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An Exploratory Study of Inactive Health Information Seekers

Sujin Kim, Ph.D. [Associate Professor]

230G, Multidisciplinary Science Building, Division of Biomedical Informatics, College of Public Health & School of Library and Information Science, College of Communication and Information, University of Kentucky, Lexington, KY 40536-0082, USA, sujinkim@uky.edu, 859-218-0110 (Telephone) 859-257-9019 (Fax)

Abstract

Purpose—This study aims to identify people who do not actively seek out health information and the demographic characteristics of Inactive Seekers. The possible determinants of inactive seeking behaviors is also explored.

Design and Measurements—A total of 14,420 survey respondents were drawn from the 2009 Annenberg National Health Communication Survey (ANHCS) data. K-means clustering was used to discriminate Inactive Seekers from Active Seekers. The inactive information seeker group was formed based on their experience with health information seeking. The potential determinants that were tested to predict inactive seeking included the following: health condition, health service use, health media exposure, and computer/Internet activities.

Results—Within this national survey data, the respondents were more likely to be included in the Inactive Seekers (N=8,312, 58.5%) compared to Active Seekers (N=5,908, 41.5%). The demographic characteristics indicated that the Inactive Seekers were identified as younger, male, highly educated, White, and high household income people. The binary logistic regression results from the study model indicated that healthier people were less likely to seek out health information than their counterparts. In addition, those who were exposed to various media were almost 1.6 times more likely to seek out health information than those who were not exposed to such media. Within this study data, the statistically significant determinants identified were health condition and health media exposure while computer/Internet activities did not show strong indications in predicting inactive seeking behavior.

Conclusion—The development of more generalizable measures for health literacy or behavioral patterns will bolster advanced study on inactive seeking relating to knowledge of technology and

Correspondence to: Sujin Kim.

Conflicts of interest

There is no conflict of interest with any financial organization regarding the material discussed in the manuscript.

Author contribution

Sujin Kim is a solo author for this manuscript who is responsible for all aspects of author contribution including study conception and design, analysis and interpretation of data, drafting of manuscript, and critical revision.

health context. Further study should be directed at estimating the negative aspects of information seeking such as information ignorance or information avoidance.

Keywords

Information Seeking Behavior; Health Care Surveys; Logistic Models; Cluster Analysis

Introduction

With the proliferation of information sources and services, health information is increasingly sought out by the public. As partners in the advancement of health information and communication technology, health consumers and their information behaviors have become a key component of health information seeking studies. These studies have reported increased use of health information on the Web [1–4] and patterns in information behaviors that are influenced by demographic profiles, preferred sources, desirable skills, and prior-knowledge to facilitate health information seeking [5–9]. Furthermore, the rise of the consumer empowerment movement offers a critical opportunity for engaging people in their information seeking for optimal health outcomes [10–15]. Whether for sick people or well people, consumer empowerment approaches show potential for increasing information seeking studies to associate individuals' health literacy with their optimal care. Yet, there is a dearth of information that addresses the reasons people do not gather or access health information.

Despite the fact that more health information is available, there are still people who do not actively engage in seeking it. The profiles of active health information seekers could be flipped over to partially answer why people do not gather health information online. For instance, the Pew Internet and American Life Project survey reported that age and education are the most significant determinants of Internet access, followed by health and disability status [16]. These findings suggest us that demographic profiles, disease status, and Internet accessibility influence a limited use of health information. In their early survey in 2002, the Pew Internet survey reported that some Internet users do not search for health information because "there are not any health or medical issues that concern me right now (47%), I am satisfied with the health and medical information I get elsewhere (46%), much of the information on the Internet cannot be trusted (12%), and I would not know where to start looking for such as information online (9%)" [17]. As indicated in these surveys, one of the important triggers related to health literacy that leads to health information seeking is having health problems or personal experiences with diseases. Notably, several cancer information seeking studies have reported that a signifiant number of people diagnosed with a serious disease intentionally avoid further information due to anxiety or stress [18–22]. People who suffer from a psychological condition such as depression also reported that they did not get much help from health information resources [23–26]. Such results imply that health status, disease experience or health service use is likely associated with why people do not actively seek out health information.

Previous studies [27–32] have also focused on demographic segmentation to target information services or health messages. Johnson and Case [33] reported that "the classic profile of high information seekers is White, middle-aged women who are members of high socio-economic status (SES) groups and are also highly educated [33]", which is the reverse profile of inactive information seekers. Ramanadhan and Viswanath [34] also reported that people who did not seek out information "came from the lowest income and education groups and scored lower on attention to, and trust in, media health information [34]. Studies on interactions among demographic factors also reported that caregivers with low education are in poorer health [33]. A demographic profile of active online information seekers echoed the 2010 Pew Internet survey [35]. This survey indicated that male respondents were less likely to pursue "information about specific diseases or medical problems, certain treatments or procedures, doctors or other health professionals, hospitals or other medical facilities, food safety or recalls, drug safety or recalls, and pregnancy and childbirth" [35]. Higher levels of education and income were also reported as a strong indicator of Internet access and health information seeking. Senior cell phone users were also less likely to use their phones to look for health information [35].

Health literacy from the point of view of limited use of health information has attracted an increased level of interest in the healthcare community. Health literacy is "the degree to which individuals have the capacity to obtain, process, and understand basic health information and services needed to make appropriate health decisions" [36,37]. Many studies have investigated the effect of health literacy and health-related outcomes. For instance, a low health literacy is associated with limited knowledge of healthcare services [38–42], a high risk of hospitalization [43, 44], high mortality [45–49], decreased probability of screening and prevention [50, 51], limited understanding of medical instructions [52–58], and less desirable health behaviors and treatment adherence [59–64]. In addition, studies using health literacy as an intervening factor addressed the effects of interventions designed to explain the effects of low health literacy. These findings revealed that literacy intervention mostly improved health outcomes such as self-efficacy [65–69], knowledge [66, 67, 70–72], medication adherence [68, 70–73], disease prevalence and severity [65, 66, 70, 74, 75], and healthcare costs [73, 74, 76]. Although the studies did not perform formal mediation analyses, "the change in these intermediate outcomes suggests that changing knowledge, increasing self-efficacy, and changing behavior may be important goals in mitigating the effects of low health literacy" [77]. Educational intervention using Web-based instruction [78] and technology-supported intervention using semi-automated lexical simplification [79] also indicated improvement in health literacy in the intervention group. Again, most of these studies emphasized that a majority of people still need further education to better use health information in ways that provide for optimal care. Lessons learned from predominant health literacy research motivated us to study the effect of limited skills or knowledge of health information to better understand inactive use of health information.

