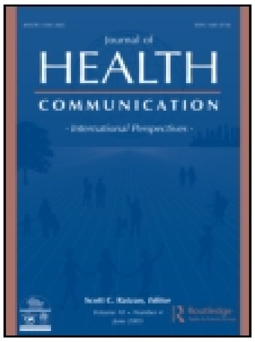

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The Intersection of Gender and Place in Online Health Activities

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This study examines how rurality and gender are related to online health activities. Rural women face greater health risks and yet have access to a weaker health system infrastructure, which has resulted in a health disadvantage. New health information technologies may ameliorate some of these disparities; thus, the authors examine the relevance of gender and place in going online to search for health information, buy medicines, participate in health-related support groups, communicate with physicians, or maintain a personal health record. Analyzing data from the National Cancer Institute's 2007 Health Information National Trends Survey, the authors found that the relations between rurality and gender vary, depending on the specific type of online health activity, and that gender may be a more salient factor than rurality in determining whether individuals engage in particular types of online health activities. This study contributes to the literature by examining how gender and place are related to online health activities, a combined area neglected in past research, and advancing research on gender and technology. This research highlights the importance of expanding high-speed access in rural locations, increasing technological and health literacy, and tailoring the Internet to specific populations.

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People in rural areas face greater health risks and have access to a weaker health system infrastructure, which has resulted in a health disadvantage, particularly for rural women (Institute of Medicine, 2005; Winbush & Crichlow, 2005). Taylor, Hughes, and Garrison (2002, p. 550) noted that "ethnicity, gender, and geography are powerful modifiers of health in this country. It is possible that *geography is more powerful than any risk factor yet to be discovered*" [italics in original]. Although the inequalities that stem from place have been well documented (Lobao, Hooks, & Tickamyer, 2008), some have suggested that new health information technologies could help to ameliorate some of these health disparities (Effken & Abbott, 2009; Hale, Cotten, Drentea, & Goldner, 2010). Although research has focused on whether individuals choose to adopt these new technologies (Whitacre & Mills, 2007), how disparities in Internet usage affect levels of digital literacy or skills (Hargittai, 2000; Mossberger, Tolbert, & Stansbury, 2003), and whether people use their connections for economic purposes or entertainment (Stern, Adams, & Elsasser, 2009), we examine a relatively understudied facet of inequality: *the intersection between rurality and gender in online health activities*, including going online to search for health information, buy medicines, participate in health-related support groups, communicate with physicians, or maintain a personal health record.

Given that 21% of the United States population lives in rural areas (U.S. Census Bureau, 2010) and women have traditionally taken care of their families' health needs (Litt, 2000), this research contributes to our understanding of online health behaviors by examining the intersection of place and gender. Women have until recently lagged behind in technology usage, although they are at the forefront of family caretaking. Rural women have several potential crisscrossing lines of inequality, such as poverty, race and gender (Norris, Zajicek, & Murphy-Erby, 2010) and less Internet access. Understanding these intersections may help us understand the reality of how people use these technologies.

The Role of Place in Rural Health Needs and Practices

There are two reasons people in rural areas experience health disparities. First, they tend to be older, less educated, and have lower income than their suburban and urban counterparts (Institute of Medicine, 2005; Rogers, 2002). These demographic characteristics are associated with lower health status (Link & Phelan, 1995; Schoenborn, Vickerie, & Powell-Griner, 2006). For example, individuals with less education and income experience more environmental threats (e.g., pollution) and inadequate housing (Link & Phelan, 1995). Second, according to the Institute of Medicine (2005), "Rural populations exhibit poorer health behaviors (i.e., higher rates of smoking and obesity and lower rates of exercise) relative to most urban populations" (p. 3). Consequently, they experience greater disability and more inactive years, lower health status, and higher mortality rates for many chronic conditions (Institute of Medicine, 2005; Rogers, 2002; Singh, 2003; Taylor et al., 2002).

Despite the need, rural residents experience problems accessing health care (Glasgow, Wright Morton, & Johnson, 2004; Jones, Parker, Ahearn, Mishra & Variyam, 2009). They travel longer distances to see a provider, and they have less access to transportation (Logan, Stevenson, Evans, & Leukefeld, 2004). Rural residents rely on hospitals, public health departments, emergency services, and community health centers, but there are fewer resources and providers, especially given the growing hospital closures (Brems, Johnson, Warner, & Roberts, 2006; Morton, 2003; Rosenblatt, Andrilla, Curtin, & Hart, 2006; Winbush & Crichlow, 2005). Only 11% of physicians in the United States practice in rural areas (Ballance, Kornegay, & Evans, 2009). This results in rural residents experiencing longer waiting times, seeing less qualified providers, and receiving fewer preventive services, which contributes to greater morbidity and mortality (Logan et al., 2004). Therefore, it is important to examine whether Internet usage can ameliorate some of these disadvantages.

Rural Internet Access and Usage

It is important to look beyond the dichotomy of the Internet haves and have-nots to address the often interrelated issues of types of Internet access (e.g., broadband or dial-up modem), web skills, and the varied uses of the Internet (e.g., Davison & Cotten, 2009; Hargittai, 2010; Stern, Adams, & Elsasser, 2009). Researchers have used Rogers' (2003) model for technological diffusion, the S-Curve, to explain the slow diffusion of broadband Internet access to rural areas, which represents a form of digital inequality (Lenhart & Horrigan, 2003).

