], as well as by researchers examining health insurance coverage and tobacco use in the U.S. [127].

Head-banging is able to smooth data by controlling for spikes and edges. Spikes represent isolated extremes, such as outliers, that may not represent the true sample or population. Spikes can arise from measurement error, “noise” in the mapped area, or extremes due to a small sample size [126]. Edges, on the other hand, are areas of rapid transition between geographic units (i.e., DMAs) in the variable of interest. Such transitions that occur between large cities and suburbs may represent real trends. Thus, based on the sampling methodology and standard error of estimates, the head-banging method is able to retain spikes and edges when adequate data are available as well as smooth unreliable points using more reliable data [126]. This is accomplished through use of a median-based smoothing algorithm as compared with mean-based smoothing (the mean-based method has been shown to inappropriately blur spikes and edges).

The head-banging smoothing process contains four steps: 1) define a smoothing window, usually comprised of 10 to 30 neighboring units; 2) identify three collinear triples with the same center point (the center point is the point under investigation); 3) determine smoothing by using weighted “low screen” or “high screen” values from the triples; and 4) repeat the above steps based on a determined number of iterations [128]. These steps are described in greater detail below.

First, each unit of analysis (i.e., a DMA) contains a smoothing window made up of a determined number of neighboring units. Ten to thirty units provide a sufficient size to allow regional patterns to emerge while retaining distinct geographic patterns from more reliable data. These neighboring units make up the sampling frame from which collinear triples are taken.

Second, three nearly collinear triples are used to smooth the unit of interest. Figure 3.5 displays an example of this process [126]. Each dots represent a unit of analysis (i.e., a DMA) and the numbers by the dots represent the weighted average or mean of a variable of interest (i.e., internet use). The numbers in parentheses are the smoothing weights (i.e., the standard errors of the parameter estimates) and help determine if the center point will be smoothed or not.

Third, based on these triples, a “low screen” and a “high screen” are used to determine if the center point needs to be smoothed in either direction, or if it can remain as is. Using the example provided in Figure 3.5, the low screen is the weighted median of the low values (2, 4, 5)=4. The high screen is the weighted median of the high values (7, 8, 9)=8. The center point (3) is below the low screen median, so the weights are used to determine if the center point should be adjusted to the low screen median.

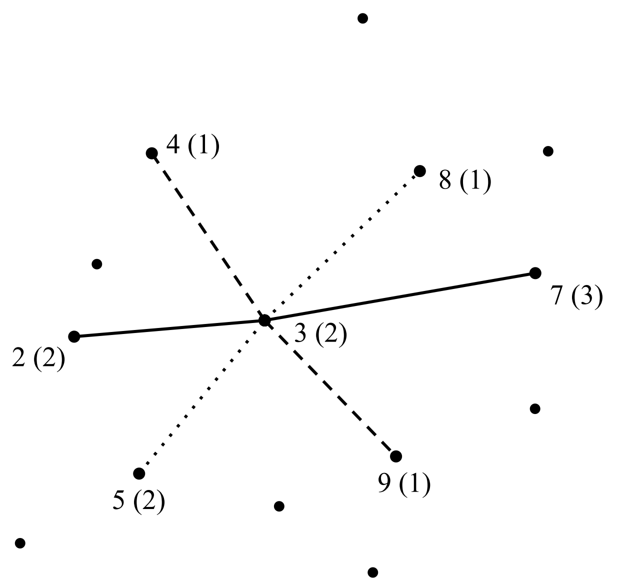

Figure 3.5 Example of collinear triples used in spatial smoothing process [122]

To determine if smoothing is necessary, the sum of the smoothing weights are compared with the triple times of the center point weight. In this case, the sum of 10 (3+2+2+1+1+1=10) is greater than the center point triple (3x2=6); thus, the center point value is smoothed to the low screen [126,128]. If the center point is between the low and high screens, the point does not change during that iteration. Finally, this process is repeated a determined amount of times (usually 10 times) drawing from other values in the smoothing window. The final value is determined as the median from the total iterations [129].

Designated market areas & head-banging

For this dissertation, the point estimates are weighted proportions of internet use in each DMA. The corresponding weights are the inverse of the standard error of each proportion; thus, the smaller the standard error, the larger the weight. By using the inverse of the standard error of weighted proportions, the smoothing process ensures that unusually high or low proportions that are reliable due to large samples are not modified (i.e., real spikes and edges are maintained).

First, weighted proportions of internet use are calculated for each DMA. Along with weighted proportions, the inverse of the standard error is calculated to serve as a weight in a geographic smoothing process. Additionally, when no data are available or the proportion of internet users is equal to one (i.e., 100% internet use), the proportion for the DMA is recoded to zero. That way, the final proportion will be based on the "low screen" from neighboring DMAs, taking a more conservative approach to internet use.

Second, spatial smoothing is accomplished through use of a 'head-banging' algorithm [126]. Head-banging uses data from neighboring DMAs to stabilize results from sparsely populated DMAs [127]. For this study, 10 neighboring DMAs comprise the "smoothing window". Again, the inverse of the standard error of internet use is used to weight internet user proportions in the head-banging algorithm. That is, populations that are reliable due to a large sample are less likely to be modified whereas values based on sparse samples are more likely to be modified based on the proportions of neighboring DMAs. This process is repeated 10 times per DMA and the median of the results is used as the final smoothed variable. Additional information is available on the head-banging method [106,126].

To better demonstrate to effect of the head-banging method on spatial data, Figures 3.6

and 3.7 show the difference between data that have been spatially smoothed and data that have not been smoothed. Figure 3.6 displays raw weighted internet use by DMA before implementing the head-banging algorithm (i.e., no spatial smoothing). There are many DMAs with no data available, leaving regional gaps that make identifying trends difficult.

Figure 3.7 displays spatially smoothed internet use data, after implementing the head-banging method. The emergence of regional trends is more evident through the head-banging process. In particular, trends in the Appalachian region, Gulf Coast, southern Texas, Dakotas, and western Nevada become clearer. Additionally, parts of New England, the Midwest, and the Southeast are less patchy and more consistent with the greater corresponding region. In this case, the head-banging process strengthened unreliable data (due to small samples or measurement error) with more reliable, neighboring data.

Regional trends and variations are more easily identifiable in Figure 3.7, containing the spatially smoothed data. While data from Figure 3.6 provides an important understanding of the crude data, trends are more difficult to identify. When analyzing overall geographic trends in data, it is useful to minimize spikes and edges so that overall regional patterns emerge. However, it is also important to retain true spikes or edges based on reliable data, highlighting disparities and areas for intervention. The head-banging process does this with a smoothing algorithm that draws from neighboring DMA data. As Figure 3.7 shows, spatial smoothing helps to more easily identify areas of need.

Now, drawing from the preceding discussion on concepts, theories, and methods in health communication, this dissertation will present three studies that describe internet use for health information, and its potential impact on health and health care decisions and behaviors.

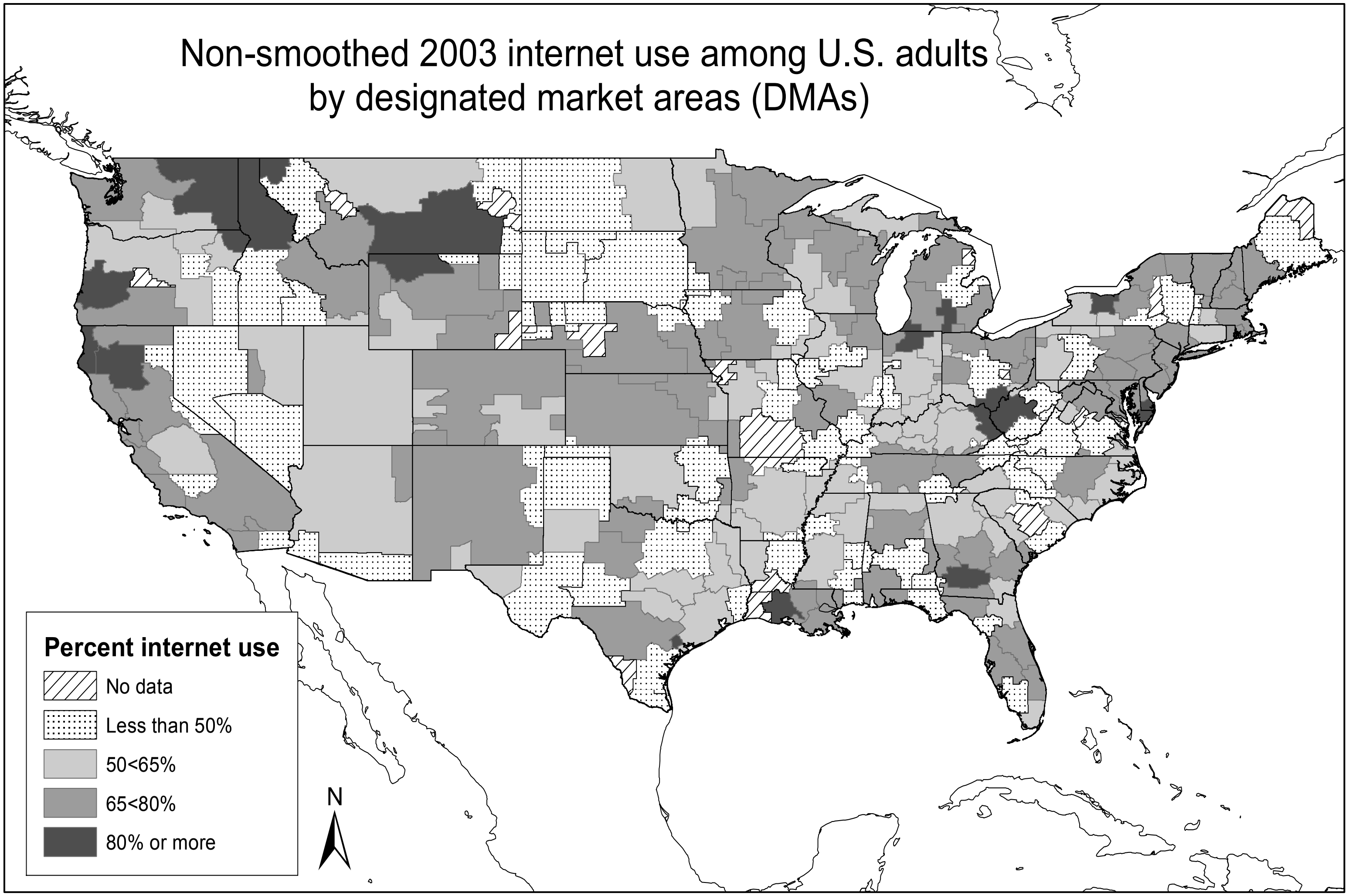

Figure 3.6 Non-smoothed internet use data, HINTS 2003

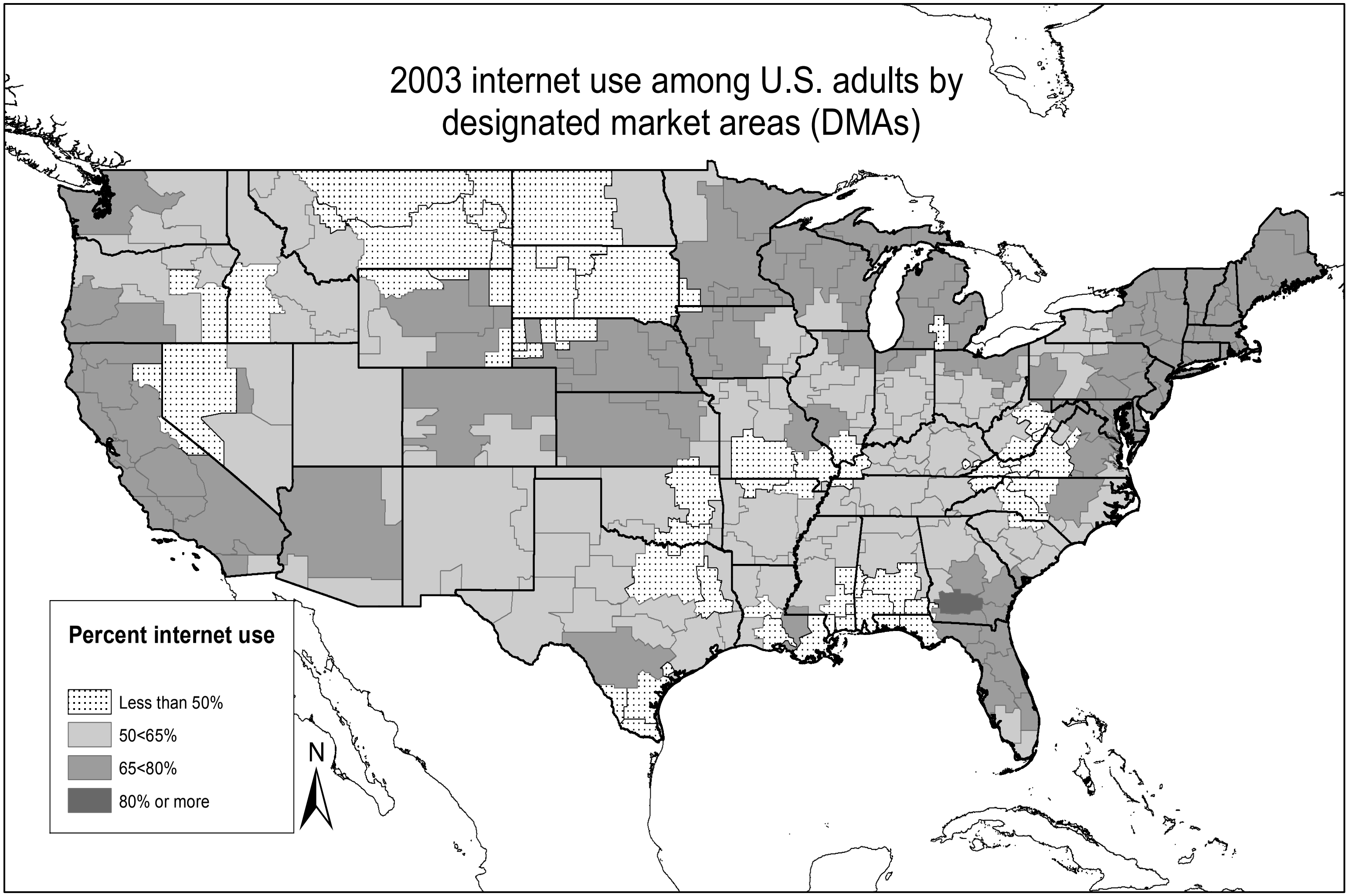

Figure 3.7 Smoothed internet use data, HINTS 2003

CHAPTER 4: STUDY 1
Internet adoption among U.S. adults: diffusion patterns and digital disparities

Abstract

Background: Internet use among the U.S. adult population has steadily grown over the past two decades, with nearly 80% use in 2012. However, despite its nearly ubiquitous use, adoption is not equally distributed among the population. For health sciences researchers and practitioners, this has major implications on access and use of the internet for health information and communication. **Objective:** To examine internet diffusion patterns among U.S. adults, highlighting disparities in adoption over time. **Methods:** Data from two waves of the Health Information National Trends Survey (HINTS 2003 & 2008), a nationally representative cross-sectional survey, are examined (N=8495). Multiple logistic regression is used to examine predictors of internet use as well as adoption and diffusion patterns. Spatial analysis is used to examine geographic patterns of internet use. **Results:** Women ages 50-64 are among the fastest growing groups of internet users. Furthermore, disparities in internet use are growing between men and women, with women internet users increasing at significantly greater rates compared to men. While not increasing over time, other internet use disparities based on race/ethnicity, income, and education remain constant – vulnerable populations remain relatively disadvantaged. Internet adoption continues to spread throughout the U.S., with only a few rural communities indicating less than 50% use. **Conclusion:** This study supports a disparities diffusion model that highlights disparities in both internet adoption rates as well as adoption saturation levels. Health researchers and practitioners can use this information to better develop interventions to help vulnerable populations transition into the ever-expanding digital age of health care and health promotion.

Introduction

Internet use among adults in the United States has steadily increased over the past 20 years. In 1995, 14% of U.S. adults used the internet – in 2012 this percentage has risen to 78% [1]. However, when examining the prevalence of internet use over time, adoption is not linear. Data from the Pew Research Center demonstrates differing adoption rates among populations. In 2011, though 78% of the general population uses the internet, the distribution is inequitable across age groups. Younger age groups have higher rates of utilization (18-29 years at 95%) compared with lower rates of utilization among older age groups (65+ years at 42%) [1]. Disparate internet use patterns across populations is important information for practitioners and researchers in the health sciences to understand so that entrenched health disparities are not reinforced through poorly designed interventions or programs. As more and more health programs and interventions are created that leverage digital resources – the internet is and will continue to be a critical medium through which health information is communicated and exchanged – it is essential to continue to reach the most vulnerable populations (often characterized as having low access to digital and internet technologies).

To examine differences in internet adoption over time based on individual characteristics and other related factors, this study takes a digital disparities perspective and examines changes in internet use between 2003 and 2008. This study contributes to the literature by investigating diffusion patterns of the internet over time, thus providing a more in depth perspective of the phenomenon than examining only a single cross-sectional survey. The following research question will guide the investigation: What factors are associated with differences in internet use between 2003 & 2008?

Cross-sectional data show that internet use is most highly associated with younger age, higher education, and greater household income [1–7]. Conversely, older age, a lack of high school education, and having a low household income are negatively associated with internet use. The disparate use of the internet suggests that adoption of an innovation (i.e., the internet) occurs at different rates among different populations, over time.

Given the inequitable use of an innovation based on certain population characteristics, such as age and geography, this study examines the rate of adoption of the internet by looking at two points in time. Studies examining predictors of internet use often focus on one point in time, neglecting the rate of adoption when compared to previous points in time. While examining one point in time provides useful information on current disparities in access or use, it does not provide a picture as to whether these differences or disparities increase or decrease over time. This is important when evaluating the effectiveness of policies or programs that target the reduction of such disparities. Moreover, few studies use a theoretical perspective to examine different rates of internet adoption.

Diffusion of innovations

The diffusion of innovations theory attempts to understand why members of a society or social group adopt innovations at different rates over time [8]. The theory posits that diffusion occurs among members of a social system that include individuals, groups, complex organizations, or other subsystems [9]. The theory uses categories to describe adoption among members at various stages of the S-shaped curve, including: innovators, early adopters, early majority, late majority, and laggards.

The S-shaped curve, or sigmoid curve, shows that early adoption occurs slowly in a positive acceleration phase, then increases rapidly approaching exponential adoption, and finally declines in a negative acceleration phase [10]. Key to the S-shaped curve is the inflection point, marking the 50% point in population adoption as well as where acceleration changes from positive to negative (from growth to decline). The maximum rate of adoption is found at the inflection, and also represents the point where late majority adopters begin adopting the innovation. Figure 4.1 provides a diffusion model of internet adoption highlighting various adopter categories. The S-shaped curve represents the overall rate of internet adoption, whereas the bell-shaped curve represents the population by adopter categories.

