A regression-based study using jackknife replicates of HINTS III data: Predictors of the efficacy of health information seeking

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Abstract

The current study determines and assesses the effects of the statistically significant predictors of the efficacy of health information seeking through a regression-based analysis of the 2007 edition of the Health Information National Trends Survey (HINTS) data. The HINTS III data were collected through list-assisted random digit dialing and mail-in questionnaire with a natural corresponding unstratified and cluster sampling design with jackknife replicates and were analyzed using generalized linear models with jackknife parameter estimation based on the complete and 50 jackknife replicate datasets. The resampling-based analytic approaches, such as the jackknife and bootstrap, generally provide unbiased parameter estimates and are the preferred methods for complex survey data analyses. We implemented an exhaustive search through all potential predictors of the efficacy in health information seeking combined with model building based on forward selection and backward elimination of covariates to derive the best predictive model. This model-based and data-driven approach to detect and assess the relative effects of the significant predictors of the aforesaid outcome variable of interest is a greatly advantageous alternative to the common hypotheses-based analyses. Our results show that numeracy, education, patient health care satisfaction (with the health information given by their health provider), health information dissatisfaction, general health, and psychological distress are the optimal covariates significantly associated with the efficacy of health information seeking. Interestingly, many usually important background covariates such as race, income, gender, geographical location, and others were not significant predictors of the outcome variable of interest. The conclusions of our analysis reveal new insights into the complexity of the efficacy of health information seeking and will undoubtedly have important implications on the design and success of future health care messages and campaigns.

Keywords: Health literacy, Numeracy, Health communication, Health information-seeking

Effective health communication is a central component in the provision of health care and the understanding of public health information. Informed health care consumers have access to more tools that can aid them in more effective health care decision-making and better health outcomes.[1–3] Health literacy plays a crucial role in health information acquisition, understanding, and processing, health information efficacy especially as related to numeracy. Becoming health literate can lead to better health outcomes through improved cultural competence, oral and written communication, and numeracy.[4] Understanding the importance of numeracy as associated with efficacy of health information seeking has a number of potentially important implications related to health care decision-making and health outcomes. Thus, the purpose of this paper is to examine numeracy in relation to education, patient health care satisfaction (with the health information given by their health provider), health information dissatisfaction, and general health as covariates associated with the efficacy of information seeking.

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An individual's health literacy is dependent upon and determined by a number of factors, including literacy level, the structure and complexity of the material given, linguistic barriers, differing cultural contexts, and the efficacy of the method in which health messages are communicated,[5] all of which can greatly impact an individual's ability to process and understand numerical information as related to health information efficacy. While this general lack of health literacy is prominent in many sectors of the population, it is particularly disproportionate among certain demographic groups, showing that certain populations are marginalized.[6]

Many consumers have not acquired the skills needed to use health information, particularly when it comes to numbers and statistics. At the same time, health information often involves uncertainty, and many individuals lack the skills to process such information, manage their health care, and make informed choices, particularly when it comes to innumeracy. Innumeracy is an element of poor health literacy and is associated with the comprehension and use of important health information.[7] As such, numeracy, or the ability to process and understand numerical data, is an important construct for understanding patients' needs for health information, as well as their abilities to access and utilize such health information and messages for critical health decision-making.

Information-seeking is defined as 'the purposive gathering of information' that is intentional and goal-directed.[8] Individuals employ a variety of sources when seeking information. The advent of the Internet has provided health information seeking opportunities that were previously unimaginable. Using Google to search the term 'Health Information' produces nearly 800 million hits and with the pervasiveness of Internet access anyone within arms distance of a web browser can access more health information than they could consume in a lifetime.

One reason medical, public health, and health communication researchers have become interested in health information seeking behavior is that it is such a popular use of the technology. Fox[9] suggests 80% of adults surveyed have searched for health information online and 53% of them indicated they used the information found in health decisions. Similarly, Madden and Fox[10] found that 58% of the caretakers surveyed reported that the Internet was an important tool for making health decisions.

