American Journal of Men's Health
2018, Vol. 12(5) 1358–1367

DOI: 10.1177/1557988316650625
journals.sagepub.com/home/jmh
SAGE

Examining the Correlates of Online Health Information–Seeking Behavior Among Men Compared With Women

Irene A. Nikoloudakis, B.Com[1], Corneel Vandelanotte, PhD[2], Amanda L. Rebar, PhD[2], Stephanie Schoeppe, PhD[2], Stephanie Alley, B(Psyc)[2], Mitch J. Duncan, PhD[3], and Camille E. Short PhD[1]

Abstract

This study aimed to identify and compare the demographic, health behavior, health status, and social media use correlates of online health-seeking behaviors among men and women. Cross-sectional self-report data were collected from 1,289 Australian adults participating in the Queensland Social Survey. Logistic regression analyses were used to identify the correlates of online health information seeking for men and women. Differences in the strength of the relation of these correlates were tested using equality of regression coefficient tests. For both genders, the two strongest correlates were social media use (men: odds ratio [*OR*] = 2.57, 95% confidence interval [CI: 1.78, 3.71]; women: *OR* = 2.93, 95% CI [1.92, 4.45]) and having a university education (men: *OR* = 3.63, 95% CI [2.37, 5.56]; women: *OR* = 2.74, 95% CI [1.66, 4.51]). Not being a smoker and being of younger age were also associated with online health information seeking for both men and women. Reporting poor health and the presence of two chronic diseases were positively associated with online health seeking for women only. Correlates of help seeking online among men and women were generally similar, with exception of health status. Results suggest that similar groups of men and women are likely to access health information online for primary prevention purposes, and additionally that women experiencing poor health are more likely to seek health information online than women who are relatively well. These findings are useful for analyzing the potential reach of online health initiatives targeting both men and women.

Keywords

health information seeking, Internet, gender, correlates

In the past decade, there has been a substantial emphasis toward empowering patients to become proactive participants in their health care (Kontos, Blake, Chou, & Prestin, 2014). This involves being able to make informed decisions regarding one's illnesses, treatments, and health behaviors (Salmon & Hall, 2004). Alongside this movement, information technology has continued to evolve with the development of highly interactive websites and applications creating a plethora of opportunities for informational and communicative needs to be satisfied through the Internet (Kontos et al., 2014). With the interplay of these two momentums, it is therefore unsurprising that large numbers of individuals are turning to the Internet to search for health information (Andreassen et al., 2007; Fox & Jones, 2009; Kontos et al., 2014). This presents a unique health promotion opportunity for broader audiences to be reached for both primary and tertiary prevention. To capitalize on this opportunity, an understanding of the characteristics of those seeking health information online is necessary (Andreassen et al., 2007). This will allow for the development and delivery of more targeted online services.

To date, the majority of research examining individual characteristics associated with seeking health information online has focused on sociodemographic factors. According to this research, being female (Carpenter et al., 2011; Hallyburton & Evarts, 2014; Powell, Inglis, Ronnie, & Large, 2011; Stern, Cotten, &

[1]University of Adelaide, Adelaide, South Australia, Australia
[2]Central Queensland University, Rockhampton, Queensland, Australia
[3]The University of Newcastle, Callaghan, New South Wales, Australia

Corresponding Author:
Camille E. Short, Level 7, South Australian Health Medical Research Institute, North Terrace, Adelaide, South Australia 5000, Australia.
Email: camille.short@adelaide.edu.au

Drentea, 2012; Thackeray, Crookston, & West, 2013), having a higher income and education (Cotten & Gupta, 2004; Kontos et al., 2014; Shahab, Brown, Gardner, & Smith, 2014), being married or in a de facto relationship (Hallyburton & Evarts, 2014), being of younger age (Andreassen et al., 2007; Bansil, Keenan, Zlot, & Gilliland, 2006; Kontos et al., 2014), living outside of an urban area (Ruggiero, Gros, McCauley, de Arellano, & Danielson, 2011), and having access to the Internet both at work and home (Atkinson, Saperstein, & Pleis, 2009) are associated with health information seeking online. Associations between some behavioral and health characteristics with online help seeking have also been investigated, though to a lesser extent. The existing evidence suggests that health status is an important correlate of online health information seeking (Houston & Allison, 2002), as is online behavior, such as utilizing social media and social networking sites (Feng & Xie, 2015). Health-related behaviors, however, such as physical activity, diet, alcohol consumption, and smoking, have not consistently been reported to be associated with online health information–seeking behavior (Shahab et al., 2014). This is surprising, given the link between health behaviors and health conditions.

