International Journal of Technology Assessment in Health Care, **17:4** (2001), 590–600.

WHO USES SELF-CARE BOOKS, ADVICE NURSES, AND COMPUTERS FOR HEALTH INFORMATION?

Todd H. Wagner
VA Palo Alto Health Care System
Stanford University

Judith H. Hibbard
University of Oregon

Abstract

Objectives: While evaluating the effect of a community-wide informational intervention, this study explored access, health, and demographic factors related to the use of medical reference books, telephone advice nurses, and computers for health information.
Methods: A random sample of households in the intervention city (Boise, Idaho) and two control cities were surveyed about their use of health information in 1996. Shortly thereafter, the Healthwise Communities Project (HCP) distributed health information to all Boise residents. A follow-up survey was conducted in 1998. Overall, 5,909 surveys were completed for a 54% response rate.
Results: The HCP intervention was associated with statistically significant increases in the use of medical reference books and telephone advice nurses. The increased use of computers for health information was marginally significant. Few access, health, or demographic factors were consistently associated with using the different resources, except that people with depression used more of all three information resources, and income was not a significant predictor.
Conclusion: Providing free health information led to an increase in use, but access, health, and demographic factors were also important determinants. In particular, poor health status and presence of a chronic illness were associated with health information use. These results suggest that healthy consumers are less interested in health information, and it may take other incentives to motivate them to learn about prevention and healthy behaviors.

Keywords: Self-care, Information, Interactive health communications, Intervention

Traditional forms of self-care information, such as books and advice nurses, have been used by consumers for decades. Recently, however, there has been a large increase in the availability of consumer health information and self-care resources. New information technology is a key ingredient contributing to this growth. In particular, the Internet is revolutionizing

Todd Wagner was supported by a dissertation grant from the Agency for Health Research and Quality (R03 HS09997) and by a grant from the Russell M. Grossman Medical Research Fund. Judith Hibbard was supported by a grant from the Robert Wood Johnson Foundation. The authors thank Merwyn Greenlick, Holly Jimison, Lynn Kunkel, Jeff Capizzi, Teh-wei Hu, Keith Humphreys, and John Piette for their comments. Approval of human subjects was obtained from the Oregon Health Sciences University and the University of California, Berkeley. All conclusions and comments are the authors' and do not reflect sponsoring or affiliated organizations.

the way consumers get health information and make decisions, and a growing number of consumers are using the internet for health-related advice. Despite large private and public investments in health information systems, we know little about who uses them (7;9;21;22).

Of the handful of studies that have been conducted, most have used randomized clinical trials with intent-to-treat analysis to assess the effects of providing people with health and self-care information (18;20;25). This methodology is preferred for assessing efficacy, yet it does not provide information on who uses health information.

Understanding more about who uses consumer health information is important for health promotion interventions that want to choose the best medium for disseminating information. This topic is also of interest to those developing consumer- or patient-directed health information systems. Common perception is that health plans will purchase or make these information systems for their enrollees. Yet, if people with a chronic illness, such as diabetes or asthma, have a strong desire for health information, then health plans may choose not to provide health information for fear of attracting high-cost, chronically ill patients.

The primary goal of this study was to determine who uses medical reference books, telephone advice nurses, and computers for health information. We focused on these three mediums, in particular, because the data were from an evaluation of a community-wide informational intervention, the Healthwise Communities Project (HCP). Therefore, a secondary goal of this study was to determine whether the free distribution of health information from the intervention had a significant impact on the use of self-care resources.