Research supports the notion that patient satisfaction information is connected to service quality and serves as a predictor of health-related behavior,[11] which may indicate that certain patient characteristics are predictors of health efficacy. Further, research has indicated that patients who perceive their physicians as caring and competent were more likely to be satisfied with the medical treatment and the health information.[12] Prior research from the NCI 2005 Health Information National Trends Survey (HINTS) indicates that when participants were asked 'Where would you go for cancer information' 50% stated that they would go to their provider followed by Internet (34%), library (5%), family (4%), and print media (4%). Research has revealed that family members of patients reported being significantly more satisfied with the Internet in terms of health information sources, whereas patients themselves reported more satisfaction with doctors and nurses as health information sources.[13] Time constraints, competing demands for attention, and a lack of training in effective communication impair physician's communication with patients,[14] which most certainly influences patient health information seeking behaviors and can greatly impact on medical adherence and decision making for patients.[15]

Research suggests that when it comes to complex and detailed health information, health care consumers prefer more certainty and higher quality health information. Exploratory findings suggest that magazines are the preferred source for such quality information and decreased uncertainty.[16] In a study of breast cancer patients, high monitors (i.e. active information seekers) were more likely to use newspapers and magazines as cancer information sources than low monitors.[17] Further, individuals with diabetes reported frequently turning to their friends and family for information, as well as passively acquiring information from sources such as newspaper and television,[18] whereas the Internet was a popular source for prescription medication information.[19] According to Buller *et al.*,[20] individuals who are faced with risky, uncertain health situations where multiple courses of action are possible will actively search for information.

Dutta-Bergman[21] suggests that health information seeking is predicated on the need for or interest in health information and the belief that health information seeking efforts will result in success. Without the motivation or the feelings of efficaciousness, individuals are disinclined to seek health information on their own. Bodie and Dutta[22] stated 'a health motivated consumer actively participates in health-related issues, actively searches out relevant health information, and is better able to recall this information when appropriate'.[22–27]

Like Bandura,[28,29] Bodie and Dutta[22] recognize that motivation alone is not sufficient for explaining health information seeking. Given that feelings of self-efficacy is one of the best predictors of behavior[30–33] it comes as no surprise that individuals with strong feelings of efficaciousness about health information seeking are more likely to actually seek health information.[34,35]

Efficacy displayed in the performance of a particular task (such as health information seeking) can be viewed as a single facet of a subject's general capability in handling complex problems. Further, there has been an extensive range of research focused on the state of psychological distress, mostly in the directions of detection and assessment,[36,37] identification of the most common causes[38–42] as well as analyses of and elaboration on the consequences of the presence of the condition with respect to other disorders,[43] and quality-of-life characteristics.[44] Previous studies have not explored the intricate relationship between the efficacy of health information seeking and the distinct levels of psychological distress.

We undertake a study to detect and assess the effects of the statistically significant predictors of the efficacy in health information seeking through analysis of the 2007 edition of the HINTS III data designed and collected by the Health Communication and Informatics Research Branch (HCIRB) of the Division of Cancer Control and Population Sciences (DCCPS) at National Cancer Institute. HINTS data contain survey responses from national representative samples with items focused on divulging the complexities of how the American public gather and use cancer information. The 2007 HINTS dataset consists of nearly 260 survey items that cover important background information of the responders regarding their socioeconomic status, race, gender, place of origin, as well as important questions about their cancer-related perceptions and behavior.

Data

An extensive analysis of the 2007 edition of the HINTS III data was conducted to obtain the best predictive model for the outcome variable of interest that measures the efficacy of health information seeking. The 2007 HINTS III data collection was completed in 2008 and released to the public in February 2009. All of the nearly 260 items asked of the responders were included in the analysis as potential predictors.