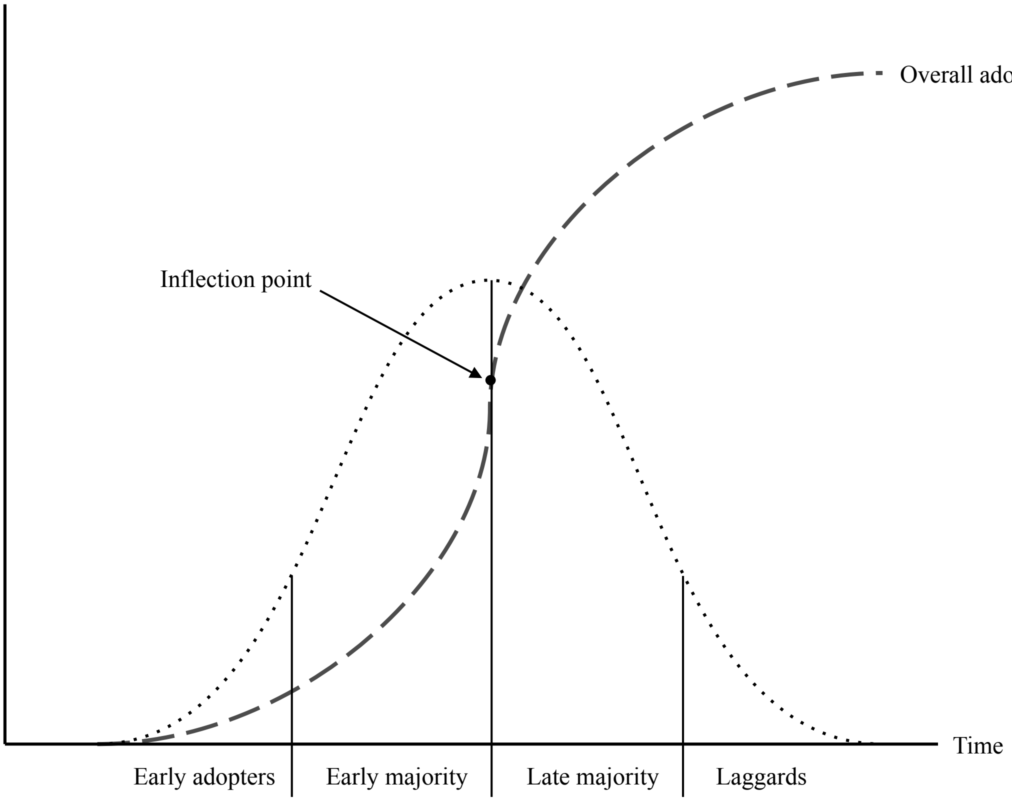

Figure 4.1 Diffusion model of internet use by adopter category

Rogers [8] makes a series of assertions based on diffusion theory that are relevant to this study, including: early adopters are younger in age than later adopters; early adopters have a more favorable financial situation than later adopters; and adopter distributions follow a bell-shaped curve over time and approach normality. Based on these assertions and the diffusion of innovations theory more broadly, this study proposes the following hypotheses:

> ***H1:*** *Internet use in 2008 will be significantly higher than in 2003.*
>
> ***H2****: Middle-aged adults (late majority) will show significant changes in internet use between 2003 and 2008.*
>
> ***H3:*** *Younger adults (early adopters) will not show significant changes in internet use between 2003 and 2008.*
>
> ***H4:*** *Racial minority populations (late majority) will have significant changes in internet use between 2003 and 2008.*

Digital disparities

Traditionally, differences in internet access and use are described using a digital divide perspective. While this framework is useful in identifying the 'haves' and 'have nots', internet use may be better characterized along a gradient or continuum [11]. Specifically, as more and more of the U.S. population goes online, a dichotomous approach is no longer sufficient in describing inequalities in internet and media use. While internet use is increasing in most every group, the gaps are widening between some groups, supporting a digital disparities framework as opposed to a digital divide [12]. Moreover, by focusing on inequalities in digital access (i.e., internet use), researchers are able to identify disparities across segments of the population. This study hypothesizes that:

> ***H5:*** *Disparities in internet use will decrease between 2003 and 2008 based on: race/ethnicity, educational attainment, annual income, and urbanicity.*

Gender is another factor related to disparities in internet use. Studies show that men are more likely than women to use the internet, but that this gender gap is closing [13–15]. Additionally, findings support an interaction effect between gender and age, where among younger respondents, women use the internet at higher rates, and among older respondents, men use the internet at higher rates [16]. Based on these findings, this study proposes:

> ***H6:*** *Gender gaps in internet use will continue to decrease between 2003 and 2008.*

Digital disparities can also be characterized by geography [17–20]. Pew finds that only 68% of adults in rural communities have access to the internet, compared with 80% in suburban communities and 78% in urban communities [21]. Additionally, one study uses GIS to examine disparities in computer ownership at the state level and finds the largest inequalities are observed among the Southern states and the smallest among the Pacific and Mountain regions [22]. However, this study also finds that income inequality in computer ownership may be declining. Based on these findings along with a digital disparities framework and diffusion theory, this study hypothesizes that:

H7: *Rural areas will show significant changes in internet use between 2003 and 2008.*

Through investigation of these hypotheses, this study identifies current diffusion patterns of internet use so as to highlight changes in disparities over time.

Methods

Data and sample

Data from the 2003 and 2008 Health Information National Trends Survey (HINTS) are used to examine diffusion patterns in internet adoption among U.S. adults [23]. HINTS, a nationally representative repeated cross-sectional survey, is developed and implemented by the National Cancer Institute (NCI) to measure knowledge, attitudes, and practices related to health information and media use, reflecting the growing reliance on internet sources for health and illness information.

HINTS 2003 data were collected from October 2002 through April 2003 and HINTS 2008 data were collected from January through April 2008. Data for HINTS 2003 were collected using computer-assisted telephone interviewing (CATI) with oversampling of minority populations. In response to declining response rates from telephone-based sampling, HINTS

2008 administered two modes of data collection: telephone and mail data collection. Mail data collection is stratified by high-minority and low-minority strata.

Due to the dual sampling method in 2008, examining differences in outcome variables based on sampling mode is necessary [24]. This study compares differences in internet use among 2008 respondents who completed the survey over the telephone compared with paper-and-pencil (mail). Significant differences in internet use are present based on data collection method. Among 2008 telephone respondents, 66.2% (95% CI: 64.1, 68.4) indicate internet use, compared with 71.1% (95% CI: 69.3, 72.3) of mail respondents. These data suggest that responses to internet use are significantly different based on the mode of data collection. Thus, to limit bias and maintain consistency with HINTS 2003 sampling methods, only telephone respondents from HINTS 2008 are included in the study sample.

The study sample includes respondents who completed the questionnaire by telephone and do not have missing data on internet use or other key covariates. A total of N=8495 respondents are included in this study: n=5458 from HINTS 2003 and n=3037 from HINTS 2008. Response rates are 55% (HINTS 2003) and 42% (HINTS 2008) at the household screening level, and 60% (HINTS 2003) and 57% (HINTS 2008) at the sampled person interview level. These response rates are consistent with prior studies in public opinion research [25,26].

Measures

Internet use: This is the main outcome for this study. Respondents are asked if they have ever gone online to access the internet or world wide web, or to send and receive email (yes/no).

Adoption categories (key independent variables): Based on prior research [8], age (18-34, 35-49, 50-64, 65-74, and 75 years or older); income (<$20,000, $20,000-$34,999, $35,000-$49,999, $50,000-$74,999, and $75,000 or more); and educational attainment (less than high school, high school graduate, some college, and college graduate) are used as indicators for early, middle, and late adopters of internet use. Early adopters are generally younger, have higher incomes, and have more education. Conversely, late adopters of internet use are generally older, have lower incomes, and have less education.

Additional variables (key covariates): Gender (male, female); race (non-Hispanic white, non-Hispanic black, Hispanic, and other); and urbanicity (metro area, rural area).

Health-related covariates: Doctor visits in the past year (none, 1 visit, 2 to 4 visits, and more than 5 visits) and cancer history (have you ever been diagnosed with having cancer, yes or no) are used to capture predisposing factors that may be related to internet use.

Geographic area: Designated market areas (DMAs), defined and developed by Nielsen Research Media Company, are geographic areas comprised of counties that make up particular television markets. Each county belongs to only one DMA and no DMAs overlap. There are 206 unique areas, ranging from metropolitans such as New York, to smaller cities such as Raleigh-Durham, to still smaller communities such as Missoula. This variable is used to examine differences in internet adoption among rural and urban areas. Because the internet is a form of media, using DMAs to examine internet use may provide a more accurate picture compared to aggregate, state-level data.

Analysis

Data are weighted to produce nationally representative estimates of the U.S. adult population. Weights include a base weight, a weight to adjust for non-response, and a calibration weight (based on data from the Current Population Survey and American Community Survey). The jackknife technique is used to produce 50 replicate weights for each year (100 replicate weights in total) to provide statistically valid standard errors for the parameter estimates [27].

Univariate analysis is used to examine characteristics of the sample in both 2003 and 2008. Bivaraite analysis is used to examine internet use by respondent characteristics, including adopter-related categories such as age, education, and income, as well as other covariates. Analysis is stratified by survey year (2003 and 2008) to examine changes in internet use. Two-tailed t-tests are used to determine if changes between 2003 and 2008 are statistically significant.

The main analytic procedure is a multiple logistic regression analysis, with the outcome variable being internet use as a function of predictor variables. Two models are developed to examine determinants of internet use. The first model examines predictors of use using combined data from both survey years. One interaction term (gender*age) is included in the model. Linear combination calculations as well as the margins command in Stata 12 are used to properly report interaction effects. In many cases, the crude model output of the interaction term is reported as the effect or odds ratio, which is incorrect. The crude model output is the ratio of the odds ratios of the two groups; thus, linear combinations are used to report accurate interaction effects of internet use between gender and age.

The second model focuses on diffusion patterns of internet use by including survey year interaction terms with predictor variables. Here again the crude model outputs of the interaction effects are the ratio of the odds ratios. Due to the multiple interaction terms included in the model, the margins command in Stata 12 is used to examine internet use patterns over time, controlling for all other covariates and interactions in the model. Thus, differences in odds of using the internet between 2003 and 2008 are more easily examined.

Geographic Information Systems (GIS) is used to examine geographic variation in adult internet users between 2003 and 2008. The designated market area (DMA) for each respondent serves as an indicator of geography. First, weighted proportions of internet use are calculated for each DMA. Along with weighted proportions, the inverse of the standard errors is calculated to serve as a weight in a geographic smoothing process. Additionally, when no data are available or the proportion of internet users is equal to one (i.e., 100% internet use), the proportion for the DMA is recoded to zero. That way, the final proportion will be based on the lower smoothing median of neighboring DMA proportions, providing a more conservative estimate.

Second, spatial smoothing is accomplished through use of a 'head-banging' algorithm. Head-banging is a weighted two-dimensional median-based smoothing algorithm used to minimize outliers or rapid geographic transitions due to measurement error, sampling bias, or inherent noise in the measured variable [28]. Head-banging uses data from neighboring DMAs to stabilize results from sparsely populated DMAs [29]. For this study, 10 neighboring DMAs comprise the "smoothing window". The inverse of the standard error of internet use is used to weight internet user proportions in the head-banging algorithm. That is, populations that are reliable due to a large sample are less likely to be modified whereas values based on sparse samples are more likely to be modified based on the proportions of neighboring DMAs. Additional information is available on the head-banging method [28,30].

Regression analyses are conducted in STATA 12 [31] as this software can account for complex survey design and weights. Geographic analyses are conducted in ArcGIS 10.1 [32].

Results

Table 4.1 describes the HINTS 2003 and 2008 weighted sample characteristics. Compared with the 2003 sample, the 2008 sample has a greater number of middle-aged respondents, has fewer non-Hispanic white respondents, has more college graduates, has a higher average annual income, and has more doctor visits in the past year. Despite the slight decrease from 2003 to 2008, both years have large proportions of non-Hispanic white respondents (about

70%). Furthermore, most respondents in both years are from a metro area (about 80%). Additionally, internet use increases from 2003 (64.8%) to 2008 (68.4%). In general, the typical respondent in both years is 35-49 years of age, identifies as non-Hispanic white, has at least a high school degree, earns more than $50,000 a year, lives in a metro area, has not had a cancer diagnosis, has gone to the doctor at least two times in the past year, and has used the internet.

Table 4.1 Descriptive weighted statistics of U.S. adults, HINTS 2003 & 2008, N=8495

	2003 (N=5458)		**2008** (N=3037)		**2008-2003**
	% weighted	*SE (%)*	*% weighted*	*SE (%)*	% change
Age group					
18-34	30.7	0.4	29.9	0.8	-0.8
35-49	33.0	0.3	30.2	0.7	-2.7
50-64	21.5	0.3	25.0	0.5	3.5
65-74	9.0	0.3	7.7	0.3	-1.3
75+	5.9	0.3	7.2	0.3	1.3
Gender					
Female	51.0	0.3	50.4	0.8	-0.5
Race/ethnicity					
Non-Hispanic white	72.5	0.5	69.0	0.9	-3.5
Non-Hispanic black	10.2	0.3	11.6	0.6	1.4
Hispanic	11.6	0.3	13.5	0.7	1.9
Other non-Hispanic	5.7	0.4	5.9	0.5	0.1
Education					
Less than high school	15.8	0.3	13.1	0.6	-2.7
High school graduate	31.4	0.3	30.1	0.9	-1.3
Some college	27.6	0.2	31.0	0.9	3.4
College graduate	25.1	0.2	25.8	0.4	0.7
Annual income					
Less than $20,000	19.5	0.7	15.8	1.0	-3.7
$20,000-$34,000	22.3	0.6	17.2	1.0	-5.1
$35,000-$49,000	17.5	0.6	13.6	0.9	-3.9
$50,000-$74,999	17.7	0.6	21.4	1.4	3.6
$75,000 or more	23.0	0.6	32.0	1.2	9.1
Urbanicity					
Metro (v. Rural)	80.6	0.5	80.4	1.0	-0.3
Cancer history					
Had cancer diagnosis	10.6	0.5	7.2	0.3	-3.4
Doctor visit in past year					
None	18.0	0.7	14.9	1.2	-3.1
1 time	18.2	0.6	16.3	1.0	-1.9
2 to 4 times	39.1	0.7	40.1	1.3	1.0
More than 5	24.8	0.8	28.7	1.0	3.9
Use Internet					
Yes	64.8	0.8	68.4	1.2	3.6

Table 4.2 describes weighted proportions of internet use in 2003 and 2008 by respondent characteristics. The largest increase in internet use occurs among respondents aged 65-74 (28.1% to 43.6%). Other significant increases occur among respondents aged 50-64, women, non-Hispanic whites, high school graduates, respondents living in rural areas, and respondents who have visited a doctor at least twice in the past year.

Table 4.2 Changes in internet use by sample characteristic, HINTS 2003 & 2008, N=8495

	Internet use *(weighted %)*				**% difference**
	2003 [1]	*SE*	2008 [2]	*SE*	2008-2003
Overall internet use	64.8	*0.8*	68.3	*1.2*	3.5
Age group					
18-34	79.3	1.3	80.1	2.7	0.8
35-49	73.2	1.0	76.0	1.5	2.9
50-64	59.5	1.5	67.5	1.9	8.0^{+}
65-74	28.1	1.6	43.6	2.7	15.5^{+}
75+	18.1	2.2	16.7	2.4	-1.4
Gender					
Male	65.9	1.1	66.1	1.8	0.2
Female	63.7	0.8	70.6	1.2	6.9^{+}
Race/ethnicity					
Non-Hispanic White	70.0	0.9	75.9	1.3	5.9^{+}
Non-Hispanic Black	55.1	2.5	58.1	4.7	3.0
Hispanic	39.6	1.7	38.3	3.8	-1.3
Non-Hispanic Other	67.4	3.0	70.0	5.9	2.7
Education					
Less than high school	25.5	2.3	18.4	3.4	-7.1
High school graduate	51.9	1.4	58.6	2.5	6.7*
Some college	78.3	1.2	79.2	2.2	0.9
College graduate	90.9	0.6	92.2	1.0	1.4
Annual Income					
Less than 20K	30.9	2.0	29.0	2.9	-1.9
20K to less than 35K	50.0	1.4	45.3	2.8	-4.7
35K to less than 50K	68.5	2.1	67.9	3.4	-0.5
50k to less than 75K	82.2	1.4	81.5	2.6	-0.7
75K or more	91.7	0.9	91.6	1.2	-0.1
Urbanicity					
Urban	67.6	0.9	69.7	1.4	2.1
Rural	53.0	1.7	62.8	2.8	9.9^{+}
Cancer history					
No cancer diagnosis	66.3	0.8	69.2	1.2	2.9
Had cancer diagnosis	52.3	2.2	58.1	2.9	5.8
Doctor visit in past year					
None	60.1	2.3	55.7	3.9	-4.4
1 time	70.3	1.8	73.8	2.8	3.5
2 to 4 times	65.7	1.2	71.1	1.9	5.4*
More than 5	62.7	1.5	68.1	2.2	5.3*

* p<0.05; $^{+}$ p<0.01; [1] n=5458; [2] n=3037

Though not significant, internet use among respondents with less than a high school degree declines between 2003 and 2008 (25.5% to 18.4%). Also, a small non-significant decline in internet use is seen among Hispanic respondents (39.6% to 38.3%). In 2008, college graduates represent the sub-population with the greatest percentage of internet users, at 92.2%.

Table 4.3 displays a multiple logistic regression model with adjusted odds ratios. This model combines data from survey years and examines internet use as a function of respondent characteristics. When examining racial differences in internet use, compared with respondents identifying as Hispanic, all other respondents have significantly higher odds of using the internet.