While the above research provides some insight into the characteristics of online health information seekers overall, information relating to particular subgroups is lacking. In particular, the extent to which the correlates of health seeking among women and men differ, if at all, is currently unknown. This is an important consideration, given that current evidence overwhelmingly suggests that men and women exhibit different patterns of help seeking in the community, in part due to different influences on their behavior and health (Carpenter et al., 2011; Hallyburton & Evarts, 2014; Powell et al., 2011; Stern et al., 2012; Thackeray et al., 2013). As a consequence of this, there have been recent calls for more gendered approaches to health promotion, especially in regard to men (Lohan, Aventin, Oliffe, Han, & Bottorff, 2015). To inform such approaches in an online setting, a greater understanding of the correlates of help seeking among men relative to women is needed. The present study therefore aims to examine possible correlates of online health information seeking among men and women separately and to determine whether these correlates differ significantly from each other. This research is timely, given that men are increasingly turning to the Internet to seek health information, and since online health promotion initiatives targeting men are growing in popularity in recognition of this trend (Lohan et al., 2015).

Method

Participants and Procedure

Cross-sectional self-report data were collected between July and August 2013 as part of the Queensland Social Survey (QSS). This is an annual omnibus statewide survey conducted by the Population Research Laboratory at Central Queensland University. The QSS covers a range of topics including sociodemographic, health behaviors, and health status. Trained interviewers and a computer-assisted telephone interviewing system were used to contact a random sample of adults aged 18 years or older residing in Queensland, Australia. The overall response rate of the QSS was 41.2% (n = 1,293). Further details regarding the sampling and interview procedures employed have been published elsewhere (Duncan, Gilson, & Vandelanotte, 2014). Before the QSS was administered to the general public, approval by the Human Ethics Research Review Panel at the Central Queensland University was obtained.

Measures

Online Health Information Seeking. The primary variable of interest, online health information seeking, was assessed by a single item: "Have you ever used the Internet to look for health information?" (response options: 1 = *yes*, 2 = *no*, 3 = *do not use/have access to the Internet*). Responses were dichotomized into 1 "has sought health information online" (Option 1) and 0 "has not sought health information online" (Options 2-3). The source of information accessed online was assessed using a single item "Which of the following types of site have you used to seek health-related information (select all that apply)," with response options: government department website, health organization website (nongovernment), online group forum or discussion groups, blogging site, social networking site (e.g., Facebook), media sharing sites (e.g., YouTube), none of these.

Demographic Variables. Demographic variables included age, marital status ("married/defacto," "other"), level of education ("high school or below," "technical school," "university"), household income ("<AUD $52,000" and "≥AUD $52,000," based on the Australian Taxation Department's criteria of eligibility for low-income tax offsets), and geographical location ("major city" and "nonmajor city"). Self-reported postcodes were used to classify participants into their respective geographical location on the basis of the Australian Standard

Geographical Classification system (Australian Bureau of Statistics, 2005; Australian Institute of Health and Welfare, 2004), which has been used in previous research (Short, Vandelanotte, Rebar, & Duncan, 2014).

Health Behavior Variables. Fruit intake was assessed using a single item: "How many serves of fruit do you eat on a usual day?" Participants were considered to have a sufficient fruit intake if they satisfied the National Dietary Guidelines of consuming two or more serves of fruit on a typical day (National Health and Medical Research Council, 2013).

Vegetable intake was measured by the following item: "How many serves of vegetables do you eat on a usual day?" Participants were considered to have a sufficient vegetable intake if they consumed five or more serves of vegetables on a typical day, based on the National Dietary Guidelines (National Health and Medical Research Council, 2013).

Sitting behavior (hours) was measured using the Workforce Sitting Questionnaire (Chau, van der Ploeg, Dunn, Kurko, & Bauman, 2011). The items addressed the duration of sitting in transport, for work, while using a computer and during leisure activities on both a work and nonwork day. Time spent sitting in each domain was truncated to a maximum of 12 hours a day and the total time spent sitting on a typical work or nonwork day was truncated to 16 hours a day, to exclude time spent sleeping. Participants not in paid employment or who had not worked in the past 7 days reported their sitting time on a "typical day." Participants who had worked in the past 7 days in paid employment reported their sitting time for both a typical work and nonwork day and their daily sitting time was calculated by averaging across the work and nonwork days. The Workforce Sitting Questionnaire has demonstrated adequate test–retest reliability (intraclass correlation coefficient = 0.63) and validity (r = .45; Chau et al., 2011). Time spent sitting was categorized as "≤8 hours sitting" and ">8 hours sitting," with participants in the latter category considered at risk of developing a chronic disease (van der Ploeg, Chey, Korda, Banks, & Bauman, 2012).

Physical activity was measured using the Active Australia Survey (AAQ), which assesses the duration and frequency of participating in walking, moderate intensity activities, vigorous intensity activities, and gardening or yard work. Total physical activity was computed using the following formula: walk time + moderate activity time + (2 × vigorous activity time), which is based on the guidelines for analyzing and reporting AAQ items (Australian Institute of Health and Welfare, 2003). The AAQ has demonstrated good test–retest reliability (intraclass correlation coefficient = 0.64) and validity (r = .61; Fjeldsoe, Winkler, Marshall, Eakin, & Reeves, 2013). Participants were considered sufficiently active for health benefits if they had accumulated at least 150 minutes of total physical activity over 1 week, based on the National Physical Activity Guidelines for Australians (Australian Government, Department of Health, 2014).