Connection type affects one's ability to use the Internet (e.g., Fox, 2008; Horrigan & Murray, 2006). Individuals without regular or efficient access will not become as proficient in navigating the Internet (Hargittai, 2002; Stern et al., 2009). Faster connections make websites that contain numerous graphics or complex operations manageable (Mossberger, Tolbert, & McNeal, 2008). Online health websites are often sophisticated, so given that there are lower rates of broadband Internet access in rural areas, it is not surprising that individuals living in these areas are less likely to search online for health information (Flynn, Smith, & Freese, 2006). Davison and Cotten (2009) found that lack of access to broadband Internet access was a better predictor of the frequency of online activities than were traditional digital divide factors (e.g., income, education, location), except for age. Consequently, the U.S. government allocated billions of dollars to improve broadband Internet access diffusion through the American Recovery and Reinvestment Act of 2009 (Committee on Appropriations, 2009; Hargittai, 2010).

This past research justifies examining how rurality affects technological diffusion. Researchers must account for geographical differences when considering the Internet because there are dissimilar levels of access and thus varied benefits.

Gender and the Internet

Multiple sociodemographic factors influence the way people use technology. Rogers' (2003) diffusion model addresses characteristics such as gender, age, ethnicity, and income, which determine whether individuals adopt new technologies, as well as how they use them (Whitacre, 2007). Women's Internet access and usage in the United States has all but met parity with men's since 2000 (Ono & Zavodny, 2007). Yet, Royal (2008) argued that women are more likely to have negative feelings about certain aspects of web searching and that these gender differences are not explained by traditional measures of Internet proficiency or skill. Rural women, especially those who are most disadvantaged, such as African American, Hispanic, and Native American female-headed households, are the least likely to have sufficient resources such as education and income to be prolific computer users (Snyder, McLaughlin, & Findeis, 2006).

Research has suggested that rural women are the *guardians* of Internet knowledge, meaning that rural men see the Internet as women's domain (Larson, 2007). Gilbert, Karahalios, and Sandvig (2010) found that women represented a much larger proportion of the rural people who use social network sites in comparison with urban users. We expect that women will use the Internet more than men for online health information; moreover, we expect rural women to use the Internet more than rural men.

Gender and Place in Online Health Activities

Our research examines how gender and place affect Eysenbach's (2003) four types of health-related Internet use: seeking information, purchasing products, participating in online communities, and communicating. First, people in rural areas can use the Internet to search for health information, especially given problems with health care access and stigma. It is difficult to be anonymous in small towns, thus seeking health care for sexual and reproductive issues may be more difficult, as individuals do not want to see the only doctor in town (Campbell, 2005). This extends to mental health problems, as research suggests that rural residents hold more stigmatized attitudes towards mental health assistance (Hoyt, Conger, Gaffney Valde, & Weihs, 1997). We expect these activities to be gendered because women are more likely than men are to search for health information online (Hale et al., 2010; Pandey, Hart, & Tiwary, 2003) for themselves and their family members (Stern, Cotten, & Drentea, 2012).

Second, the importance of stigma and privacy extends to purchasing health-related products, such as prescription drugs. Rural pharmacies have been declining, but remote and telepharmacy are expanding (Helseth, 2009). Online pharmacies increase the rural population's access to drugs, especially drugs they may be uncomfortable buying at their local pharmacy, such as birth control pills. We expect that women are more likely to use the Internet to purchase health-related products, because women have traditionally taken care of their families' health needs (Litt, 2000).

Third, people in rural areas can use the Internet to increase their social networks by participating in online communities (Collins & Wellman, 2010). For example, Campbell (2005) found that rural Canadian girls (ages 12–14 years) used the Internet to overcome geographical isolation. In particular, these girls mentioned that they use social support groups (e.g., for getting help with eating disorders), because of a lack of anonymity in their small towns. We expect these activities to be gendered because women are typically more likely than men to use the Internet for social support, and are more active in online social support groups (Drentea & Moren-Cross, 2005).

Last, we hypothesize that rural individuals, especially women, would have greater use of the Internet to communicate with health care providers and track health care information, again because women often manage family member's health needs (Litt, 2000). This will enable them to overcome barriers to accessing health care for themselves and their family (Cotten, 2001; Eysenbach, 2008).

Given that the literature that has suggested that rural residents and women experience greater health disparities and barriers to accessing care, we examine how both gender and place affect online health activities such as buying medicine and contacting doctors, which could help ameliorate some of these disparities. We expect to find a significant interaction between gender and place. Specifically, we expect that rural women would make greater use of the Internet for all four health-related activities than rural men.

Method

Data

We use the National Cancer Institute's 2007 Health Information National Trends Survey (HINTS). The 2007 HINTS uses a dual-frame, mixed mode design (random digit dialing telephone and self-administered mail surveys; Cantor et al., 2009). The overall response rate for the telephone frames was 24% ($n = 4{,}092$) and mail was 31%

($n = 3{,}582$). The two modes yield a combined sample of 7,674 participants. To test for survey mode effects, we follow the procedures in the *User's Directions* (National Cancer Institute, 2009) and the *Analytic Methods to Examine Changes Across Years Using HINTS 2003 and 2005 Data* (Rizzo, Moser, Waldron, Wang, & Davis, 2008).

Our sample was restricted to two subsamples: (a) health information seekers ($n = 5{,}576$) and (b) Internet users ($n = 5{,}025$). We exclude non–health seekers because we are only interested in those who seek health information. We imputed household income using an ordered logit regression model and the predictor variables of education and marital status. Imputation added 555 observations in the health seeker sample and 469 observations in the Internet user sample. The final size for the health seeker sample is 4,959 and for the Internet user sample is 4,535.

