Health Information—Seeking Behaviors, Health Indicators, and Health Risks

James B. Weaver III, PhD, MPH, Darren Mays, PhD, MPH, Stephanie Sargent Weaver, PhD, MPH, Gary L. Hopkins, MD, DrPH, Doğan Eröğlu, PhD, and Jay M. Bernhardt, PhD, MPH

Internet access is a widely available technology in the United States. Among the variety of online activities, searching for and using health information appear to be particularly prevalent, undertaken by between 40% and 70% of US adults. Hoping to take advantage of the Internet’s potential, public health practitioners, clinicians, and researchers have contributed to an emerging literature detailing characteristics of individuals engaging in health information—seeking behaviors (HISBs), exploring motives for engaging in HISBs, and documenting the types of health and medical information being sought.

Previous HISB research has primarily examined how patients seek and use health information across diverse health care contexts, yielding the recurrent observation that individuals striving to deal with stressful health challenges—such as a recent illness diagnosis or chronic disease management—were strongly motivated to engage in Internet HISBs. Several population-based studies, many of which have also conceptualized HISB primarily as “a key coping strategy in health-promotive activities and psychosocial adjustment to illness,” have yielded corresponding evidence. It should be recognized, however, that a cluster of these studies were informed by a common evidentiary resource (i.e., Pew Internet and American Life Project data), potentially exaggerating the apparent consistency of the “disease and illness” motivation for HISB.

Although informative, the predominant focus in previous research on a “disease and illness” motive for HISB has left the hypothesis that healthy individuals may pursue information to maximize positive health outcomes essentially unexplored. A small but growing body of findings suggests, however, that many individuals actively seek out wellness information (e.g., information promoting a healthy lifestyle). Specifically, emerging evidence reveals a positive association between a self-reported “health-conscious” or “health-active” orientation and engaging in wellness information—seeking behavior. Indeed, since 2000, the proportion of American adults reporting that they have looked online for diet, exercise, or fitness information has increased substantially and generally exceeds the proportion seeking online information about disease and illness topics (e.g., cancer, arthritis, diabetes).

Pandey et al. have asked, “Is it a disease or an affliction that motivates the use of the internet, or is it that the well and the healthy use the internet in a proactive manner?” As this question highlights, the nearly exclusive focus in previous research on Internet HISB as a response to health-threatening situations has left questions regarding the potential positive health outcomes motivating HISB unanswered. We aimed to fill this knowledge gap and further expand understanding of linkages between HISB and health perceptions and behaviors. Specifically, we compared mental and physical health indicators and health risk factors across 4 discrete categories of Internet HISBs—no use, illness content only, wellness content only, and illness and wellness content combined—among a sample of adults in the Seattle–Tacoma, Washington area to explore motivations of HISB.

METHODS

Adults living in the Seattle–Tacoma Designated Market Area (DMA) were administered an Internet-based survey in the summer of 2006. The Seattle–Tacoma DMA includes 18 counties encompassing most of the western half of Washington State. Approximately 72% of the total Washington State population (4.6 million people) lives within the Seattle–Tacoma DMA.

The Seattle–Tacoma DMA was selected for its size (13th largest US media market) and the prevalence of Internet use (ranked first in the nation). The sample was drawn from...
a panel of more than 60,000 participants maintained by e-Rewards Marketing Research (www.erewardsresearch.com). This panel was chosen, in part, because it was constructed and is maintained with a “by-invitation-only” recruitment methodology designed to facilitate effective demographic normalization while reducing the potential for self-selection bias.

A sample of panel members (n = 3140) were solicited via e-mail by e-Rewards to complete a consented survey, linked via a separate secure server, about their self-perceptions and media use. e-Rewards managed a stratified, multiwave invitation procedure with oversampling of less responsive demographic groups designed to maximize sample representativeness. This process yielded an American Association for Public Opinion Research adjusted response rate of 23.69%, which is comparable to those of other single-invitation online surveys and met the survey quota in approximately 48 hours.

Responses were analyzed from 559 adults, most of whom were between 35 and 54 years old (48.5%), female (51.9%), White (82.2%), married (62.9%), college graduates (63.7%), and reporting a household income of $75,000 or more (56.5%). These characteristics (Table 1) were consistent with those samples derived via random-digit-dialing sampling in the Seattle–Tacoma DMA, with 2 exceptions: respondents reported both higher household income and educational achievement. These differences were anticipated, however, on the basis of the demographic characteristics of Internet users.