Weighted analysis of the 7674 responses regarding racial background reveal that 68.8% described themselves as non-hispanic white, 11.4% reported their race/ethnicity as non-hispanic black, 12.7% described themselves as hispanic, and 4.4% identified as non-hispanic Asian while 0.7% provided a non-informative answer. Approximately 51% of the respondents were female. The census responses revealed participants were from the following regions of the United States (Northeast = 18.7%; Midwest = 22.1%; South = 36.4%; and West = 22.8%). The average age of the responders was 45.9 years with standard deviation of 16.8 years; the most populous age group was 18–34 years of age accounting for 30.6% of the population followed by ages 35–49 accounting for 29.4% and ages 50–65 accounting for 23.0% of the population. A total of 53.5% reported being married, followed by single (25.9%), divorced (8.8%), and widowed (6.4%). About 24.7% of the responders attained an undergraduate college degree, 28.6% attended college, 33.7% completed high school, with 13.9% reported not completing high school. Numeracy was measured on a 4-level scale with numbers 1, 2, 3, and 4 denoting progressively decreasing ability to understand medical statistics with corresponding percentage of responders per category of 11.8, 50, 39, and 6.6, respectively. Next, the income distribution of the survey shows that 18.2% make less than \$10 000, 28.1% earn between \$20 000 and \$50 000, 28.3% make between \$50 000 and \$100 000, 13.5% earn between \$100 000 and \$200 000, and the remaining 3.5% make over \$200 000 per year. Additional details for the distributions of these general background variables are shown in Table 1.

Further, 7.2% reported that they have had cancer in their lifetime. The self-assessed health item (HD01GeneralHealth) responses show that 36.5, 36.1, and 11% of the survey participants described their health as good, very good, and excellent while 13.5 and 2.6% declared their health as fair and poor, respectively, with only 0.1% providing non-informative answers. Further, health information dissatisfaction was measured by four items (HC05aLotOfEffort-HC05dTooHardUnderstand) on a unidirectional 4-level scale with levels 1, 2, 3, and 4 denoting progressively greater satisfaction (measured by the following aspects, search for health information required effort, caused frustration, caused concern about the information quality, and was too hard to understand) with corresponding percentage of responders per category of 9.5, 27.4, 34.3, and 28.6, respectively. Similarly, the satisfaction with the provided health care was measured by five items (HS07aAskQuestions-HS07fDrTakecareNeeds) on a unidirectional 4-level scale with levels 1, 2, 3, and 4 denoting progressively decreasing satisfaction with the provided health care (measured by the following aspects, chance to ask questions, attention to your feelings and

Table 1: General background characteristics ($N = 7674$)

Survey item*	n (%)**
(1) Age in years ($n = 7649$)	
18–34	69 (30.6)
35–49	66 (29.4)
50–64	52 (23.0)
65–74	19 (8.3)
75+	18 (8.0)
(2) Gender ($n = 7665$)	
Male	109 (48.6)
Female	116 (51.4)
(3) Region ($n = 6421$)	
Northeast	42 (18.7)
Midwest	50 (22.1)
South	82 (36.4)
West	51 (22.8)
(4) Ethnicity ($n = 7178$)	
Non-hispanic white	146 (68.8)
Non-hispanic black	24 (11.4)
Hispanic	27 (12.7)
Non-hispanic Asian	9 (4.4)
Non-hispanic multiple races	3 (1.3)
(5) Highest education ($n = 7316$)	
Less than 8 years	8 (3.5)
Between 8 and 11 years	22 (10.4)
High school	57 (26.5)
Post-high school training	13 (6.2)
Some college	61 (28.6)
College graduate	35 (16.1)
Post-graduate	18 (8.6)
(6) Marital status ($n = 7320$)	
Married	115 (53.5)
Single	56 (25.9)
Divorced	19 (8.8)
Widowed	14 (6.4)
Living as married	7 (3.1)
Separated	4 (2.0)
(7) Income ($n = 6315$)	
0–20 000	37 (18.2)
20 000–34 999	31 (15.3)
35 000–49 999	26 (12.8)
50 000–74 999	36 (17.5)
75 000–99 999	22 (10.8)
100 000–199 999	28 (13.5)
200 000+	7 (3.5)
(8) Numeracy ($n = 7264$)	
Very good	25 (11.8)
Good	108 (50.0)
Poor	67 (30.9)
Very poor	14 (6.6)