Measures

Our dependent variables are created from two sets of questions that assess source of health information and specific types of online health activities. The first, *online health information seeking*, is a dichotomous variable created from the question, "The most recent time you looked for information about health or medical topics, where did you go first?" Responses are recoded to 1 = Internet and 0 = all other sources (e.g., books, family, friends, health care provider).

The second set of dependent variables includes a series of items that measure whether participants have engaged in various types of *online health activities* during the past 12 months. Questions ask whether respondents (a) "bought medicine or vitamins online;" (b) "participated in an online support group for people with a similar health or medical issue;" (c) "used email or the Internet to communicate with a doctor or a doctor's office;" (d) "used a website to help you with your diet, weight, or physical activity;" (e) "looked for a healthcare provider;" (f) or "kept track of personal health information, such as care received, test results, or upcoming medical appointments." Responses for each item are coded 1 = yes and 0 = no.

We have two key independent variables. *Gender* is measured as 1 = female. *Rural* is measured using the 2003 rural-urban continuum (RUC) codes created by the U.S. Department of Agriculture's Economic Research Service. The RUC code was created using 2000 U.S. Census data to classify counties as one of nine types ranging from 1 (*counties in metro areas of 1 million population or more*) to 9 (*completely rural or less than 2,500 urban population, not adjacent to a metro area*) (U.S. Department of Agriculture, 2007). As a result of the small number of rural participants, we have recoded all nonmetropolitan counties (RUC codes 4–9) as rural = 1, and metropolitan counties (RUC codes 1–3) as urban = 0 (the reference category).

We have several control variables. These include *marital status* (married; other), *children in household* (1 or more children in the household; none), *race/ethnicity*[1] (non-Hispanic White; other), *occupational status* (employed; other), *age* in years (18–34; 35–49; 50–64; 65–74; 75 and older), *education* (high school graduate or less education; some college; college graduate), and *household income* (less than \$20,000; \$20,000 to

[1]Although African Americans and Hispanics comprise a relatively large number of observations (687 and 622, respectively), few live in rural areas (85 and 44, respectively) and few report engaging in online health activities. This necessitated collapsing all non-White racial/ethnic groups into one category.

less than \$35,000; \$35,000 to less than \$50,000; \$50,000 to less than \$75,000; \$75,000 or more).

Two measures of health status are included, *poor or fair health* and *serious psychological distress*, to ensure that health status is not confounding our results. *Poor or fair health* is measured by a single question that asks, "In general, would you say your health is …?" Responses were recoded to create a dichotomous variable with 1 = poor or fair health and 0 = good, very good, or excellent health. *Serious psychological distress* is a dichotomous variable created from the Kessler K6 scale that assesses frequency of depressive symptoms during the past 30 days (see Kessler et al., 2002). Serious psychological distress is indicated by a score of 13–24 (Kessler et al., 2004) and coded as 1; a score of 0–12 is coded as 0.

Last, we include two other independent variables. The variable *who looking for* is included as a series of indicator variables constructed from the question, "The most recent time you looked for information about health or medical topics was it for …?" In Table 2, three indicator variables were constructed to measure who one last looked for health information: *yourself* (the reference category), *someone else*, or *both*. In Tables 3 and 4 not all participants have ever looked for health information. Therefore, we created four indicator variables: *looked for yourself* (the reference category), *never looked for health information*, *looked for someone else*, and *both (looked for self and others)*. We also control for Internet connection through including the variable *broadband* coded as 1 = a cable or satellite modem or a DSL modem and 0 = a telephone modem, a wireless device, or other.

Analytic Strategy

We begin the multivariate analyses by using logistic regression to examine respondents' use of online health resources versus other sources of information. We use five additive models, adding theoretically based blocks of factors. The next two tables (see the Results section) address the effect of rurality, gender, sociodemographics, health status, and connection type on specific types of online health activities. Because we are interested in how relationships may differ by gender, we tested interactions between gender and all of the independent variables: most important, Gender × Rural. We include the Gender × Rural interaction term in all models and other interaction terms that are significant at the $p < .01$ level. The results are presented as exponentiated coefficients, or odds ratios, with standard errors in parentheses. When the odds ratios ($\text{Exp}(\beta)$) are below 1 this indicates that the probability of searching for online health information versus other sources is reduced by the independent variable (e.g., see Table 2 in the Results section). In contrast, when the odds ratios are above 1, this indicates that the probability of searching for online health information versus other sources is increased based on the levels of the independent variable.

Results

Table 1 provides descriptive statistics for the health seeker and Internet user samples. The most frequently reported online health activities among health seekers and Internet users were (a) using a website to assist with diet, weight, or physical activity (35.5% and 38.4%); and (b) searching for information on a health care provider (31.9% and 35.3%). Among health seekers, 48.9% reported looking for health information for themselves, 22.8% for someone else, and 28.3% reported looking for health

Table 1. Descriptive information from the Health Information National Trends Survey 2007

