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IS THERE SUCH A THING AS AN ONLINE HEALTH LIFESTYLE? Examining the relationship between social status, Internet access, and health behaviors

The purpose of this paper is to examine the use of the Internet for health-related purposes and whether this usage is part of larger pattern of health-promoting behaviors, or health lifestyle. Pierre Bourdieu's concept of habitus *provides the key theoretical concept that links health lifestyle and the digital inequality framework to explain how social conditions (i.e. social status and quality of Internet access) influence attitudes and behaviors. Path analysis is used to examine the relationship between key endogenous variables on attitudes, health behavior, health status, and online health-related activities, while controlling for demographics and other factors. Data comes from the National Cancer Institute's 2007 Health Information National Trends Survey. The results demonstrate that online health behaviors can be usefully conceptualized as elements of health lifestyle. The combination of health lifestyle and digital inequality provides a broader theoretical framework that highlights the importance of social conditions to influence people's Internet habitus and routine health-promoting behaviors. The combination of health lifestyle and digital inequality provides a useful theoretical framework for future research investigating persistent social disparities in health and the potential for the growing reliance on information and communication technologies to contribute to socially patterned health outcomes.*

Keywords Internet; health information seeking; online health lifestyle; digital inequality; habitus

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The Internet has become ubiquitous and central to a range of daily activities (Fuchs 2008; Hargittai 2008). On a daily basis people use the Internet to search for and share information, read the news, check the weather, find directions, keep track of appointments, balance their checkbook and pay bills, communicate with family and friends, and a variety of other things (Fuchs 2008). The Internet has also become an important source of health information and means to carry out a range of health-related activities. In 2010, about 59 percent of all adults, or 80 percent of adult Internet users, have ever searched for health information online (Fox 2011, p. 5) with 19 percent doing so once a week or more often (Fox & Jones 2009, p. 21).

The purpose of this paper is to examine the relationship between social conditions (i.e. social status and quality of Internet access) and online health activities, and whether this usage is related to offline health behaviors as a broader pattern of health behaviors or health lifestyle. Most research on health-related Internet use has focused on health information seeking and the assumption that poor health or medical problems are the primary reasons people search for health information online (Lambert & Loiselle 2007). Previous research, however, has produced conflicting results. Some researchers find that healthier individuals are more likely to search for health information online (Cotten & Gupta 2004), while other researchers find that individuals in poor health are more likely to search online (Houston & Allison 2002; Baker *et al*. 2003; Goldner 2006).

Other researchers have focused on the relative strength of health behaviors and health status to predict seeking health information online. Pandey *et al*. (2003) hypothesized that individuals who engage in healthy behaviors tend to have a proactive approach to health, which they called a *wellness model*, and would be more likely to seek health information online regardless of their current health status. They found that an index measuring seven healthy behaviors was associated with a greater likelihood of seeking health information online. Health status, however, was not significant after controlling for differences in health behavior and sociodemographic variables. Other researchers have also found that individuals who engage in healthy behaviors are more likely to seek health information online (Dutta-Bergman 2004; Ramanadhan & Viswanath 2006).

I build on existing theoretical frameworks to examine online health activities as behaviors that represent a *health lifestyle*. To do so, I draw on Cockerham's (2005) conceptualization of health lifestyle, which he defines as 'collective patterns of health-related behavior based on choices from options available to people according to their life chances' (p. 55). The concept of health lifestyle highlights the influence of social class to shape people's life chances and experiences that are in turn, internalized as status-specific ways of perceiving and acting (e.g. health behaviors, such as physical exercise, food choices, smoking tobacco).

Cockerham's conceptualization of health lifestyles draws heavily on the work of Max Weber and Pierre Bourdieu. Weber's key contribution is the conceptualization of lifestyle as the dialectical interplay of life choices and life chances. Life choices refer to individual agency in the selection of behavior, whereas life chances refer to social conditions (structure), which determine the probability that the individual will realize their choices. Therefore, people's lifestyle choices are not entirely autonomous, but are constrained or enabled by their social status and their access to economic and other resources.