**Health Information–Seeking Behaviors**

HISBs were assessed by asking respondents “about how much time” they spent “during a typical week” obtaining information online related to 6 content domains: diet, exercise, illness or disease, medications, parenting, and treatments. The 6 items assessing information content domains were selected from a pool of several potential items following factor analysis of formative pilot-test data drawn from members of the sampling frame. For each item, responses were computed to reflect usage per week in minutes and transformed with a base-10 logarithm to improve normality.

Principal component factor analysis, employed to isolate the primary HISB content dimensions, yielded a 2-factor solution that accounted for 62% of the variance. Varimax rotation to simple structures revealed that the first factor, labeled illness information–seeking behavior (eigenvalue = 2.50), was defined by high factor loadings (correlation coefficients between the variables and the direct factor indices) on the illness or disease (0.79), medications (0.86), and treatments (0.78) items. Factor 2, labeled wellness information–seeking behavior (eigenvalue = 1.22), was defined by high factor loadings on the exercise (0.88), diet (0.82), and parenting (0.40) items.

Dichotomous factor indices were created by summing the variables defining each factor and then coding all sums greater than zero as indicative of the illness or wellness information–seeking behavior and all those equal to zero as not. An HISB measure with 4 discrete levels was created, and respondents were classified as no use (50.6%), illness only (14.1%), wellness only (15.2%), and illness and wellness combined (20.0%) for subsequent analyses.

**Health Indicators**

Six questions adopted from the 2006 Behavioral Risk Factor Surveillance Survey (BRFSS) instrument assessed respondents’ perceptions of their health. These included health status (“Would you say that in general your health is excellent [5], very good [4], good [3], fair [2], or poor [1]?”), diminished physical health (“Now thinking about your physical health, which includes physical illness and injury, for how many days during the past 30 days was your physical health not good?”), diminished mental health (“Now thinking about your mental health, which includes stress, depression, and problems with emotions, for how many days during the past 30 days was your mental health not good?”), and poor quality of life (“During the past 30 days, for about how many days did poor physical or mental health keep you from doing your usual activities, such as self-care, work, or recreation?”). Respondents were asked their height and weight, and body mass index was calculated by a standard formula. The variables for diminished physical and mental health and poor quality of life were transformed with a base-10 logarithm to improve normality.

**Health Risk Factors**

Three health risk factors were assessed. Smoking and physical activity behaviors were measured by the BRFSS questions: “Do you now smoke cigarettes every day, some days, or not at all?” and “During the past month, other than your regular job, did you participate in any physical activities or exercises such as running, calisthenics, golf, gardening, or walking for exercise?” Dichotomous variables were computed for each, with the “not at all” or “no” responses set as 0 and all other responses as 1. Respondents were also asked “Do you purchase prescription medications?” as a proximal measure of any ongoing medical condition requiring pharmaceutical therapy. Responses were coded as “yes” (1) or “no” (0).

**Covariates**

Building from previous research, we examined 4 measures as covariates: respondent’s age, household income, perceptions of health information importance, and overall Internet use. Respondent’s age (mean = 44.7 years; SD = 13.1) was assessed with the question, “What is the YEAR of your birth?” Household income (mean = $86,829.84; SD = $58,194.34) was measured by asking respondents to “please indicate your gross family income.” The perceived importance of health information was assessed through respondents’ ratings of “how important” they considered “health information,” with response options including “I don’t use” (0) and a scale ranging from “not at all important” (1) to “extremely important” (9). All respondents attributed some importance to health information, with responses ranging from 2 to 9 (mean = 5.67; SD = 1.96). Respondents were also asked how much time they spent during a typical week “surfing the Internet” outside of work or school responsibilities to assess overall Internet use (mean = 7.39 h/wk; SD = 8.77). The variables for household income and Internet use were transformed with a base-10 logarithm to improve normality.

**Statistical Analyses**

The primary predictor variable for all analyses was HISB (no use, illness only, wellness only, and illness and wellness combined). The 5 health indicators and 3 health risk factors were the outcome variables. Bivariate analyses (Table 1) revealed that only 1 demographic characteristic—respondent’s sex—varied significantly as a function of
HISB. In light of this finding and previous research, sex was incorporated as a moderator of HISB in subsequent analyses. Consequently, the focal relationships between HISB and the 8 health outcome measures were tested with multivariate linear (for the 5 health indicators) and logistic (for the 3 health-risk factors) regression models parameterized in a sex-by-HISB (2 × 4) factorial design with covariate adjustment. Post hoc comparisons were computed with the t test (linear models) or the Wald $\chi^2$ test (logistic models).