Variable	Health seekers ($n = 4{,}959$) %	Health seekers ($n = 4{,}959$) n	Internet users ($n = 4{,}535$) %	Internet users ($n = 4{,}535$) n
Where last sought health information				
Online	63.0	2,970	61.1	2,871
Doctor, printed materials, other	37.0	1,989	21.0*	1,084
Online health activities				
Buy medicine	13.0	731	14.4	780
Support group	4.5	204	4.8	216
Talk with doctor	12.9	650	13.8	677
Diet, weight, physical activity	35.5	1,608	38.4	1,699
Provider	31.9	1,480	35.3	1,579
Personal health record	11.8	643	13.8	705
Location				
Rural	16.1	875	14.8	743
Urban	83.9	4,084	85.2	3,792
Gender				
Female	55.5	3,165	52.4	2,791
Male	44.5	1,794	47.6	1,744
Age (years)				
18–34	29.6	739	36.5	844
35–49	30.9	1,305	32.2	1,341
50–64	25.7	1,742	23.6	1,619
65–74	7.9	707	5.4	530
75+	5.9	466	2.3	201
Race/ethnicity				
Non-White	25.2	1,017	24.7	886
White	74.8	3,942	75.3	3,649
Marital status				
Married	61.2	3,103	59.8	2,932
Not married	38.8	1,856	40.2	1,603
Children in household				
One or more children	40.3	1,521	44.0	1,571
No children	59.7	3,438	56.0	2,964
Occupational status				
Employed	61.3	2,788	65.8	2,835
Not employed	38.7	2,171	34.2	1,700
Education				
High school graduate or less	29.8	1,212	27.5	919
Some college	38.7	1,591	39.8	1,474
College graduate	31.5	2,156	32.7	2,142
Household income				
Less than $20,000	14.4	669	11.0	444
$20,000 to <$35,000	14.3	727	12.8	574

(*Continued*)

Table 1. Continued

Variable	Health seekers ($n = 4{,}959$) %	Health seekers ($n = 4{,}959$) n	Internet users ($n = 4{,}535$) %	Internet users ($n = 4{,}535$) n
$35,000 to <$50,000	13.6	666	14.2	598
$50,000 to <$75,000	21.4	1,015	22.9	1,003
$75,000 or more	36.4	1,882	39.1	1,916
Home Internet connection				
Broadband	57.4	2,760	69.2	3,119
Dial-up, other, or no Internet	42.6	2,199	30.8	1,416
Self-rated health				
Excellent, very good, good	85.0	4,258	88.2	4,041
Poor, fair	15.0	701	11.8	494
Psychological distress				
Distressed	6.7	270	5.4	211
Not distressed	93.3	4,689	94.6	4,324
Who look for				
Look for yourself	48.9	2,446	38.7	1,872
Look for someone else	22.8	1,146	20.4	1,031
Look for both	28.3	1,367	22.9	1,052
Has never looked for health info	0.0	0	17.9	580

Note. Percentages may not total 100 because of rounding errors. Weighted percentages estimated using final sample and 100 replicate weights.

*Does not total 100% because 17.9% have "never looked for health information."

information for themselves and for others. About 18% of Internet users have never looked for health information from any source.

Multivariate Analyses

Table 2 presents odds ratios from the multivariate analyses examining respondents' use of online health resources versus other sources of information. The first logistic regression model contains rural and gender variables, along with control variables. Rural residents are significantly less likely to use online health resources versus other sources of information ($\text{Exp}(\beta) = 0.583$, $p < .001$) and women are more likely than men to do so ($\text{Exp}(\beta) = 1.192$, $p < .05$). In addition, age plays a significant role; the older one gets the less likely he or she is to use online health resources. In the second model, we add traditional variables associated with the digital divide, educational attainment and household income. Both variables have a positive relation with our dependent variable and reach significance. Rurality and gender both remain significant in this model.

The third model in Table 2 includes several questions concerning self-health appraisal and whether one searched for themselves or others. The relations for rurality and gender remain the same.

The fourth model includes broadband Internet access, which is positively and significantly related to use of online health resources ($\text{Exp}(\beta) = 3.177$, $p < .001$). Rurality falls from significance yet gender does not. This may indicate that rural residents with broadband Internet access do not differ from their suburban and urban counterparts.

Table 2. Online health information seeking versus other sources regressed on location, sociodemographics, health status, and connection type

	Model 1	Model 2	Model 3	Model 4	Model 5
Rural	0.583*** (0.068)	0.697** (0.078)	0.697** (0.078)	0.831 (0.095)	0.876 (0.151)
Female	1.192* (0.104)	1.260* (0.118)	1.263* (0.120)	1.292* (0.128)	1.789*** (0.246)
Age (years)					
35–49	0.767† (0.107)	0.694* (0.097)	0.687** (0.096)	0.768† (0.112)	0.773† (0.112)
50–64	0.472*** (0.064)	0.442*** (0.062)	0.439*** (0.062)	0.485*** (0.066)	0.488*** (0.066)
65–74	0.207*** (0.035)	0.208*** (0.038)	0.206*** (0.037)	0.259*** (0.047)	0.258*** (0.047)
75+	0.076*** (0.016)	0.078*** (0.017)	0.077*** (0.016)	0.112*** (0.024)	0.238*** (0.073)
Race, non-White	0.513*** (0.059)	0.598*** (0.073)	0.607*** (0.073)	0.700** (0.092)	0.702** (0.093)
Married	1.227* (0.107)	0.986 (0.104)	0.980 (0.102)	0.923 (0.099)	0.910 (0.095)
Child in household	1.014 (0.141)	1.039 (0.145)	1.036 (0.147)	0.987 (0.146)	0.985 (0.144)
Employed	1.291* (0.134)	1.073 (0.116)	1.067 (0.113)	1.092 (0.128)	1.101 (0.130)
Education					
Some college		1.781*** (0.221)	1.794*** (0.227)	1.643*** (0.221)	1.633*** (0.219)
College graduate		1.962*** (0.231)	1.954*** (0.234)	1.599*** (0.198)	1.563*** (0.193)
Household income					
\$20,000 to <\$35,000		1.180 (0.235)	1.187 (0.239)	1.099 (0.217)	1.127 (0.221)
\$35,000 to <\$50,000		2.809*** (0.444)	2.780*** (0.454)	2.443*** (0.399)	2.471*** (0.398)
\$50,000 to <\$75,000		2.150*** (0.395)	2.132*** (0.396)	1.762** (0.347)	1.823** (0.362)
\$75,000 or more		2.430*** (0.400)	2.403*** (0.406)	1.832*** (0.323)	2.579*** (0.552)
Poor or fair self-rated health			1.096 (0.151)	1.201 (0.169)	1.212 (0.171)
Psychological distress			0.839 (0.167)	0.862 (0.189)	0.857 (0.187)
Who did you last look for?					
Looked for someone else			1.158 (0.148)	1.135 (0.148)	0.891 (0.156)
Looked for both			0.901 (0.108)	0.909 (0.114)	0.884 (0.113)
Broadband Internet access				3.177*** (0.307)	4.208*** (0.738)
Female × Rural					0.908 (0.200)