Within the context of user skills and knowledge, technology-related activities have been heavily discussed as a facilitator of information seeking. It is believed that health information accessible through electronic tools has little value if individuals lack adequate skills to effectively use them. With nearly half the adult population in the United States showing an unsatisfactory level of health literacy, the implication of using information technology to promote effective use of health information is considerable [80]. A profile of active engagement in technology-related activities offers an important aspect of active information seeking with relevance to the limited use of health information. In particular, there is little information on whether Internet-related activities have any influence on active pursuit of health information online. People with low literacy were found to be less effective in health information seeking [81–84]. With the increased use of emerging technology in health information seeking, it is not difficult to find research that supports the benefits of technology as a medium for better storage and retrieval, distribution and accessibility, enhanced access to other sources, easy transformation to another medium, massive computation for data analytics, etc. [81–85]. Again, there is evidence that "individuals with low health literacy skills are less likely to use Internet technology (e.g., email, search engines and online health information seeking), and people with low health numeracy skills are less likely to have access to Internet technology (e.g., computers and cell phones)" [81–85].

Some trends associated with social technologies have impacted health information consumers who become active participants in data collection and information sharing. For example, the recent Pew Internet survey reported a growing number of "people tracking their workout routines, posting reviews of their medical treatments, and raising awareness about certain health conditions" [86]. Subsequent research has confirmed that technological advancements, such as social networking or mobile computing, positively influence the dynamics of chronic disease management in areas such as diabetes, high blood pressure, depression, obesity, etc. [87–94]. Consequently, active participation in "patient networks for behavior-dependent (chronic) diseases" becomes critical to achieving positive care results [95]. From the health information seeking perspective, it is interesting to identify a group of people who do not (or cannot) participate in the leading edge of healthcare information stream.

In general, the notion of information seeking with relevance to health literacy is viewed as a purposive attempt to acquire what is needed to fulfill a knowledge gap. Sometimes, information seeking can be adventitious in that "in routine use of media or in their conversations with people in their networks, people are likely to come across useful information for their own health care" [37]. Whether the seeking is purposive or incidental, people are exposed to various channels of health information resources. For instance, people use mass media or Internet for health information though they generally prefer reputable sources from their providers. Information obtained from media is largely believed to be a positive exposure to information seeking, but mixed reports exist. Clarke and Everest [18] reported that "the pattern of coverage in the media, in effect, acts to reinforce negative public attitudes about cancer and heighten fear" but it is not certain whether media exposure is negatively or positively associated with information seeking on a large scale [18]. A more important question is how to support information use once a medium of information sources is selected.

Based on the aforementioned literature, profile sketches of the notable groups of inactive health information seekers were the major objective of this exploratory study. Given the potentially influential information seeking factors, including demographic variants, health condition, health service use, media exposure, and computer/Internet activities, this study attempted to identify people who are not actively seeking health information and how they are different from active seekers of health information within the national survey data. The study also identified the potentially important determinants of inactive seeking behaviors.

Methods

Study Sample

This study used data from the 2009 Annenberg National Health Communication Survey (ANHCS)[1]. This publicly available data set with a user agreement for research purposes was used to explore health information seeking behaviors among "a nationally representative sample of adults in the United States" [96]. Out of 18,426 ANHCS participants, a total of 14,420 survey respondents (78.26%) were included in this study as they answered all of the seven information seeking questions. The study data included male (N=6723, 47.3%) and female (N=7497, 52.7%) respondents. Age distribution is as follows: 18–24 (N=1160, 8.2%), 25–34 (N=2198, 15.5%), 35–44 (N=2913, 20.5%), 45–54 (N=2871, 20.2%), 55–64 (N=2672, 18.8%), and 65 + (N=3231, 46.0%). In addition, the most dominant education group was people with some college (N=3027, 21.3%) followed by bachelor's degree (N=2559, 18.0%). The study data predominantly includes White (N=11,338, 83.5%) followed by Black or African American (N=1275, 9.4%). For the detail background information about the chosen survey participants, the study included age, gender, education, ethnicity, and household income in the descriptive analysis in Table 1. The following two research questions were used to identify people who are not actively seeking out health information and the determinants of the Inactive Seekers.

Research Questions

- RQ1: Are there any distinguishable characteristics of Inactive Seekers within the study data in terms of their health condition, health service use, health media exposure, and computer/Internet activities?
- RQ2: What are major factors that influence inactive information seeking?

Dependent Variable

This study used Johnson's comprehensive model of information seeking (CMIS) to define information seeking actions (as a dependent variable) based on media use. Johnson asserts that "searches for information involve conscious choices among channels and sources" so that an individual's information seeking actions can take place [33]. In this study, health information seeking was operationally defined with a series of seven questions on whether respondents had actively sought health information via seven different media: *Television, Newspapers, General Magazines, Health Magazines, Internet, Family and Friends, and Doctors and Healthcare Professionals*. Responses were: a lot (1), some (2), a little (3), and not at all (4). Using K-means clustering analysis, a group of inactive information seekers

[1]"The Annenberg National Health Communication Survey (ANHCS) is a national survey which is designed to capture national trends relating health behavior and behavioral intentions to media exposure, health knowledge and beliefs, and policy preferences and beliefs." Since its inception in January 2005, ANHCS has collected data monthly from a nationally representative sample of adults in the United States. The data are archived by month and will be made publicly available each year through the ANHCS website at http://anhcs.asc.upenn.edu.

was formed based on the combined responses from the set of the seven survey questions. An overall reliability coefficient for the set of information seeking questions is 0.849 (Cronbach's alpha), which indicates a high level of internal consistency for inactivity on the information seeking scale within this study sample. Two clusters were formed to represent inactive seekers (1) and active seekers (0). Once the two groups were formed, the study used the cluster membership as an outcome variable for Binary Logistic Regression (BLR) to identify potential predictors for inactive seeking status (outcome variable =1).

Predicting Variables

The study used the following predictor variables selectively modified from the 2009 ANHCS data. These included the following: *Health Condition, Health Service Use, Media Exposure, and Computer/Internet Activities*. These variables were used to predict major factors that affect inactive information seeking status (outcome variable=1). Predicting variables with relevance to media exposure are adopted from Johnson's CMIS framework. Johnson mentioned that "(media) channels have proliferated greatly due to the application of computers and telecommunications to older media", so this study not only included traditional mass media related variables but also computer/Internet channels that carry health information [33].

Health Condition and Health Service Use

Three variables were included in this study to represent the effect of an individual's health condition in predicting health information seeking status. *Health Condition* indicated the severity of a health condition by summing up confirmed diagnoses reported by the respondents for 0 to 24 different diseases. *Medication Use* also indicated the severity of a health condition by summing up medications taken for 0 to 22 different drugs. The list of diagnoses and medications was taken from the ANHCS survey. In addition, *Caregiver Status* referred to an aggregate score indicating the number of health conditions that a respondent dealt with as a caregiver. *Health Service* referred to an aggregate score indicating the number of health services they used for the past year. The services include prescription service, medical service, drug assistance program, alternative treatment, and retail clinic visits. In addition, any experiences with healthcare cost were also captured as part of the health service measure.