METHODS

Overview

Healthwise Incorporated, a private nonprofit organization, initiated the HCP intervention in Boise, Idaho in the third quarter of 1996. The community-wide intervention was specifically designed to give people health information and self-care resources. First, every household was sent the *Healthwise Handbook*, which is a self-care reference guide. The book spans more than 300 pages with coverage of consumer tips, wellness and prevention, and self-care management and coping. The book is not designed to replace professional medical care, but rather it is designed to encourage appropriate utilization. While information on self-treatment is provided, all sections provide guidelines on when to call a doctor for a health problem. The second part of the intervention involved establishing a toll-free health information and assistance telephone line staffed by a nurse. Third, information stations, which included computers connected to information databases and/or a web-based program, books, and other health consumer information, were set up in public libraries, businesses, and healthcare settings throughout the Boise area. People could use the information stations to access the computerized database. Alternatively, they could access the database through a semi-restricted web site if their zip code was in the Boise area. The computerized databases were similar to the *Healthwise Handbook*, although they had more detail, had color pictures, and allowed greater searching. Fourth, Healthwise Inc. sponsored free workshops to help Boise residents develop self-care and health-related communication skills. Fifth, health professionals were asked to attend free workshops on how to help patients use self-care resources. To raise awareness of these new resources, Healthwise conducted an extensive advertising campaign, including radio, television, and billboard advertisements. All the HCP resources were provided to Boise residents only.

Prior to the start of the HCP, Healthwise had taken steps to ensure the information's quality. The telephone advice line was staffed with nurses. The *Healthwise Handbook* and the computer database, referred to as the Healthwise Knowledgebase, were scrutinized by a medical review board. The current board membership can be viewed on Healthwise's web page (8).

Selection of Communities and Participants

The Healthwise Communities Project was evaluated using a quasi-experimental design. Boise was chosen as the experimental site because it was home to Healthwise, Inc. Eugene and Billings were chosen as matched control communities based on their proximity to Idaho, and similarities in metropolitan and health system characteristics.

Baseline data were collected in January 1996 through postal surveys mailed to randomly selected households in the three cities. In each city, a list of householder names was purchased from a national marketing firm. Randomly selected householders were then sent a survey. After approximately 3 weeks, reminder cards with information on how to obtain a replacement survey were sent out. To maximize response rates, up to three reminders were sent before the person was considered a nonrespondent. Of the 7,500 baseline surveys, 1,048 were returned as undeliverable and one was returned indicating that the recipient was deceased. A total of 3,067 (47.5%) surveys were completed. Those who completed the baseline survey were sent a follow-up survey in January 1998. In addition, a second random sample of 3,600 households (1,200 per site) was surveyed. The decision to collect a second random sample stemmed from a concern that there might be substantial attrition in the longitudinal sample. The follow-up and reseeded samples completed the same survey. In 1998, 6,667 households in the same three cities were sent a questionnaire; of these, 2,090 were returned as undeliverable, 12 were marked as deceased, and 2,842 were completed, for an adjusted response rate of 62%. Overall, 5,909 surveys were completed for a response rate of 54%. One limitation of these methods is that no data were collected from nonrespondents.

Analysis

The three dependent variables were: a) use of any medical reference book in the last few months; b) use of any telephone advice nurse in the last few months; and c) use of any computer for health information in the last few months. Bivariate analysis used Pearson's chi-squared statistics. Logistic regression models were used for the multivariate analysis.

The dummy variable *site* was used to differentiate the intervention from the control sites (Table 1). Another dummy variable, *time*, was used to identify before and after the intervention. The HCP intervention effect was identified as the interaction between the *site* and *time* dummy variables (*site* $\times$ *time*).

We also included a dummy variable (*media*) that identified whether the person had seen any HCP-related advertisements. This allowed us to separate the "free information" effect from the advertising effect.

The other explanatory variables were categorized by whether they represented access, health status, or demographics (Table 1). To measure access to information and medical care, we included health insurance, employment status, travel time to one's physician, living in a rural neighborhood, ownership of a computer, and access to the Internet. Health insurance was categorized as none, any private, or only public (i.e., Medicare or Medicaid). Employment status was categorized as working full- or part-time, retired or homemaker, unemployed or student.

To measure health status, we included the question "In general, would you say your health is: excellent, very good, good, fair, or poor?" Fair and poor were combined because of the small sample sizes. In addition, participants were given a list of 10 chronic illnesses and asked whether a doctor or other health professional had ever told them that they had any (Table 1).