Table 4.3 Multiple logistic regression on internet use with a gender*age interaction, N=8495

	Odds ratio	*95% CI*			*Odds ratio*	*95% CI*	
Survey year				**Income**			
2003	1.0			Less than $20,000	1.0		
2008	1.08	*0.90*	*1.31*	$20,000-$34,000	1.86*	*1.45*	*2.40*
Women[1]				$35,000-$49,000	3.04*	*2.29*	*4.02*
18-34	1.0			$50,000-$74,999	5.41*	*4.01*	*7.31*
35-49	0.47*	*0.34*	*0.66*	$75,000 or more	9.23*	*6.92*	*12.32*
50-64	0.26*	*0.19*	*0.36*	**Race/ethnicity**			
65-74	0.07*	*0.05*	*0.10*	Hispanic	1.0		
75+	0.02*	*0.01*	*0.03*	Non-Hispanic White	4.22*	*3.25*	*5.48*
Men[1]				Non-Hispanic Black	2.36*	*1.61*	*3.47*
18-34	1.0			Other non-Hispanic	2.45+	*1.56*	*3.85*
35-49	0.33*	*0.21*	*0.51*	**Education**			
50-64	0.12*	*0.07*	*0.19*	Less than high school	1.0		
65-74	0.05*	*0.03*	*0.08*	High school graduate	2.10*	*1.59*	*2.77*
75+	0.04*	*0.02*	*0.06*	Some college	5.52*	*3.98*	*7.64*
Gender[2]				College graduate	13.33*	*9.80*	*18.12*
18-34	1.08	*0.71*	*1.65*	**Cancer history**			
35-49	0.75	*0.53*	*1.04*	No cancer diagnosis	1.0		
50-64	0.50*	*0.38*	*0.65*	Had cancer diagnosis	0.99	*0.80*	*1.23*
65-74	0.79	*0.54*	*1.18*	**Doctor visit in past year**			
75+	1.74	*1.00*	*3.02*	None	1.0		
Urbanicity				1 time	1.28	*0.92*	*1.77*
Metro	1.0			2 to 4 times	1.49+	*1.10*	*2.02*
Rural	0.76+	*0.62*	*0.94*	More than 5	1.58*	*1.22*	*2.05*
Intercept	0.85	*0.54*	*1.36*				

[1] Odds ratio for age groups among men and women; [2] Odds ratio within age groups (reference group: women); + p<0.05; * p<0.01; F=56.28, p<0.000

For education, compared with respondents who have less than a high school education, all other respondents have greater odds of using the internet. Based on income level, respondents making more than $20,000 have greater odds of using the internet compared with respondents making less than $20,000. Additionally, compared with respondents from metro areas, rural respondents have lower odds of internet use (OR=0.76). Compared with respondents who did not visit the doctor in the past year, respondents who visited 2 to 4 times or more than 5 times have higher odds of using the internet (OR=1.49, OR=1.58, respectively). Importantly, no significant changes in the odds of using the internet are observed when comparing 2003 respondents with 2008 respondents.

Figure 4.2 displays the interaction term (gender*age) included in the Table 4.3 model. When looking within age groups, only one gender*age group interaction is significant – the 50-64 year old age group. That is, among 50-64 year olds, men have significantly lower odds of using the internet (OR=0.50) compared with women of the same age. By plotting the probability of internet use by age group and gender using the margins command in Stata 12, Figure 4.2 demonstrates the gap widening among 50-64 year olds. Table 4.3 also displays the main effect for gender. Among women, all older age groups have lower odds of using the internet compared with the youngest age group, 18-34 years olds. The same pattern is seen among men.

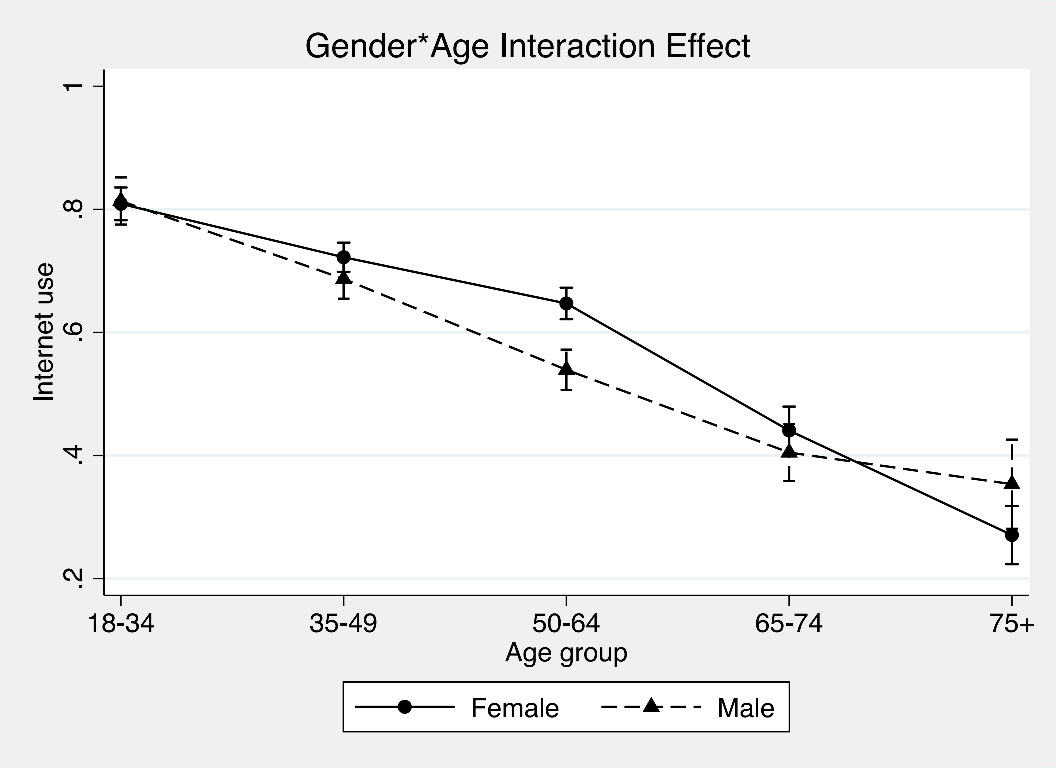

Figure 4.2 Interaction effect between gender and age on internet use, HINTS 2003 & 2008; N=8495

Table 4.4 displays a model examining changes in internet use over time. The first column displays the main effects of the predictor variables and the second column displays coefficients of the interaction effects. To better understand changes over time, the margins command in Stata 12 is used to graphically display probabilities of internet use over time. Figure 4.3 highlights changes in internet use over time controlling for all covariates in Table 4.4 – that is, the interaction effect of survey year with age group, gender, race/ethnicity, education, annual income, and urbanicity.

For most groups, disparities in internet use observed in 2003 persist in 2008. For example, among racial/ethnic groups, Hispanic respondents have a significantly lower probability of using the internet in 2003 compared with all other groups. This disparity, or gap, widens in 2008 when comparing Hispanic and non-Hispanic white respondents; however, when compared with non-Hispanic other respondents, the gap narrows.

Table 4.4 Multiple logistic regression on diffusion patterns of internet use, N=8495

	Main effect (2003)			**Interaction (Variable * 2008)**		
	Coefficient	*95% CI*		*Coefficient*	*95% CI*	
Age group (ref: 18-34)						
35-49	-0.91^{*}	-1.13	-0.70	-0.07	-0.73	0.58
50-64	-1.78^{*}	-2.06	-1.51	0.08	-0.62	0.78
65-74	-2.94^{*}	-3.27	-2.61	0.19	-0.50	0.89
75+	-3.30^{*}	-3.70	-2.91	-0.69	-1.54	0.16
Gender (ref: Women)						
Men	-0.01	-0.18	0.16	-0.59^{*}	-0.92	-0.26
Race/ethnicity (ref: Hispanic)						
Non-Hispanic white	1.22^{*}	0.96	1.48	0.43	-0.13	0.99
Non-Hispanic black	0.70^{*}	0.35	1.06	0.21	-0.61	1.03
Other non-Hispanic	0.98^{*}	0.55	1.41	-0.34	-1.24	0.56
Education (ref: Less than high school)						
High school graduate	0.57^{*}	0.25	0.89	0.46	-0.16	1.07
Some college	1.56^{*}	1.17	1.95	0.34	-0.33	1.02
College graduate	2.37^{*}	2.04	2.71	0.53	-0.11	1.18
Annual income (ref: Less than $20,000)						
$20,000-$34,000	0.55^{*}	0.31	0.80	0.17	-0.37	0.72
$35,000-$49,000	1.01^{*}	0.68	1.33	0.30	-0.29	0.89
$50,000-$74,999	1.56^{*}	1.26	1.86	0.33	-0.28	0.95
$75,000 or more	2.09^{*}	1.72	2.47	0.31	-0.26	0.89
Urbanicity (ref: Metro)						
Rural	-0.40^{*}	-0.64	-0.15	0.21	-0.25	0.67
Survey year (ref: 2003)						
2008	-0.52	-1.22	0.19	---	---	---
Cancer history (ref: Never had cancer)						
Had cancer diagnosis	0.04	-0.18	0.25	---	---	---
Doctor visit in past year (ref: None)						
1 time	0.22	-0.09	0.54	---	---	---
2 to 4 times	0.38^{+}	0.07	0.68	---	---	---
More than 5	0.46^{*}	0.21	0.71	---	---	---
Intercept	-1.40^{*}	-1.76	-1.03			

$^{+}p<0.05$; $^{*}p<0.01$; F=49.87, p<0.000

Two significant changes occur between 2003 and 2008 – the first based on gender and the second based on urbanicity. Between 2003 and 2008, disparities in internet use increase based on gender. Specifically, internet use among women is increasing at disproportionate rates compared with internet use among men. However, when examining urbanicity, the internet use disparities narrow, with rural respondents “catching up” to their urban counterparts.

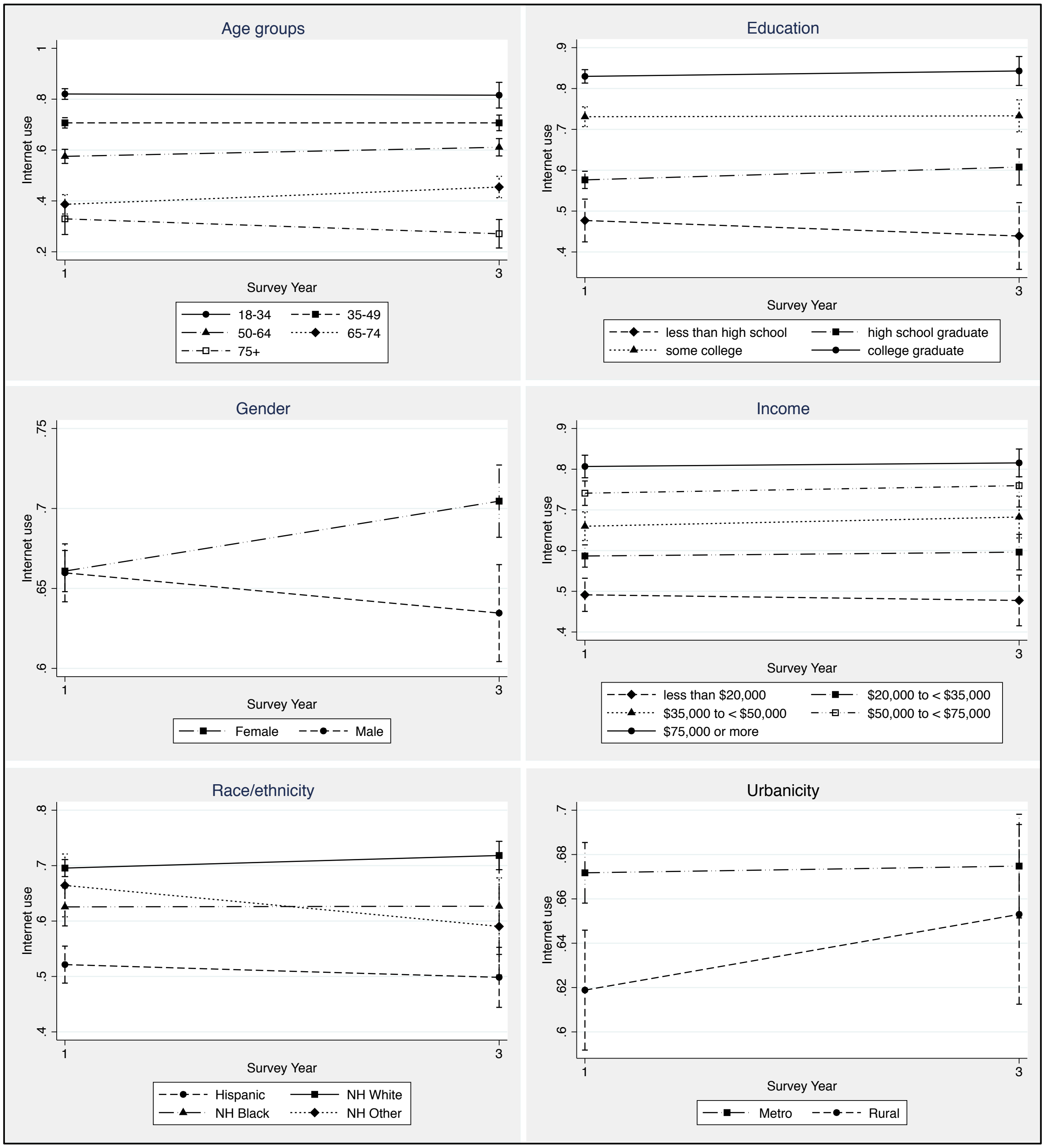

Figure 4.3 Diffusion patterns of internet use based on interaction effects with survey year, controlling for model covariates from Table 4.4, HINTS 2003 & 2008, N=8495

GIS Results

Figures 4.4 and 4.5 display geographic variation in internet use among adults in the U.S. between 2003 and 2008. Compared with 2008, in 2003 (Figure 4.4) more designated market areas (DMAs) in the U.S. show less than 50% internet use (shown as white areas with dots). In particular, the Gulf Coast, the Dakotas, eastern Appalachia, portions of the Midwest, western Nevada, and southern Texas display low proportions of internet users. The coasts exhibit relatively high proportions of internet users, particularly the Northeastern part of the U.S.

Data from 2008 (Figure 4.5) reveal noteworthy changes in internet use based on geographic areas. In particular, areas with less than 50% internet users diminish. This is the case in the Dakotas, the Midwest, Nevada, and portions of the Gulf Coast and Appalachia. However, in certain areas, including southern Texas and parts of Louisiana, Georgia, South Carolina, and West Virginia, internet use remains below 50%.

These geographic changes in internet use suggest a diffusion pattern that is supported in the multivariable model in Table 4.3. In particular, when compared with white respondents, minority respondents have lower odds of using the internet. Southern Texas, southwestern Louisiana, central South Carolina, and southeastern Georgia all have relatively large minority populations. Moreover, the model in Table 4.3 shows that income and urbanicity are highly associated with internet use. Parts of Appalachia that are highlighted in both maps are among the poorest areas in the country, as well as some of the most rural.

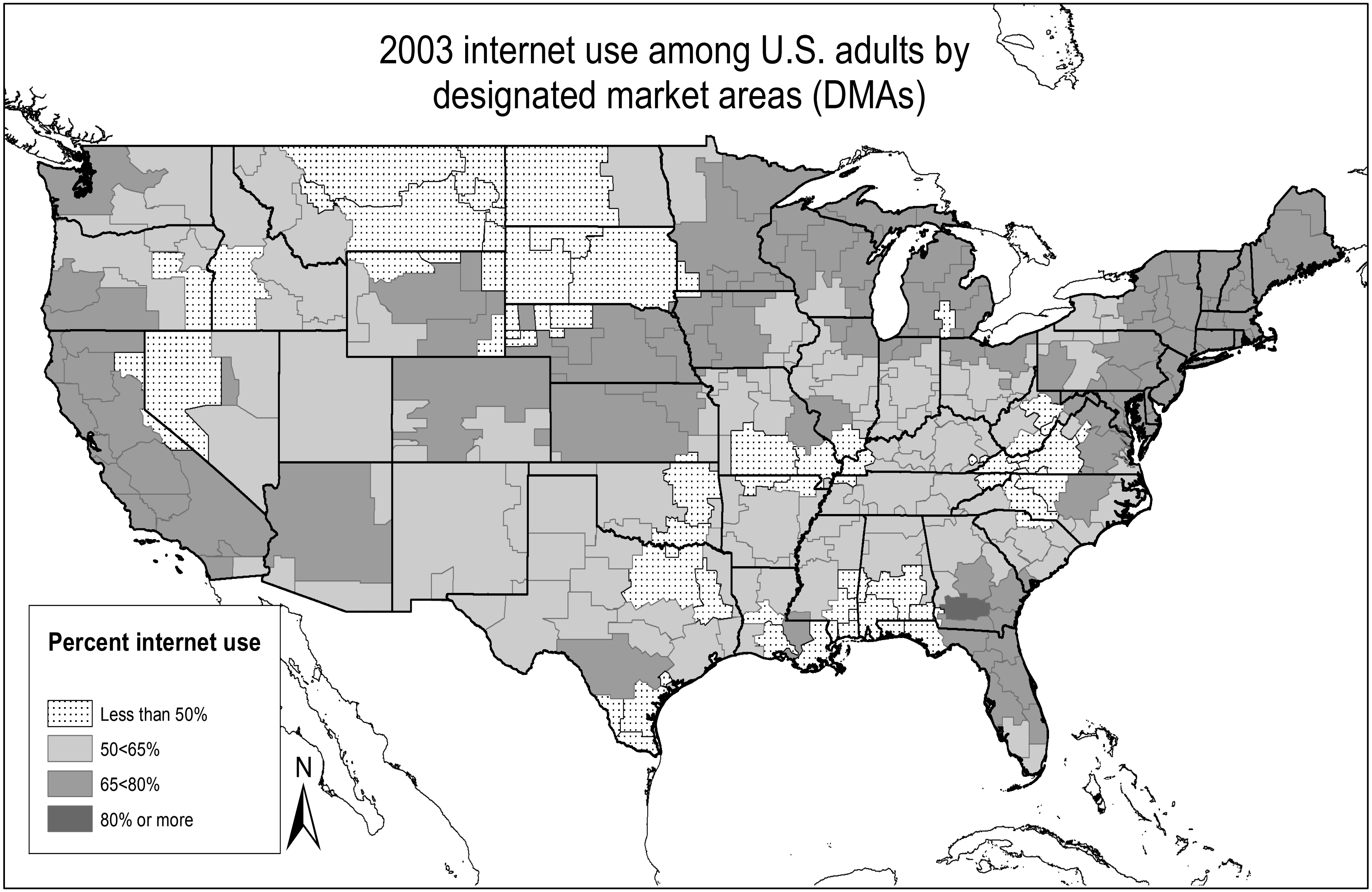

Figure 4.4 Internet use among U.S. adults by designated market areas (DMAs), HINTS 2003

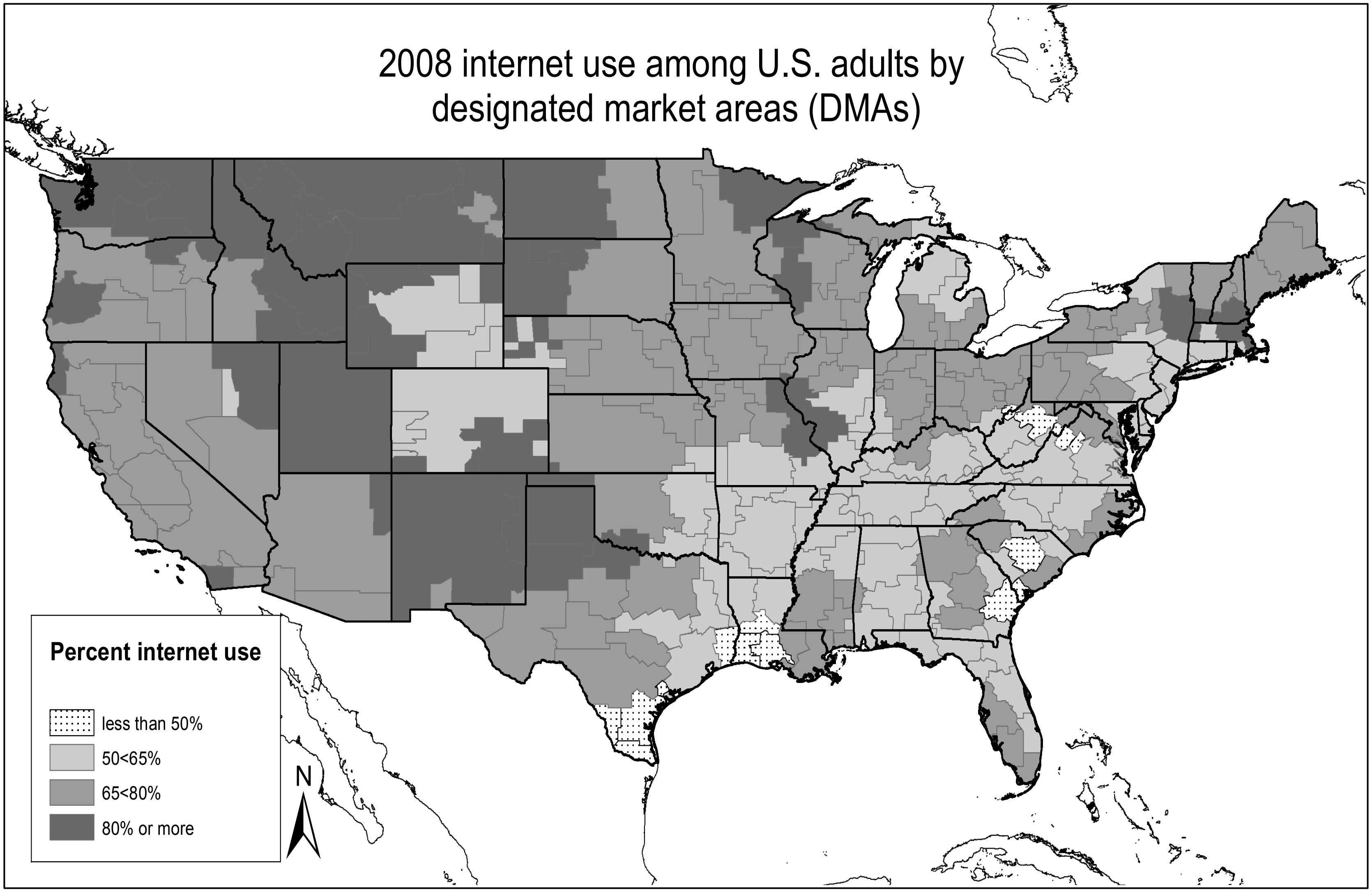

Figure 4.5 Internet use among U.S. adults by designated market areas (DMAs), HINTS 2008

Discussion

This study provides a picture of diffusion patterns of internet adoption among a U.S. adult population. Drawing from diffusion theory, certain sub-populations (namely late majority adopters) are experiencing significant increases in internet use. Late majority adopters include: respondents ages 50-64 and 65-74, respondents with a high school diploma, those living in rural areas, and women.