Bourdieu's concept of *habitus* provides the key concept linking social conditions to the development of status-specific patterns of behavior that are reproduced across time (Swartz 1997). The habitus represents embodied tendencies to perceive and act in ways that are consistent with the opportunities and constraints of the individual's social class background (Bourdieu 1990). Thus, habitus can be understood as a cognitive map of social conditions that produces enduring and routine patterns of perception and thought that when acted upon tends to reproduce the social conditions from which they are derived (Cockerham 2000, p. 164).

To advance our understanding of health-related Internet use as a form of health lifestyle, I draw on the *digital inequality* framework. Similar to the concept of health lifestyle, the digital inequality framework explains how social status contributes to differences in Internet access, skills, and use that in turn, are important for people's life chances and the potential reproduction of social inequalities (DiMaggio *et al*. 2004; DiMaggio & Bonikowski 2008; Hargittai 2008). Digital inequality scholars have also drawn on Bourdieu's concept of habitus to explain how structural conditions influence peoples' attitudes and Internet usage (Kvasny & Truex 2000; Robinson 2009; Zillien & Hargittai 2009; Hargittai 2010) that can be described as representing an 'Internet habitus'. For example, Zillien and Hargittai (2009) found that among adults, social status was positively associated with using the Internet for information gathering activities and personal financial transactions, even after controlling for differences in equipment, access, technology experience, and general interest in technology. Social status and quality of Internet access influence people's experience using the Internet and contributes to the development of distinct forms of 'information habitus' (Robinson 2009) and that may consist of increased sense of self–efficacy to find health information online and greater trust of online information sources that predicts health-related Internet usage (Rains 2007, 2008).

Figure 1 presents the full conceptual model. The primary independent variables are measures of social conditions that measure socioeconomic status (SES as education and income) and structural conditions that measure Internet access (i.e. broadband Internet connection, number of Internet access places). Habitus is measured as a cognitive dimension (health and Internet-related attitudes) and a behavioral dimension (i.e. offline health-related behaviors and

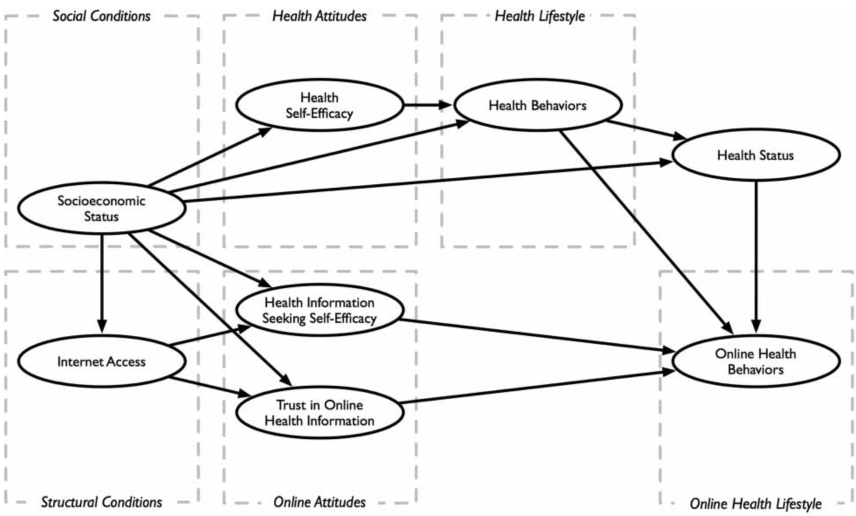

FIGURE 1 Conceptual model.

online health-related behaviors). The dependent variable is measured by online health-related activities (OHRA). Based on this model, the primary hypotheses are: (1) health status will not be significantly related to OHRA, (2) health behavior (i.e. physical activity, diet, smoking) will be positively associated with online health behavior (i.e. OHRA), and (3) social conditions will be positively related to health attitudes, Internet attitudes, and health behaviors.

Methods

Data comes from the National Cancer Institute's 2007 Health Information National Trends Survey (HINTS) collected between December 2007 and April 2008. HINTS is a cross-sectional survey that collects nationally representative data about health communication. Although the focus of the survey is on cancer communication, the survey includes many general questions about communication channels, health behavior, and information seeking.