(*Continued*)

Table 2. Continued

	Model 1	Model 2	Model 3	Model 4	Model 5
Female × Age 75+					0.281*** (0.092)
Female × Broadband Internet Access					0.606* (0.123)
Mail Mode × Household Income <$20,000					0.583* (0.124)
Mail Mode × Look for Someone Else					1.604* (0.378)
Mail mode	0.580*** (0.050)	0.594*** (0.050)	0.601*** (0.052)	0.602*** (0.050)	0.656** (0.086)

Note. Health Information National Trends Survey 2007 health information seekers ($n = 4,959$). Model 1 variables measure place, demographics, children in household, and employment status; Model 2 adds variables measuring level of education and household income; Model 3 adds variables measuring participant's health status and who they last looked for health information; Model 4 measures speed of Internet connection; Model 5 adds the gender and place interaction term, all statistically significant interactions, and a dichotomous variable indicating survey mode. Results are presented as exponentiated coefficients or odds ratios, standard errors are in parentheses. Analysis conducted using the sample and 100 replicate weights.

$^{\dagger}p < .10$. $^{*}p < .05$. $^{**}p < .01$. $^{***}p < .001$.

The fifth model in Table 2 includes interaction terms for gender and place and all other significant interaction effects. Gender is still significant, meaning women are more likely than men to use online health resources (Exp(β) = 1.789, $p < .001$). Age, education, income, and broadband Internet access remain significant. The interaction of gender and place is not significant. The interaction for age and gender suggests that among women, those older than 74 years of age are less likely to use online resources. The interaction for female and broadband Internet access is significant (Exp(β) = 0.606, $p < .05$).

In Tables 3 and 4 we present findings from models that assess the effect of rurality, gender, sociodemographics, health status, connection type, and interactions on specific types of online health activities. Starting with buying medicine (first two models of Table 3), we find that age, income, and having broadband Internet access are positively and significantly related to this type of use; however, people with a child in the home are significantly less likely to buy medicines online (Exp(β) = 0.734, $p < .05$). Rurality and gender are not related to this use of the Internet. When the interaction effects are included in the model, we find that among women, those aged 65–74 years are less likely to buy medicines online (Exp(β) = 0.445, $p < .05$).

Turning to participation in an online support group, only psychological distress, searching for information for yourself and others, and poor health self-rating reach significance at conventional levels (Exp(β) = 2.355, $p < .05$; Exp(β) = 1.995, $p < .01$; and Exp(β) = 3.028, $p < .001$, respectively). Rurality is unrelated to this use, but women are more likely to participate in online health support groups (Exp(β) = 1.478, $p < .10$). The interaction of gender and place is not significant in Model 2.

Looking at the final model in Table 3, rural residents are significantly less likely than are their suburban and urban counterparts to use a website to help with dieting, physical activity and exercise (Exp(β) = 0.579, $p < .05$); however, women are much more likely than men (Exp(β) = 1.610, $p < .05$). The interaction between female and broadband Internet access is again significant (Exp(β) = 0.599, $p < .05$), suggesting that the effects of broadband Internet access are less influential for women. Age is negatively related to this use (Exp(β) = 0.227, $p < .001$, for 75 years or older), whereas education is positively related (Exp(β) = 1.723, $p < .001$, for college graduates).

In Table 4, we find that women are significantly less likely to talk to their doctors online (Exp(β) = 0.652, $p < .05$), and the interaction shows that this is especially true for women aged 65–74 (Exp(β) = 0.416, $p < .05$). In addition, people who are searching for health information for others are significantly more likely to talk to doctors online (Exp(β) = 1.528, $p < .001$) compared to people who only search for information for themselves.

Regarding searching for information on a health provider online in Table 4, rurality is negatively related to this use (Exp(β) = 0.477, $p < .01$). Being married, achieving higher levels of education, having higher household income, and suffering from psychological distress are all positively and significantly related to searching for information on a health provider, while age is negatively related. Women ages 35–49 years are less likely to search online for information about providers compared to other women (Exp(β) = 0.631, $p < .05$). The *rural × look for someone else* interaction term shows people living in rural areas are more likely to be looking online for information about a provider compared to people in suburban and urban areas (Exp(β) = 1.784, $p < .05$).