Alcohol consumption was assessed using the Alcohol Use Disorders Identification Test, which is a valid and reliable three-item alcohol screen scored on a scale ranging from 0 to 12 (Bush, Kivlahan, McDonell, Fihn, & Bradley, 1998). A higher score indicates more hazardous alcohol consumption. Male participants were classified as potentially hazardous drinkers or having an active alcohol use disorder if they scored four points or more and female participants were classified as potentially hazardous drinkers or having an active alcohol use disorder if they scored three points or more, on the basis of the Alcohol Use Disorders Identification Test guidelines (Bush et al., 1998). Smoking status was assessed using a single item: "Are you presently a smoker (smoked at least one cigarette per day for the past month)?" (yes or no).

Health Status Variables. Global health status was assessed using a single item: "Would you say that in general your health is" (response options: *excellent, very good, good, fair*, or *poor*); and was recoded as *good/excellent* and *fair/poor* (Duncan, Kline, et al., 2014). Height and weight were self-reported and used to calculate body mass index (BMI), according to the following formula: kg/m^2.

Comorbidity status was measured by the item: "Have you ever been told by a doctor that you have any of the following chronic health problems" (response options: *heart disease, high blood pressure, stroke, cancer, depression/anxiety, diabetes, arthritis, chronic back/neck pain, asthma, chronic obstructive pulmonary disease, chronic kidney/renal disease*, and/or *other*). The categories were recoded as: *cardiovascular disease, cancer* (excluding skin cancers other than melanoma), *musculoskeletal disease, respiratory disease*, and *chronic kidney/renal disease* (1 = *yes*, 0 = *no*), based on the largest contributors to the total burden of disease (Australian Institute of Health and Welfare, 2014) and the leading causes of death in Australia (Australian Bureau of Statistics, 2013). Item scores were summed to create a comorbidity index ranging from zero to five.

Social Media Use. Social media use was measured by one item: "How often do you use the Internet to go on social media websites, such as Facebook, YouTube, Blogspot, or Twitter?" (response options: 1 = *at least once every hour*, 2 = *several times each day*, 3 = *once a day*,

Table 1. Type of Site Participants Reported Using to Seek Health Information Online, % (n).

	All health information seekers (n = 844)	Females (n = 429)	Males (n = 415)	p
Government department website	47.75 (403)	46 (198)	49 (205)	.35
Nongovernment/health organization website	80 (672)	77 (329)	83 (343)	.03*
Online group forum or discussion groups	17 (142)	16 (67)	18 (75)	.34
Blogging site	7 (57)	5 (23)	8 (34)	.10
Social networking site (e.g., Facebook)	13 (107)	15 (63)	11 (44)	.08
Media sharing sites (e.g., YouTube)	14 (115)	13 (54)	15 (61)	.37
None of the above	4 (35)	5 (23)	3 (12)	.07

4 = *several times each week*, 5 = *once a week*, 6 = *once a month*, 7 = *less than once a month*, 8 = *never*) and was recoded into a binary variable ("social media users" [Options 1-7] and "social media nonusers" [Option 8]).

Analyses

Descriptive statistics were calculated for the entire sample. Differences in the characteristics of online health seekers and nonhealth seekers were compared using chi-square tests for categorical variables and two-group t tests for continuous variables. Logistic regression models were conducted to determine the demographic, health behavior, health status, and social media use correlates of online health information seeking for men and women separately. Equality of regression coefficient tests were conducted to test for significances between the separate model parameters for men and women (Clogg, Petkova, & Haritou, 1995). Comparison of the estimated regression coefficients were calculated when the correlate variables were significantly associated with the outcome in one or both of the models. p values of less than .05 were considered statistically significant. All analyses were conducted using Stata version 11 (StataCorp, 2009) unless otherwise indicated.

Handling of Missing Data. Participants who did not report whether they had ever used the Internet to seek health information were excluded from the analyses (n = 4; 0.31%), which resulted in a sample size of 1,289. However, 54% (n = 697) of these participants had at least one missing response on the correlates of interest, and this high percentage of missing data was predominately attributed to the low response rate for household income (n missing = 444; 34%). Therefore, for the logistic regression analyses, multiple imputation with chained equations was employed with five imputed data sets using R (Buuren & Groothuis-Oudshoorn, 2011; R Development Core Team, 2015). The imputed data replaced the missing responses on the correlates of interest.

Selection of Variables. To avoid issues with multicollinearity, the correlations between all predictor variables of interest (i.e., age, marital status, education level, income, geographical location, physical activity, vegetable intake, fruit intake, sitting status, smoking status, alcohol intake, global health, BMI, comorbidity status, and social media use) were examined using a correlation matrix. No high correlations between predictor variables were identified. Unadjusted bivariate regression analyses were performed with online health seeking regressed onto each of the demographic, health behavior, health status, and social media use variables. Only correlates with coefficients of a p value of .25 or less were selected for inclusion in the final regression models (Hosmer & Lemeshow, 2000). Based on these analyses, geographical location, physical activity, vegetable intake, and alcohol intake were excluded from the final analyses. All remaining variables were included in the final logistic regression models (Hosmer & Lemeshow, 2000). Sensitivity analyses were conducted to further ensure no multicollinearity issues were present (output can be obtained from the study page on open science framework: osf.io/tscyq). No adjustments to the models were made on this basis.