Among the demographic factors included in the model were education, gender, age, and race. Due to small samples, self-identified race was categorized as white versus nonwhite. Also to allow for nonlinear effects, age was separated into four categories (18–29, 30–44, 45–64, 65+).

Table 1. Summary Statistics for the Independent Variables

	Complete data %	Control n = 4,010		Exp. n = 1,899	
		(%)	(SE)	(%)	(SE)
Intervention effects					
Year: 0 = 1996; 1 = 1998	100%	48.6	0.79	46.9	1.15
Site: 0 = control; 1 = experimental	100%	0.0	0.00	100.0	0.00
Site × year: interaction of year with site	100%	0.0	0.00	47.0	1.15
Media: saw HCP-related advertisement	92%	0.0	0.00	18.7	0.89
Access effects					
Income: <$15,000	88%	19.8	0.74	14.2	0.87*
Income: $15,000–$24,999	88%	33.4	0.81	29.4	1.10*
Income: $25,000–49,999	88%	19.6	0.70	21.7	1.02
Income: $50,000+	88%	27.2	0.73	34.6	1.18*
Employment: working full- or part-time	92%	54.4	0.86	64.1	1.12*
Employment: retired or homemaker	92%	40.5	0.80	31.6	1.10*
Employment: unemployed or student	92%	5.1	0.40	4.3	0.49
Health insurance: none	93%	9.4	0.53	8.7	0.69
Health insurance: any private	93%	77.2	0.77	82.9	0.94*
Health insurance: only public	93%	13.5	0.56	8.4	0.67*
Owns a computer	94%	46.4	0.82	56.2	1.16*
Has access to the Internet	89%	33.9	0.75	42.2	1.13*
Rural (% rural)	88%	20.1	0.63	18.3	0.89
Travel time to MD: <15 minutes	93%	57.9	0.81	57.0	1.15
Travel time to MD: 15–30 min.	93%	35.1	0.78	35.5	1.13
Travel time to MD: >30 min.	93%	7.0	0.41	7.6	0.64
Health status					
Health status: excellent	95%	14.8	0.57	17.6	0.91*
Health status: very good	95%	36.5	0.78	36.9	1.11
Health status: good	95%	34.2	0.76	34.1	1.11
Health status: fair or poor	95%	14.4	0.57	11.4	0.75*
High blood pressure	95%	22.5	0.72	20.8	0.99
High cholesterol	95%	21.2	0.65	17.2	0.88*
Arthritis	95%	21.1	0.67	21.6	0.95
Chronic back pain	95%	13.4	0.55	14.1	0.82
Cancer	95%	3.9	0.31	3.8	0.44
Heart disease	95%	6.6	0.39	4.8	0.50*
Diabetes	95%	4.8	0.34	4.4	0.48
Depression	95%	12.1	0.54	12.9	0.78
Asthma	95%	7.2	0.42	7.0	0.59
Chronic bronchitis	95%	3.3	0.29	3.2	0.41
Demographics					
Education: high school	89%	33.3	0.81	25.1	1.06*
Education: some college	89%	33.0	0.79	33.1	1.14
Education: college graduate	89%	20.3	0.66	22.2	1.01
Education: postgraduate work	89%	13.4	0.66	19.6	0.93*
Sex (% female)	92%	68.6	0.75	69.0	1.25
White (% yes)	97%	96.7	0.28	96.8	0.40
Age: 18–29	85%	8.7	0.47	11.6	0.74*
Age: 30–44	85%	27.1	0.71	35.2	1.17*
Age: 45–64	85%	38.3	0.79	35.5	1.16*
Age: 65+	85%	25.9	0.73	17.7	0.91*
Has children: (% yes)	92%	29.8	0.72	37.4	1.11*
Married (% yes)	93%	67.8	0.75	70.0	1.08

May not add due to rounding.
Missing data = (1 − complete data).
* $p \leq .05$ between sites.

https://doi.org/10.1017/S0266462301107130 Published online by Cambridge University Press

No single variable had more than 15% missing data. However, estimating the logistic models without taking missing data into account reduced the sample size from 5,909 to approximately 2,900 (50%). To minimize missing data bias, we used well-established missing data techniques. AMELIA replicated the original data set five times (12). Across these five data sets, the observed values were held constant. When AMELIA encountered data missing from a cell, the EM algorithm imputed a missing value, allowing the values to vary across the five data sets. Estimation was then run as usual on each of the five "complete" data sets. The results were averaged across the five data sets (16). This complicates data analysis, but it is preferred to other imputation methods (28).