**RESULTS**

The sample comprised 559 adults, 49.4% of whom reported HISB during a typical week. More women (60.5%) than men (39.5%) reported HISB (odds ratio [OR]=1.99; 95% confidence interval [CI]=1.42, 2.79), with substantial sex differences evident across the 4 HISB categories (Table 1).

Table 2 displays the test statistics resulting from linear and logistic models examining the sex (female, male) by HISB (no use, illness only, wellness only, and illness and wellness combined) factorial model, adjusted for the covariates. The HISB main effects were significant ($P<.05$) for 5 of the 8 health measures: health status, diminished physical health, poor quality...
of life, physical activities, and prescription medications (Table 2). The age, income, and overall Internet use covariates were significant but modest ($\eta^2_p < 0.02$) contributors to some models, as indicated in Table 2.

Table 3 displays the resulting means and percentages associated with the significant HISB main effects. These results reveal that wellness-information seekers reported the most positive health indicators—compared with the other groups, they had the highest health status, the fewest days of diminished physical health, and the lowest poor-quality-of-life assessment (Table 3). In addition, wellness-information seekers were among the most likely to engage in physical activities and the least likely to use prescription medications (Table 3). Illness-information seekers, on the other hand, reported poorer health indicators than wellness-information seekers, including lower health status, more diminished physical health days, and a poorer quality of life (Table 3). Furthermore, illness-information seekers were more likely to report health risks—they were less likely than wellness-information seekers to engage in physical activities and were more likely to use prescription drugs (Table 3).

**DISCUSSION**

The findings demonstrate that health information seeking among Seattle–Tacoma Internet users is a prevalent behavior. Consistent with much previous research on HISB,11,27 about half of the sample (49.4%) reported spending time during a typical week obtaining either illness (14.1%), wellness (15.2%), or both types (20.1%) of health information online. HISB was more prevalent among women (60.5%) than men (39.5%).

**Types of Health Information Sought**

This report is one of the first to explore differences in health perceptions and behaviors among individuals seeking different types of online health information. We discovered considerable variability in health indicators and health risk factors across the 4 levels of HISB, with prominent differences between individuals exclusively seeking wellness information and those in the other 3 HISB groups. Overall, wellness-information seekers reported the most positive health indicators and the lowest levels of health risks. The opposite pattern was evident for illness-information seekers, who tended to report the most negative health indicators and more health risks. These differences suggest that distinct motivations may underlie HISBs,27,40 a phenomenon frequently overlooked in previous research.11

One key conclusion of this study, illustrated by these trends, is that a substantial portion of health information seekers (30.8%) perceive

### TABLE 2—Analyses of Health Indicators and Health Risk Factors as a Function of Online Health Information-Seeking Behavior (HISB) and Respondent’s Sex: Seattle–Tacoma, Washington, 2006

<table>
<thead>
<tr>
<th>Health indicator, F ($\eta^2_p$)</th>
<th>HISB (df = 3)</th>
<th>Sex (df = 1)</th>
<th>Interaction (df = 3)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Health status</td>
<td>5.75** (0.03)</td>
<td>0.13 (&lt; 0.01)</td>
<td>1.36 (0.01)</td>
</tr>
<tr>
<td>Diminished physical health$^a$</td>
<td>3.52** (0.02)</td>
<td>0.49 (&lt; 0.01)</td>
<td>0.68 (&lt; 0.01)</td>
</tr>
<tr>
<td>Diminished mental health$^{ab}$</td>
<td>1.12 (&lt; 0.01)</td>
<td>1.55 (0.01)</td>
<td>2.45 (0.01)</td>
</tr>
<tr>
<td>Poor quality of life$^{abc}$</td>
<td>2.74* (0.02)</td>
<td>1.92 (&lt; 0.01)</td>
<td>1.73 (&lt; 0.01)</td>
</tr>
<tr>
<td>Body mass index$^{ab}$</td>
<td>0.34 (&lt; 0.01)</td>
<td>3.69 (0.01)</td>
<td>1.52 (0.01)</td>
</tr>
<tr>
<td>Health risk factor, $\chi^2$ ($\eta^2_p$)</td>
<td>1.96* (0.02)</td>
<td>0.78 (&lt; 0.01)</td>
<td>0.99 (&lt; 0.01)</td>
</tr>
<tr>
<td>Physical activities$^{ab}$</td>
<td>7.96* (0.02)</td>
<td>2.00 (&lt; 0.01)</td>
<td>0.52 (&lt; 0.01)</td>
</tr>
<tr>
<td>Prescription medications$^a$</td>
<td>16.19** (0.03)</td>
<td>0.02 (&lt; 0.01)</td>
<td>3.18 (&lt; 0.01)</td>
</tr>
<tr>
<td>Smoking</td>
<td>4.65 (0.01)</td>
<td>0.02 (&lt; 0.01)</td>
<td>3.18 (&lt; 0.01)</td>
</tr>
</tbody>
</table>

Note. A 2 × 4 factorial design with respondent’s sex (male, female) and HISB (no use, illness only, wellness only, and illness and wellness combined) was parameterized for all linear and logistic regression models.