Results

Of those who responded to the QSS, 65% reported that they had used the Internet to search for health information. The most common sources of health information were health organization and government websites (see Table 1). The characteristics of the online health information seekers and nonseekers are presented in Table 2. In comparison to nonseekers, online health information seekers were more likely to be female, have a university education, be younger, earn an income above $52,000, and use social media. A significantly greater proportion of nonseekers were current smokers and reported sitting for more than 8 hours on a typical day. Conversely, online health information seekers were significantly less likely to suffer from three chronic illnesses or more, when compared with nonseekers. No significant differences were identified for marital status, geographical location,

Table 2. Characteristics of Seekers and Nonseekers of Online Health Information.

Variable	Seekers of online health information, *N* (%)	Nonseekers of online health information, *N* (%)	*p*
Demographics			
Gender			
Male (*n* = 670)	415 (49.17)	255 (57.3)	.01*
Female (*n* = 619)	429 (50.80)	190 (42.7)	
Age (*n* = 1,289)[a]	52.82 (15.04)	62.94 (14.63)	.01**
Education			
High school and below (*n* = 517)	258 (30.6)	259 (58.6)	.01**
Technical school (*n* = 305)	208 (24.7)	97 (21.9)	
University and above (*n* = 463)	377 (44.7)	86 (19.5)	
Household income			
≥$52,000 (*n* = 529)	397 (68.6)	132 (49.6)	.01**
<$52,000 (*n* = 316)	182 (31.4)	134 (50.4)	
Marital status			
Married/de facto (*n* = 939)	628 (74.8)	311 (70.0)	.07
Other (*n* = 345)	212 (25.2)	133 (30.0)	
Geographical location			
Major city (*n* = 671)	446 (53.3)	225 (50.90)	.49
Nonmajor city (*n* = 605)	391 (46.7)	214 (48.42)	
Health behaviors			
Physical activity			
Sufficiently active for health (*n* = 703)	475 (64.5)	228 (66.9)	.46
Insufficiently active for health (*n* = 374)	261 (35.5)	113 (33.1)	
Fruit intake			
Sufficient fruit intake (*n* = 763)	514 (60.90)	249 (55.60)	.09
Insufficient fruit intake (*n* = 526)	330 (39.10)	196 (44.04)	
Vegetable intake			
Sufficient vegetable intake (*n* = 232)	150 (17.79)	82 (18.43)	.78
Insufficient vegetable intake (*n* = 1,056)	693 (82.21)	363 (81.57)	
Sitting hours			
≤8 hours (*n* = 743)	476 (62.47)	267 (70.82)	
>8 hours (*n* = 396)	286 (37.53)	110 (29.18)	.01**
Smoking status			
Non–current smoker (*n* = 1,145)	766 (90.87)	379 (85.17)	.01**
Current smoker (*n* = 143)	77 (9.13)	66 (14.83)	
Alcohol intake			
Nonmisuse of alcohol (*n* = 732)	480 (56.87)	252 (56.63)	.93
Misuse of alcohol (*n* = 557)	364 (43.13)	193 (43.37)	
Health			
Health status			
Excellent/very good/good (*n* = 1,041)	692 (81.99)	349 (78.43)	.12
Fair/poor (*n* = 248)	152 (18.01)	96 (21.57)	
Comorbidity			
0 Chronic illnesses (*n* = 570)	388 (45.97)	182 (40.90)	.05*
1 Chronic illness (*n* = 376)	252 (29.86)	124 (27.87)	
2 Chronic illnesses (*n* = 206)	128 (15.17)	78 (17.53)	
≥3 Chronic illnesses (*n* = 137)	76 (0.09)	61 (13.71)	
BMI[a]	27.68 (6.07)	27.57 (6.24)	.76
Internet			
Social media use			
User of social media (*n* = 664)	550 (65.24)	114 (30.65)	.01**
Nonuser of social media (*n* = 551)	293 (34.76)	258 (69.35)	

Note. BMI = body mass index.
[a]*M* (*SD*).
*$p \le .05$. **$p \le .01$.

Table 3. Correlates of Online Health Information Seeking by Gender.