Goodness-of-fit statistics, including Hosmer and Lemeshow's (13) goodness-of-fit test and Pregibon's (26) link test, and visual plots of the residuals (17) were run for each model. The hypothesis of a good fit was never rejected.

RESULTS

Sample Characteristics

Two-thirds of the respondents were female and approximately 10% of the respondents were under age 30 (Table 1). More people in the intervention city (Boise) reported having private health insurance. Also, more Boise respondents had computers and Internet access.

Intervention Effect

Healthwise Inc. tracked the provision of information. As of October 1998, they had sent out over 132,000 *Healthwise Handbooks*. They also report that the telephone advice nurse had received more than 25,000 calls from more than 21,000 unique families. Healthwise conducted over 540 workshops, reaching more than 7,500 residents. In addition, Healthwise provided over 64 workshops, attended by over 160 physicians and 450 other healthcare providers.

Our data show that the HCP intervention was associated with a large increase in the use of self-care resources. Most noticeably, residents of the intervention city increased their use of the self-care books compared with residents in the control cities. The bivariate analysis reported in Table 2 shows that this effect was large (17.7%) and statistically significant.

Table 2. Use of Health Information Sources

	Year	Control (%)	Exp. (%)	Difference	
				Bivariate	Multivariate[a]
Book	1996	41.6	48.7	7.1	
	1998	46.2	71.0	24.8	
	Difference	4.6	22.3	17.7[b***]	16.0[b***]
Advice nurse	1996	31.0	25.1	−5.9	
	1998	29.6	28.9	−0.7	
	Difference	−1.4	3.8	5.2[b*]	6.1[b*]
Computer	1996	7.8	7.8	0.0	
	1998	15.0	19.3	4.3	
	Difference	7.2	11.5	4.3[b]	2.2[b]

Analysis accounts for missing data.
May not add due to rounding.
[a] Predicted probabilities were calculated at the means of the other covariates (see Table 3 for covariates).
[b] These are difference-in-differences.
* $p \leq .05$.
** $p \leq .01$.
*** $p \leq .001$.

Even after controlling for other explanatory variables, including advertising, the use of self-care books was highly significant (16%). In addition, the HCP was related to a 6% increase in the use of the telephone advice nurses. As for changes in the use of computers, the data show that all three sites had a significant increase in the use of computers for health information over time. This is not surprising given that the number of households with computers increased by approximately 20% in 1997 (3). Despite this secular trend, residents in the intervention city were marginally more likely to use computers for health information than persons in the control sites ($p = .06$). Statistical significance for the use of computers varied slightly by the statistical model ($.03 < p < .10$).

Access

Access variables were important predictors of use (see Table 3). As was expected, ownership of a computer and access to the Internet were highly associated with using a computer for health information. In addition, people with a computer were more likely to use a self-care book.

For the most part, health insurance was not related to the use of health information. We did see, however, that compared with people without insurance, those with private insurance were more likely to use a computer for health information. This is perhaps indicative of the on-line services that many health plans have made available to their members.

Interestingly, household income and employment status were not related to using any of the three information sources. People with household incomes above $50,000 were no more or no less likely to use the self-care resources than people with less income.

Health

Generally, people in poor health and those with a chronic illness were more likely to use health information. For these variables, most odds-ratios were greater than one, but few were statistically significant. We found that those with high cholesterol and chronic back pain were more likely to use a book. However, the most intriguing finding was that people with depression consistently used more of all three resources.