Computer/Internet Activities and Media Exposure

The extent to which technology plays a role in health information seeking is essential to identifying predictors for the seeking status. Therefore, this study included survey questions assessing computer and Internet use and activities. They included questions asking about 17 computer activities and nine Internet activities. Additional questions asking about specific Internet resources the respondents used were also included as part of the *Computer Activities* variable in the analysis. To what extent individuals are exposed to media is a major study variable in health communication literature. This study also used *Media Exposure* as a predictor variable for information seeking status. A set of relevant survey questions was identified from the ANHCS data to assess whether media exposure is an important factor in predicting information seeking status. The media exposure variable included how much the respondents have heard about specific health issues from the media, how many medical show episodes the respondents watch, how often the respondents read health sections from magazines or newspapers, and how often they have heard/seen drug advertisements about certain health conditions.

Data Analysis

The study performed K-means clustering to discriminate inactive seekers from active seekers. Two pre-determined clusters, Inactive (1) and Active (0), were entered in a K-means clustering analysis. The cluster membership for individual survey respondents were used for further BLR analysis. Cross-tabulation was then used to describe identifiable characteristics of inactive seekers that are different from active seekers. Binary Logistic Regression (BLR) was performed to identify statistically strong predictors for information seeking status. The analyses were performed using IBM SPSS Statistics (Version 21).

Results

Demographic Characteristics

A total of 14,220 items of survey data was included in this analysis. Two clusters were formed to represent Inactive Seekers (N=8312, 58.5%) and Active Seekers (N=5908, 41.5%). Among the Inactive Seekers, 83.34% of the respondents answered that they have *never* actively sought out health information while 91% of respondents in the Active Seeker group answered that they have actively sought information *a lot* for the past 30 days. The average age of the Inactive Seekers (Avg=47.48, Std=16.31) is approximately one year younger than the Active Seekers (Avg=48.43, Std=16.42). The difference between the Inactive and the Active Seekers was more obvious in younger respondents (61.4% vs. 38.6%) compared to senior groups (56.1% vs. 43.9%). Interestingly, male respondents were found to be dominant Inactive Seekers (N=4,228, 62.9%), while only slightly more females were found in the Inactive Seeker group (N=4084, 54.5%).

People with higher education (Bachelor’s Degree or higher = 29.5% vs. 27.7%) were more likely to be clustered in the Inactive Seeker group while more respondents with a low level of education were clustered in the Active Seeker group (*less than high school* = 10.5% vs. 14.5%). A total of 83.5% of respondents (N=11,338) were White, followed by Black or African American respondents (N=1,275). It is interesting to note that 61% of the White respondents (N=6,912) were clustered in the Inactive Seekers, while the rest of the races had almost equal distribution between the Inactive and the Active clusters. Regarding household income, the study’s findings suggest that respondents from higher income households are more likely to be clustered in the Inactive Seeker group (>$125K = 62.1% vs. 37.9%) than those from low income households (<$25K = 52% vs. 48%). In summary, the Inactive Seekers in this study’s data are identified as younger, male, highly educated, White, and high household income people. This result is a surprising finding considering that highly educated males with high income not from a minority group are not popular in health communication studies as a target population to deliver health messages.

Health Condition

The study sought to address whether disease-related variables such as confirmed diagnoses, medicine taken, and caregiver status have an influence on information seeking status. The most numerous confirmed diagnoses that the Inactive Seeker groups reported are High Blood Pressure (N=1,627, 27.3%) followed by High Cholesterol (N=1,485, 24.9%). The detailed data is described in Table 2. The high profile diseases reported included the following: Acid Reflux Disease (N=817, 13.7%), Seasonal Allergies (N=831, 14.0%), and Depression (N=742, 12.5%). In terms of the total number of confirmed diagnoses reported, the Inactive Seekers (Avg = 1.89, Std. = 2.0) reported fewer diagnoses than the Active Seekers (average = 1.89, Std. = 2.5). This result confirms that those who have medical disorders actively seek out health information compared to people who do not. However, the difference is not large and the sample may under represent those with disorders. Only slightly more than 30% of the respondents indicated that they have a confirmed diagnosis.

This result is consistent with data on medicine taken. Among the Inactive Seekers (N=6,155, 61.7%), the most common disorders for which people have taken medicine are the following: Allergies (N=1,509, 24.51%), High Blood Pressure (N=1,361, 22.11%), Sinus Infection (N=1,045, 16.97%), and High Cholesterol (N=1,044, 16.96%). In the data on medicine taken, the number of disorders for which medicine is taken, such as Cold Sores (N=440, 57.29%), High Cholesterol (N=1,044, 56.34%), Sinus Infection (N=1,045, 55.59%), and Hemorrhoids N=444, 55.36%), is higher among Inactive Seekers than among Active Seekers. In proportion, the greater differences between Inactive and Active Seekers are found in the drugs used for such disorders as Allergies (−7.23%), High Blood Pressure (−7.27%), Heartburn (−7.91%), Arthritis (−8.52%), and Acid Reflux (−7.32%). This greater difference indicates that the Inactive Seekers with these popular drugs do not seek out information compared to the Active Seekers. As a part of the disease-specific analyses, the study also assessed the status of family caregivers to see if there is any difference between information seeker groups. Again, the major finding is that those with more care-giving responsibilities are clustered in the Active Seeker group rather than the Inactive Seeker group. The caregivers for people with the most common diseases, such as High Blood Pressure, High Cholesterol, Diabetes, and Seasonal Allergies, are in the range of 28.5% to 12.3% of the total Inactive Seekers (N=4,095, 58.27%).

Health Services

The Inactive Seekers were less likely to suffer hardship for healthcare expenses than Active Seekers in this study group. Ironically, the Inactive Seeker group reported that they used more prescription refill services than Active Seeker groups. In addition, the Inactive groups were more likely to use medical services, including regular doctor visits (N=4,669, 56.70% vs. N=3,560, 43%). This debatable result does not support the study assumption in which the Inactive Seekers are less likely to use health services than Active Seekers. Other health services such as drug assistance programs, alternative treatment, and retail clinic use were reported to be less likely used by the Inactive Seekers. Table 3 shows details of the analysis according to the two clusters.

Media Exposure

The study assumed that more media exposure about health issues would influence health information seeking status. For the media exposure, the respondents reported that they heard, watched, and read mass media such as TV, newspaper, genera/health magazine, and medical journals about health issues. The most popular issues in these media include the following: overweight or obesity (N=13,313, 94%), insurance coverage (N=12,939, 91.30%), HIV and AIDS (N=9539, 67.50%), and cancer (N=12,702, 89.70%). The study also assessed popular TV shows, such as ER House, and the difference between viewers from Inactive versus Active seeker clusters was not consistent across the shows.