	Men, n = 670; $\chi^2(14)$ = 147.81; p < .01; pseudo R^2 = .17 β [CI]	Women, n = 622; $\chi^2(14)$ = 164.59; p < .01; pseudo R^2 = .21 β [CI]	Equality of coefficient test Z
Demographics			
Age	0.97 [0.96, 0.99]**	0.96 [0.94, 0.97]**	1.37
Education			
High school or below			
Technical school	1.50 [0.96, 2.35]	1.77 [1.05, 2.99]*	−0.47
University	3.63 [2.37, 5.56]**	2.74 [1.66, 4.51]**	0.85
Income <$52,000	0.96 [0.65, 1.42]	0.70 [0.43, 1.15]	
Married/de facto	1.07 [0.69, 1.65]	1.23 [0.79, 1.92]	
Health behaviors			
Sitting >8 hours	1.36 [0.95, 1.96]	1.04 [0.69, 1.58]	
Sufficient fruit intake	1.20 [0.83, 1.72]	1.34 [0.88, 2.03]	
Non–current smoker	2.25 [1.31, 3.85]**	2.54 [1.28, 5.04]**	−0.27
Health			
Fair/poor health status	0.79 [0.49, 1.28]	1.80 [1.00, 3.23]*	−2.13*
Comorbidity			
No chronic illness			
1 Chronic illness	1.37 [0.89, 2.12]	1.21 [0.74, 1.97]	
2 Chronic illnesses	0.98 [0.57, 1.67]	2.45 [1.29, 4.65]**	−2.15*
≥3 Chronic illnesses	1.01 [0.54, 1.90]	1.25 [0.60, 2.63]	
BMI	1.00 [0.98, 1.02]	0.99 [0.97, 1.00]	
Internet			
Social media use	2.57 [1.78, 3.71]**	2.93 [1.92, 4.45]**	−0.46

Note. CI = confidence interval.
*$p \le .05$. **$p \le .01$.

physical activity, fruit intake, vegetable intake, alcohol intake, health status, and BMI.

The results of the final logistic regression analyses for the online health information seekers by gender are presented in Table 3. The proportion of variability in online health information seeking explained by the models for men and women was 17% and 21%, respectively. For both genders, the two strongest correlates of online health information seeking were social media use (men: *OR* = 2.57, 95% CI [1.78, 3.71]; women: *OR* = 2.93, 95% CI [1.92, 4.45]) and having a university education (men: *OR* = 3.63, 95% CI [2.37, 5.56]; women: *OR* = 2.74, 95% CI [1.66, 4.51). The odds of online health information seeking also decreased by approximately 3% to 4% for every 1-year increase in age for both genders (men: *OR* = 0.97, 95% CI [0.96, 0.99]; women: *OR* = 0.96, 95% CI [0.94, 0.97]). Furthermore, not being a smoker (men: *OR* = 2.25, 95% CI [1.31, 3.85]; women: *OR* = 2.54, 95% CI [1.28, 5.04]) was positively associated with online health information seeking for men and women.

For women only, reporting a fair/poor health status was positively associated with online health information seeking (*OR* = 1.80, 95% CI [1.00, 3.23]) and having a technical school education was associated with a higher odds of seeking health information online when compared with respondents with a high school education or less (*OR* = 1.77, 95% CI [1.05, 2.99]). Finally, suffering from two chronic illnesses (when compared with not suffering from any chronic illness) was positively associated with seeking health information online, but in women only (*OR* = 2.45, 95% CI [1.29, 4.65]). There were no other significant correlates of online health information seeking.

The strength of the associations between age, university education, non–current smoking, and social media use and online health information seeking were equivalent across genders ($1.96 \le Z \ge -1.96$). However, having a fair/poor chronic health status and suffering from two chronic illnesses were both more strongly related to the odds of online health information seeking for women, compared with men ($Z > 1.96$).

Discussion

The aim of the present research was to examine the correlates of online health information seeking among men and women and determine whether the observed correlates differed significantly between genders. In agreement with previous research (Carpenter et al., 2011; Hallyburton & Evarts, 2014; Powell et al., 2011; Stern et al., 2012), this study indicated that women were more likely to use the Internet to seek health information than men. However, in extension to this literature, two statistically significant differences in the correlates of online health information seeking between men and women were identified based on the equality of regression coefficient test. Women who reported suffering from two chronic illnesses were more likely to search for health information online than women with no chronic illnesses. This was not the case for men, whose online health information seeking was the same irrespective of the number of chronic diseases they reported. Additionally, women with a fair or poor health status were more likely to use the Internet to search for health information than those with a better self-reported health status. This was also not observed in men. The reason for these differences is unclear. It may be that men are more likely to delay help seeking when a problem presents due to a greater tendency to self-monitor or "wait and see" (Galdas, Cheater, & Marshall, 2005). However, this would be in contrast to recent research suggesting that men are more likely to seek help for a long-standing health complaint compared with women (Rowley, Johnson, & Sbaffi, 2015), and that self-monitoring by men usually involves information seeking from a variety of different sources, including the Internet (Smith, Braunack-Mayer, Wittert, & Warin, 2008). Another possible explanation is that men are equally likely to utilize the Internet to seek health information relating to maintaining good health as they are for managing or improving poor health. Indeed, this would be in line with recent research suggesting that men are interested in their health (Smith, Braunack-Mayer, & Wittert, 2006) and that they are most likely to search for information online relating to a health topic they have had a long-standing interest in (Rowley et al., 2015). As the implications of this finding are largely dependent on why this discrepancy exists, further research elucidating why health status is differentially associated with health seeking among men and women is recommended.