$^a$Income included as significant covariate in model.

$^b$Age included as significant covariate in model.

$^c$Overall Internet use included as significant covariate in model.

$^d$Participation in “any physical activities or exercises” was assessed.

*P < .05; **P < .001.

### TABLE 3—Differences in Respondents’ Health Indicators and Health Risk Factors as a Function of Online Health Information-Seeking Behavior (HISB): Seattle–Tacoma, Washington, 2006

<table>
<thead>
<tr>
<th>Health indicator, mean (SE)</th>
<th>No Use (n = 283)</th>
<th>Illness (n = 79)</th>
<th>Wellness (n = 85)</th>
<th>Combined (n = 112)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Health status</td>
<td>3.81 (0.53)</td>
<td>3.52 (0.10)</td>
<td>4.05 (0.10)</td>
<td>3.65 (0.09)</td>
</tr>
<tr>
<td>Diminished physical health</td>
<td>0.22 (0.02)</td>
<td>0.31 (0.05)</td>
<td>0.14 (0.05)</td>
<td>0.31 (0.04)</td>
</tr>
<tr>
<td>Diminished mental health</td>
<td>0.26 (0.03)</td>
<td>0.33 (0.05)</td>
<td>0.26 (0.05)</td>
<td>0.34 (0.04)</td>
</tr>
<tr>
<td>Poor quality of life</td>
<td>0.15 (0.02)</td>
<td>0.24 (0.04)</td>
<td>0.11 (0.04)</td>
<td>0.20 (0.03)</td>
</tr>
<tr>
<td>Body mass index</td>
<td>27.15 (0.36)</td>
<td>27.19 (0.65)</td>
<td>27.04 (0.64)</td>
<td>27.77 (0.57)</td>
</tr>
<tr>
<td>Health risk factors, %</td>
<td>78.8$^a$</td>
<td>82.3$^a$</td>
<td>94.1$^a$</td>
<td>86.6$^a$</td>
</tr>
<tr>
<td>Physical activities$^{ab}$</td>
<td>63.6$^a$</td>
<td>83.5$^a$</td>
<td>57.7$^a$</td>
<td>80.4$^a$</td>
</tr>
<tr>
<td>Prescription medications$^a$</td>
<td>13.8</td>
<td>15.2</td>
<td>4.7</td>
<td>12.5</td>
</tr>
</tbody>
</table>

Note. For the health indicators, least square means having different superscripts (””) differ at $P < .05$ by the 2-tailed t test. For health risk factors, percentages having different superscripts (””) differ at $P < .05$ by the Wald $\chi^2$ test. Missing data on body mass index excluded 16 respondents (total respondents, n = 543; no use, n = 272; illness, n = 77; wellness, n = 84; illness and wellness combined, n = 110).

$^a$Participation in “any physical activities or exercises” was assessed.
themselves as well and healthy and are using online health information about wellness perhaps, as others have suggested, “in a proactive manner for health promotion.” This suggests that, with thoughtful formative research and effective targeting, the Internet could provide an efficient channel for primary health promotion and disease prevention activities, encouraging many individuals engaged in HISB to maintain a healthy lifestyle.

By contrast, the findings also show that many who engage in HISB pursue content about medical concerns (e.g., illness or disease, medications, or treatments) and that these illness information seekers (28.6%) report less positive health indicators and more health risks. This would suggest that, consistent with the bulk of previous research, seeking health information may be a common behavioral response among those facing health challenges and that online health information may effectively bolster secondary and tertiary prevention interventions.

At the same time, the observation that many health information seekers sought both illness and wellness information (40.6%; combined HISB group) was somewhat unexpected and needs further investigation. One can quickly envision a number of circumstances in which there may be coexisting needs for different types of health information. Therapies for prevalent chronic diseases (e.g., cardiovascular disease, diabetes), for instance, often involve both medically supervised treatments and healthy-lifestyle behavioral changes. Notably, however, there was essentially no variability in health indicators, health risk factors, perceived importance of health information, overall Internet use, and demographic characteristics between the illness-only and combined groups.