Computer/Internet Activities

The study analyzed computer and Internet activities asking whether the respondents used computer and Internet for the listed activities. Across the activities, the study data confirmed that there was infrequent use of computers and Internet among Inactive Seeker clusters compared to Active Seeker groups. The study data also indicated that respondents were highly interested in *Searching for information* which was further confirmed in the Internet activity of searching or Health-related Web sites (N=2836, 27.7%). Interestingly, the most popular activity reported, *Searching health websites*, was more likely sought out by the Inactive Seekers (N=1473, 51.9%) compared to Active Seekers (N=1363, 48.1%). In addition, the study found that the greatest difference between the Inactive and Active were found in health-related activities like looking for cost information for prescription drugs (5.6%), looking for quality ratings for physicians and hospitals (3.8%), reading health-related blogs (3.2%), and communicating with healthcare professionals (3%). This confirmed that the health related activities through the computer/Internet medium are less frequently used by the Inactive Seekers.

Predictors of Inactive Seekers

The second research question sought to identify core factors that predicted the seeker group that will not actively seek out health information through any major media. The outcome variable for this study is coded as an inactive information seeker is 1 and otherwise 0. A binary logistic regression was applied to 14,420 observations to predict the probability of being an inactive health information seeker from variables dealing with the health status, health service, media exposure, and computer/Internet activities. Table 6 shows the differences between the two cluster groups. The total number of confirmed diagnoses was slightly less in the Inactive group (N=1.35, Std.=2.003) compared to the Active group (N=1.89, Std.=2.522). The results were consistent in the other measures. While slightly less than 2 medicines taken were reported by the Inactive Seekers, there were 2.31 medicines reported by Active Seekers. The total number of the caregiver status also confirms that the Inactive Seekers were less likely to be supporting their family members for healthcare (Inactive=0.05 versus Active=0.11). While the total number of Internet activities shows noticeable gaps between the clusters (Inactive=0.52 vs. Active=0.8), computer activities (Inactive=3.64 vs. Active=3.65) were reported to have an insignificant difference. Table 6 shows the details of the predictor variables by the two clusters.

In the BLR analysis, four blocks of independent variables were utilized. Block one consisted of the aggregate number of confirmed diagnoses (diagnosis), the aggregate number of medicines taken (medicine), and the aggregate number of being a caregiver (caregiver-adult, caregiver-child). Block two consisted of the aggregate number of computer activities (computer) and the aggregate number of Internet activities (Internet). Block three consisted of the aggregate number of health media exposed to (media) and block four included the aggregate number of health services received (service).

The first model, in Block one, included disease-specific variables. The results from Model 1 indicated that healthier people are less likely to seek out health information than unhealthy people. Three coefficients on the disease-specific variables (diagnosis, medicine, caregiver-adult, caregiver-child) had a Wald statistic equal to 82.44, 47.04, 51.46, and 31.20 which are all significant at the .01 level (99% confidence level) with a critical value of 332.811 [df=4]. The overall model is significant at the .01 level according to the model chi-square statistic. The model predicts 60.20% of the responses correctly. The Nagelkerke R square is .031.

Model 2 included additional theoretically important independent variables: Media Exposure (Topic, TV Shows, Types, and Ads). According to the block chi-square statistic, Model 2 is superior to Model 1 in terms of overall model fit. The block chi-square statistic is significant at the .01 level (critical value = 3302.315 [df=8]): the percentage of correct predictions increases by 11%, and the Nagelkerke R square value is greatly improved (.279). The coefficients on the Media Exposure (Topic, TV Shows, Types, and Ads) variables are statistically significant at the .05.

Model 3 included Computer and Internet variables to determine if technology played a role in the information seeking to pursue health information. Inactive Seekers were less likely to seek out the Computer and Internet and Activities at a significant level while Internet Resources was not statistically significant according to the Wald test. The block chi-square statistic is significantly different from zero at the .05 level. The percentage of correct predictions increased slightly while the Nagelkerke R square statistic increased by about .3%. According to statistical performance, Model 3 is slightly superior to Model 2. The Internet Resources variable was less statistically significant (P=0.723). Model 4 did not show any prediction improvement. Two variables, Internet Resources and the Medical Health Services, were found to be not statistically important.

The "odds ratio" of Media Exposure by popular resources is 1.589 with a 95% confidence interval of [1.543, 12.78]. This implies that people who are exposed to various media are almost 1.6 times more likely to seek out health information than people who are not exposed to such media. The "odds ratio" for the Adult Caregiver coefficient is 1.465 with a 95% confidence interval of [1.320, 1.626]. This suggests that the caregivers for adult family members are almost 1.469 times more likely to seek out health information than others. The other independent variables, such as Caregiver for Child, and the remaining three Media exposure variables are found to be significant while the remaining variables, such as Health Service and Computer/Internet activities, are insignificantly different from zero or continuous, and the interpretation of the magnitude has little meaning in logistic regression.

Discussion

This study hypothesized that people who are relatively healthy do not seek out health information. The results confirmed that people who reported fewer confirmed diagnoses, less medicine taken, or fewer caregivers for family members were inactively seeking out health information compared to the other cluster members. This is not surprising given that people after diagnosis may face issues like anxiety, side effects, guilt feelings, powerlessness, pain, death, etc. [97, 98]. Within the context of diseased status, active information seeking is pursued to relieve or make sense of diagnoses, medications, and health services. This finding was anticipated considering strong evidence from health communication research. The evidence indicated that "individuals' personal experience with disease" is the most important trigger to health-related information seeking [99,100]. These results were confirmed by other studies reporting that people with more experience with diseases sought the Internet for hereditary information [97]. Additionally, people with a history of cancer in their family were more active information seekers [98].

Although the study could not confirm the disease specific differences among the study samples, it is worthwhile to emphasize that nearly half of the Inactive Seekers with confirmed diagnoses, medication use, and caregiver status remained a silent group in seeking necessary health information. Slightly more than 55% of the cancer patients in this sample (N=343) answered that they do not actively seek out health information from any given media channels. Although the prevalence in the study sample is rather small, the cancer medication users (Inactive=60 vs. Active=72) also reported that they do not actively seek out health information and the results were not trivial in the caregivers' of cancer patients (Inactive=58 and Active=97). This finding not only suggests that health information service should target inactive users with less experience with disease, but also the service should plan with disease specific profiles [101,102]. Therefore, the disease specific profile of health information should be actively circulated at the time of confirmed diagnoses, medication dispensing, and at the notification of caregivers.