The remaining correlates that were identified as significant were consistent across genders. In particular, being younger, having a university education and social media use were all positively associated with seeking health information online for both men and women. These findings concur with previous research (Bansil et al., 2006; Feng & Xie, 2015; Kontos et al., 2014), and suggest that key characteristics that predict high use and knowledge of technology (i.e., being young and educated), also play a predominant role in predicting online health information seeking in both men and women (Czaja et al., 2006). This suggests that online health promotion approaches may be a particularly promising means of reaching individuals with these characteristics and in turn that additional strategies are likely needed to encourage and engage older and less educated adults to utilize resources available online. Promisingly, risk behaviors (other than smoking) were not significantly associated with online health-seeking behavior, which confirms the previous findings of Shahab et al. (2014). These results may suggest that websites offering online health information are not only reaching those who are already performing the behavior (i.e., preaching to the converted; Marcus, Owen, Forsyth, Cavill, & Fridinger, 1998) and thus have real public health potential.

While this study has provided good insight into the area of online health information seeking, its limitations must be acknowledged. First, given that the results were based on self-reported data, recall and response bias may have influenced the results. Second, there was oversampling of adults aged 55 years and undersampling of adults aged younger than 35 years. This may be due to the use of landline only sampling. While there is some previous research to suggest that the exclusion of mobile only households does not significantly influence survey results (Grande & Taylor, 2010), it is possible that this sampling method led to response bias, since younger people increasingly live in a mobile only household. Third, though the type of websites searched were assessed, the topic of health information sought and the timing and frequency of online information seeking were not assessed. In addition, the quality of the health information sought was also not assessed. While most participants reported seeking health information from government and health organization websites (which are generally considered trusted sources), it is possible that the information obtained from these sites and others contained false or misleading health information, or advice with little or no scientific basis (Vandelanotte et al., 2014). Future research is recommended to determine the correlates of seeking good-quality health information on the Internet. Fourth, as this was a cross-sectional study, the direction of association cannot be determined. For example, it is unclear if smoking status influenced help-seeking behavior or if help seeking influenced smoking status. Thus, longitudinal studies are needed to disentangle relationships and determine the causal patterns of the correlates of online health information seeking. Finally, no psychological factors (e.g., self-efficacy, outcome expectations, perceived social support) were included as correlates. As psychological factors usually account for a large portion of variability in behavior (Plotnikoff, Lippke, Courneya, Birkett, & Sigal, 2008), this may explain the relatively small proportion of the variability in online health seeking explained in each model (17% for males, 21% for females). Future research examining the relationship between psychological factors, health-seeking behavior and gender is thereby recommended.

Despite the above-mentioned limitations, the study has several strengths such as the large, randomly recruited, and gender-balanced sample. A broad range of correlates were also considered, including those that have been identified as important but seldom studied in this context. Furthermore, to our knowledge, this is the first study that has examined the correlates of information seeking among men and women separately and contrasted them empirically.

Conclusion

While the majority of female and male participants (69% and 61%, respectively) reported using the Internet to search for health information online, there were significant differences in the demographic, health status, health behavior, and social media profiles among seekers and nonseekers. The results indicate that access is likely to be highest among those who are young, those with a higher education, and those who use social media. Access may also be higher among women who have a preexisting health condition or poor health status, and thus, the Internet may be useful for reaching these individuals for tertiary prevention. Research investigating ways to better engage men, older adults, and those with lower education levels in online health promotion interventions is recommended.

Authors' Note

All procedures performed in studies involving human participants were in accordance with the ethical standards of the institutional and/or national research committee and with the 1964 Helsinki declaration and its later amendments or comparable ethical standards.

Declaration of Conflicting Interests

The author(s) declared no potential conflicts of interest with respect to the research, authorship, and/or publication of this article.

Funding

The author(s) disclosed receipt of the following financial support for the research, authorship, and/or publication of this article: The study was funded by a Queensland Social Survey Grant provided by Central Queensland University. CES is supported by a National Health and Medical Research Council ECR Fellowship (ID 1090517). IN Scholarship was funded by Freemasons Foundation for Men's Health. ALR is supported by a National Health and Medical Research Council ECR Fellowship (ID1105926). CV (ID 100427) is supported by a Future Leader Fellowship from the National Heart Foundation of Australia. MJD is supported by a Future Leader Fellowship (ID 100029) from the National Heart Foundation of Australia.

References

Andreassen, H. K., Bujnowska-Fedak, M. M., Chronaki, C. E., Dumitru, R. C., Pudule, I., Santana, S., . . . Wynn, R. (2007). European citizens' use of E-health services: A study of seven countries. *BMC Public Health*, *7*, 53. doi:10.1186/1471-2458-7-53

Atkinson, N. L., Saperstein, S. L., & Pleis, J. (2009). Using the Internet for health-related activities: Findings from a national probability sample. *Journal of Medical Internet Research*, *11*(1), e4. doi:10.2196/jmir.1035

Australian Bureau of Statistics. (2005). *Australian Standard Geographical Classification (ASGC)*. Canberra, ACT: Author.