Based on diffusion theory, late majority adoption generally occurs around the inflection point, indicating that 50% of the population has adopted an innovation. By the time adoption reaches the inflection point in the general population, early adopters have already adopted the innovation, and to some extent so have the early majority adopters. Late majority adopters, however, are going through rapid changes of adoption; thus, the inflection point marks the tipping point towards near ubiquitous adoption. Additionally, significant predictors of internet use (seen in Table 4.3) support findings from prior studies [1]. Specifically, younger, more educated, and higher income earners have higher odds of using the internet.

While overall internet use increases from 2003 (64.8%) to 2008 (68.3%), the increase is not significant, failing to support *Hypothesis 1*. This may be because overall internet use has passed the inflection point and is approaching a saturation point (defined as having negative acceleration), or a point where those who will use the internet have already started using it. The diffusion model suggests that the largest changes in adoption occur when about 50% of the population has adopted the innovation. However, both before and after the 50% mark, adoption will be slower. With overall internet use at 64.8% in 2003, a non-significant increase to 68.3% in 2008 supports the diffusion model.

Hypotheses 2 & 3 are both supported by study findings. The greatest changes in internet use between 2003 and 2008 are seen among late majority adopters (i.e., middle-aged adults), while younger adults (early adopters) do not show significant changes. This indicates that adults ages 50-64 and 65-74 are adopting the internet at the greatest rates compared to other age groups. While their overall use may still be less than younger adults, these age groups are going through a significant transition period that will likely lead to similar overall internet use observed in younger populations. Younger adults (early adopters) have already gone through a critical adoption phase and thus, according to the diffusion model, use is nearly at its saturation point.

When examining internet use among racial/ethnic groups, racial minority populations (categorized as late majority adopters in this study) do not exhibit significant changes in internet use between 2003 and 2008. Thus, findings do not support *Hypothesis 4*. While both non-Hispanic black and ‘other’ racial categories show small increases in internet use, Hispanic respondents exhibit a decrease. Drawing from the diffusion model, both non-Hispanic black and ‘other’ respondents have passed the critical 50% adoption mark; that is, adoption has passed the tipping point and will likely continue among these sub-populations. Hispanic respondents, on the other hand, have yet to reach the 50% mark of adoption; thus, use of the internet is likely to vary more between years and may remain stagnant at times until the 50% tipping point is reached.

Furthermore, when examining predictors of internet use, Hispanic respondents have significantly lower odds of internet use compared with all other racial/ethnic categories. Compared with Hispanic respondents, non-Hispanic black respondents have 2.36 greater odds of using the internet. Again, this can be understood by the relatively higher proportion of internet users among non-Hispanic black respondents compared with Hispanic respondents.

Drawing from both diffusion theory as well as a digital disparities perspective, the model in Table 4.4 examines variable*year interaction effects. Findings suggest that the only characteristic in *Hypothesis 5* that demonstrates a reduction in disparities is in urbanicity. Compared with 2003, the 2008 gap in internet use between urban and rural respondents narrows. However, based on race/ethnicity, educational attainment, and annual income, little to no change in internet use is observed between 2003 and 2008. This suggests that while internet use may be lower among disadvantaged populations, disparities in use are not increasing over time. On the other hand, disparities are not decreasing over time; thus, vulnerable populations remain relatively disadvantaged.

Prior studies show that gender gaps in internet use have decreased over the past 15 years [16]. Through *Hypothesis* 6, this study examines whether this trend continues from 2003 to 2008. Findings suggest that the gender gap in internet use is not decreasing, but in fact increasing. However, the increasing disparity is opposite of previous findings, with women outpacing men in internet adoption. The gender*year interaction displayed in Figure 4.3 suggests that women internet users are increasing at significantly greater rates compared to men internet users – that is, the gender gap is widening.

Furthermore, the interaction effect in Table 4.3 and in Figure 4.2 suggests that among respondents aged 50-64, men have significantly lower odds of using the internet compared to their female counterparts. This finding provides a more nuanced understanding of a sub-population that shows significant changes in internet use – women in this age group may be the driving force behind significant changes over time. Thus, women ages 50-64 may be prime targets for programs or interventions that leverage internet technologies.

While overall internet use among rural respondents increased significantly between 2003 and 2008, thus supporting *Hypothesis 7*, respondents living in a metro area still have higher rates and odds of internet use. Figures 4.4 and 4.5 indicate that overall prevalence is growing with only a few areas still showing less than 50% use in 2008. Additionally, the reduced disparity in internet use among rural and urban respondents from 2003 to 2008 seen in Figure 4.3, coupled with the patterns of internet use in Figures 4.4 and 4.5 supports movement toward a digital disparities perspective in lieu of a digital divide. While the overall "divide" has narrowed or even disappeared (as observed in Figure 4.3), certain populations may still be at a disadvantaged based on more specific geography as well as demographic and socio-economic characteristics.

Though data for this study come from a health-focused, nationally representative survey, findings have implications in an array of fields. While this information is important for health professionals in terms of disseminating health information and designing health interventions, it can also extend to other areas including the economic sector and job development. Specifically for health professionals, understanding past diffusion patterns in internet use will help inform future studies and programs that leverage digital technologies and resources for health promotion and maintenance.

Disparities diffusion model

Findings from this study support a disparities diffusion model proposed in Figure 4.6. This model displays diffusion patterns by different sub-populations, highlighting disparities in adoption and saturation over time. Population A represents a typical reference group, whereas Populations B and C represent minority or vulnerable populations. X_1 represents the disparity in adoption rate between Populations A and B. More specifically, X_1 is the difference in time that Population A reaches its inflection point (i.e., 50% adoption) compared to Population B's inflection point. X_2 is the time difference between inflection points for Populations A and C. $X_2 – X_1$ represents the inflection point disparity between the two minority populations.

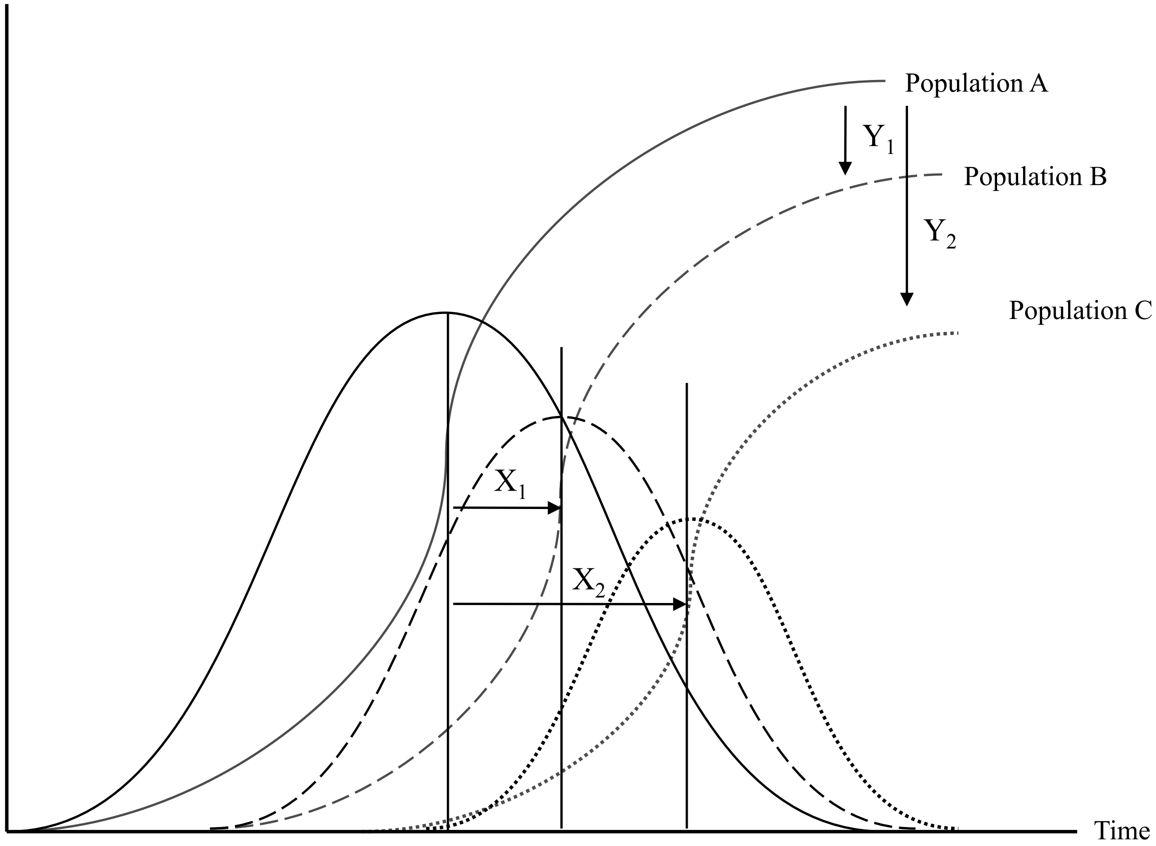

Figure 4.6 Disparities diffusion model

The Y arrows, on the other hand, represent the disparity in saturation point of adopters. Saturation occurs when all potential users have adopted the innovation. Y_1 is the difference in saturation of internet users between Populations A and B, whereas Y_2 is the difference between Populations A and C. $Y_2 - Y_1$ is the difference in adopter saturation between the two minority or vulnerable populations. Differences in saturation suggest that at the end of the diffusion process, the percent of the sub-population that adopted the innovation will not be the same. That is, there will always be individuals who do not use the internet, but that percentage will vary according to the sub-population.

A major limitation of this study is the use of cross-sectional data. Longitudinal or matched data would provide a better understanding of changes in internet adoption over time;

however, these data are not available through the HINTS. Cross-sectional data, while not as strong as longitudinal data, do provide a general picture of changes in internet use among large, more general populations. Furthermore, examining two points in time provides a better understanding of diffusion phenomenon both within and between sub-populations.

Additionally, the head-banging procedure that is used for spatial smoothing is based on geographic proximity. Thus, there is the assumption that internet adoption has some geographic characteristic. While this may be the case in terms of technological infrastructure, rural populations that are more sparsely represented in the data set may display biased results. However, to limit this bias, this study uses 10 neighboring geographic data points to help "smooth" potentially unreliable data (those with large standard errors).

Conclusion

This study provides a picture of diffusion patterns of internet adoption among U.S. adults, highlighting digital disparities based on socio-demographic characteristics as well as geography. Findings highlight sub-populations that may be ripe for health interventions or outreach using internet technologies – in particular, women ages 50-64 are among the fastest growing internet user subgroups. Findings also identify sub-populations with lower access and use of internet technologies, based on demographic characteristics or geography, that may be left behind or marginalized as the health sector and larger economy continues in the digital revolution.

Among U.S. populations, the digital divide perspective of "haves" and "have nots" may be dated and encourage a false dichotomy in internet use. Findings from this study support a digital disparities approach to diffusion theory that provides a more nuanced picture of adoption patterns that can be leveraged for intervention. While diffusion is likely to continue at varying rates among various populations, targeted interventions can help reduce disparities in adoption as well as use saturation among particular subgroups.

Importantly, findings are not only relevant in health-related fields, but can also be applied to workforce development programs or other economic arenas. Specifically, as the U.S. economy continues to value a highly skilled workforce, developing computer and new media literacies among vulnerable populations becomes paramount. Taking a digital disparities perspective highlights areas of need, both in terms of population characteristics and geographies, in order to build digital competencies that will help the U.S. workforce remain among the most skilled and accomplished in the global economy.

CHAPTER 5: STUDY 2

Use of the internet as a first source for cancer information among internet users and non-users

Abstract

Background: While many studies have looked at changes in internet use over time, few have examined changes in sources of health information, particularly how it relates to internet access and use. Moreover, given that over half of online health information searches are done on behalf of someone else, the role of surrogate seekers is growing. **Objective:** To describe changes in the first source for cancer-related health information and to explore source differences among internet users and non-users. **Methods:** Data from two iterations of the Health Information National Trends Survey (HINTS 2003 & 2008) are used to examine changes in first source of cancer-related health information (n=3210). Multinomial logistic regression is used to model predictors of first source of cancer information, including: the internet, a health professional, or print material. **Results:** In 2008, internet use as a first source for cancer information remains high among internet users (75%) and is growing among non-users (12%), presumably through surrogates. Use of print material is declining (users: 10%; non-users: 38%) and getting information from health professionals is increasing (users: 15%; non-users: 50%). Among internet users, older individuals and Hispanic/Latino respondents have a higher relative risk of using print material compared to the internet for health information. Among non-users, the relative risk of using the internet for health information compared to print material increases from 2003 to 2008 (RRR=2.7). **Conclusion:** Information seeking is multifaceted and will become more interactive as information and communication technologies continue to develop and expand their reach to health issues. Health care organizations and public health agencies should leverage the interactive nature (i.e., the “team approach”) of information seeking to develop better information resources and ensure access by all populations.

Introduction

More and more Americans are turning to the internet as a source for health information – a 2013 report by the Pew Internet and American Life Project estimates that 72% of adult internet users in the U.S. look online for health information, up from 40% in 2002 [1]. Not only are people looking for information online, but 60% of online seekers say that the information they find influences health care decisions [2]. Seeking and using information to determine health care and wellness decisions, especially with information found on the internet, is likely to continue and even increase in the coming years as more emphasis is placed on disease management and prevention, coupled with increased access to information and communication resources.

Health information seeking

Health information seeking is most broadly defined as the "purposive acquisition of information from selected information carriers" [3]. It encompasses the ways in which individuals look for and obtain information, including information about their health, health promotion activities, health risks, and illness [4,5]. Health information seeking has been studied in many different contexts, including coping with a health-threatening situation, participation and involvement in medical decision-making, and behavior change and preventive behaviors [4].

Among internet users, younger, more educated, higher income earners, and individuals who preferred numbers are more likely to use the internet as a *first source* for health information [6]. On the other hand, groups least likely to look for health information online include: African Americans, Latinos, adults living with disability, adults age 65 years or older, adults with high school education or less, and adults in low-income households [7–9].

The internet offers many advantages for finding health information. Immediacy, accessibility, confidentially, and interactivity are just a few such advantages. However, while these factors are advantageous to many, they may also serve as disadvantages to neophytes on the internet. In particular, accessibility can vary greatly (regarding both connectivity as well as website literacy), privacy issues may be a concern, and credibility of sites and information can be difficult to ascertain. These barriers are often most relevant among vulnerable populations or populations with little internet experience and may be associated with using another source for health information [10].

According to a Pew report, the top four reasons that adults look for health information online include: specific disease or medical condition (55%); certain medical treatment or procedure (43%); how to lose or control weight (27%); and health insurance (25%). This study looks specifically at cancer-related health information seeking. Sources of cancer-related information are likely to change depending on the cancer diagnosis, the cancer care continuum, and perceived risk factors. Additionally, health professionals are the most trusted and used source of information among cancer patients, with print material ranking second [11,12].

While there is literature on using the internet as a first source for health information, little research has been done that examines predicting characteristics associated with the first source for health information, particularly when comparing a doctor or print material with the internet. Even fewer studies examine the use of health information sources over time. The following research question is used to guide this study: How has the first source for cancer-related information changed over time?

Surrogate seekers

Because of its pervasive role as an information source and a communication technology, the internet provides a practical and cost-efficient medium through which to access health information. As this information source becomes more ubiquitous, online information seeking will become more nuanced and multi-leveled, particularly as individuals, families, and larger groups partake in this behavior. This is evidenced in a Pew report that finds that over half of online health information searches are on behalf of someone else; less than 40% of internet users who looked online for health information do so only for themselves [1]. The report finds that older adults are less likely than younger adults to look for online information for others. Additionally, parents are more likely than non-parents to look on behalf of someone else (44% compared to 36%).

Research on surrogate seekers generally focuses on the surrogate and not for whom the information is intended. However, emerging research is helping to reframe the concept of health information seeking as a "team sport" [13]. This perspective may shed new light on research related to differences between surrogate seekers and individuals who get health information through a surrogate. Literature suggests that individuals who use the internet for health information and individuals who do not use the internet for such information are different [10]. But again, this research does not account for non-users who get online health information through a surrogate.

Few studies have examined the first source for health information using both internet users as well as non-users in the same sample. Thus, in addition to examining the first source of cancer information, this study also explores the first source of cancer-related health information among both internet users as well as non-users. Specifically, this study explores the use of the internet for health information among respondents who indicate that they do not use the internet.