The study found a somewhat debatable finding from the analysis of the health service variables. Based on previous studies, personal exposure to disease can increase awareness of active information seeking. However, the comparative findings from the health service by the two clusters suggest that the Inactive Seekers are those who require more medical service and more prescription fill services than the other cluster members. Inconsistently, for services related to drug-assistance programs, alternative treatments, and retail clinic visits were found to be positively related to active health information seeking, which means that more Active Seekers use more of these types of health services. This result may be indicative of less important factors to predict Inactive Seekers in the logistic regression analysis.

The impact of technology-related activities was thought to be important in seeking health information. Previous studies indicated that people with more computer exposure were more likely to pursue health information [103–105]. However, this study shows some mixed results. For example, people with more general computer activities are less likely to pursue health information than other computer users. Compared to general computer activities, Internet activities were found to be more positively related to active information seeking. This result is consistent with the majority of Internet studies reporting people sought health information actively on the Internet. Considering that seeking of health information on the Internet is one of the most prevalent Internet uses, it is not surprising that the Internet (or Web) is considered a driving force of the health information portal. Among the Internet activities reported, posting and looking for quality ratings for health professionals and services were found to be the most distinguishable activities between inactive and active seeker clusters.

This result implied two important points. First, unlike Internet activities, general computer activities were not a direct impact on inactive information seeking while Internet activities is a predictor for inactive seeking. On the other hand, the computer activities asked about in this survey might not have been framed appropriately in that it did not measure the degree of general computer activities. In particular with the measure issue, the study introduces a further challenge for developing a technology literacy scale in the health context for use as a variable to measure personal skills and knowledge.

Lastly, the study ran a logistic regression to assess whether inactive information seeking can be predicted based on four distinct study measures: *health status*, *health services*, *media exposure*, and *computer/Internet activities*. The result suggested that media exposure was the strongest indicator for predicting inactive information seekers. This means that people with less exposure to mass media, such as TV, newspapers, magazines, etc., did not actively seek out health related information compared to those who had more exposure to media. As shown in model 3 and model 4, additional measures, such as computer activities and health services, only increased by 0.3% prediction accuracy for inactive information seekers. Although the measures used in this study are exploratory in profiling Inactive Seekers, the study findings are important indicators for profiling people who are not seeking out health information actively.

The limitations of this study are as follows. The measures for computer/Internet activities should consider competency so that how well people use a computer can be studied with relevance to health information seeking. Only two groups of information seekers were identified in this study. The degree of information seeking with reference to a comprehensive understanding of individuals from various aspects was limited in this study. Within this context, variables including seekers' knowledge and competencies, personal disease experiences, media exposure, and health beliefs and behaviors are to be carefully measured for advanced analysis. Cognitive factors such as health beliefs and behaviors are to be further studied to develop a personalized information source. In line with an "information pathways" approach, Beaudoin and Hong [91] emphasized inconsistent and dynamic information needs of individuals who may approach information seeking through diverse information carriers. Thus, further research on activating or intervening factors related to personal preference would be important to profiling inactive seekers.

Conclusions

The purpose of this study was to develop a model to predict the factors that influence inactive information seekers in national survey data. The survey results indicate that patterns from existing health information seeking theories are only partially supported: healthier people are not likely to respond to active information seeking. People with less media exposure in health issues are inactive information seekers. Slightly less than 60 percent of the respondents were clustered as Inactive Seekers. Further research should pay close attention to why people do not seek out health information. Profiles of people who are not seeking health information is not simply the reverse of people who are seeking health information. Moreover, investigation of inactive seekers should not focus on the benefits of active seeking. Rather, further research should be directed at estimating the negative aspect of information seeking such as information ignorance or information avoidance [103–106]. The measures explored in this study with the national survey will be an important step to reducing forces preserving inactivity of non-responsive groups. Paradoxically, the general public is excited about more information becoming accessible so they can become informed and responsible health consumers. Yet, it is time to repeat the question of how we address people without information or people without motivation to pursue information.

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Highlights

- Inactive Seekers require much attention for healthcare information service.
- Healthier people do not actively seek out health information compared to sick people.
- Media exposure is an important predictor of inactive health information seeking.

Summary Table

• Health information seeking has been identified as a major driving force for informed healthcare decisions.
• There have been numerous reports on the positive impacts of health media to promote awareness of health information.
• The demographic characteristics of active information seekers were reported as people who were female, highly educated, White, and had a high household income.

Table 1

Demographic Characteristics of Inactive vs. Active Seekers

Demographics / Clusters	Inactive Seekers (N=8,312, 58.45%)	Active Seekers (N=5,908, 41.55%)	Total Respondents (N=14,220, 100%)
Age			
18–29	1404 (16.9%)	881 (14.9%)	2285 (16.1%)
30–44	2326 (28%)	1660 (28.1%)	3986 (28%)
45–59	2554 (30.7%)	1777 (30.1%)	4331 (30.5%)
60+	2028 (24.4%)	1590 (26.9%)	3618 (25.4%)
Education			
Less than high school	873 (10.50%)	854 (14.50%)	1727 (12.10%)
High school	2579 (31%)	1733 (29.30%)	4312 (30.30%)
Some college	2411 (29%)	1682 (28.50%)	4093 (28.80%)
Bachelor's degree or higher	2449 (29.50%)	1639 (27.70%)	4088 (28.70%)
Race			
White	6912 (86.4%)	4426 (79.3%)	11338 (83.5%)
Black or African American	604 (7.5%)	671 (12%)	1275 (9.4%)
American Indian or Alaska Native	55 (0.7%)	68 (1.2%)	123 (0.9%)
Asian	104 (1.3%)	116 (2.1%)	220 (1.6%)
Native Hawaiian/Pacific Islander	23 (0.3%)	22 (0.4%)	45 (0.3%)
2+ races	303 (3.8%)	280 (5%)	583 (4.3%)
Income			
< $25,000	1476 (17.8%)	1365 (23.1%)	2841 (20%)
$25,000–$50,000	2560 (30.8%)	1906 (32.3%)	4466 (31.4%)
$50,000–$75,000	1865 (22.4%)	1139 (19.3%)	3004 (21.1%)
$75,000–$125,000	1737 (20.9%)	1087 (18.4%)	2824 (19.9%)
> $125,000	674 (8.1%)	411 (7%)	1085 (7.6%)