Australian Bureau of Statistics. (2013). *Causes of death, Australia, 2011*. Retrieved from http://www.abs.gov.au/ausstats/abs@.nsf/Lookup/3303.0Chapter42011

Australian Government, Department of Health. (2014). *Australia's Physical Activity and Sedentary Behaviour Guidelines*. Retrieved from http://www.health.gov.au/internet/main/publishing.nsf/content/health-pubhlth-strateg-phys-act-guidelines

Australian Institute of Health and Welfare. (2003). *The Active Australia Survey: A guide and manual for implementation, analysis and reporting*. Retrieved from http://www.aihw.gov.au/publication-detail/?id=6442467449

Australian Institute of Health and Welfare. (2004). *Rural, regional and remote health: A guide to remoteness classifications*. Retrieved from http://www.aihw.gov.au/publication-detail/?id=6442467589

Australian Institute of Health and Welfare. (2014). *Australia's health 2014*. Retrieved from http://www.aihw.gov.au/WorkArea/DownloadAsset.aspx?id=60129548150

Bansil, P., Keenan, N. L., Zlot, A. I., & Gilliland, J. C. (2006). Health-related information on the web: Results from the HealthStyles Survey, 2002-2003. *Preventing Chronic Disease*, *3*(2), A36.

Bush, K., Kivlahan, D. R., McDonell, M. B., Fihn, S. D., & Bradley, K. A. (1998). The AUDIT alcohol consumption questions (AUDIT-C): An effective brief screening test for problem drinking. Ambulatory Care Quality Improvement Project (ACQUIP). Alcohol Use Disorders Identification Test. *Archives of Internal Medicine*, *158*, 1789-1795.

Buuren, S. V., & Groothuis-Oudshoorn, K. (2011). Mice: Multivariate imputation by chained equations in R. *Journal of Statistical Software*, *45*(3), 1-67.

Carpenter, D. M., DeVellis, R. F., Hogan, S. L., Fisher, E. B., DeVellis, B. M., & Jordan, J. M. (2011). Use and perceived credibility of medication information sources for patients with a rare illness: Differences by gender. *Journal of Health Communication*, *16*, 629-642. doi:10.1080/10810730.2011.551995

Chau, J. Y., van der Ploeg, H. P., Dunn, S., Kurko, J., & Bauman, A. E. (2011). A tool for measuring workers' sitting time by domain: The Workforce Sitting Questionnaire. *British*

Journal of Sports Medicine, *45*, 1216-1222. doi:10.1136/bjsports-2011-090214

Clogg, C. C., Petkova, E., & Haritou, A. (1995). Statistical methods for comparing regression coefficients between models. *American Journal of Sociology*, *100*, 1261-1293. doi:10.2307/2782277

Cotten, S. R., & Gupta, S. S. (2004). Characteristics of online and offline health information seekers and factors that discriminate between them. *Social Sciences & Medicine*, *59*, 1795-1806. doi:10.1016/j.socscimed.2004.02.020

Czaja, S. J., Charness, N., Fisk, A. D., Hertzog, C., Nair, S. N., Rogers, W. A., . . . Sharit, J. (2006). Factors predicting the use of technology: Findings from the Center for Research and Education on Aging and Technology Enhancement (CREATE). *Psychology and Aging*, *21*, 333-352. doi:10.1037/0882-7974.21.2.333

Duncan, M. J., Gilson, N., & Vandelanotte, C. (2014). Which population groups are most unaware of CVD risks associated with sitting time? *Preventive Medicine*, *65*, 103-108. doi:10.1016/j.ypmed.2014.05.009

Duncan, M. J., Kline, C. E., Vandelanotte, C., Sargent, C., Rogers, N. L., & Di Milia, L. (2014). Cross-sectional associations between multiple lifestyle behaviors and health-related quality of life in the 10,000 steps cohort. *PLoS ONE*, *9*(4), e94184. doi:10.1371/journal.pone.0094184

Feng, Y., & Xie, W. (2015). Digital divide 2.0: The role of social networking sites in seeking health information online from a longitudinal perspective. *Journal of Health Communication*, *20*, 60-68. doi:10.1080/10810730.2014.906522

Fjeldsoe, B. S., Winkler, E. A., Marshall, A. L., Eakin, E. G., & Reeves, M. M. (2013). Active adults recall their physical activity differently to less active adults: Test–retest reliability and validity of a physical activity survey. *Health Promotion Journal of Australia*, *24*, 26-31. doi:10.1071/he12912

Fox, S., & Jones, S. (2009). *The social life of health information* (Pew Research Center). Retrieved from http://www.pewinternet.org/2009/06/11/the-social-life-of-health-information

Galdas, P. M., Cheater, F., & Marshall, P. (2005). Men and health help-seeking behaviour: Literature review. *Journal of Advanced Nursing*, *49*, 616-623. doi:10.1111/j.1365-2648.2004.03331.x

Grande, E., & Taylor, A.(2010). Sampling and coverage issues of telephone surveys used for collecting health information in Australia: results from a face-to-face survey from 1999 to 2008. *BMC Medical Research Methodology*, *10*, 77. DOI: 10.1186/1471-2288-10-77

Hallyburton, A., & Evarts, L. A. (2014). Gender and online health information seeking: A five survey meta-analysis. *Journal of Consumer Health on the Internet*, *18*, 128-142. doi:10.1080/15398285.2014.902268

Hosmer, D. W., & Lemeshow, S. (2000). *Applied logistical regression* (2nd ed.). New York, NY: John Wiley.