Demographics

While many demographic factors were associated with using self-care resources, few variables were consistently associated with all three information sources. When we assessed who used the self-care book, educational attainment was an important explanatory variable. However, the effect of education was not linear, possibly because it was a proxy for literacy. People with a high school education or less were less likely to use self-care books, but there were no differences among persons with higher levels of education. Interestingly, education was not associated with using a telephone advice nurse or a computer.

Older adults were much less likely to use a telephone advice nurse than younger adults. In fact, this effect was quite strong and it increased with each age group. While age and education were associated with the use of self-care books and telephone advice nurses, neither were related to using computers for health information.

DISCUSSION

The results show that the HCP intervention was associated with significant increases in the use of reference books and telephone advice nurses. The use of computers for health information increased as well, but the effect was less dramatic, in part because of the secular trend to buy computers and to search the Internet for health. In addition, the analysis shows that the increased use of the health information was largely due to the "free information" effect rather than to an advertising effect.

Table 3. Use of Self-care Information from Logistic Regression Models

	Reference book		Telephone advice nurse		Computer	
	OR	*t* stat	OR	*t* stat	OR	*t* stat
Interventions effects						
Year: 0 = 1996; 1 = 1998	1.267	3.292***	0.961	−0.505	1.444	3.118**
Site: 0 = control; 1 = experiment	1.224	2.266*	0.648	−4.412***	0.703	−2.193*
HCP effect (site × year interaction)	1.806	4.184***	1.366	2.103*	1.381	1.506
Media	1.635	2.962**	0.995	−0.032	1.248	1.130
Access						
Income: <$15,000			Reference group			
Income: $15,000–$24,999	1.153	1.325	0.909	−0.929	1.029	0.140
Income: $25,000–49,999	1.184	1.299	0.988	−0.100	1.344	1.277
Income: $50,000+	1.100	0.686	0.816	−1.588	1.259	1.008
Employment: working FT or PT			Reference group			
Employment: retired or homemaker	1.070	0.857	1.081	0.969	1.207	1.428
Employment: unemployed or student	1.086	0.570	0.943	−0.398	1.160	0.639
Health insurance: none			Reference group			
Health insurance: any private	0.947	−0.450	0.926	−0.699	1.637	2.319*
Health insurance: only public	1.044	0.275	1.167	1.021	1.211	0.654
Owns a computer	1.272	3.380***	0.946	−0.757	3.455	8.741***
Has access to the Internet	0.905	−1.359	0.915	−1.154	5.546	11.876***
Rural (1 = rural)	1.122	1.481	0.713	−3.815***	1.018	0.120
Travel time to MD: <15 min.			Reference group			
Travel time to MD: 15–30 min.	0.929	−1.168	1.096	1.369	0.907	−0.912
Travel time to MD: >30 min.	1.263	1.943	1.223	1.463	1.415	1.420
Demographics						
Education: high school			Reference group			
Education: some college	1.608	5.624***	1.109	1.192	0.994	−0.042
Education: college graduate	1.994	6.843***	1.007	0.079	1.032	0.184
Education: postgraduate work	2.096	6.942***	1.160	1.354	1.099	0.554
Sex (1 = female)	1.396	4.601***	1.141	1.747	0.916	−0.844
Race (1 = white)	1.363	1.984*	1.057	0.335	0.900	−0.456
Age: 18–29			Reference group			
Age: 30–44	1.018	0.152	0.613	−4.026***	1.046	0.260
Age: 45–64	0.977	−0.196	0.454	−6.787***	0.806	−1.220
Age: 65+	0.691	−2.698**	0.304	−7.392***	0.656	−1.764
Health status						
Health status: excellent			Reference group			
Health status: very good	1.069	0.794	1.209	1.955*	0.984	−0.129
Health status: good	1.108	1.076	1.266	2.062*	1.039	0.268
Health status: fair or poor	1.100	0.760	1.496	3.030**	1.417	1.578
High blood pressure	1.066	0.848	1.106	1.158	0.803	−1.547
High cholesterol	1.205	2.465**	1.082	0.935	0.994	−0.043
Arthritis	1.114	1.361	1.080	0.817	1.203	1.256
Chronic back pain	1.281	2.553**	1.141	1.239	1.239	1.292
Cancer	1.144	0.913	1.021	0.122	0.831	−0.657
Heart disease	1.005	0.037	0.990	−0.071	0.802	−0.700
Diabetes	1.081	0.539	0.992	−0.055	1.068	0.212
Depression	1.389	3.696***	1.324	2.949**	1.368	2.179*
Asthma	1.193	1.550	1.059	0.479	0.953	−0.262
Chronic bronchitis	1.067	0.364	1.088	0.473	1.254	0.690
Has children: (1 = yes)	1.215	2.700**	1.988	8.859***	0.932	−0.659
Married: (1 = yes)	1.627	6.565***	1.459	4.469***	1.036	0.267