Table 2

Top 15 Diagnosis, Medicine, and Caregiver Status by Two Clusters

Diagnosis Confirmed	**Inactive Seekers (N=5954, 58.14%)**	**Active Seekers (N=4287, 41.86%)**	**Total Respondents (N=10,241, 100%)**
High blood pressure	1627 (27.3%)	1393 (32.5%)	3020 (29.5%)
High cholesterol	1485 (24.9%)	1204 (28.1%)	2689 (26.3%)
Acid reflux disease	817 (13.7%)	863 (20.1%)	1680 (16.4%)
Seasonal allergies	831 (14%)	794 (18.5%)	1625 (15.9%)
Depression	742 (12.5%)	765 (17.8%)	1507 (14.7%)
Chronic pain	595 (10%)	679 (15.8%)	1274 (12.4%)
Diabetes	570 (9.6%)	580 (13.5%)	1150 (11.2%)
Asthma, chronic bronchitis or COPD	547 (9.2%)	544 (12.7%)	1091 (10.7%)
Something else	541 (9.1%)	531 (12.4%)	1072 (10.5%)
Osteoarthritis	493 (8.3%)	566 (13.2%)	1059 (10.3%)
Sleep disorders	409 (6.9%)	501 (11.7%)	910 (8.9%)
Anxiety disorder	392 (6.6%)	481 (11.2%)	873 (8.5%)
Migraine	373 (6.3%)	431 (10.2%)	804 (7.9%)
Cancer (except skin cancer)	343 (5.8%)	279 (6.5%)	622 (6.1%)
Heart disease	276 (4.6%)	290 (6.8%)	566 (5.5%)
Medicine Taken	**Inactive Seekers N=6155 (61.74%)**	**Active Seekers (N=3815, 38.26%)**	**Total Respondents (N=9970, 100%)**
Allergies	1509 (24.52%)	1211 (31.74%)	2720 (27.28%)
High blood pressure/Hypertension	1361 (22.11%)	1121 (29.38%)	2482 (24.89%)
Heartburn or indigestion	1067 (17.34%)	963 (25.24%)	2030 (20.36%)
Arthritis	994 (16.15%)	941 (24.67%)	1935 (19.41%)
Acid reflux	1000 (16.25%)	899 (23.56%)	1899 (19.05%)
Sinus infections	1045 (16.98%)	835 (21.89%)	1880 (18.86%)
High cholesterol	1044 (16.96%)	809 (21.21%)	1853 (18.59%)
Chronic back pain or back problems	901 (14.64%)	829 (21.73%)	1730 (17.35%)
Vision / Problem seeing	661 (10.74%)	560 (14.68%)	1221 (12.25%)
Migraine headaches	642 (10.43%)	541 (14.18%)	1183 (11.87%)
Depression	583 (9.47%)	584 (15.31%)	1167 (11.71%)
Diabetes	439 (7.13%)	392 (10.28%)	831 (8.34%)
Hemorrhoids	444 (7.21%)	358 (9.38%)	802 (8.04%)
Anxiety disorders	379 (6.16%)	408 (10.69%)	787 (7.89%)
Cold sores / Fever blisters	440 (7.15%)	328 (8.6%)	768 (7.7%)
Caregiver Status	**Inactive Seekers (N=4095, 69.8%)**	**Active Seekers (N=2972, 42.29%)**	**Total Respondents (N=7027, 100%)**
High blood pressure	1168 (28.5%)	962 (32.4%)	2130 (30.3%)
High cholesterol	903 (22.1%)	765 (25.7%)	1668 (23.7%)
Diabetes	585 (14.3%)	522 (17.6%)	1107 (15.8%)

Diagnosis Confirmed	Inactive Seekers (N=5954, 58.14%)	Active Seekers (N=4287, 41.86%)	Total Respondents (N=10,241, 100%)
Seasonal allergies	504 (12.3%)	438 (14.7%)	942 (13.4%)
Acid reflux disease	469 (11.5%)	447 (15%)	916 (13%)
Depression	443 (10.8%)	373 (12.6%)	816 (11.6%)
Asthma, chronic bronchitis or COPD	347 (8.5%)	368 (12.4%)	715 (10.2%)
Cancer (all types except skin cancer)	398 (9.7%)	315 (10.6%)	713 (10.1%)
Chronic pain	322 (7.9%)	339 (11.4%)	661 (9.4%)
Heart disease	327 (8%)	293 (9.9%)	620 (8.8%)
Osteoarthritis, joint pain or inflammation	265 (6.5%)	292 (9.8%)	557 (7.9%)
Sleep disorders/ sleep apnea or insomnia	273 (6.7%)	267 (9%)	540 (7.7%)
Heart attack	247 (6%)	217 (7.3%)	464 (6.6%)
Skin cancer	185 (4.5%)	155 (5.3%)	340 (4.8%)
Stroke	153 (3.7%)	126 (4.3%)	279 (4%)

Table 3

Health Service Uses by Two Clusters

HELATH SERVICES	Inactive (N=5954, 58.14%)	Active (N=4287, 41.86%)	Total (N=10,241, 100%)
Cost Hardship			
Postponed a visit to the doctor for an annual physical visit because of cost	1012 (17%)	935 (21.8%)	1947 (19%)
Postponed a visit to the doctor for a specific medical problem due to cost	1046 (17.6%)	965 (22.5%)	2011 (19.6%)
Did not get a recommended diagnostic or lab test because of cost	689 (11.6%)	736 (17.2%)	1425 (13.9%)
Did not fill a prescription because of cost	937 (15.7%)	950 (22.2%)	1887 (18.4%)
Did not take a prescription medication as directed because of cost	644 (10.8%)	715 (16.7%)	1359 (13.3%)
Talked to a doctor about less expensive treatment options	1289 (21.6%)	1403 (32.7%)	2692 (26.3%)
Talked to a pharmacist about getting a less expensive prescription drug	1260 (21.2%)	1325 (30.9%)	2585 (25.2%)
Medical Service			
there is one doctor	4669 (78.4%)	3560 (83%)	8229 (80.4%)
using birth control	435 (7.4%)	328 (7.8%)	763 (7.5%)
received a vaccine for HPV	55 (0.9%)	48 (1.1%)	103 (1%)
using hormone replacement therapy	69 (1.2%)	59 (1.4%)	128 (1.3%)
seen for counseling or therapy	1829 (30.7%)	1443 (33.7%)	3272 (32%)
visited a dentist	4043 (99.1%)	2881 (98.6%)	6924 (98.9%)
had joint replacement surgery	58 (1.4%)	69 (2.4%)	127 (1.8%)
traveled outside the US for medical treatment	64 (1.1%)	121 (2.9%)	185 (1.8%)
Retail Clinic			
used a retail health clinic-for my personal care	632 (10.6%)	765 (17.8%)	1397 (13.6%)
used a retail health clinic-for my child/children	198 (3.3%)	303 (7.1%)	501 (4.9%)
used a retail health clinic-for an adult in my care	106 (1.8%)	128 (3%)	234 (2.3%)
Prescription Fill			
prescriptions filled-chain pharmacy	2363 (39.7%)	1935 (45.1%)	4298 (42%)
prescriptions filled-local independent drug store	627 (10.5%)	580 (13.5%)	1207 (11.8%)
prescriptions filled-discount store or warehouse	874 (14.7%)	694 (16.2%)	1568 (15.3%)
prescriptions filled-grocery store pharmacy	801 (13.5%)	558 (13%)	1359 (13.3%)
prescriptions filled-hospital pharmacy	310 (5.2%)	292 (6.8%)	602 (5.9%)
prescriptions filled-through the mail	907 (15.2%)	716 (16.7%)	1623 (15.8%)
prescriptions filled-via the Internet	67 (1.1%)	68 (1.6%)	135 (1.3%)
used Prescription drug samples from doctor	1972 (33.1%)	1880 (43.9%)	3852 (37.6%)
Drug assistance			
used coupons or vouchers from a prescription drug company	548 (9.2%)	656 (15.3%)	1204 (11.8%)
used a patient assistance program	234 (3.9%)	339 (7.9%)	573 (5.6%)
used Together Rx, a drug discount card for lower income people	142 (2.4%)	245 (5.7%)	387 (3.8%)
used coupons or vouchers for over-the-counter medications	893 (15%)	936 (21.8%)	1829 (17.9%)
used an internet-based pharmacy for imports prescription drug	87 (1.5%)	103 (2.4%)	190 (1.9%)