Methods

Data and sample

This study uses secondary data from the 2003 and 2008 Health Information National

Trends Survey (HINTS). HINTS is a nationally representative repeated cross-sectional survey of the U.S. non-institutionalized adult population. The survey enables researchers to assess the impact of knowledge, attitudes, and practices along with changes in the health communication environment on health behaviors and outcomes [14,15]. As HINTS is developed by the National Cancer Institute, special emphasis is placed on cancer communication, prevention, and treatment. This study draws from this strength and will focus on cancer-information seeking.

HINTS 2003 data were collected from October 2002 through April 2003 and HINTS 2008 data were collected from January through April 2008. HINTS 2003 used computer-assisted telephone interviewing (CATI) with oversampling of minority populations, including African Americans and Hispanics/Latinos. Based on declining telephone response rates, HINTS 2008 implemented a mixed mode data collection method using both telephone and mail methods.

When comparing HINTS findings across years it is necessary to investigate differences in sampling mode [16]. This study compares mode differences in key variables, including internet use and the first source of cancer information. Significant differences in internet use are present based on the sampling mode (telephone: 66.3% vs. mail: 71.1%). Thus, to limit bias and match the mode of data collection from HINTS 2003, only telephone respondents from HINTS 2008 are included in the sample. Response rates were 55% (HINTS 2003) and 42% (HINTS 2008) at the household screening level, and 60% (HINTS 2003) and 57% (HINTS 2008) at the sampled person interview level. These response rates are consistent with prior studies in public opinion research [8,17].

The subsample of respondents in this study includes respondents who complete a telephone survey, indicate that they have looked for cancer information, and do not have missing data in any covariates (n=3210). Among all internet users in the combined 2003 and 2008 dataset, 50.5% indicate looking for cancer information. Among non-users in the combined dataset, 26.7% indicate looking for cancer information. A total of 2027 respondents are from HINTS 2003 and 1183 are from HINTS 2008.

Measures

First source of cancer information: This is the main outcome for this study. Respondents who indicate looking for cancer information are asked to identify the first source that they use. The original variable contains 12 nominal responses. The variable is recoded to have three nominal categories, including: internet, health professional, and print material.

Key independent variables: Internet use is determined by asking respondents if they have ever gone online to access the internet or world wide web, or to send or receive email. Respondents who indicate that they have done this are considered internet users, whereas respondent who have not are non-users.

Presence or exposure to cancer is also an important variable to control for as this represents a predisposing factor to look for cancer information. Respondents are asked if they have ever been diagnosed with having cancer, as well as if any of their family members have ever had cancer. In addition to cancer, exposure to the health care system (i.e., the number of times a respondent had been to the doctor in the past year) is a key variable to include in analysis as this may represent an enabling factor to seek information from a health professional.

Socio-demographic variables: Age (18-34, 35-49, 50-64, 65-74, and 75 years or older); gender; race (non-Hispanic white, non-Hispanic black, Hispanic, and other); annual income (<$20,000, $20,000-$34,999, $35,000-$49,999, $50,000-$74,999, and $75,000 or more); and educational attainment (less than high school, high school graduate, some college, and college graduate).

Additional variables: urbanicity (metro area, rural area); self-rated overall health status (poor, fair, good, very good, excellent); body mass index (underweight, normal, overweight, obese); high-speed internet access (yes, no).

Analysis

Data are weighted to produce nationally representative estimates of the U.S. adult population. Survey weights include a base weight (the reciprocal of the probability at both the household and respondent level of the respondent being sampled), a weight to adjust for non-response, and a calibration weight (based on data from the Current Population Survey and American Community Survey). The jackknife technique is used to produce 50 replicate weights for each year (100 replicate weights in total) to provide statistically valid standard errors for the parameter estimates [18].

Univariate analysis is used to examine the frequency and distribution of the study variables among internet users and non-users who indicate ever looking for cancer information. Statistics are presented for each HINTS iteration (2003 & 2008), as well as percent change between the two iterations. A 2x3 table is used to examine unadjusted distributions of first source of cancer information among internet users and non-users.

Multinomial logistic regression is used to model the nominal outcome variable, first source of cancer information. The main outcome is categorical and contains three possible responses: the internet, a health professional, or print material. As there is no logical order to these responses, ordinal logistic regression is not appropriate. In the multinomial model, the log odds of the outcomes are modeled as a linear combination of the predictor variables.

Multinomial logistic models present conditional findings based on a reference outcome variable [19]. Two multinomial logistic models are developed, separated by internet use. Among internet users, the internet is used as the reference category. Among non-users, the reference category is print material. Reference categories are chosen based on the largest N so as to maximize model stability. Analyses are conducted in STATA 12 as this software can account for complex survey design and weights [20].

Results

Table 5.1 shows an unadjusted 2x3 table of first source of cancer information by internet use. Among internet users, the internet is the most common first source of cancer information (70.7%). Interestingly, nearly 1 in 10 respondents who indicate that they do not use the internet also indicate that the internet is their first source of cancer information.

Table 5.1 Unadjusted distribution of first source of cancer information by internet use, HINTS 2003 & 2008

	Internet user	
First source of cancer info	No	Yes
Internet	72 (9.9%)	1754 (70.7%)
Health professional	255 (34.9%)	266 (10.7%)
Print material	403 (55.2%)	460 (18.5%)
Total	730	2480

Table 5.2 displays descriptive statistics among respondents who have ever looked for cancer information. Respondents are separated by internet users and non-users. Among respondents who ever looked for cancer information (n=3210), 2480 indicate prior internet use and 730 indicate no prior internet use.

Internet users

Between 2003 and 2008, internet users who look for cancer information shifts towards older users, with the greatest increase among 50-64 year olds (from 23.1% to 29.6%). In both years, more than 80% of internet users who look for cancer information are non-Hispanic white. In addition, an increase is seen among respondents who earn more than $75,000 a year and among those who indicate going to the doctor more than 5 times in the past year, from 29% in 2003 to 35% in 2008.

Table 5.2 Descriptive statistics of sample of internet users and non-users who look for cancer information, HINTS 2003 & 2008

	Internet users *(weighted %)*		**Percent difference**	**Non-users** *(weighted %)*		**Percent difference**
	2003 [1]	2008 [2]	2008-2003	2003 [3]	2008 [4]	2008-2003
Age group						
18-34	33.2	26.2	-7.0	11.5	3.5	-8.0
35-49	39.2	35.9	-3.3	25.1	24.8	-0.3
50-64	23.1	29.6	6.5	32.5	25.0	-7.5
65-74	3.7	5.5	1.8	17.3	20.3	3.0
75+	0.8	2.7	1.9	13.6	26.4	12.8
Gender						
Female	56.4	56.7	0.3	65.4	53.0	-12.4
Race/ethnicity						
Non-Hispanic white	81.9	82.6	0.7	69.9	64.0	-5.9
Non-Hispanic black	7.2	8.3	1.1	13.2	14.1	0.9
Hispanic	5.0	4.5	-0.5	11.9	14.1	2.2
Other non-Hispanic	5.9	4.7	-1.2	5.0	7.8	2.8
Education						
Less than high school	5.2	2.5	-2.7	24.5	24.3	-0.2
High school graduate	20.9	20.4	-0.5	42.2	35.9	-6.2
Some college	31.8	34.0	2.1	22.2	26.8	4.7
College graduate	42.1	43.2	1.1	11.1	12.9	1.7
Annual income						
Less than $20,000	7.6	4.9	-2.7	31.1	22.5	-8.6
$20,000-$34,999	14.0	9.5	-4.5	31.9	35.0	3.1
$35,000-$49,999	15.0	12.2	-2.8	19.7	16.4	-3.3
$50,000-$74,999	24.4	23.0	-1.3	10.3	11.7	1.4
$75,000 or more	39.1	50.3	11.3	7.0	14.4	7.4
Cancer history						
Has cancer history	13.0	10.5	-2.5	27.4	19.0	-8.4
Family cancer history						
Family with cancer	72.9	82.8	9.9	74.1	74.9	0.8
Doctor visit in past year						
None	12.4	9.4	-3.0	10.6	7.5	-3.1
1 time	17.9	15.5	-2.4	11.4	11.6	0.1
2 to 4 times	40.7	40.0	-0.7	43.6	42.4	-1.3
More than 5	29.0	35.2	6.2	34.3	38.6	4.2
Internet connection						
Highspeed	34.5	85.8	51.3	---	---	---
First source of cancer information						
Internet	71.1	75.4	4.4	10.2	12.0	1.7
Health professional	7.0	15.0	8.0	27.0	49.7	22.7
Print material	21.9	9.5	-12.4	62.8	38.4	-24.4

[1] n=1563; [2] n=917; [3] n=464; [4] n=266

In both 2003 and 2008, the typical internet user who looks for cancer information is a non-Hispanic white woman between the ages of 35-49 who graduated from college, earns more than $75,000 in annual income, has family history with cancer, and visited the doctor 2-4 times in the past year.

Non-users

Compared with respondents who use the internet, respondents who *do not* use the internet and look for cancer information are on average older in both years. Based on age, the greatest decline among non-users between 2003 and 2008 occurs among 18-34 and 50-64 year olds. In 2003, 18-34 year olds make up 11.5% of the non-users compared with 3.5% in 2008. Similarly, the percentage of 50-64 year old non-users decreases from 32.5% in 2003 to 25% in 2008. In addition, from 2003 to 2008 the percentage of women non-users declines from 65.4% to 53%. A decrease is also observed among respondents who had cancer history, dropping from 27.4% in 2003 to 19% in 2008.

The typical non-user who looks for cancer information in 2008 is a non-Hispanic white woman above the age of 75 who is a high school graduate, earns between $20,000-$34,999, has family history with cancer, and visited the doctor 2-4 times in the past year. In general, compared to respondents who use the internet, those who do not use the internet have lower incomes, are less educated, and are older.

First source for cancer information

Figure 5.1 displays changes in first source of cancer information between 2003 and 2008. The percentage of respondents who use print material for the first source of cancer information declines from 2003 to 2008 among both internet users (by 12% points) and non-users (by 24% points). On the other hand, the percentage of respondents who use a health professional for the first source increases from 2003 to 2008 in both groups. Among internet users, respondents who use a health provider for the first source of information increases from 7% to 15% and among non-users it increases from 27% to nearly 50%. However, what is not clear from the data is whether or not the respondent consults the health professional in person or through other means, such as over the telephone or through email.

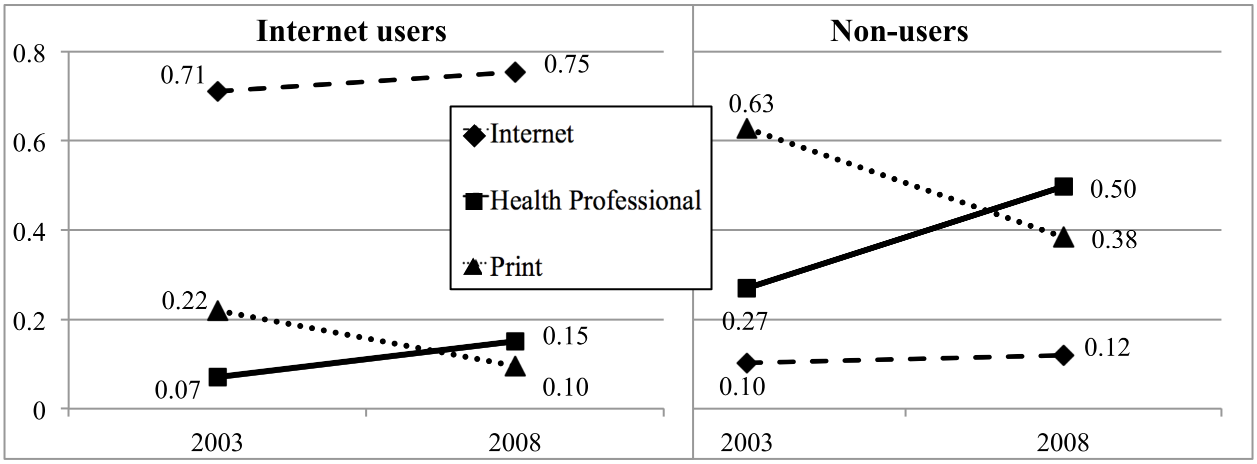

Figure 5.1 Changes in first source for cancer information among internet users and non-users, HINTS 2003 & 2008

The internet remains the most used source for health information among internet users – on average 7 in 10 use the internet as a first source for cancer information. Respondents who use the internet as a first source of cancer information also increases *among non-users* from 10% to 12%. Thus, among respondents who indicate that they have never used the internet, on average 1 in 10 use it as a first source for cancer information in both 2003 and 2008.

HINTS 2003 includes a question asking "Has anyone ever looked for cancer information for you, and if so, who has looked for you?" Among respondents who do not use the internet but indicate that they use it as a first source for cancer information (n=41), nearly 70% indicate that a family member other than their spouse looked for cancer information for them. Unfortunately, this question is not asked in HINTS 2008.

Multinomial logistic regression

Tables 5.3 and 5.4 display multinomial logistic regression models on source of cancer information among internet users and non-users, respectively. In Table 5.3, among internet users, the internet is the reference category for outcome variables. In Table 5.4, among non-users, print material is the reference category. In addition to the covariates listed, non-significant control variables in the model are omitted from the tables to conserve space. These variables include: annual income, urbanicity, insurance status, overall health status, and body mass index.

Internet users (Health professional vs. internet)

Compared with internet users in 2003, internet users in 2008 have a significantly greater relative risk of using a health professional as a first source of cancer information compared to the internet (RRR=2.3). While the overall use of a health professional for cancer information remains low, the increase from 2003 to 2008 relative to the increase in internet use is enough to suggest a significant change. This significant finding speaks more to the decreasing disparity between using the internet or a health professional for the first source of cancer information, rather than the overall shift towards using a health professional. In both survey years, the internet as a first source for cancer information remains the most used source.

In addition, age shows a significant association with using a health professional as a first source of information – compared to the youngest age group (18-34 year olds), the oldest age group (75 years or older) has greater relative risk of using a health professional compared to the internet (RRR=3.9). Moreover, compared to respondents with no cancer history, those with a history of cancer have significantly greater relative risk of using a health professional for cancer information compared to the internet (RRR=2.1). Finally, compared with respondents who did not see a doctor in the past year, respondents who saw a doctor 2 to 4 times or more than 5 times have significantly greater relative risks of using a health professional for the first source of cancer information compared to the internet (RRR=3.5 & RRR=5.3, respectively).

Table 5.3 Multinomial logistic regression on source of cancer information among internet users[1], HINTS 2003 & 2008 combined, n=2480

	Health professional*			**Print***		
	RRR	*95% CI*		RRR	*95% CI*	
Survey year						
2003	1.0			1.0		
2008	2.3^{+}	*1.4*	*3.6*	0.5^{+}	*0.3*	*0.7*
Age group						
18-34	1.0			1.0		
35-49	1.0	*0.5*	*1.7*	1.8^{+}	*1.2*	*2.8*
50-64	1.2	*0.6*	*2.3*	2.4^{+}	*1.5*	*3.8*
65-74	1.9	*0.8*	*4.2*	4.0^{+}	*2.1*	*7.5*
75+	3.9^{+}	*1.2*	*12.9*	14.0^{+}	*4.9*	*39.9*
Gender						
Female	1.0			1.0		
Male	1.1	*0.7*	*1.8*	0.6	*0.4*	*0.8*
Race/ethnicity						
Non-Hispanic white	1.0			1.0		
Non-Hispanic black	0.7	*0.1*	*4.7*	0.8	*0.5*	*1.4*
Hispanic	1.9	*0.9*	*4.1*	2.5^{+}	*1.2*	*5.3*
Other non-Hispanic	0.3^{+}	*0.1*	*0.7*	0.6	*0.3*	*1.0*
Cancer history						
No cancer diagnosis	1.0			1.0		
Had cancer diagnosis	2.1^{+}	*1.3*	*3.3*	0.8	*0.5*	*1.2*
Family cancer history						
Family with no cancer	1.0			1.0		
Family with cancer	1.5	*0.9*	*2.5*	0.9	*0.6*	*1.2*
Doctor visit in past year						
None	1.0			1.0		
1 time	2.1	*0.7*	*6.1*	0.7	*0.4*	*1.3*
2 to 4 times	3.5^{+}	*1.4*	*8.8*	0.7	*0.4*	*1.2*
More than 5	5.3^{+}	*1.8*	*15.2*	0.7	*0.4*	*1.2*
Education						
Less than high school	1.0			1.0		
High school graduate	2.2	*0.6*	*8.1*	1.1	*0.3*	*3.8*
Some college	1.5	*0.4*	*5.1*	1.4	*0.4*	*4.5*
College graduate	1.2	*0.3*	*4.1*	1.6	*0.5*	*4.9*
High-speed internet						
No	1.0			1.0		
Yes	0.7	*0.4*	*1.1*	0.6^{+}	*0.4*	*0.8*
Intercept	0.0	*0.0*	*0.2*	0.9	*0.1*	*8.3*

*Internet as reference category; $^{+}$p<0.05; [1]controlling for: annual income, urbanicity, insurance status, overall health status, and body mass index; F=6.92, p<0.000

Internet users (Print material vs. internet)

Compared with internet users in 2003, Table 5.3 shows that internet users in 2008 have a significantly lower relative risk (RRR=0.5) of using print material compared with the internet for the first source of cancer information. On the other hand, when compared to the youngest age category (18-34 year olds), all other age categories have significantly greater relative risks of using print material compared to the internet for cancer information. Among racial/ethnic categories, when compared with non-Hispanic white respondents, Hispanic/Latino internet users have a significantly higher relative risk of using print material for a first source of cancer information compared to the internet (RRR=2.5). Lastly, having high-speed access to the internet is significantly associated with using the internet as a first source for health information compared to print material (RRR=0.6).

Non-users (Health professional vs. print material)

Compared with non-users in 2003, Table 5.4 shows that non-users in 2008 have a significantly greater relative risk of using a health professional as a first source for cancer information compared to print material (RRR=3.3). Compared to respondents with less than a high school education, respondents who attended some college or graduated from college have significantly lower relative risks of using a health professional for the first source of cancer information compared to print material (some college RRR=0.3; college graduate RRR=0.4). This greater use of print material compared to a health professional among higher educated non-users may be related to higher literacy levels.

Non-users (Internet vs. print material)

Compared with respondents in 2003 who do not use the internet, Table 5.4 shows that 2008 non-users have a significantly higher relative risk of using the internet for the first source of cancer information compared with print material (RRR=2.7). No other associations are significant when comparing internet and print material as a first source for health information.