(Continued)

https://doi.org/10.1017/S0266462301107130 Published online by Cambridge University Press

Table 3. *(Continued)*

	Reference book		Telephone advice nurse		Computer	
	OR	*t* stat	OR	*t* stat	OR	*t* stat
Model information[a]						
Sample size	5,909		5,909		5,909	
Chi-squared	657.48***		416.02***		968.45***	
(degrees of freedom)	(39)		(39)		(39)	
Pseudo R^2	0.0803		0.0585		0.2263	
Hosmer-Lemeshow goodness-of-fit[b]	NS		NS		NS	
Pregibon link test[c]	NS		NS		NS	

[a] Model statistics presented are for the worst fitting of the five imputed data sets.
[b] Data from Hosmer and Lemeshow (13).
[c] Data from Pregibon (26).
* $p < .05$.
** $p < .01$.
*** $p < .001$.
NS = not significant.

A unique contribution of this study is the opportunity to understand who uses health information. One of the intriguing findings is that people with depression used more of all types of information. There have been newspaper reports that a large percentage of Internet health users want mental health information (27). Yet, this is the first study that we are aware of to document that people who reported having depression consistently used more self-care resources. In addition, we also found that people with depression in the intervention city were significantly more likely to use the telephone advice nurse than persons with depression in the control sites (results not shown). Given the concerns about providing health information, and specifically mental health information, over the Internet (1;14;27), future studies should assess the quality of on-line mental health advice and whether this information affects utilization, costs, and quality of life.

Another unique aspect of this study is that it was based on a random household survey. In contrast, most studies have assessed the efficacy of health information by using randomized controlled trials. While such trials are optimal for assessing efficacy, we believe that researchers should continue to strive to learn why health information is at times successful and at other times is not (6;18;19;20). We suspect that this is partly influenced by an individual's motivation, which can be idiosyncratic. But culture and language can be important mediators. Piette (24), for example, found that Spanish-speaking persons with diabetes were much more likely to use language-specific automated telephone advice than English-speaking persons with diabetes.

One limitation with this study is the response rates. Although the rates in this study are equal to or higher than other postal surveys that did not use financial incentives (15;23), comparing our sample to census data for the three metropolitan statistical areas showed that our sample was disproportionately female (69% versus 51%, respectively) and had a higher percentage with at least some college education (73% versus 41%, respectively). While we statistically adjusted for site differences, we have no data on nonrespondents that would allow us to speculate about potential nonresponse biases.

A second concern is the suitability of the matched control sites. Because this was not a randomized trial, some other factor could be responsible for the effects that we attribute to the HCP. In the survey, respondents were also asked how often they seek information from family or friends, health columns, pharmacists, nurses, and physicians. The data indicate that for each of these other sources, the intervention had no effect. Given that the intervention

was not designed to impact these sources of information, this was reassuring and it lessens the concern that something else was affecting the use of information in the intervention city during the intervention.

Another limitation is that all of the data under investigation were based on self-report. We were concerned about recall bias when we developed the survey, and therefore we just asked whether the person had used the information source in the past few months. If we had asked the number of times they used a computer for health information or the web sites that they viewed, then we expect that the reliability and validity may be questionable. We are not aware of any study that has validated this type of self-report data. Future research may want to consider this topic as the use of health information becomes more widespread.