HELATH SERVICES	**Inactive (N=5954, 58.14%)**	**Active (N=4287, 41.86%)**	**Total (N=10,241, 100%)**
Alternative treatment			
used acupuncture	105 (1.8%)	119 (2.8%)	224 (2.2%)
used homeopathic treatment	145 (2.5%)	171 (4%)	316 (3.1%)
used-massage therapy	524 (8.9%)	431 (10.2%)	955 (9.4%)
used-physical therapy	472 (8%)	548 (13%)	1020 (10.1%)
used pro-biotic products	493 (8.4%)	518 (12.2%)	1011 (10%)
used vitamins or nutritional supplements	3055 (56.6%)	2347 (43.4%)	5402 (100%)

Table 4

Media Exposure by Two Clusters

Media Exposure	Inactive Seekers (N=8284, 58.48%)	Active Seekers (N=5881, 41.52%)	Total Respondents (N=14165, 100%)
I heard from media:			
About people being overweight or obese	7555 (91.2%)	5758 (97.9%)	13313 (94%)
About cancer	7031 (85%)	5671 (96.5%)	12702 (89.7%)
About heart disease	1598 (82.9%)	1155 (96.3%)	2753 (88%)
About the role genes play in health	1197 (62.1%)	1024 (85.5%)	2221 (71%)
About health care insurance coverage	7241 (87.4%)	5698 (96.7%)	12939 (91.3%)
About possible terrorist attacks	6304 (76.1%)	5260 (89.3%)	11564 (81.6%)
About HIV or AIDS	4781 (57.8%)	4758 (81.1%)	9539 (67.5%)
About new research in medical journals	3356 (52.8%)	3767 (80.4%)	7123 (64.5%)
About genetic testing	2879 (45.3%)	3414 (73%)	6293 (57.1%)
About buying genetic tests	71 (20.1%)	90 (46.2%)	161 (29.3%)
I watched TV shows:			
The Biggest Loser	519 (12.9%)	698 (22.1%)	1217 (16.9%)
Grey's Anatomy	1281 (20.2%)	1315 (28.2%)	2596 (23.6%)
ER	978 (15.5%)	1191 (25.6%)	2169 (19.7%)
Scrubs	1057 (16.7%)	1012 (21.8%)	2069 (18.8%)
Nip/Tuck	22 (6.3%)	19 (9.8%)	41 (7.5%)
City M.D.	1 (0.5%)	2 (2%)	3 (1%)
House	2140 (33.7%)	1942 (41.6%)	4082 (37%)
Dr. 90210	27 (7.6%)	21 (10.8%)	48 (8.8%)
Strong Medicine	104 (1.7%)	395 (8.7%)	499 (4.7%)
3 lbs.	6 (1.7%)	6 (3.1%)	12 (2.2%)
Desperate Housewives	832 (16.9%)	892 (23.4%)	1724 (19.7%)
I have done:			
Read magazines or newsletters that focus on health	2935 (35.5%)	4192 (71.5%)	7127 (50.5%)
Watched such health segments	5397 (65.1%)	5031 (85.6%)	10428 (73.6%)
Watched television shows about health	4327 (52.3%)	4567 (78%)	8894 (62.9%)
Talked with family or friends about health	6749 (81.5%)	5536 (94.3%)	12285 (86.8%)
Read health information on the Internet when not wanted	4121 (49.7%)	1723 (29.3%)	5844 (41.2%)
Read information in the Internet	3631 (87.1%)	4003 (96.4%)	7634 (91.8%)
Talked to family member, relative or friend about drugs	5993 (94.1%)	4493 (95.7%)	10486 (94.8%)
Advertisements for drugs for Depression	1762 (91.3%)	1161 (96.7%)	2923 (93.4%)
Advertisements for Erectile Dysfunction	1700 (88.1%)	1113 (92.8%)	2813 (89.9%)
Advertisements for drugs for Acid Reflux	1780 (92.4%)	1159 (96.6%)	2939 (94%)
Advertisements for drugs for Cholesterol	1793 (93.1%)	1165 (97.2%)	2958 (94.7%)