Possible Motives for Health Information-Seeking Behavior

Taken together, the direct linkages between health assessments and the type of health information sought online observed in this study suggests that different health-related motives may underlie each type of HISB. This observation appears inconsistent with explanations for Internet HISB built on concepts such as the “cyberchondriac” – a word frequently “used to describe anyone who seeks health-related information on the Internet during leisure time or ‘incidental health information use’ (e.g., inadvertent or nonpurposive use of health information). Instead, the data at hand suggest that further exploration of individual-level antecedents of HISB particularly the cognitive and affective components of health anxiety could prove a fruitful avenue for future research.

Equally important, the fact that most (50.6%) of this Seattle–Tacoma sample reported no HISB raises critical questions about the viability of the Internet as a channel for health promotion and disease prevention that require further consideration. The consistency of this observation across numerous studies highlights the need for research to extend our understanding of why so many people apparently ignore easily accessible information resources that could aid in maximizing their health. The current results offer few insights, since several potential determinants (e.g., poor health literacy and media literacy, demographics) seem unlikely contributors given the characteristics of the sample (i.e., Internet users with elevated income and education levels).

Clearly, if our goal is to convey health-promoting content to the broadest audience, further research examining the barriers and motives influencing HISB is necessary to facilitate engagement with those who are not actively seeking health information.

Although this study reveals new insights regarding HISB, there are several limitations to acknowledge. First, this is a cross-sectional study and attribution of causality is not warranted. In addition, the sample characteristics (e.g., concentrated in western Washington State, drawn from an Internet-based panel) limit generalizability. Finally, although informed by formative research and more detailed than most previous research, the 6 health information-seeking domains examined here were not comprehensive and left considerable room for respondents’ interpretation. Future studies of HISB can substantially advance our understanding by refining measures to capture in greater detail the characteristics of respondents’ choices and preferences regarding health information.

In conclusion, the findings reveal distinct patterns in the health information content sought by adult Internet users in western Washington State and highlight unique linkages between the type of health information sought (e.g., wellness, illness, and so on) and several health indicators and health risk factors. As reported in previous research, much HISB seems to be disease or illness oriented. Actively seeking wellness information, on the other hand, emerges as a unique behavior among many health-conscious individuals. These findings demonstrate “that consumers who are active health information seekers are not a monolithic group, and should not be treated as one.”

The findings suggest that integration of a basic communication-tailoring strategy, targeted toward specific health indicators and health risks, into Internet health communication endeavors could substantially improve the efficacy of the Internet as a channel for primary, secondary, and tertiary prevention.

About the Authors

James B. Weaver, III, Darren Mays, Stephanie Sargent Weaver, Doğan Eroğlu, and Jay M. Bernhardt are with the National Center for Health Marketing, Centers for Disease Control and Prevention, Atlanta, GA. Gary L. Hopkins is with the Center for Media Impact Research, Institute for the Prevention of Addictions, Andrews University, Berrien Springs, MI.

Correspondence should be sent to James B. Weaver, III, Centers for Disease Control and Prevention, 1600 Clifton Road MS-E21, Atlanta, GA 30333 (e-mail: jm.weaver@cdc.gov). Reprints can be ordered at http://www.ajph.org by clicking on the ‘Reprints/Eprints’ link.

This article was accepted December 8, 2009.

Contributors

James B. Weaver, III originated the study and supervised all aspects of the preparation of the article. Darren Mays and Stephanie Sargent Weaver assisted with data analysis and interpretation and assumed a primary role in writing the article. All other authors conceptualized ideas, interpreted results, and reviewed drafts of the article.

Acknowledgments

This research was supported in part by a grant from the Center for Media Impact Research in the Institute for Prevention of Addictions at Andrews University and by appointments of D. Mays and S.S. Weaver to the Research Participation Program at the Centers for Disease Control and Prevention (CDC) administered by the Oak Ridge Institute for Science and Education through an interagency agreement between the US Department of Energy and the CDC.

We are indebted to Richard E. Dixon, Wendi Kannenberg, Duane C. McBride, John V. Stevens Jr, and the anonymous reviewers for their significant contributions to this project.

Note

The findings and conclusions in this article are those of the authors and do not necessarily represent the
views of the CDC or the US Department of Health and Human Services.

**Human Participant Protection**

The institutional review boards of Andrews University, Loma Linda University, and Virginia Polytechnic Institute and State University approved the protocol for this study.

**References**