Neither rurality nor gender is related to using online personal health records. Older adults ages 75 years and over are more likely to use online personal health records (Exp(β) = 2.172, $p < .01$), whereas having children in the home has a negative relationship

Table 3. Online health activities regressed on location, sociodemographics, health status, and connection type

	Buy medicine		Support group		Diet	
	Model 1	Model 2	Model 1	Model 2	Model 1	Model 2
Rural	0.990 (0.153)	1.079 (0.297)	1.419 (0.436)	0.703 (0.662)	0.706** (0.092)	0.579* (0.123)
Female	0.956 (0.113)	1.029 (0.142)	1.478† (0.316)	1.311 (0.312)	1.152 (0.116)	1.610* (0.333)
Age (years)						
35–49	1.507† (0.322)	1.510† (0.322)	1.260 (0.367)	1.263 (0.371)	0.922 (0.103)	0.922 (0.104)
50–64	2.374*** (0.412)	2.377*** (0.413)	0.877 (0.229)	0.890 (0.235)	0.675** (0.088)	0.673** (0.088)
65–74	1.910** (0.408)	2.765*** (0.752)	0.508† (0.198)	0.526 (0.204)	0.466*** (0.086)	0.464*** (0.088)
75+	3.010*** (0.769)	3.016*** (0.771)	0.217† (0.189)	0.220† (0.192)	0.228*** (0.069)	0.227*** (0.069)
Race, non-White	1.101 (0.189)	1.098 (0.189)	0.972 (0.247)	0.979 (0.247)	1.316* (0.167)	1.329* (0.169)
Married	1.188 (0.185)	1.172 (0.184)	0.748 (0.186)	0.748 (0.187)	0.943 (0.114)	0.962 (0.115)
Child in household	0.735* (0.104)	0.734* (0.104)	1.015 (0.228)	1.021 (0.228)	0.911 (0.096)	0.901 (0.094)
Employed	1.000 (0.144)	1.004 (0.145)	0.832 (0.223)	0.836 (0.225)	1.140 (0.131)	1.135 (0.130)
Education						
Some college	1.246 (0.214)	1.243 (0.213)	2.044† (0.768)	2.023† (0.761)	1.539** (0.225)	1.517** (0.222)
College graduate	1.255 (0.200)	1.241 (0.198)	1.714 (0.662)	1.713 (0.668)	1.743*** (0.231)	1.723*** (0.230)
Household income						
$20,000 to <$35,000	1.540 (0.427)	1.536 (0.427)	0.949 (0.402)	0.964 (0.408)	0.977 (0.216)	0.992 (0.220)
$35,000 to <$50,000	1.770† (0.551)	1.752† (0.542)	1.109 (0.559)	1.118 (0.567)	0.998 (0.218)	1.008 (0.221)

$50,000 to <$75,000	1.961* (0.524)	1.955* (0.522)	0.981 (0.415)	0.996 (0.418)	1.201 (0.236)	1.216 (0.239)
$75,000 or more	2.048** (0.534)	2.048** (0.534)	1.154 (0.530)	1.153 (0.530)	1.124 (0.219)	1.131 (0.221)
Poor or fair self-rated health	1.038 (0.167)	1.039 (0.167)	3.028*** (0.796)	3.007*** (0.792)	1.230 (0.197)	1.230 (0.196)
Psychological distress	1.191 (0.346)	1.177 (0.343)	2.355* (0.803)	2.368* (0.802)	1.489 (0.379)	1.500 (0.377)
Who did you last look for?						
Never looked for health information	0.565* (0.152)	0.568* (0.153)	0.553 (0.255)	0.549 (0.252)	0.244*** (0.045)	0.242*** (0.045)
Looked for someone else	0.987 (0.129)	0.995 (0.130)	1.424 (0.360)	1.423 (0.360)	0.719** (0.087)	0.718** (0.087)
Looked for both	1.215 (0.164)	1.218 (0.164)	1.995** (0.422)	1.986** (0.427)	1.112 (0.150)	1.100 (0.148)
Broadband Internet Access	1.932*** (0.289)	1.941*** (0.291)	1.315 (0.310)	1.321 (0.314)	1.337* (0.160)	1.810** (0.382)
Female × Rural		0.854 (0.267)		2.500 (2.253)		1.356 (0.350)
Female × Age 65–74		0.445* (0.143)				
Female × Broadband Internet Access						0.599* (0.137)

Note. Health Information National Trends Survey 2007 Internet users ($n = 4,535$). For each of the dependent variables above, Model 1 variables measure place, demographics, whether there are children in the household, employment status, level of education, household income, health status, who they last looked for health information, and speed of Internet connection; Model 2 adds the gender and place interaction term and all significant interactions. Preliminary tests indicated no statistically significant mode effect for these dependent variables. Therefore, the models do not include a mode variable or mode interactions. Results are presented as exponentiated coefficients or odds ratios, standard errors are in parentheses. Analysis conducted using the sample and 100 replicate weights.

$^{\dagger}p < .10$. $^{*}p < .05$. $^{**}p < .01$. $^{***}p < .001$.