Table 5.4 Multinomial logistic regression on source of cancer information among non-users[1], HINTS 2003 & 2008 combined, n=730

	Health professional*			**Internet***		
	RRR	*95% CI*		RRR	*95% CI*	
Survey year						
2003	1.0			1.0		
2008	3.3^{+}	2.0	5.5	2.7^{+}	1.3	5.6
Age group						
18-34	1.0			1.0		
35-49	1.3	0.4	4.8	1.2	0.2	9.7
50-64	0.8	0.2	2.5	0.8	0.1	5.5
65-74	0.9	0.2	3.2	0.4	0.1	3.8
75+	1.1	0.3	4.1	0.1	0.0	1.2
Gender						
Female	1.0			1.0		
Male	1.0	0.6	1.7	0.8	0.3	2.0
Race/ethnicity						
Non-Hispanic white	1.0			1.0		
Non-Hispanic black	0.7	0.3	1.5	0.9	0.2	3.8
Hispanic	0.9	0.4	2.3	0.5	0.1	4.1
Other non-Hispanic	0.7	0.3	1.8	0.3	0.0	1.6
Cancer history						
No cancer diagnosis	1.0			1.0		
Had cancer diagnosis	1.7	0.9	3.0	2.3	1.0	5.2
Family cancer history						
Family with no cancer	1.0			1.0		
Family with cancer	1.1	0.6	1.9	1.6	0.6	4.4
Doctor visit in past year						
None	1.0			1.0		
1 time	0.9	0.2	3.1	0.3	0.0	3.3
2 to 4 times	1.4	0.5	4.2	0.7	0.1	5.1
More than 5	1.6	0.5	5.1	1.0	0.1	7.6
Education						
Less than high school	1.0			1.0		
High school graduate	0.7	0.3	1.3	2.5	0.6	10.3
Some college	0.3^{+}	0.2	0.7	0.7	0.2	3.7
College graduate	0.4^{+}	0.2	0.9	1.9	0.4	8.6
Intercept	2.8	0.2	43.4	1.7	0.0	129.2

*Print material as reference category; $^{+}p<0.05$; [1]controlling for: annual income, urbanicity, insurance status, overall health status, and body mass index; F=2.74, p<0.001

Discussion

Between 2003 and 2008, among both internet users and non-users, more individuals are using the internet and health professionals for a first source of cancer information and fewer are turning to print materials (fewer than one in ten). Additionally, as individuals continue to adopt and use internet technologies, older, minority populations are likely to represent the largest proportions of groups that remain non-users. In other words, individuals who indicate that they have never used the internet are likely to represent the most vulnerable populations or populations in most need of health information, who are at a disadvantage as health information and communication continues to shift from print to digital methods.

Findings from this study expand the literature by supporting a multilevel approach to examining health information seeking. Traditionally investigated at the individual level, the increasing role of surrogate seekers as well as expanding information and communication technologies supports the need to expand this area of inquiry to include a more interactive or “team” approach to information seeking. This is evidenced in this study by the use of the internet as a first source for cancer information among respondents who have never used the internet.

Furthermore, this study finds that internet use may not be requisite for using the internet as a first source for health information. When comparing respondents in 2003 to respondents in 2008, there appears to be a shift towards using the internet for health information regardless of the respondent’s internet use status. In both 2003 and 2008, one in ten non-users indicate that they use the internet as a first source for cancer information. This finding builds upon prior research suggesting more and more individuals are having others (including family members or friends) look for health information on their behalf [13]. One study finds that as many as 1 in 5 non-users have family or friends search for health information on internet [21]. As people continue to rely on others to help them find health information, understanding the interactive nature of not only the search but also how the information is then applied will become important. This is particularly important as access to and use of digital and mobile technologies continues to increase, coupled with a growing emphasis on electronic health information and health records.

Another important finding is the increase in use of a health professional for health information. In 2008, nearly 50% of non-users (up from 27% in 2003) and 15% of internet users (up from 7% in 2003) use a health professional as a first source for health information. Traditionally, health professionals have been a source of treatment or care, but are now also becoming a source for health information. This change may speak to the shift towards shared decision-making between health consumer and provider. Furthermore, better access and use of communication technologies that allow for asynchronous communication may result in increased communication between busy health providers and their patients.

Importantly, findings highlight differences in information seeking among certain subpopulations. For instance, when compared with white internet users, Hispanic/Latino internet users have significantly higher relative risks of using print material as a first source for health information compared to the internet. This reflects the relatively low number of Hispanic respondents that use the internet to look for cancer information (5.0% in 2003 and 4.5% in 2008). Thus, even though use of print material is declining, it may still benefit certain populations to provide print materials that are culturally and linguistically appropriate. However, there is a greater risk with print materials that health information will be outdated. This is not to say that online health information is guaranteed to be up-to-date or even accurate, but given the time and costs associated with print production, print materials are not able to keep pace with materials produced in electronic format.

Additionally, compared to younger internet users, older internet users have a greater relative risk of using print materials compared to the internet. This may a fleeting association as the overall use of print materials continues to decline; however, this is useful information for health care organizations as older populations continue to adopt and use internet technologies (though more slowly than younger populations). This information can be used to provide health information to subpopulations through relevant channels or sources.

Health information seeking is becoming more interactive, incorporating interpersonal, organizational, and other mediated communication sources; thus, public health research must respond appropriately by gathering relevant data for program and policy development. Currently, survey items are often worded in terms of an individual action or attitude related to looking for health information. For example: ‘How much do *you* trust information from the internet or from a health professional’. Future research will need to examine the role of surrogate seekers and the interactive nature of information seeking to better understand trust and ultimately application.

To this end, future survey research should not only ask if an individual has looked for health information for themselves or someone else, but also ask if someone looked for information for them. Furthermore, examining how the information is used to inform health care and medical decisions, as well as other healthful behaviors, may elucidate the interactive nature of health information seeking and its subsequent application to health decisions. This information could also help health care organizations and providers better serve their clients by providing appropriate information resources.

Additionally, as the Patient Protection and Affordable Care Act (ACA) is implemented, greater emphasis will be placed on digitizing health information and medical records, as well as on providing electronic communication methods between health care consumer and health care providers, organizations, and insurers. Thus, developing resources that embrace the “team approach” to allow for the maximum number of individuals, families, or other defined unit to participate in information seeking and ultimately care coordination is necessary.

The use of cross-sectional data is a limitation in this study. When examining changes over time, longitudinal data provide a better understanding of changes and more importantly, predictors associated with those changes. Moreover, additional information regarding internet-related behaviors among non-users would provide a better picture as to how non-users are accessing information over the internet. One question in HINTS 2003 attempts to capture surrogate-seeking behaviors, but data are limited – this question is not included in HINTS 2008.

Additionally, a better understanding is needed on how respondents conceptualize and define information sources. More specifically, how do respondents define the source of information if it comes from the internet but is procured or presented by a family member? For instance, if a grandmother asks her granddaughter to look online for information regarding a particular cancer or ailment, does the grandmother then conceptualize the information as coming from her granddaughter or from the internet? Do different conceptualizations change the level of trust or application of the information? Additionally, among internet users as well as non-users, do responses related to a health professional source vary if the information is collected in person, over the telephone, or through the internet? Depending on the method of communication, the respondent may define the information source differently. This is particularly important in survey research where responses are subject to respondent interpretation and conceptualization.

Finally, as is the case with all survey research, findings are limited by recall bias. This is a particular concern for questions framed in the past 12 months or when questions ask what respondents did the “last time”. The study’s main outcome variable is subject to this bias.

Conclusion

Information seeking is multifaceted and is likely to become more interactive as information and communication technologies continue to expand their role in the health care system. Surrogate seekers are likely to not only influence the information-seeking process, but may also influence the application of information and resulting decisions. Future models of information seeking will need to consider a multi-level, multi-source approach. That is, focusing solely on an individual's behavior may neglect other interpersonal influences or interactive components.

Understanding what resources individuals and their families use for health information is important information, particularly for healthcare organizations, provider groups, or other public health agencies that wish to market materials or resources for health maintenance and health promotion. More resources are needed not only to create and curate reputable online health information sources, but also to market these resources to interested parties as well as keep the resources up-to-date and relevant. Additionally, such resources should leverage the interactive nature of information seeking (that is, the "team approach") to ensure that all populations have access to information that is necessary for health promotion and ultimately improve health outcomes.

CHAPTER 6: STUDY 3

Does source of health information matter? Examining its impact on the patient-provider encounter

Abstract

Background: In 2013, 72% of internet users say that they look online for health information. Additionally, more and more health consumers are discussing what they find online with their health provider. **Objective:** To examine the impact of using the internet as a first source for health information on the patient-provider encounter. **Methods:** Cross-sectional data (n=2925) are examined from the 2008 Health Information National Trends Survey (HINTS). The elaboration method using multiple linear regression is used to examine the focal relationship between health information source and the health consumer rating of the patient-provider encounter (PPE, measured by the first component score of six items). A final model is developed using exclusionary and inclusionary steps that include the examination of two potential mediating variables: gratification from the last information search and trust in the information source. **Results:** Compared with respondents who use a health provider as a first source for health information, respondents who use the internet or print material have on average a lower PPE score (internet: -0.625; print: -0.716). The effect of gratification on the focal relationship is modified by race/ethnicity and trust in the information source demonstrates partial mediation. **Conclusion:** To maintain a positive patient-provider encounter, health providers and organizations must develop strategies to manage and respond to the growing number of health consumers who bring health information found online to the consultation. This is particularly relevant for collaborative care models for chronic disease that emphasize patient-oriented care and incorporate patient satisfaction and quality of care measures to evaluate performance.

Introduction

Greater responsibility for the management of health and health care is being placed on the health care consumer. This is evidenced by the development of the collaborative care model for chronic disease in primary care [1] that emphasizes a team approach to patient-oriented care, as well as through health plans shifting towards consumer-directed plans that provide consumers with information on comparative costs and quality of care [2]. The result: an increased onus on the consumer to be knowledgeable, skilled, and motivated to participate as an active member of the care team.

A tool that has emerged as a major resource for the active, informed health consumer is the internet – specifically, the use of the internet for health information. With its vast amounts of websites and sources, the internet is both a robust and complex resource for health information. Seventy two percent (72%) of internet users say that they looked online for health information within the past year [3]**.** Among these users, eight out of ten start their inquiry from a search engine (i.e., Google or Bing). Only one in ten indicate using a specialized health information website, such as WebMD, to begin their inquiry.

Despite the growth in access to and use of online health information, the patient-provider encounter remains a central focus in the delivery of health care as well as in the maintenance of health. Therefore, examining the influence of health information seeking on this encounter will be beneficial as the role of the health care consumer continues to change. The purpose of this study is to examine the effect of using the internet as a first source of health information (compared to a health provider or print material) on the patient-provider encounter. Specifically, this study asks: What role does the first source of consumer health information have on the quality of the health care experience?

Online health information and health care experiences

Individuals are not just searching for health information online, but many are using online information to influence health and health care decisions [4]**.** About 50% of online health seekers indicate that the information they find online leads them to think that they need medical care**.** Moreover, health consumers are bringing what they find online to their health provider. According to a recent Pew report, 53% of online health seekers speak with their health provider about what they find online [3].

As the internet becomes the preferred first source for health information for more individuals, studies are emerging that examine the impact of looking online for health information on the patient-provider encounter [5–7]. Findings suggest that online health information may contribute to professional blurring of the traditional patient-provider relationship [8]. That is, online information may serve to lessen the knowledge gap and ultimately reduce the asymmetrical care relationship.

From a provider perspective, online health information often has a negative impact on the encounter. Specifically, providers say that online health information often generates greater confusion, can lead to misinformation, and often results in unrealistic patient expectations [9,10]. Additionally, unless the health provider has an encyclopedic knowledge of medical conditions and etiologies, information found online by the patient may catch providers off guard or they may be unfamiliar with certain rare or infrequent procedures [11].

Studies also highlight positive effects, particularly from the patient perspective. One study finds that men with prostate cancer feel as though they have more “control” over their illness when they look for health information online [12]. Findings from this study also suggest that patients who look online for health information feel less inhibited when discussing treatment options or other medical concerns with their provider.

Based on the prior literature, one of the hypotheses this study tests is the following:

> ***H1:*** *Compared to using a health provider as a first source for health information, using another source (i.e., the internet or print material) is negatively associated with the quality of the patient-provider encounter.*

Consumer-rated health care

Studies examining consumer ratings of health care experiences find that poorer ratings are associated with identifying as a minority race, showing higher psychological distress, not having a regular doctor, not having insurance, and lacking confidence in self-care [13]. Hou & Shim [14] examine how individuals' perceptions of the quality of patient-provider communication are associated with consumer internet use for health-related activities, such as participating in an online support group or using the internet to help with diet or physical activity. They find that individuals who perceive communication with providers to be less patient-centered are more likely to use the internet for health-related behaviors [14].

The present study takes a similar yet distinct path. Hou & Shim examine the impact of the patient-provider encounter on health-related internet behaviors – this study examines the relationship from a converse direction, focusing on the impact of using the internet as a first source for health information on the quality of the patient-provider encounter. Additionally, this study highlights information-seeking behaviors and not other online health-related behaviors, such as participating in a support group. Many patients find that speaking with their doctor about online health information that they found enhances the utility of the information [6]. This study builds upon this research by using a more robust, multi-item outcome for the quality of the patient-provider experience as well as by examining other key variables (such as gratification, self-efficacy, and trust) that may mediate or moderate the relationship.

Theoretical considerations

This investigation draws from the Uses and Gratifications Theory (UGT) as well as from models of patient-provider encounters to examine the influence of information source on the patient-provider encounter [15]. The UGT, a theory used in communication studies, posits that people use media differently to satisfy needs, and that perceptions (i.e., trust) of media are important factors motivating media use [16]. This study extends the definition of media to include three common health information sources: the internet, print material, and health providers.

The UGT attempts to understand why people choose certain media to gratify their needs, given that a variety of media alternatives exist [17,18]. In the context of information seeking for specific health concerns, gratification of needs would include accurate relevant information about symptoms, diagnosis, prognosis, available treatments, side effects of treatments, and the like. Furthermore, the amount of gratification one gets from using an information source is likely to influence outcomes related to that information [17]. That is, poor gratification from one information source may be associated with using another source for the same information. For example, after turning to the internet for health information, does lower gratification reported by the respondent impact the patient-provider encounter differently than respondents who report high gratification from the internet? In other words, this study examines whether the influence of the information source on the patient-provider encounter is really determined by the amount of gratification the respondent gets from the informational source. Based on the UGT, the following two hypotheses are tested:

> ***H2:*** *Using the internet as a first source for health information is positively associated with gratification of informational needs from that source.*
>
> ***H3:*** *Gratification of informational needs mediates the relationship between first source*

of health information and the quality of the patient-provider encounter.

Studies find that as individuals gain access to a growing number of information resources, they often experience greater ambiguity as to what information is credible, as well as which sources can be trusted [19]. This is particularly salient when it comes to health conditions as it can impact ones overall health and wellbeing – in other words, when ones health is on the line, health information seeking is a high stakes game. Thus, trust in the information source can play a critical role in determining whether or not health information is acted upon. For instance, trust in a health provider is shown to increase use of preventive services, adherence to treatment plans, and patient satisfaction [20].

Additionally, studies show that online searches about serious health concerns are approached with greater skepticism by patients [21]. A Pew report finds that during serious health episodes, health providers remain the most used and trusted source for health information – 70% of adults got information, care, or support from a health professional [3]. However, additional findings show that distrust in traditional information sources (i.e., health providers and family) is associated with increased use of the internet for health information [22]. Importantly, trust occurs along a continuum. That is, someone can trust two things simultaneously (i.e., a health provider and the internet), but one more than the other [10]. Based on this research about trust in information sources, this study tests the following three hypotheses:

H4: *Trust in a health provider is positively associated with the patient-provider encounter.*

H5: *Trust in the internet is negatively associated with the patient-provider encounter.*

H6: *Trust in the information source mediates the relationship between first source of information and the quality of the patient-provider encounter.*

Methods

Data and sample

This study uses secondary data from the 2008 Health Information National Trends Survey (HINTS). HINTS is a nationally representative repeated cross-sectional survey of the U.S. adult population conducted by the National Cancer Institute. The survey enables researchers to assess the impact of knowledge, attitudes, and practices along with changes in the health communication environment on health behaviors and outcomes [23]. HINTS 2008 data were collected from January through April 2008.

HINTS 2008 uses a mixed data collection method of both telephone and mail sampling. Due to the dual sampling methodology of HINTS 2008, it is necessary to investigate mode differences among key variables, including the main predictor: first source of health information; the main outcome: patient-provider encounter; and key covariates: gratification scores and trust variables [24]. Only the predictor variable is significantly different based on the mode of data collection. Respondents who indicate using the internet as a first source of health information are more prevalent among respondents who complete the questionnaire over the telephone (86%) compared to those who complete a paper-and-pencil version (76%). Thus, to limit bias, survey weights developed for each sampling mode are applied during analysis. In addition, sampling mode (telephone vs. mail) is included in the regression analysis to control for differences.

Survey response rates are 42% (telephone-based) and 40% (address-based) at the household screening level, and 57% (telephone-based) and 77% (address-based) at the sampled person interview level. These response rates are consistent with prior studies in public opinion research [25,26]. The final subsample for this national study includes respondents who indicate that they have looked for health information in the past year, use the internet, and do not have missing data in any of the independent variables (N=2935). A total of 1357 respondents are from the telephone mode and 1578 are from the mail mode.

Measures

Main outcome: A patient-provider encounter (PPE) variable, consisting of six items, is the main outcome in this study. This concept assesses the quality of the last patient-provider encounter by asking respondents: “How often did doctors or other health providers”: 1) listen carefully to you; 2) explain things in a way that you could understand; 3) show respect for what you had to say; 4) spend enough time with you; 5) involve you in decisions about your health care as much as you wanted; and 6) give you the chance to ask all the health-related questions you had. Responses include: always, usually, sometimes, and never.

Main predictor: The first source of health information is the main predictor for this study. Respondents who indicate looking for health information are asked to identify the first source that they use. The original variable contains 12 nominal responses. For this study, the variable is recoded to three nominal categories, including: internet, health provider, and print material.

Covariates: Prior research operationalizes gratification using single items of trust [14,22]. This study moves this research forward by using a more robust group of items. The gratification variable contains four items assessing the self-rated success of the last search for health information from any source. The items are worded: “Based on the results of your most recent search for information about health or medical topics, how much do you agree or disagree with the following statements?” The statements include: 1) It took a lot of effort to get the information; 2) You felt frustrated during your search for information; 3) You were concerned about the quality of the information; and 4) The information you found was hard to understand. Responses are on a 5-point Likert scale and range from strongly agree to strongly disagree.

Trust in an information source is collected by asking respondents how much they trust health or medical topics from: a) a health provider, and b) the internet. Responses are on a 4-point scale and include ‘a lot’, ‘some’, ‘a little’, and ‘not at all’.

The respondent’s ability to take care of his or her own health is measured by asking: “Overall, how confident are you about your ability to take good care of your health?” Responses are on a 5-point Likert scale and range from ‘completely confident’ to ‘not at all confident’. This could serve as an alternative independent variable that influences the patient-provider encounter.

Sociodemograhpic variables include: age (18-34, 35-49, 50-64, 65-74, and 75 years or older); gender; race (non-Hispanic white, non-Hispanic black, Hispanic, and other); annual income (<$20,000, $20,000-$34,999, $35,000-$49,999, $50,000-$74,999, and $75,000 or more); and educational attainment (less than high school, high school graduate, some college, and college graduate).