*Unweighted sample sizes are reported.
**Weighted sample sizes (in millions) and percentages are reported.

emotions, involvement in decisions, make sure you understand next steps) with corresponding percentage of responders per category of 52, 31.7, 13.4, and 2.5, respectively. Next, psychological distress was measured by six items (HD03aSad-HD03fWorthless) on a unidirectional 4-level scale with levels 1, 2, 3, and 4 denoting progressively greater psychological distress (measured by the following aspects: sadness, nervousness, restlessness, hopelessness, everything is an effort, worthlessness) with corresponding percentage of responders per category of 52, 31.7, 13.4, and 2.5, respectively. Finally, the efficacy of health information seeking (HC06ConfidentGetHealthInfo) was measured on a 5-level scale with levels 1, 2, 3, 4, and 5 denoting progressively decreasing ability to obtain health-related advice and information with corresponding percentage of responders per category of 24.8, 33.8, 29.4, 7.8, and 3.6, respectively. Additional details for the distributions of these health-related background variables are shown in Table 2.

Table 2: Health-related background characteristics ($N = 7674$)

Survey item*	n (%)**
(1) General health ($n = 7314$)	
Excellent	24 (11.0)
Very good	78 (36.1)
Good	78 (36.5)
Fair	30 (13.7)
Poor	5 (2.6)
(2) Health insurance ($n = 7544$)	
Yes	183 (82.4)
No	38 (17.3)
(3) Efficacy of health information seeking ($n = 7596$)	
Excellent	56 (24.8)
Very good	76 (33.8)
Good	66 (29.4)
Fair	17 (7.8)
Poor	8 (3.6)
(4) Health information dissatisfaction (search for health information required effort, caused frustration, caused concern about the information quality, and was too hard to understand) ($n = 5424$)	
Strongly agree	15 (9.5)
Somewhat agree	42 (27.4)
Somewhat disagree	53 (34.3)
Strongly disagree	44 (28.6)
(5) Satisfaction with provided health care (chance to ask questions, attention to your feelings and emotions, involvement in decisions, make sure you understand next steps) ($n = 6668$)	
Always	96 (51.3)
Usually	59 (31.7)
Sometimes	25 (13.4)
Never	5 (2.5)
(6) Psychological distress (sad, nervous, restless, hopeless, everything is an effort, worthless) ($n = 7202$)	
All the time	4 (1.7)
Most of the time	13 (6.3)
Some of the time	44 (20.6)
A little bit of the time	52 (24.4)
None of the time	115 (54.0)
(7) Cancer ($n = 7338$)	
Yes	16 (7.2)
No	200 (92.7)

We implemented multiple data manipulation steps that included various ways of recoding categorical variables (to ensure unidirectional effects of the covariates) and averaging among multiple closely related questions that characterize multifaceted behavioral and emotional states such as patient health care satisfaction, health information dissatisfaction, and psychological distress. Averaging similarly directed items in an effort to reduce collinearity and multidimensionality is a conventional data analysis step that originates from the classical principal component analysis where the most important first principal component usually represents the average of all items.[45]

Very low response rate (<10) and non-informative categories such as: 'Refused to Answer' and 'Don't Know' were removed from dataset and their corresponding statistical weights were uniformly distributed among the remaining subjects in the data. Finally, missing and incomplete data problems were handled via classical hot deck imputation. Hot deck imputation is the practice of replacing missing data by substituting data from other complete cases and is generally regarded as an alternative superior to the removal of incomplete data or mean value imputation.[46] In this case, an adjustment for variance inflation was not necessary because the rates of non-response were so low.[46]