POLICY IMPLICATIONS

Health information is becoming widely used and highly valued by consumers. A nationally representative survey found that 70 million Americans, or approximately 74% of those with access to the Internet, used the Internet for health information in 1999 (29). Despite this secular trend, our data show that providing consumers with free health information will lead to more widespread use. However, it is unknown whether this information will be used in conjunction with medical care or as a substitute for care. There are implications for either. If consumers are using health information while getting medical care, then this may affect communication between the patient and provider. Healthcare communication has received attention recently, and it was added as an indicator for Healthy People 2010 (4). While using information has the potential to enrich the patient–provider relationship, this relationship will also be affected by poor quality information on the Internet because providers will be asked to filter the good information from the bad. In this regard, it is easier to monitor information that is provided by telephone advice nurse or by book. The downside is that it is much more expensive to update these information sources, and this translates into either higher book prices or restricted access to telephone advice nurses.

If consumers are seeking health information as a substitute for medical care, then we need to make sure that consumers are reducing inappropriate care rather than appropriate care. We have found that the HCP was associated with no changes in overall self-report utilization among adults (31) and small decreases in overall reported utilization among children (30). Analysis of the claims data also found reason to believe that the HCP affected utilization (10); however, in most cases we were not able to differentiate between appropriate and inappropriate utilization. These findings were relatively consistent with previous randomized trials (18;20;25), except that our sample was community-based rather than chronically ill and our results were generally not as large. One explanation is that people with a chronic illness are more motivated to use health information. In fact, this pattern is evident with our data. This relationship may be intuitive, but it also suggests that healthy consumers are less interested in health information, and it may take other incentives to motivate them to learn about prevention and healthy behaviors.

Given that people with chronic illnesses are more likely to use health information, an important issue for future research is whether people consider the provision of health information when choosing a health plan. Some health plans, including Kaiser Permanente, actively provide health information and self-care resources to their members. Yet, as there is for mental health benefits (5), adverse selection may create a disincentive for plans to provide state-of-the-art consumer health information. Because these data show that people tend to seek health information when ill, prepaid health plans cannot afford to attract the high-cost, high-risk patients unless they are financially compensated for doing so. If it can be shown that adverse selection is not an issue, then this may encourage more health plans

to take a proactive role in providing disease management and wellness information to their enrollees.

By focusing on the use and effects of health information, it is easy to forget that a large percentage of the population does not use computers or the Internet. Lower rates of using computers and the Internet have been found to be particularly noticeable among lower income African Americans (2). While efforts are under way to reduce the digital divide, unknown is the number of people who seek but do not find any information. Even if a person finds relevant information, it may be too technical, it may be in a different language, or it may be overwhelming (11). Concerted private and public efforts will be required to narrow this divide; otherwise, the potential benefits from health information will not reach many of those in need.