Additional covariates include: regular doctor (yes, no); self-rated overall health status (poor, fair, good, very good, excellent); has health insurance (yes, no); history of cancer (yes, no); psychological distress score (summed score of six-item assessment of depressive symptoms from the National Health Interview survey, ranging from 0 to 24); and urbanicity (metro area, rural area).

Analysis

Survey weights specific to the mode of data collection (telephone vs. mail) are used to produce nationally representative estimates of the U.S. adult population. Weights include a base weight (the reciprocal of the probability at both the household and respondent level of the respondent being sampled), a weight to adjust for non-response, and a calibration weight (based on data from the Current Population Survey and American Community Survey). The jackknife technique is used to produce 50 replicate weights for each mode (100 replicate weights in total) to provide statistically valid standard errors for the parameter estimates [27].

Univariate analysis is used to examine frequency and distribution of the study variables among internet users who indicate ever looking for health information. Chi-square tests are used to examine differences between internet users in the final sample and those excluded due to missing data. Additionally, bivariate analysis is used to examine differences in the patient-provider encounter score (PPE) stratified by the respondent's first source of health information.

A factor analysis is used to determine which items in the PPE and gratification variables load on single factors. This is followed by a principle components analysis to identify components that account for most of the variance among the items. The first principal components are used in analysis for the PPE score (66% of variance) and the gratification score (65% of variance). The Kaiser-Meyer-Olkin (KMO) measure of sampling adequacy validates each component [28]. All KMO values are above 0.88 in the PPE component and above 0.72 in the gratification component.

The elaboration method describes the relationship between the main outcome, patient-provider encounter (PPE), and the main predictor, first source of health information [29]. The model-building method is described in Figure 6.1. The PPE outcome is a continuous component made up of six items; therefore, multiple linear regression analysis is an appropriate method for model building.

The "focal" relationship (Model 1) is clarified by examining the effect of adding covariates to the model (Model 2). The hope is that the focal relationship remains significant net of the control variables. Model 3 examines the potential intervening effect of the gratification variable, controlling for potential confounders introduced in Model 2. Model 3 is a test for

Hypothesis 3, examining whether the success of the last information seeking experience (gratification of informational needs) explains away the relationship between the source of information and its effect on the PPE. Finally, Model 4 examines the effect of trust on the focal relationship, controlling for covariates introduced Models 2 and 3. Model 4 is a test for Hypothesis 6, examining whether trust in an information source explains away the relationship between the first source of health information and its effect on the patient-provider encounter.

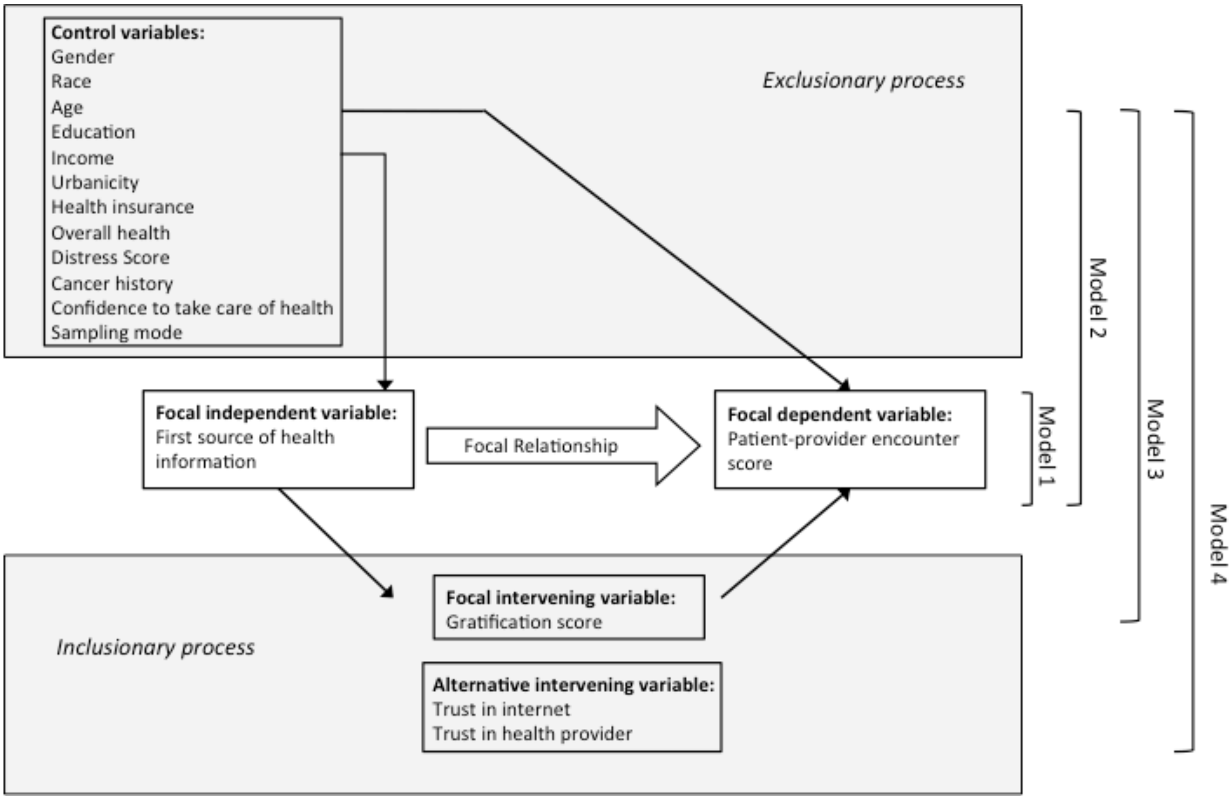

Figure 6.1 Elaboration model of focal relationship, first source of health information on patient-provider encounter

When examining the relationship between a predictor and outcome variable using the elaboration method (the focal relationship), examining the effects of confounding, mediation, and moderation is paramount to understanding the true relationship [29]. Figure 6.1 provides a conceptual model of the elaboration method, highlighting the variables used in each of the model-building steps. The exclusionary process is needed to rule out spuriousness that may confound the focal relationship, whereas the inclusionary process is used to better clarify the relationship. The parameter estimate for the focal independent variable (first source of health information) can be compared between models in order to determine the effect of each model-building step. Analyses are conducted in STATA 12 as this software can account for complex survey design and weights [30].

Results

Table 6.1 describes the frequency and distribution of all study variables. The majority of respondents are women (57.9%) and non-Hispanic white (78.1%). Most respondents have either some college education (39.9%) or are college graduates (38.0%), are 18 to 49 years of age, have an annual income greater than $50,000, live in a metro area (85.2%), have health insurance (91.2%), and have a regular doctor (80.5%). Very few respondents (6.8%) have a history with cancer.

When compared to internet users excluded from the sample, the study sample has significantly more women (57.9% v. 42.1%), more non-Hispanic white respondents (78.1% v. 68.4), more respondents with health insurance (91.2% v. 73.6%) and a regular doctor (80.5% vs. 42.2%), and more respondents with a history of cancer (6.8% v. 4.2%). Thus, findings may be slightly biased towards non-Hispanic white women with health insurance who have a regular doctor.

The internet is the most common first source for health information (80.4%), followed by print material (10.6%) and a health provider (9.0%). Over 70% of respondents indicate that they trust health information from a health provider “a lot”. On the other hand, only 24.4% of respondents trust health information from the internet “a lot” (60.7% of respondents trust it "somewhat"). Most respondents are very confident (51.6%) or completely confident (20.3%) in their ability to take care of their health.

Table 6.1 Descriptive statistics among internet users who look for health information, HINTS 2008, N=2935

	% weighted	*SE (%)*		*% weighted*	*SE (%)*
Age group			**Regular doctor**		
18-34	32.5	1.0	Yes (v. No)	80.5	1.3
35-49	34.0	0.9	**Overall health**		
50-64	26.0	0.7	Poor	2.0	0.4
65-74	5.5	0.3	Fair	10.1	0.9
75+	2.0	0.3	Good	36.6	1.2
Gender			Very good	40.4	1.3
Female	57.9	1.0	Excellent	10.9	0.7
Race/ethnicity			**Confidence to take care of own health**		
Non-Hispanic white	78.1	1.0	Not at all confident	0.6	0.2
Non-Hispanic black	8.4	0.6	A little confident	3.1	0.6
Hispanic	8.3	0.8	Somewhat confident	24.4	1.0
Other non-Hispanic	5.2	0.5	Very confident	51.6	1.2
Education			Completely confident	20.3	0.9
Less than high school	3.7	0.8	**Trust health information from internet**		
High school graduate	18.5	1.0	Not at all	1.2	0.4
Some college	39.9	1.0	A little	13.8	1.0
College graduate	38.0	0.9	Some	60.7	1.4
Annual income			A lot	24.4	1.2
Less than $20,000	8.9	0.9	**Trust health information from health provider**		
$20,000-$34,000	11.0	0.9	Not at all	0.4	0.2
$35,000-$49,000	13.9	1.0	A little	2.2	0.4
$50,000-$74,999	22.6	1.2	Some	23.5	1.1
$75,000 or more	43.6	1.3	A lot	73.9	1.2
Urbanicity			**Patient-provider encounter***	-0.14	0.06
Metro (v. Rural)	85.2	1.1	**Gratification***	0.09	0.04
First source of health information			**Distress***	4.89	0.11
Doctor	9.0	0.7	**History of cancer**		
Internet	80.4	0.8	Yes	6.8	0.3
Print material	10.6	0.7	**Has health insurance**		
Sampling mode			Yes	91.2	0.7
Address	56.9	0.9			
Telephone	43.1	0.9			

*Average weighted mean score

The patient-provider encounter score (PPE) represents the first principal component of six items that load on a single factor. The average weighted component score is -0.14, with a range of -7.05 to 1.96 and standard deviation of 1.93. Similarly, the gratification variable represents the first principal component of four items that load on one factor. The average weighted component score is 0.09 with a range of -3.93 to 2.25 and a standard deviation of 1.55. The average weighted distress score in this sample is 4.89 and ranges from 0 to 24 with a standard deviation of 4.07. Scores of 13 or greater indicate elevated distress levels [31]; thus, this sample has relatively low distress levels.

Table 6.2 describes the PPE scores stratified by what the respondent identifies as their first source of health information. Respondents who indicate that a health provider is their first source have, on average, a much higher PPE score (0.435) compared to their counterparts who indicate the internet (-0.190) or print material (-0.282).

Table 6.2 Weighted patient-provider encounter (PPE) score by source of information, HINTS 2008, N=2935

1st source health information	**PPE score**	
	Mean	SE
Health provider	0.435	0.13
Internet	-0.190	0.07
Print material	-0.282	0.15

When examining the effect of health information source on gratification, no significant associations are present (Hypothesis 2 is not supported). Compared to using a health professional as a first source for health information, those using either the internet and print material for a first source have on average a lower gratification score; however, the association is not significant (internet: p=0.459; print: p=0.305).

Elaboration method

Table 6.3 describes the elaboration method. Model 1 displays the bivariate relationship between the first source of health information (the main predictor) and PPE scores (the main outcome). Compared with respondents who use a health provider as a first source for health information, respondents who use the internet or print material have on average a lower PPE score (internet: β=-0.625; print: β=-0.716; Hypothesis 1 is supported).

Table 6.3 Model building of first source of information on patient-provider encounter, HINTS 2008, N=2935

	Model 1		**Model 2**[a]		**Model 3**[b]		**Model 4**[b]	
Variable	β	SE	β	SE	β	SE	β	SE
1st source (ref: Health provider)								
Internet	-0.625**	0.15	-0.354^{+}	0.17	-0.359^{+}	0.17	-0.245	0.17
Print material	-0.716**	0.19	-0.514^{+}	0.20	-0.508^{+}	0.20	-0.402^{+}	0.19
Gender (ref: Female)								
Male			-0.225^{+}	0.09	-0.191^{+}	0.09	-0.229**	0.09
Age (ref: 18-34)								
35-49			0.078	0.14	0.062	0.14	0.200	0.14
50-64			0.179	0.15	0.151	0.14	0.283^{+}	0.14
65-74			0.144	0.18	0.142	0.17	0.311	0.17
75+			0.544**	0.20	0.497^{+}	0.19	0.500^{+}	0.21
Education (ref: Less than HS)								
HS graduate			-0.569	0.40	-0.500	0.39	-0.267	0.32
Some college			-0.645	0.39	-0.613	0.38	-0.374	0.32
College graduate			-0.778^{+}	0.37	-0.748^{+}	0.36	-0.560	0.30
Urbanicity (ref: Metro)								
Rural			0.269^{+}	0.13	0.265^{+}	0.13	0.256^{+}	0.12
Distress score								
Score			-0.036^{+}	0.02	-0.030	0.02	-0.028	0.01
Regular doctor (ref: Yes)								
No			0.557**	0.15	0.568**	0.15	0.432**	0.14
Confidence taking care of own health (ref: Not at all)								
A little confident			1.571	0.80	1.439	0.78	1.588^{+}	0.69
Somewhat confident			2.608**	0.71	2.503**	0.70	2.502**	0.66
Very confident			3.324**	0.71	3.237**	0.71	3.163**	0.66
Completely confident			3.731**	0.72	3.626**	0.72	3.572**	0.68
Gratification*Race (ref: Non-Hispanic white)								
Non-Hispanic black					0.339**	0.11	0.315^{+}	0.12
Hispanic					0.058	0.13	0.107	0.13
Other non-Hispanic					-0.153	0.13	-0.120	0.13
Trust information from internet (ref: Not at all)								
A little							-1.810**	0.57
Some							-1.589**	0.57
A lot							-1.728**	0.57
Trust information from health provider (ref: Not at all)								
A little							0.698	1.12
Some							1.727	1.08
A lot							2.612^{+}	1.07
Intercept	0.435	0.13	-2.935	1.07	-2.636	1.05	-3.566	1.46

[a] controlling for: race/ethnicity, income, sampling mode, had cancer, health insurance, overall health, confidence in getting health information (all non-significant)

[b] controlling for: ([a]) variables in addition to gratification (main effect)

**p<0.001; $^{+}$p<0.05

Model 2, the exclusionary step, adds potential confounders and other covariates to the model to investigate whether the focal relationship remains significant. While the main predictor coefficients do decrease in magnitude, they still remain significantly negative (internet: β= -0.354; print: β=-0.514). In addition, compared with women, men on average have a lower PPE score (β=-0.225). Similarly, compared to respondents who are not high school graduates, college graduates report on average a lower PPE score (β=-0.778).

Additionally, compared with 18-34 year olds, respondents 75 years or older have significantly higher PPE scores (β=0.544). Furthermore, compared with respondents who do not have a regular doctor, respondents with a regular doctor have on average higher PPE scores (β=0.557). Finally, compared with respondents who are not confident in taking care of their health, respondents who are somewhat confident (β=2.608), very confident (β=3.324), or completely confident (β=3.731) all have on average higher PPE scores.

Model 3 represents the first inclusionary step. The purpose of this step is to better understand the focal relationship by adding a potential mediating variable (or moderating variable) to the model. For the added variable to show mediating properties, the focal relationship should decrease in magnitude or even disappear and become non-significant. Model 3 shows that the addition of the gratification variable (the potential mediating variable) does not reduce the magnitude or significance of the focal relationship (Hypothesis 3 cannot be supported). It does, however, show a significant interaction effect with race/ethnicity – particularly among non-Hispanic black respondents. Compared to their white counterparts, non-Hispanic black respondents with positive gratification ratings report on average a higher PPE score (β=0.339). That is, among non-Hispanic black respondents, more positive experiences with the last information search translate to a significantly more positive experience with the health provider, compared with white respondents.

Model 4 examines the effect of trust in an information source on the focal relationship. Two variables are added in this step: trust in information from the internet and trust in information from a health provider – both variables show significant relationships with the outcome variable. Compared to respondents who do not trust information from the internet at all, respondents who trust a little (β=-1.810), some (β=-1.589), or a lot (β=-1.728) all have on average significantly lower PPE scores (Hypothesis 4 is supported). On the other hand, compared to respondents who do not trust information from a health provider at all, respondents who trust a lot have on average a significantly higher PPE score (β=2.612, Hypothesis 5 is supported). No other relationships are significant in the health provider trust category.

Importantly, the focal relationship in Model 4 changes significantly. Once trust in an information source is added to the model, the significant relationship between first source of information (specifically the internet compared to a health provider) and the patient-provider encounter becomes non-significant. That is, trust mediates the relationship between first source of health information from the internet compared to a health provider on the PPE score (Hypothesis 6 is supported). Interestingly, when comparing print material with a health provider source, the relationship remains significantly different (β=-.402). This could be due to the nature of the trust variables added to the model – they do not capture trust related to print sources.

No other relationships between covariates and the outcome significantly change between Models 3 and 4. This strengthens the unique role that trust plays in the relationship between source of information and the overall PPE score.

Table 6.4 summarizes the study's hypotheses and whether they are supported by study findings. Four out of the six hypotheses are supported by study findings.

Table 6.4 Summary of study hypotheses and findings

	Hypothesis	Supported
H1	*Compared to using a health provider as a first source for health information, using another source (i.e., the internet or print material) is negatively associated with the quality of the patient-provider encounter.*	Yes
H2	*Using the internet as a first source for health information is positively associated with gratification of informational needs from that source.*	No
H3	*Gratification of informational needs mediates the relationship between first source of health information and the quality of the patient-provider encounter.*	No
H4	*Trust in a health provider is positively associated with the patient-provider encounter.*	Yes
H5	*Trust in the internet is negatively associated with the patient-provider encounter.*	Yes
H6	*Trust in the information source mediates the relationship between first source of information and the quality of the patient-provider encounter.*	Yes

Discussion

Building upon prior literature, this study identifies a significant relationship between consumer source of health information and the quality of the patient-provider encounter. Specifically, compared to individuals who use a health provider as their first source for health information, individuals who use the internet or print material have significantly less satisfying experiences with their health provider. Thus, Hypothesis 1 is supported by study findings.

Findings do not support Hypothesis 2. Namely the source of information is not associated with gratification. That is, compared with a health provider, respondents do not find the internet or print material any more or less gratifying when looking for health information (gratification defined as the amount of effort or frustration associated with the last information search). Additionally, gratification does not mediate the relationship between information source and the quality of the patient-provider encounter; thus Hypothesis 3 is not supported.

On the other hand, gratification is associated with the patient-provider encounter, though the effect is modified by race/ethnicity. This suggests that positive experiences looking for health information may influence groups differently. In particular, compared to white respondents, non-Hispanic black respondents who indicate a positive experience with their last information search (that is, it took little effort, they were satisfied with results, they were able to effectively evaluate the information) have more positive experiences with their health provider. Prior literature suggests that minority populations, including African Americans and Hispanics, are more likely to use health information they find to influence health care decisions [32]; thus, findings from this study substantiate this observation.