The 2007 HINTS uses a dual-frame, mixed mode design that is intended to counteract the trend of declining response rates to random digit dialing (RDD) administered surveys (Cantor *et al.* 2009). One frame used a list-assisted RDD and the second frame used a mail survey and a stratified sample that oversampled minorities. The mail mode sample ($N = 3{,}582$) is used in this study, following the recommendations of Cantor and McBride (2009), who found significant mode effects for questions about Internet use and health information seeking. The household response rate in the mail sample was 40 percent, the within household response rate was 77.4 percent, and the over-all response rate was 31 percent.

The analytic sub-sample is restricted to participants, who are Internet users (*N* = 2,526). Type of Internet connection (i.e. dial-up modem, high-speed broadband) was asked only of participants with home Internet access and further restricts the analytic sample to participants with home Internet access (*N* = 2,191). Excluding participants without home Internet access focuses the analysis on the difference between dial-up modem access and high-speed broadband access. The size of the analytic sub-sample was further reduced due to cases with missing data on variables used in the statistical models. Household income was imputed using a regression modeling technique for 104 observations yielding a final analytic sub-sample of 1,887 observations.

Measures

Dependent variable. Online health behaviors are measured by OHRA, a summated index measuring the participant's use of a range of online health behaviors during the past 12 months. The index is constructed from six items that assess whether participants have: (1) bought medicine or vitamins online; (2) participated in an online support group for people with a similar health or medical issue; (3) used email or the Internet to communicate with a doctor or a doctor's office; (4) used a website to help you with your diet, weight, or physical activity; (5) looked for a healthcare provider; (6) kept track of personal health information, such as care received, test results, or upcoming medical appointments. Responses for each item are coded 0 = no and 1 = yes. To ensure there were no cells with few or no observation, the index was collapsed, recoding cases with a score of 6 as 5 and yielding a range of 0–5. Factor analysis show the four items load on a single factor that explains 49.2 percent of the variance. Chronbach's alpha is .572.

Independent variables. Health behavior (HB) is measured using a summated index created from four items that assess: (1) daily fruit servings, (2) daily vegetable servings, (3) physical activity during the past week, and (4) tobacco use. Items were recoded to create dichotomous variables that indicate 1 = meeting healthy behavior recommendations outlined in Healthy People 2020 (US Department of Health and Human Services 2010) and 0 = not meeting recommendations. The HB index was created only for cases with no missing data on any of the four items. The index has a range of 0–4, with a higher score representing engaging in a greater number of healthy behaviors or a healthier lifestyle. Factor analysis shows the four items load on a single factor that explains 47.6 percent of the variance. Chronbach's alpha is .432.

Health self–efficacy (HSE) is measured using a single item that assesses participants' sense of confidence to take good care of their health. HSE is coded as one of five Likert–type options ranging from 1 = not confident at all to 5 = completely confident.

Online health information seeking attitudes are measured using two items. The first, health information seeking self–efficacy (HISSE) measures participants' general feeling of confidence that they can find health information. HISSE is Likert coded from 1 = not confident at all to 5 = completely confident. The second item is trust in online health information (TRUST). TRUST is measured by a single item that is Likert coded from 1 = not at all to 4 = a lot.

Two variables are used to measure socioeconomic status. Education (EDU) is measured as the highest grade or level of schooling completed and coded as one of five ordinal-level options: 1 = less than high school to 5 = postgraduate, post–baccalaureate degree. Household income (HHINC) is measured as combined household income and coded as one of five ordinal–level options: 1 = less than $20,000 to 5 = $75,000 or more.

Internet access is measured by two variables, home Internet access and number of places a participant accesses the Internet. Broadband (ACCESSBB) is coded 1 = high speed (i.e. digital subscriber line, satellite, or cable) home connection and 0 = telephone dial–up modem or other. Internet access places (PLACES) is the total number of places from where participants use the Internet, selected from a list of seven locations: (1) home, (2) work, (3) school, (4) public library, (5) community center, (6) someone else's house, and (7) some other place. To ensure there were no cells with few or no observation, cases with a score of 6 and 7 were recoded to 5. The analytic sample is restricted to participants, who have home Internet access. Therefore, the minimum number of PLACES is 1, and values range from 1 to 5.