Table 4. Online health activities regressed on location, sociodemographics, health status, and connection type

	Talk doctor		Provider		Personal health records	
	Model 1	Model 2	Model 1	Model 2	Model 1	Model 2
Rural	0.724† (0.124)	0.937 (0.250)	0.628*** (0.086)	0.477** (0.112)	0.726 (0.145)	0.825 (0.279)
Female	0.899 (0.118)	0.652* (0.125)	1.074 (0.101)	1.226 (0.156)	0.821 (0.105)	0.843 (0.117)
Age (years)						
35–49	0.944 (0.194)	0.955 (0.196)	0.958 (0.134)	1.228 (0.220)	1.120 (0.191)	1.119 (0.191)
50–64	0.767 (0.136)	0.776 (0.138)	0.568*** (0.078)	0.564*** (0.078)	0.978 (0.178)	0.976 (0.178)
65–74	0.983 (0.224)	1.446 (0.462)	0.318*** (0.057)	0.316*** (0.057)	1.263 (0.331)	1.258 (0.328)
75+	0.896 (0.318)	0.898 (0.329)	0.168*** (0.057)	0.341* (0.153)	2.179** (0.609)	2.172** (0.610)
Race, non-White	1.197 (0.181)	1.207 (0.185)	1.244† (0.158)	1.243† (0.157)	1.524** (0.225)	1.523** (0.226)
Married	1.215 (0.201)	1.211 (0.201)	1.262* (0.143)	1.261* (0.143)	1.281 (0.210)	1.282 (0.211)
Child in household	0.996 (0.159)	0.991 (0.157)	0.889 (0.103)	0.890 (0.103)	0.698* (0.103)	0.698* (0.103)
Employed	0.898 (0.143)	0.900 (0.142)	1.183 (0.125)	1.170 (0.124)	0.843 (0.122)	0.841 (0.121)
Education						
Some college	1.065 (0.251)	1.075 (0.256)	1.445* (0.206)	1.428* (0.203)	1.327 (0.259)	1.329 (0.261)
College graduate	1.546† (0.351)	1.554† (0.354)	2.269*** (0.316)	2.273*** (0.317)	1.660** (0.287)	1.660** (0.287)
Household income						
$20,000 to <$35,000	0.745 (0.272)	0.765 (0.282)	1.448† (0.310)	1.434† (0.304)	0.895 (0.237)	0.893 (0.236)
$35,000 to <$50,000	0.954 (0.346)	0.962 (0.352)	1.653* (0.324)	1.672** (0.327)	1.162 (0.321)	1.161 (0.321)
$50,000 to <$75,000	0.981 (0.296)	0.978 (0.297)	1.516* (0.292)	1.515* (0.289)	0.750 (0.194)	0.748 (0.193)
$75,000 or more	1.464 (0.427)	1.482 (0.434)	1.618** (0.277)	1.627** (0.279)	0.965 (0.254)	0.966 (0.254)

Poor or fair self-rated health	1.431 (0.317)	1.418 (0.318)	0.947 (0.178)	0.946 (0.178)	1.234 (0.254)	1.235 (0.254)
Psychological distress	0.701 (0.190)	0.686 (0.181)	2.150** (0.503)	2.126** (0.497)	1.308 (0.394)	1.308 (0.396)
Who did you last look for?						
Never looked for health information	0.352*** (0.093)	0.350*** (0.093)	0.497*** (0.090)	0.490*** (0.089)	0.839 (0.208)	0.841 (0.209)
Looked for someone else	1.498** (0.223)	1.528** (0.223)	1.413** (0.182)	1.309* (0.177)	1.261† (0.170)	1.264† (0.170)
Looked for both	1.339† (0.220)	1.332† (0.218)	1.273† (0.173)	1.278† (0.173)	1.090 (0.175)	1.092 (0.176)
Broadband Internet Access	1.358* (0.192)	1.327† (0.191)	1.262† (0.150)	1.263† (0.151)	1.500* (0.249)	1.498* (0.248)
Female × Rural		0.614 (0.212)		1.252 (0.332)		0.789 (0.318)
Female × Age 65–74		0.416* (0.162)				
Mail Mode × Female		2.432*** (0.615)				
Female × Age 35–49				0.631* (0.116)		
Mail Mode × Age 75+				0.213* (0.138)		
Rural × Look for Someone Else				1.784* (0.488)		
Mail mode	0.730** (0.086)	0.458*** (0.084)	1.309* (0.144)	1.324* (0.146)	0.656*** (0.081)	0.657*** (0.081)

Note. Health Information National Trends Survey 2007 Internet users ($n = 4{,}535$). For each of the dependent variables, Model 1 variables measure place, demographics, whether there are children in the household, employment status, level of education, household income, health status, who they last looked for health information, and speed of Internet connection; Model 2 adds the gender and place interaction term and all significant interactions. Preliminary tests indicated statistically significant mode effects for each dependent variable. Therefore, the models include a mode variable and all significant mode interactions. Results are presented as exponentiated coefficients or odds ratios, standard errors are in parentheses. Analysis conducted using the sample and 100 replicate weights.

†$p < .10$. *$p < .05$. **$p < .01$. ***$p < .001$.

to this type of activity (Exp(β) = 0.698, $p < .05$). In addition, broadband Internet access and education (i.e., college graduate) are positively and significantly related to using online personal health records (Exp(β) = 1.498, $p < .05$; Exp(β) = 1.660, $p < .01$).

Discussion

This study examines how gender and place are related to online health activities, a combined area neglected in prior research. Our results suggest that these relations vary depending upon specific types of online health activities. Also, they suggest that gender may be a more salient factor than rurality in whether individuals engage in particular types of online health activities, advancing research on gender and technology.

Rural residents were less likely to report searching for information on a health care provider and using a website to assist with diet, weight, or physical activity (Tables 3 and 4). Given that rural residents have less access to providers and may be less likely to talk to providers about stigmatized illnesses (e.g., Hoyt et al., 1997), engaging in online health activities could be beneficial; however, it appears that for various reasons they are not fully benefitting from these resources. Broadband Internet access seems to be the key.