REFERENCES

1. Biermann JS, Golladay GJ, Greenfield ML, Baker LH. Evaluation of cancer information on the Internet. *Cancer*. 1999;86:381-390.
2. Brodie M, Flournoy RE, Altman DE, et al. Health information, the Internet, and the digital divide. *Health Aff*. 2000;19:255-265.
3. Carlton J. Cheaper PCs start to attract new customers. *Wall Street Journal*. January 26, 1998:B1(E), B1(W).
4. Centers for Disease Control. Healthy People 2010. Available at: http://www.health.gov/healthypeople/document/HTML/Volume1/11HealthCom.htm.
5. Frank R, Huskamp H, McGuire T, Newhouse J. Some economics of mental health "carve-outs." *Arch Gen Psychiatry*. 1996;53:933-937.
6. Gustafson DH, Hawkins R, Boberg E, et al. Impact of a patient-centered, computer-based health information/support system. *Am J Prev Med*. 1999;16:1-9.
7. Gustafson DH, Robinson TN, Ansley D, et al. Consumers and evaluation of interactive health communication applications. The Science Panel on Interactive Communication and Health. *Am J Prev Med*. 1999;16:23-29.
8. Healthwise Incorporated. Healthwise: About Us: Medical Board. Available at: http://www.healthwise.org/a_medical.html.
9. Hibbard JH, Greenlick M, Jimison H, et al. Prevalence and predictors of the use of self-care resources. *Evaluation and the Health Professions*. 1999;22:107-122.
10. Hibbard JH, Greenlick MR, Jimison H, et al. The impact of a community-wide self-care information project on a self-care and medical utilization. *Evaluation and the Health Professions*. In press.
11. Hibbard JH, Slovic P, Jewett JJ. Informing consumer decisions in health care: Implications from decision making research. *Milbank Q*. 1997;75:395-414.
12. Honaker J, Joseph A, King G, et al. AMELIA: A program for missing data. Boston, 1999.
13. Hosmer DM, Lemeshow S. *Applied logistic regression*. New York: John Wiley & Sons; 1989.
14. Jadad AR, Gagliardi A. Rating health information on the Internet: Navigating to knowledge or to Babel? *JAMA*. 1998;279:611-614.
15. Jones R, Pitt N. Health surveys in the workplace: Comparison of postal, email and World Wide Web methods. *Occup Med*. 1999;49:556-558.
16. King G, Honaker J, Joseph A, Scheve K. Listwise deletion is evil: What to do about missing data in political science. Working paper presented at the 1998 American Political Science Association Conference, 1999. Available at: http://gking.harvard.edu/files/evil.pdf.
17. Landwehr JM, Pregibon D, Shoemaker AC. Graphical methods for assessing logistic regression models. *JAMA*. 1984;79:61-71.
18. Lorig KR, Sobel DS, Stewart AL, et al. Evidence suggesting that a chronic disease self-management program can improve health status while reducing hospitalization: A randomized trial. *Med Care*. 1999;37:5-14.
19. Montgomery EB Jr, Lieberman A, Singh G, Fries JF. Patient education and health promotion can be effective in Parkinson's disease: A randomized controlled trial. PROPATH Advisory Board. *Am J Med*. 1994;97:429-435.

20. Osman LM, Abdalla MI, Beattie JA, et al. Reducing hospital admission through computer supported education for asthma patients. Grampian Asthma Study of Integrated Care (GRASSIC). *Br Med J*. 1994;308:568-571.
21. Patrick K. Prevention, public health, and interactive health communication (comment). *Am J Prev Med*. 1999;16:46-47.
22. Patrick K, Robinson TN, Alemi F, Eng TR. Policy issues relevant to evaluation of interactive health communication applications. The Science Panel on Interactive Communication and Health. *Am J Prev Med*. 1999;16:35-42.
23. Perneger TV, Etter JF, Rougemont A. Randomized trial of use of a monetary incentive and a reminder card to increase the response rate to a mailed health survey. *Am J Epidemiol*. 1993;138:714-722.
24. Piette JD. Patient education via automated calls: A study of English and Spanish speakers with diabetes. *Am J Prev Med*. 1999;17:138-141.
25. Piette JD, Weinberger M, McPhee SJ, et al. Do automated calls with nurse follow-up improve self-care and glycemic control among vulnerable patients with diabetes? *Am J Med*. 2000;108:20-27.
26. Pregibon D. *Data analytic methods for generalized linear models* [dissertation]. Toronto: University of Toronto; 1979.
27. Roan S. Cyber analysis. *Los Angeles Times*, March 6, 2000.
28. Schafer JL. Analysis of incomplete multivariate data. In Cox DR, Isham V, Keiding N, et al, eds. *Monographs on statistics and probability*. London: Chapman & Hall; 1997.
29. Taylor H. *Explosive growth of "cyberchondriacs" continues*. New York: Louis Harris; 1999.
30. Wagner TH, Greenlick MR. When parents are given greater access to health information, does it affect pediatric utilization? *Med Care*. 2001;39:848-855.
31. Wagner TH, Hibbard JH, Greenlick MR, Kunkel L. Does providing consumer health information affect self-reported medical utilization? Evidence from the Healthwise Communities Project. *Med Care*. 2001;39:836-847.