Health status is measured as self–rated health (SRH), using a single question that asks, 'In general, would you say your health is . . .?' Responses are coded 1 = poor to 5 = excellent.

Control variables. Several demographic variables are included as controls. Age (AGE) is measured in years. Race/ethnicity is measured by the variable Non-White (NONWHITE) coded as 1 = African American, Hispanic, Asian, or other race/ethnicity and 0 = white non-Hispanic. Sex is measured by the variable female (FEMALE), coded 1 = female and 0 = male. Marital status is measured by the variable married (MARRIED), coded 1 = married and 0 = single, divorced, widowed, or other marital status. CHILD, is coded 1 = child in household and 0 = no children in household.

Health insurance is recoded as uninsured (UNINS), a dichotomous variable coded 1 = does not have health insurance and 0 = does have health insurance. Regular health care provider (REGHCP) is coded 1 = have a regular health care provider and 0 = does not have a regular health care provider. Rural (RURAL) is measured using the 2003 Rural–Urban Continuum codes (US Department of Agriculture 2007) to classify counties as 1 = rural or 0 = urban. A series of dummy variables were created to measure if participants are looking for self

(LOOKSELF), looking for someone else (LOOKELSE), and looking for both myself and someone else (LOOKBOTH).

Analytic strategy

The first phase of analysis consists of generating descriptive statistics and testing for significant differences between the full mail sample and the analytic sample. The second phase uses path analysis to examine a structural model of the relationships between endogenous variables (e.g. independent variables, intervening variables, and the dependent variable OHRA), while controlling for exogenous variables (e.g. demographics, health care access, and other factors). Because the variables used in the structural models include categorical variables the weighted least squares mean variance estimator is used in Mplus. Results are presented as a path diagram with standardized probit coefficients to facilitate the comparison of the relative strength of the effect of each variable in the model. All analysis was conducted using the recommended sample and replicate weights.[1]

Results

The Internet user sub-sample is about 52 percent female, 42 years old, and 25 percent non-white race/ethnicity (see Table 1). Sixty-one percent of participants are married and 42 percent have at least one child in the household. The mean education is 3.2 which represents a little higher, on average, than attending some college (category 3 = some college). The mean, imputed household income is 3.7 which represent a level of income of about $50,000 to less than $75,000 (category 4). The mean number of places, where participants can access the Internet is about 1.8. Twenty–five percent have a modem or slower type of home Internet access and 75 percent have broadband.

Path analysis

Figure 2 depicts the path model and the probit coefficients for all direct effects that are statistically significant at the $p \leq .05$ level, while controlling for all exogenous variables. Table 2 shows the unstandardized and standardized coefficients, standard errors, and p-value for all direct relationships between variables in the model. A table listing indirect effects is available from the author. Model fit indices indicate an acceptable fit between the structural model and the data. Without survey weights, root mean square error of approximation = .036, comparative fit index = .988, and weighted root mean square residual (WRMSR) = .436. With survey weights the WRMR = .371.

Self-rated health (SRH) is not a significant predictor of OHRA ($b = .013$, $p > .050$) (see Figure 2). Thus, OHRA does not appear to be primarily due

TABLE 1 Sample characteristics HINTS 2007 mail sample and Internet user sub-sample.