Statistical analysis

The HINTS III data were collected through list-assisted random digit dialing and mail-in questionnaire with a natural corresponding unstratified and cluster sampling design with jackknife replicates.[1] The survey data were analyzed using generalized linear models with jackknife parameter estimation based on the complete and 50 jackknife replicate datasets. The resampling-based analytic approaches, such as the jackknife and bootstrap, generally provide unbiased parameter estimates and are the preferred methods for complex survey data analyses.[2,3] All computations were performed using the Survey package version 3.22–3 of the R statistical software platform[47] version 2.14.1 (http://www.r-project.org). We implemented an exhaustive search through all potential predictors of the efficacy in health information seeking combined with model building based on forward selection and backward elimination of covariates to derive the best predictive model. This model-based and data-driven approach to detect and assess the effect sizes of the significant predictors of the aforesaid outcome variable of interest is a greatly advantageous alternative to the common hypotheses-based analyses. The best predictive model and the corresponding desired unbiased effects of the predictors are never unquestionably determined unless the model building encompasses all possible potential confounders and risk factors which at the very least implies considering and testing all survey items for association with the outcome variable. Currently, hypotheses-based studies are defined in terms of existence of positive or negative correlations between an outcome variable of interest and a few candidate covariates. These hypotheses are tested via correlation analyses or unadjusted statistical models which are both susceptible to bias in the estimated effects due to unaccounted confounding. In extreme cases such naive approaches can lead to reverse association directions and false-positive or false-negative effect findings.[48]

Results

Results revealed that numeracy, education, patient health care satisfaction (with the health information given by their health provider), health information dissatisfaction, general health, and psychological distress were the only covariates significantly associated with the efficacy of health information seeking. The R-squared goodness-of-fit statistic was 0.39. See Table 3 for detailed output from the linear regression model and relevant associations.

Numeracy was a significant predictor of the outcome variable of interest (P value <0.001) with an estimated effect of 0.11. Therefore, after simultaneously controlling for all other covariates in the model, one unit improvement in numeracy (greater understanding of medical statistics) was associated with a 0.11 unit increase in the efficacy in health information seeking. This indicates that improvements in numeracy are associated with increased confidence in the ability to get health-related advice or information and this independent effect exists in addition to the expected effect of education. Similarly, education, general health, patient satisfaction with provided health care, health

Table 3: Summary results from the best predictive linear regression model

Variable	Estimate	SE	t value	P value
Intercept	3.28	0.18	17.75	<0.001
Numeracy	0.11	0.02	6.19	<0.001
Education	0.03	0.01	2.00	0.05
General health	0.08	0.02	3.25	0.002
Health care satisfaction	0.18	0.04	4.87	<0.001
Health information dissatisfaction	−0.46	0.03	−15.22	<0.001
Psychological distress	−0.07	0.03	−2.67	0.01

information dissatisfaction, and psychological distress are significant predictors of the outcome variable of interest (P values 0.05, 0.002, 0.001, 0.001, and 0.01) with estimated effect sizes of −0.03, 0.08, 0.18, −0.46, and −0.07. Thus, one unit increase in education level (better education as measured on the defined item scale), general health (better self-assessed health), satisfaction with provided health care (greater satisfaction), health information search satisfaction (greater satisfaction), and psychological well-being (better psychological state) are associated with corresponding 0.03, 0.08, 0.18, 0.46, and 0.07 unit increases in the efficacy in health information seeking. Interestingly, none of the common background covariates such as gender, age, race, body mass index, marital status, number of children, citizenship status, smoking status, income, geographical region, census division, and health insurance status attained statistical significance.