Supporting theories in health communication, trust plays a significant role in how individuals use and apply online health information – all trust-related hypotheses are supported by study findings. Specifically, findings show that trust in the internet is negatively associated with the patient-provider encounter, whereas trust in a health provider is positively associated with the patient-provider encounter. For individuals who do not trust online information, they may be less likely to bring up the information to a health provider or may be more open to questions or challenges raised by the health provider. This supports aspects of the UGT in that consumers who trust particular information sources may be less inclined to trust additional sources if their needs are met. Importantly, trust in an information source is shown to mediate the focal relationship. That is, trust in the information source is more important on determining the quality of the patient-provider encounter than the actual source of the information.

While this study provides an important understanding of the overall effect of online health information on the patient-provider encounter, future studies will need to investigate how competencies and abilities in looking for and evaluating health information influence gratification, trust, and ultimately the quality of the patient-provider encounter. Massey et al. [33] define these competencies as components of health literacy. An individual's health literacy, namely their ability to look for and evaluate health information as well as their understanding or perceptions of consumer rights and responsibilities, will be important in examining the role and impact of health information on health care access and use, as well as quality of care and health outcomes. This takes gratification theory one step further – not only are affective dimensions of the search important, but so are technical abilities and skills.

A main limitation of this study is the use of cross-sectional data. The elaboration method is used to help elucidate the relationship between the independent and dependent variables; however, temporal ambiguity, or whether the independent variable truly comes before the dependent variable, still limits study findings. In this case, it is difficult to rule out the possibility that a negative patient-provider encounter encourages the consumer to use the internet for health information. However, through the elaboration method, model building helps clarify the relationship as potential confounders and mediating variables are added.

Another limitation relates to the dual sampling mode of the HINTS 2008 data. Including both telephone and mail data introduces bias as respondents may respond differently to questions based on the mode of data collection. Moreover, these two modes may fundamentally sample different types of respondents, based on the availability of a landline or the propensity of certain populations to move residence. In order to limit this potential bias, mode-specific weights are used and a sampling mode covariate is included in regression models. Additionally, due to the exclusion of respondents with missing data, the final sample may be slightly biased toward non-Hispanic white women – findings should be interpreted with this in mind.

Conclusion

To maintain a high level of patient satisfaction and quality of care, health providers and organizations must develop strategies to manage and respond to the growing number of consumers who bring information found online to the consultation. As eight in ten online health searches begin through a search engine, health providers and health care organizations can do a better job recommending or providing websites that have been vetted and that are deemed appropriate for health information. Additionally, as electronic and interactive materials become more reliable and used sources for health information, health providers and organizations may consider developing and offering more of these types of materials. In particular, providing health information in electronic format at the health care office may provide consumers and clients with additional information that they need and want.

Health literacy along with other competencies related to seeking out, evaluating, and applying health information may be important factors when examining the impact of the source of health information on the patient-provider relationship [33,34]. Moving forward, studies will need to examine how to better measure the interactive nature of communication and health literacy between patient and provider. To date, most findings are presented from the patient or consumer perspective, or conversely from the provider perspective – very rarely are findings presented from both perspectives regarding the same encounter or interaction.

The patient-provider relationship is a social construct that will continue to evolve over time. As Kreps asserts, “communication is a primary social process that can help equalize power between providers and consumers of health care by promoting wide dissemination of relevant health information” [35]. Previously more asymmetrical, the patient-provider encounter will continue to shift towards shared decision making particularly as access and use of the internet for health information continues to grow. Furthermore, measures of quality of care are exceedingly important in an era marked by care coordination and chronic disease management. Interaction and communication between an informed health consumer and a health provider will play a critical role in the quality of care, and ultimately health outcomes.

CHAPTER 7: DISCUSSION

Summary

This dissertation examines the impact of internet technologies on the field of health communication. Through examining internet adoption rates, its use as a source of health information, and its influence on the patient-provider encounter, findings highlight ways in which the internet can be leveraged to help health consumers, health providers, health care organizations, and health insurance companies transition into the digital age of health care and health promotion. As new technologies continue to expand throughout populations and are integrated more into decisions regarding health and wellbeing, findings from this dissertation can be used to target intervention and policy development

Study 1 shows that disparities in internet use persist between 2003 and 2008. For some groups these disparities are growing (i.e., between women and men with women increasing their use at a disproportionate rate to men). But for many others, disparities in internet use are neither growing nor shrinking – vulnerable populations remain at a disadvantage.

This study contributes to the literature through the development of a disparities diffusion model. Importantly, this model provides researchers and practitioners with a framework to better understand diffusion phenomenon both within and between sub-populations – specifically examining whether disparities in access and use of online technologies increase, decrease, or persist over time. Moreover, by examining two or more points in time, the model can be used not only to examine current trends, but also to predict patterns of use over the next decade and generations. Thus, based on individual, group, community, or systems characteristics, the disparities diffusion model highlights disparate or delayed adoption rates, lower saturation levels, or a combination of these disparities.

Study 2 shows that internet use for health information continues to grow among both internet users as well as non-users. Additionally, health professionals continue to be an established and growing source for health information – this is likely to increase and thrive as technologies continue to develop that allow for asynchronous communication (i.e., email or electronic messaging) between health consumer and health provider. Importantly, the use of print material for health information continues to decline. However, certain sub-populations, namely Hispanic/Latino respondents, continue to rely heavily on print material for health information. Relying on more static forms of health information may lead to the use of dated materials, thus contributing to gaps in knowledge or care among vulnerable populations.

This study contributes to the literature by showing that health information seeking is more times than not a "team sport". Individuals concerned with their health or the health of others (particularly friends and family) do not look for and evaluate health information in a silo or vacuum. Rather, they interact with family, peers, health providers, teachers, the internet, and other new media technologies, to find, evaluate, and apply health information. A prevention model in health care and health promotion supports this team approach, particularly as care coordination and patient-centered care continue to be a focus in health care.

Study 3 shows that the first source an individual uses for health information can influence the patient-provider encounter. Specifically, compared with individuals who use a health provider as a first source, those who use the internet have on average a more negative experience with their provider. Importantly, trust in the information source mediates this relationship. That is, the relationship between use of an information source and its impact on the patient-provider encounter is better explained by the trust an individual has in the information source rather than the source itself. In other words, among those who use the internet for health information but do not trust it as a reliable source, the patient-provider encounter is not negatively impacted. On the other hand, the encounter is negatively affected by individuals who use the internet as a first source for health information and who also trust the source.

Findings from this study are significant as they demonstrate that activated health information seeking by the health consumer impacts the quality and satisfaction of the patient-provider encounter. Health consumers will continue to use online or other new media sources for health information; thus, acknowledging and incorporating this behavior into care coordination will improve satisfaction and communication between patient and provider, and also impact the quality of care and ultimately health outcomes. Information-seeking behaviors are likely to increase and become more diverse over the next years and decades as more and more individuals (particularly older individuals who tend to have more health concerns) become more familiar with digital and mobile information and communication technologies. Especially in the context of health care reform that simultaneously promotes improved quality of care along with cost-saving measures, provider groups, health care organizations, and health insurance companies must leverage the power of online health information and communication to improve quality of care and ultimately health outcomes.

Study Strengths and Limitations

Strengths

There are many strengths in this dissertation, including: examination of health information and communication technologies on health behavior; application of theoretical frameworks to investigate diffusion patterns and media use for health information; use of two HINTS iterations to examine changes over time; robust methodologies that investigate patterns of adoption and use of internet technologies; and analysis of spatial data to complement regression models.

First, the examination of health information and communication technologies on health behavior is an understudied area of research. This area of inquiry will continue to gain prominence in the fields of health promotion and disease prevention, health care access and utilization, and health maintenance, particularly as new technologies are made available to a wider range of audiences. This dissertation adds to the growing body of evidence that demonstrates the impact of health communication on health care along with health and wellbeing. Specifically, based on population characteristics and structural factors, access and use of internet technologies for health information varies, as does the application and influence of such information technologies on health care decisions and experiences.

Second, the application of theories in health behavior and communication strengthen the findings of this dissertation. Adoption and use patterns exhibited among certain populations support theoretical underpinnings developed by diffusion theory, specifically concerning the disparate adoption rates and saturation levels based on population characteristics. Additionally, the application of communication theories that predict media use based on perceived need bolsters findings by providing mechanisms through which trust and gratification mediate and moderate key relationships.

Third, the use of data from two HINTS iterations (2003 and 2008) allows this dissertation to look at differences in adoption rates and use of health communication technologies over time. This is particularly relevant when examining diffusion patterns both within and between sub-populations so as to highlight discrepancies and disparities that increase, decrease, or persist over time.

Fourth, robust methodologies that investigate patterns of adoption and use of internet technologies, as well as incorporating methodologies that examine mediation and moderation of key variables through theory-based analysis, is a strength of this dissertation. When analyzing two points in time, including a time-based interaction term (i.e., the HINTS 2008 iteration) allows researchers to examine whether or not differences at the baseline (i.e., the main effect in HINTS 2003) are increasing or decreasing at significant rates over time. This dissertation examines the changes in the odds of using the internet between 2003 and 2008 – findings suggest significant changes in the odds of using the internet among men and women, with women outpacing men in adoption.

Additionally, theory-based analysis provides a methodology to better understand a focal relationship between a key independent variable and the main dependent variable. In Study 3, both trust and gratification are introduced as potential mediating variables on the relationship between using a particular source for health information and its effect on the patient-provider encounter. Through model-building steps, trust in an information source is shown to mediate (that is, explain away) the relationship between the source itself and its effect on the patient-provider relationship. Thus, better understandings are developed related to pathways of intervention.

Lastly, this dissertation incorporates spatial analysis to complement regression models and to provide an illustration of diffusion patterns in internet use. Maps provide important visual representations of data that are sometimes difficult to interpret in regression models. Moreover, maps are understood by a wider audience and can provide political ammunition for intervention or policy development.

Limitations

The dissertation also has a few limitations that are necessary to discuss in order to frame study findings. These limitations include: use of cross-sectional data; bias associated with non-response rates; imperfect survey items pertaining to health information seeking and communication behaviors; and the lack of additional datasets to corroborate study findings.

First, the use of cross-sectional data reduces the ability to show exact trends over time as well as restricts the certainty when analyzing associations between dependent and independent variables. For example, adoption of an innovation is a dynamic rather than a static process. It is an assumption to say that respondents from HINTS 2003 consistently use the internet through the HINTS 2008 data collection. It is more likely that some individuals adopt the innovation, but subsequently do not use it ever again. In this sense, examining internet *use* over time among the same individuals or populations may provide a better picture of diffusion patterns compared with *adoption* rates. Additionally, longitudinal data would provide stronger correlates for changes in internet use over time. In terms of limitations associated with dependent and independent variables, temporal ambiguity, or issues with directionality of the relationship, will always be a challenge when using cross-sectional data.

Second, non-response in HINTS data may lead to biased results. HINTS 2003 and HINTS 2008 iterations are used in this dissertation because though not stellar, response rates at the household and interviewer levels are similar to other national surveys. Data from HINTS 2005 are omitted from the studies due to low response rates as well as significant differences with other national surveys based on key demographic and socioeconomic characteristics. That said, because data on HINTS non-respondents are not presently available, only a comparison with other nationally representative surveys is possible. While similar characteristics are observed between respondents from HINTS and respondents from the National Health Interview Survey (NHIS) and the U.S. Census, systematic differences may still be present between respondents and non-respondents in the HINTS data. This is likely to manifest in underrepresentation of vulnerable, low-income, and minority populations.

Third, while HINTS does an excellent job focusing on concepts related to health information seeking, health communication, media access and use, and health care experiences, items are imperfect. Additional survey questions that capture the interactive or multi-level nature of health information seeking would greatly add to the findings. Additionally, items that capture the application of health information on health decisions as well as the social and economic context in which these behaviors and decisions are made would provide better information to apply to interventions and policy development.

Finally, very few other national datasets in the U.S. incorporate health communication concepts or health information-seeking behaviors. Thus, comparison between HINTS data and other datasets is limited. Internet use is the item in this study that is most widely used in other national surveys, including the Census, Pew, World Bank indicators, and Google trends. Thus, comparisons could be made regarding internet use and comparable findings in other national surveys. However, survey items are lacking that measure and capture sources of health information; competencies and abilities to look for and apply information; influence of information on patient-provider encounters; and other questions regarding digital media use for health information and communication. While other national surveys may focus on certain illnesses, populations, or content areas, incorporating standardized health communication items will strengthen and increase the breadth of survey findings.

Recommendations

Future Research

Currently, there are both conceptual and methodological challenges that limit the study of digital technologies in health communication. Both survey research and intervention studies will help further develop this area of inquiry. First, the skills and competencies needed to find, evaluate, and apply health information for health-related decisions requires more investigation. Second, the examination of a multi-level approach to health information seeking and communication is needed as the field moves forward.

Traditionally, health literacy has been conceptualized as skills in word recognition, reading comprehension and numeracy related to health (i.e., functional health literacy) [1,2]. While functional skills are fundamental facets of the concept of health literacy, this definition may neglect broader skills necessary to attain and support health and wellbeing in the context of contemporary and evolving health care systems, particularly a system that places greater emphasis on the integration of digital and online technologies. An expanded understanding of health literacy not only incorporates skills in reading and writing, but also captures competencies needed to understand and manage complex health information and services [3,4].

An expanded perspective of health literacy, defined as a set of skills used to organize and apply health knowledge, attitudes, and practices relevant when managing one's health environment [5], can provide important insight into how individuals and groups use and apply health information to determine health care decisions, particularly information that is communicated through digital or online technologies. Future survey research could better capture these abilities and competencies to provide a better understanding of how they influence information seeking and health decisions. The HINTS dataset attempts to capture these skills, but does not examine the application of such competencies on health and health care decisions.

Examining the influence of health literacy on the adoption and use of digital technologies for health promotion and health care will provide a more nuanced understanding of pathways from information seeking to behavior change. Identifying mechanisms through which health information is understood or communicated to impact health behavior is critical for future research. In particular, digital technologies can afford interactive opportunities where patients can receive support or feedback from other health consumers or health care providers.

Additionally, a health literacy framework can help elucidate different challenges that occur along the information seeking and health care continuum, including evaluating health information, communicating health preferences and needs to health providers, navigating the health care system, or maintaining healthful behaviors. This is particularly important in the context of health care reform, as health literacy skills and competencies will be important attributes in assuring use of preventive services and care coordination.

While a few researchers have investigated possible paths from health literacy to health outcomes [6,7], more robust research is necessary, especially research that defines health literacy from a health-promotion perspective and incorporates interactive components of the concept that are used in the digital age of health communication. Importantly, health literacy should not only be examined in terms of how it influences the use of digital technologies for health promotion and health care, but should also be examined in terms of how digital technologies can help develop health literacy skills and competencies. An emerging area of research that examines this phenomenon is found at the intersection of eHealth and media literacy studies [8,9].

In addition to incorporating health literacy competencies into future research, the field of health communication will need to integrate a multi-level approach to information seeking and its application. The care model is an interactive, multi-faceted model and as such, incorporates multiple units and stakeholders. Looking for and applying health information for health promotion, disease prevention, treatment, curative or palliative care is better understood as a team approach. Thus, survey items and intervention research need to better capture and leverage this "team-oriented" approach to health information seeking.

Moreover, understanding how individuals, groups, and communities access the internet is key to strategic development and marketing of health information, messages, and communication. Not only is it important to understand the tools by which people access the internet (i.e., a computer, a mobile device, or a television), but also the social and economic circumstances in which access occurs. For example, does access and use occur with friends, family members, by ones self, or with coworkers? Also, is information accessed to supplant health care seeking, supplement health maintenance, or reduce health care costs? As more diverse and versatile means of accessing the internet emerge, it is important for research to not only collect information on the tools or mechanisms used to access the internet, but also the circumstances in which access occurs.

Implications

The findings from this dissertation have many implications in the field of health communication. As health communication technologies used in health care and health promotion continue to advance, the disparities diffusion model demonstrates that not all individuals, groups, or communities are able to adopt technologies at the same rate. Thus, vulnerable populations may remain at a relative disadvantage regarding health care advancements in health communication (such as the use of electronic health records or electronic messaging with health care providers) that are intended to increase health and wellbeing. It is imperative to ensure that differential access and use of health communication technologies do not contribute to crystalizing current health disparities or adverse health outcomes among vulnerable populations.

Already new technologies are being incorporated into health care and health promotion – from electronic health records, to online patient portals, to interactive health messaging over tablet computers, to real-time monitoring of key health indicators. As faster internet access continues to spread throughout the U.S. – witnessed by Google's commitment along with other companies to bring fiber optic speeds to cities across the nation [10] – the frontiers are limitless. Faster internet access will allow for reliable video conferencing and even 3-D video interactions in the near future. This will allow for health consumers to interact with health providers from a remote location, forgoing the costs of travel, clinic time, or hospital admission. But again, during the implementation and dissemination of such technologies, it is imperative to take steps that make adoption and use equitable across populations and geographies.

With the impending implementation of health care reform that emphasizes prevention and a managed care model [11], access and use of health care technologies will become increasingly important to manage and treat chronic conditions or other ailments. Digital and online technologies will provide the cornerstone for improving the quality of care while at the same time reducing nonessential costs. Again, drawing from the disparities diffusion model along with models of health care access and quality of care, populations will transition into and utilize the reformed health care system at different rates. The transition not only focuses on access and use of health care services, but also the adoption and use of digital technologies that will be implemented and depended upon for health promotion and health care. For the transition to be equitable, particular attention must be paid to populations that may be at a disadvantage due to individual, community, or structural factors.

Health information seeking is a high stakes game, especially for those who are ill. The means by which individuals, groups, and communities look for, evaluate, and apply health information to determine health decisions and behaviors continues to evolve. Twenty years ago, print material was the preferred method for health education, information exchange, and communication – today, the internet has overtaken the top spot. Digital technologies that leverage the internet for information and communication exchange are among the fastest growing and evolving health communication resources. Understanding current patterns of adoption and use of digital technologies is vital in predicting future trends for technologies yet to be created. Moreover, this knowledge could help mitigate current disparities and avoid future ones.

The American health care system is not the only major U.S. industry impacted by the growth of digital information technologies – some would argue that the entire U.S. economy and its educational feeder system is being shaped and reformed by the digital information age. A competent workforce skilled in computer, digital, and mobile technologies will not only be better situated to navigate a complex health care system that relies heavily on digital and online technologies, but will also thrust the U.S. into the next era of the global economy.

This dissertation describes the adoption and use of digital and online technologies for health information and communication, and also provides models and recommends frameworks to move the field forward. A disparities diffusion model offers a framework to understand and forecast differences in the adoption and use of technologies. Additionally, health information seeking and its subsequent application to carry out health behaviors or to make health care decisions may be better conceptualized as an interactive experience or “team” process. Finally, the impact of digital and online technologies on health care will continue to be an important determinant of quality of care and ultimately health outcomes especially in the context of health care reform. The field of health communication is poised to leverage and integrate digital and online technologies into a modern and evolving health care system and health promotion model that will facilitate the transition of health consumers, providers, organizations, and insurance companies into the digital health age.

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