Rural residence is only associated with online health information seeking until broadband Internet access is added to the model (Table 2). This suggests that individuals from rural and urban areas who have broadband Internet access are equally likely to search for online health information. Prior research has shown that broadband Internet connection is one of the strongest predictors of online activities (Collins & Wellman, 2010; Davison & Cotten, 2009; Stern et al., 2009). Thus, it is not surprising that this factor negated the importance of rurality in online health information seeking. By looking at not just place but also gender, we find that broadband Internet access seems to be less important for women. Among women, those with broadband Internet access were less likely to turn to the Internet first for health information and less likely to use a website for assistance with diet, weight, or physical activity. This increases our knowledge of how gender and technology are related.

Supporting our hypothesis, women were more likely than men to use online health resources versus other sources of information (Table 2), and more likely to use a website for help with their diet, weight, or physical activity (Table 3). Women were significantly less likely to communicate with a physician online. Thus, our results lend partial support to past research, which has stressed that women are the health care gatekeepers of the family (Litt, 2000; Stern et al., 2012). Our research advances work in this area by providing a more nuanced understanding of women's roles in U.S. society and how this relates to online health activities.

We had hoped that rural women would make greater use of the Internet for health-related activities to overcome the barriers to accessing care and isolation; however, this was not the case. Thus, our article speaks to the possibilities of how rural women could use the Internet for health purposes, rather than the reality of how they actually use it. There is a mismatch between needs and behavior. When thinking about rurality, we must think about gender and all of the crisscrossing intersections of one's social location, including poverty, age, race, education, broadband Internet access, health literacy, and computer literacy in order to target computer health usage to rural men and women (Norris et al., 2010).

There are several policy implications. We need to continue supporting initiatives to expand broadband Internet access and Internet literacy in rural locations (Institute of

Medicine, 2005). Swanson and Brown (2003, p. 399) argued that we need "policies that enhance the capacity of rural people and communities to help themselves … [which] makes sense in the context of current institutional neglect." Improving broadband Internet access should allow more rural residents to use the Internet for health-related information and communication to achieve this goal. However, providing broadband Internet access alone is not sufficient for ensuring that rural individuals, especially women, can sufficiently use the Internet for health purposes. Eighty-seven million adults have a hard time understanding health information (Powell, 2009), especially those who are older, less affluent and from rural areas (Kreps, 2005; Oldfield & Dreher, 2010). Given that lower health literacy is associated with poorer health outcomes (Berkman et al., 2011), ensuring that individuals can find, understand, and apply health information will be important for decreasing health disparities as more information moves online (Birru & Steinman, 2004).

There is certainly a need for good health information, and more work should be done to tailor the information to rural populations and their lifestyle, education and literacy levels. For example, Atkinson and colleagues' (2009) ground-breaking work addresses this content gap in information by involving rural women in creating health websites to meet their interests and needs. This is a step in the right direction. As most who turn to the Internet for health information tend to be younger and of higher socioeconomic status, we should think about how to engage those who are older and less affluent as they tend to be less healthy (Koch-Weser, Bradshaw, Gualtieri, & Gallagher, 2010). Designing interventions to increase health literacy training of these populations and providing tailored information for these groups may do more to ameliorate health and digital inequalities than simply providing Internet and broadband Internet access.

Given the mismatch between needs and usage, these initiatives should be coupled with efforts to strengthen the health care infrastructure in rural communities. This includes addressing provider shortages through a variety of mechanisms such as monetary incentives (Rosenblatt et al., 2006), and making health care more accessible through innovative strategies such as electronic health records, telemedicine, and mobile clinics (Brems et al., 2006; Effken & Abbott, 2009; Institute of Medicine, 2005; Sherrill et al., 2005; Winbush & Crichlow, 2005).

There are several study limitations. First, the response rate is low, which could affect generalizability of our results. This problem is not unique to HINTS, but it reflects a general decline in the response rate to surveys (Keeter, Kennedy, Dimock, Best, & Craighill, 2006). To address this problem, the 2007 HINTS used a dual mode design consisting of a mail and random digit dialing survey. The mail survey is intended to increase the response rate and reduce coverage error. This strategy does help ameliorate some of the issues threatening generalizability, and is preferable to surveys administered only through random digit dialing. Also, we used the final sample weights recommended by National Cancer Institute, which reduces the magnitude of nonresponse bias and calibrates estimates on key demographic characteristics to known population parameters.

Second, we do not know whether respondents found the online health activities beneficial, overwhelming, confusing, and so forth. It is important to examine perceptions of online health information, which differ by gender and locality (Larson, 2007; Royal, 2008; Stern et al., 2012), because this will affect usage.

Last, we need more information on the diversity between rural communities. Brems and colleagues (2006) find greater health barriers in smaller rural areas. The

Institute of Medicine (2005) noted differences caused by race/ethnicity, remoteness, and economic characteristics. Future research may reveal other differences.

In summary, our research has peeled back one layer of this complex and ever-changing story to better understand how gender and place are related to online health activities. Our research suggests that Internet use alone is not sufficient for eliminating health disparities among those in rural areas or for women. Although individuals in rural areas should potentially benefit the most from the use of online health activities, past research shows that they are disadvantaged in other ways, particularly health literacy. The Internet is not an elixir that can eliminate disparities; it is merely a tool that can be used. Future research should explore the extent to which making new health information technologies available, increasing technological literacy, and tailoring the Internet to specific groups may help to ameliorate some of the health disparities rural women and other groups experience, especially as technologies evolve.

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