Discussion

One of the major findings of our research is that numeracy, education, general health, satisfaction with the provided health care, health information dissatisfaction, and psychological distress comprise the complete set of significant predictors of the efficacy of information seeking. Moreover, the effect sizes derived from the implemented linear model are unbiased due to the statistical adjustment for the effects of the other important covariates in the model. These findings are supported by prior research indicating feelings of self-efficacy being one of the best predictors of behavior.[30–33]

The model further suggests that the motivation (e.g. need for the health information) and feelings of efficaciousness about health information seeking should predict health information seeking behavior. Previous research[34,35] revealed that those with strong feelings of efficaciousness about health information seeking are more likely to actually seek health information, which provides further support of our research findings. In fact, patients who are highly health motivated are more likely to seek out health information on their own, more likely to be involved in health decisions, and are more successful at recalling health information when tested.[21,23,25–27,49,50] In addition, these highly motivated patients are also more likely to search for health information from sources other than their primary care physician[24] and more likely to actively seek such information from the Internet than their less highly health-oriented counterparts.[24]

The direction of the covariate effects range from intuitive and predictable aligning with previous research to somewhat surprising. For instance, the link between numeracy and education is intuitive and predictive, as higher education and numeracy levels clearly and expectedly increase the efficacy of health information seeking. Our results show the importance of the existence of separate effects of these two covariates.

However, general health, health satisfaction, health information dissatisfaction, and psychological distress reveal a more interesting and subtle trend. Better general health, higher health care satisfaction, lower levels of health information dissatisfaction, and lower levels of psychological distress are associated with higher efficacy of health information seeking. The interesting and important aspect of these conclusions contradict the likely expectation that decreased self-assessed health, low health care satisfaction, and high health information dissatisfaction could have a motivating effect and potentially yield an increased efficacy of health information seeking. These results are novel research findings that reveal complex and intricate nuances of the effects of the significant predictors on the efficacy of information seeking.

Using the jackknife parameter estimation based on the complete and 50 jackknife replicate datasets in the analysis provides the most robust analysis of health information data to date. Jackknife estimations reduce concerns over biased parameter estimates as well as reducing the likelihood of both Types I and II errors, and such techniques are recommended by the National Cancer Institute's stable of statisticians.[1]

This investigation illustrates that feelings of efficaciousness are influenced by quantitative reasoning skills and education level of the patient. Further, patient relationships' with their health care provider also contribute to feelings of health efficacy, which is supported by prior research.[12] As Sparks *et al.*[14] point out, physician's lack of time and attention with patients, and a lack of training in effective communication all affect provider' communication with patients, which certainly impact on patient feelings of health efficacy. Finally, patient health and patient satisfaction are also predictors of health efficacy, which supports prior research that patient satisfaction information is connected to service quality and serves as a predictor of health-related behavior.[11] These findings further suggest how important it is to develop patient feelings of efficacy throughout the lifespan and how feelings of patient efficacy can be developed. Clearly, education and quantitative reasoning skills are important and need to be cultivated through the educational system. Further, it appears that that the relationship between patients and their health care providers also promote feelings of efficacy and is strongly supported by research in this arena.[12] This is yet another reason to be concerned with patient–physician interaction and ultimately patient–physician relationships. Given the healthcare reform agenda and related issues, increasing quality of care and patient satisfaction with health care providers will be more important at this time than perhaps any other time in history.

Future research needs to further examine HINTS III utilizing these robust regression jackknife techniques to obtain a more complete understanding of health information seeking behaviors. Such research needs to examine additional predictors as well as a variety of outcome variables including health knowledge and beliefs, attitudes toward health, and ultimately health behaviors. Other predictors including computer literacy, health literacy, and the individuals' past experiences using the Internet also need to be examined. It would also be interesting to better understand caregivers and family members' health information use as indicated by more recent health information sources' research findings.[13] Ultimately, it would be an important next step for researchers to ascertain which factors contribute most to e-health and m-health usage. Such tests would go a long way in increasing our understanding of the antecedents to health information seeking behavior and subsequent health behavior.

Finally, the conclusions of our study bring novel multifaceted insight into the intricate associations between the efficacy of health information seeking and its significant predictors, which in turn will provide an improved understanding of the designs of future health-related campaigns and messages.

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