Table 5

Computer and Internet Activity by Two Clusters

Computer Activity	Inactive Seekers (N=7104, 61.57%)	Active Seekers (N=4434 38.43%)	Total Respondents (N=11538, 100%)
Audio or video editing	649 (9.1%)	509 (11.5%)	1158 (10%)
Finances (e.g., banking or paying bills)	2577 (36.3%)	1813 (40.9%)	4390 (38%)
Checking news, weather, or sports	3274 (46.1%)	2348 (53%)	5622 (48.7%)
Creating web pages	466 (6.6%)	347 (7.8%)	813 (7%)
Educational purposes	2281 (32.1%)	1726 (38.9%)	4007 (34.7%)
Job searches	1146 (16.1%)	901 (20.3%)	2047 (17.7%)
Listening to or downloading music	1853 (26.1%)	1306 (29.5%)	3159 (27.4%)
Making phone calls	166 (2.3%)	138 (3.1%)	304 (2.6%)
Participating in chat rooms or message boards	731 (10.3%)	525 (11.8%)	1256 (10.9%)
Playing games	2569 (36.2%)	1765 (39.8%)	4334 (37.6%)
Reading newsgroups	722 (10.2%)	653 (14.7%)	1375 (11.9%)
Searching for information	3849 (54.2%)	2618 (59%)	6467 (56%)
Sending instant messages	1596 (22.5%)	1241 (28%)	2837 (24.6%)
Shopping	2851 (40.1%)	1977 (44.6%)	4828 (41.8%)
Stocks (buying/selling, looking up quotes, etc.)	689 (9.7%)	525 (11.8%)	1214 (10.5%)
Word processing	2810 (39.6%)	1852 (41.8%)	4662 (40.4%)
Work purposes	1715 (24.1%)	1132 (25.5%)	2847 (24.7%)
Something else	276 (3.9%)	198 (4.5%)	474 (4.1%)
None of these	171 (2.4%)	67 (1.5%)	238 (2.1%)
Internet Activities			
Signed up for an internet-based newsletter	197 (3.3%)	334 (7.8%)	531 (5.2%)
Communicated with a doctor or other healthcare provider via email	143 (2.4%)	232 (5.4%)	375 (3.7%)
Read and/or posted a comment on a health-related blog	239 (4%)	307 (7.2%)	546 (5.3%)
Participated in a live chat room	31.3 (0.1%)	68.8 (0.3%)	100 (0.5%)
Read and/or posted a comment in an online forum or message board	202 (3.4%)	255 (5.9%)	457 (4.5%)
Looked for quality ratings for physicians, hospitals or clinics	125 (2.1%)	255 (5.9%)	380 (3.7%)
Looked for cost information for specific prescription drug treatments	228 (3.8%)	405 (9.4%)	633 (6.2%)
Looked for cost information for specific doctors, hospitals or clinics	115 (1.9%)	213 (5%)	328 (3.2%)
Posted ratings or comments about healthcare providers	27 (0.5%)	66 (1.5%)	93 (0.9%)
Health-related websites	1473 (24.8%)	1363 (31.7%)	2836 (27.7%)
Online communities or social networks	128 (2.2%)	186 (4.3%)	314 (3.1%)
Video sharing sites	41 (0.7%)	78 (1.8%)	119 (1.2%)
Pharmaceutical company websites	106 (1.8%)	237 (5.5%)	343 (3.4%)
Websites for specific drugs	221 (3.7%)	350 (8.2%)	571 (5.6%)
Medical tourism website	7 (0.1%)	19 (0.4%)	26 (0.3%)

Computer Activity	Inactive Seekers (N=7104, 61.57%)	Active Seekers (N=4434 38.43%)	Total Respondents (N=11538, 100%)
Hospital or clinic websites	178 (3%)	288 (6.7%)	466 (4.6%)
Government websites	171 (2.9%)	244 (5.7%)	415 (4.1%)
News sites	140 (2.4%)	181 (4.2%)	321 (3.1%)
Somewhere else	127 (2.1%)	139 (3.2%)	266 (2.6%)

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Table 6

Predictor Variables of Characterizing Inactive Information Seekers

Total Number of	Inactive (N=8312)	Active (N=5908)	Total (N=14220)
	Average (Standard Deviation)		
Diagnoses	1.35 (2.003)	1.89 (2.522)	1.57 (2.248)
Medicine	1.82 (2.452)	2.31 (3.161)	2.02 (2.779)
Caregiver of Adult	0.05 (0.282)	0.11 (0.449)	0.08 (0.362)
Caregiver of Child	0.06 (0.296)	0.11 (0.435)	0.08 (0.361)
Media Exposure by Topics	5.05 (1.904)	6.19 (1.231)	5.53 (1.751)
Media Exposure by TV Shows	0.84 (1.199)	1.27 (1.607)	1.02 (1.399)
Media Exposure by Types	3.81 (1.559)	5.03 (1.233)	4.31 (1.555)
Media Exposure by Ads	1.57 (1.245)	1.54 (1.204)	1.56 (1.228)
Computer Activities	3.64 (3.97)	3.65 (4.167)	3.64 (4.053)
Internet Activities	0.16 (0.532)	0.36 (0.875)	0.24 (0.702)
Internet Resources	0.52 (1.022)	0.8 (1.378)	0.64 (1.191)
Service about Finance and Cost	0.83 (1.651)	1.19 (1.953)	0.98 (1.792)
Service about Medical Matters	1.1 (1.124)	1.22 (1.19)	1.15 (1.154)
Service about Prescription Refill	0.72 (0.719)	0.82 (0.753)	0.76 (0.735)
Service about Discount Drugs	0.47 (0.847)	0.7 (1.072)	0.57 (0.954)
Service of Alternative Treatments	0.67 (0.96)	0.79 (1.092)	0.72 (1.019)

Table 7

Binary Logistics Regression (BLR) Results

Variables	Model 1			Model 2			Model 3			Model 4		
	Coeff	t-Stat	Odds	Coeff	t-Stat	Odds	Coeff	t-Stat	Odds	Coeff	t-Stat	Odds
Diagnoses	0.074	82.441	1.077	0.048	28.029	1.05	0.034	12.943	1.034	0.039	12.731	1.04
Medicine	0.044	47.042	1.045	0.023	10.136	1.024	0.028	14.015	1.028	0.027	12.922	1.027
Caregiver (Adult)	0.382	51.455	1.465	0.313	29.557	1.367	0.288	24.787	1.334	0.274	22.479	1.316
Caregiver (Child)	0.288	31.2	1.334	0.293	25.696	1.34	0.278	23.351	1.32	0.258	19.778	1.294
Media (Topic)				0.379	613.831	1.46	0.377	604.174	1.457	0.376	600.784	1.456
Media (TV shows)				0.119	63.096	1.127	0.118	60.765	1.125	0.112	54.336	1.119
Media (Types)				0.463	937.159	1.589	0.454	894.005	1.574	0.455	892.848	1.577
Media (Ads)				−0.09	26.454	0.914	−0.082	21.809	0.921	−0.088	24.231	0.916
Computer (Activities)							−0.018	12.245	0.983	−0.017	10.567	0.984
Internet (Activities)							0.269	49.563	1.308	0.254	44.104	1.29
Internet (Resources)							0.008*	0.125	1.008	0.021*	0.872	1.021
Service (Cost Hardship)										0.041	11.322	1.041
Service (Medical)										0.01*	0.234	1.01
Service (Prescription Refill)										−0.12	11.928	0.887
Service (Discount Drugs)										0.088	14.094	1.092
Service (Alternative TX)										−0.06	7.379	0.942
Model Chi-Square [df]	332.811 [4]			3302.315 [8]			3392.271 [11]			3439.173 [16]		
Block Chi-Square [df]	332.811 [4]			2969.503 [4]			89.956 [3]			46.902 [5]		
% Correct Prediction	60.52%			71.2%			71.5%			71.5%		
Nagelkerke R square	.031			.279			.286			.289		
Constant	−0.602	651.84	0.548	−4.751	2018.782	0.009	−4.693	1928.146	0.009	−4.662	1840.714	0.009

Note:

* Indicates that the coefficient is not statistically significant at the .05 level.