Houston, T. K., & Allison, J. J. (2002). Users of Internet health information: Differences by health status. *Journal of Medical Internet Research*, *4*(2), e7. doi:10.2196/jmir.4.2.e7

Kontos, E., Blake, K. D., Chou, W. Y., & Prestin, A. (2014). Predictors of eHealth usage: Insights on the digital divide from the Health Information National Trends Survey 2012. *Journal of Medical Internet Research*, *16*(7), e172. doi:10.2196/jmir.3117

Lohan, M., Aventin, A., Oliffe, J. L., Han, C. S., & Bottorff, J. L. (2015). Knowledge translation in men's health research: Development and delivery of content for use online. *Journal of Medical Internet Research*, *17*(1), e31. doi:10.2196/jmir.3881

Marcus, B. H., Owen, N., Forsyth, L. H., Cavill, N. A., & Fridinger, F. (1998). Physical activity interventions using mass media, print media, and information technology. *American Journal of Preventive Medicine*, *15*, 362-378.

National Health and Medical Research Council. (2013). *Australian guide to healthy eating*. Retrieved from http://www.eatforhealth.gov.au/guidelines/australian-guide-healthy-eating

Plotnikoff, R. C., Lippke, S., Courneya, K. S., Birkett, N., & Sigal, R. J. (2008). Physical activity and social cognitive theory: A test in a population sample of adults with type 1 or type 2 diabetes. *Applied Psychology*, *57*, 628-643. doi:10.1111/j.1464-0597.2008.00344.x

Powell, J., Inglis, N., Ronnie, J., & Large, S. (2011). The characteristics and motivations of online health information seekers: Cross-sectional survey and qualitative interview study. *Journal of Medical Internet Research*, *13*(1), e20. doi:10.2196/jmir.1600

R Development Core Team. (2015). R: A language and environment for statistical computing [Computer software]. Vienna, Austria: Author.

Rowley, J., Johnson, F., & Sbaffi, L. (2015). Gender as an influencer of online health information-seeking and evaluation behavior. *Journal of the Association for Information Science and Technology*. Advance online publication. doi:10.1002/asi.23597

Ruggiero, K. J., Gros, D. F., McCauley, J., de Arellano, M. A., & Danielson, C. K. (2011). Rural adults' use of health-related information online: Data from a 2006 national online health survey. *Telemedicine Journal and e-Health*, *17*, 329-334. doi:10.1089/tmj.2010.0195

Salmon, P., & Hall, G. M. (2004). Patient empowerment or the emperor's new clothes. *Journal of the Royal Society of Medicine*, *97*, 53-56.

Shahab, L., Brown, J., Gardner, B., & Smith, S. G. (2014). Seeking health information and support online: Does it differ as a function of engagement in risky health behaviors? Evidence from the health information national trends survey. *Journal of Medical Internet Research*, *16*(11), e253. doi:10.2196/jmir.3368

Short, C. E., Vandelanotte, C., Rebar, A., & Duncan, M. J. (2014). A comparison of correlates associated with adult physical activity behavior in major cities and regional settings. *Health Psychology*, *33*, 1319-1327. doi:10.1037/hea0000027

Smith, J. A., Braunack-Mayer, A., & Wittert, G. (2006). What do we know about men's help-seeking and health service use? *Medical Journal of Australia*, *184*, 81-83.

Smith, J. A., Braunack-Mayer, A., Wittert, G., & Warin, M. (2008). "It's sort of like being a detective": Understanding how Australian men self-monitor their health prior to seeking help. *BMC Health Service Research*, *8*, 56. doi:10.1186/1472-6963-8-56

StataCorp. (2009). Stata: Release 11 [Statistical software]. College Station, TX: Author.

Stern, M. J., Cotten, S. R., & Drentea, P. (2012). The separate spheres of online health: Gender, parenting, and online health information searching in the information age. *Journal of Family Issues*, *33*, 1324-1350. doi:10.1177/0192513x11425459

Thackeray, R., Crookston, B. T., & West, J. H. (2013). Correlates of health-related social media use among adults. *Journal of Medical Internet Research*, *15*(1), e21. doi:10.2196/jmir.2297

van der Ploeg, H. P., Chey, T., Korda, R. J., Banks, E., & Bauman, A. (2012). Sitting time and all-cause mortality risk in 222 497 Australian adults. *Archives of Internal Medicine*, *172*, 494-500. doi:10.1001/archinternmed.2011.2174

Vandelanotte, C., Kirwan, M., Rebar, A., Alley, S., Short, C., Fallon, L., . . . Duncan, M. J. (2014). Examining the use of evidence-based and social media supported tools in freely accessible physical activity intervention websites. *International Journal of Behavioral Nutrition and Physical Activity*, *11*, 105. doi:10.1186/s12966-014-0105-0