	Mail sample (N = *3,582)*		*Internet users* (N = *1,887)*	
Variable name	M	*SD*	M	*SD*
Education: five levels	2.817	1.369	3.173	1.034
Household income: five levels	3.215	1.539	3.688	1.395
Household income: five levels, imputed	3.208	1.536	3.685	1.397
Gender: female	0.515	0.500	0.518	0.498
Age	45.929	17.834	41.698	15.231
Race/ethnicity: nonwhite	0.306	0.461	0.248	0.430
Marital status: married	0.565	0.496	0.609	0.486
Child in household	0.373	0.484	0.418	0.491
Occupational status: employed	0.598	0.490	0.677	0.466
Location: rural	0.165	0.372	0.109	0.310
Health insurance: uninsured	0.172	0.378	0.133	0.338
Regular health care provider	0.672	0.470	0.696	0.458
Who look for				
Look for yourself	0.429	0.495	0.471	0.497
Look for someone else	0.150	0.357	0.187	0.388
Look for both	0.195	0.396	0.211	0.406
Has never looked for health info.	0.226	0.418	0.132	0.337
OHRA: 0–5	0.853	1.115	1.265	1.154
Buy medicine	0.109	0.312	0.162	0.367
Support group	0.035	0.185	0.054	0.226
Talk with doctor	0.086	0.280	0.123	0.327
Diet, weight, physical activity	0.283	0.451	0.420	0.491
Provider	0.266	0.442	0.405	0.489
Personal health record	0.084	0.278	0.118	0.322
Self-rated health	3.401	0.910	3.256	0.876
Health behavior: 0–4	1.614	1.057	1.708	1.055
Meet fruit recommendation	0.213	0.410	0.223	0.415
Meet vegetable recommendation	0.267	0.443	0.292	0.453
Meet weekly recommended exercise	0.352	0.478	0.394	0.487
Non-smoker	0.781	0.414	0.798	0.399
Health self-efficacy	3.772	0.877	3.819	0.810
Health information seeking self-efficacy	3.717	0.979	3.833	0.903
Trust online health information	2.838	0.835	3.019	0.669

Continued

TABLE 1 Continued

	Mail sample (N = *3,582*)		*Internet users* (N = *1,887*)	
Variable name	M	*SD*	M	*SD*
Places where access Internet: 0–4	1.201	1.086	1.798	0.884
Home Internet connection				
No home connection	0.380	0.485	0.000	0.000
Modem or other	0.155	0.362	0.251	0.438
Broadband	0.465	0.499	0.749	0.432

Note: Weighted means.

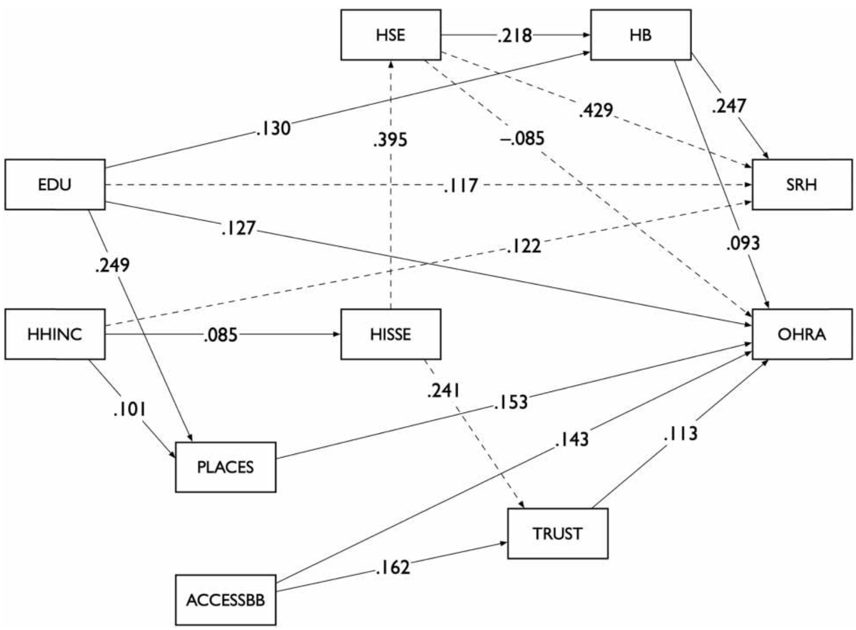

FIGURE 2 Path model and probit coefficients of the direct effects between socioeconomic status, Internet access, health and information seeking attitudes, health behavior, and self-rated health on OHRA HINTS 2007 Internet user sub-sample (N = 1,887).

to poor health. As hypothesized, health behavior (HB) has a small, but statistically significant positive relationship to OHRA ($b = .093$, $p < .010$) indicating that people, who engage in healthy behaviors offline tend to engage in a greater number of OHRA. Education (EDU) has a very small, but significant indirect relationship to OHRA via health behavior (HB, $b = .012$, $p < .050$), providing

TABLE 2 Direct effects, OHRA HINTS 2007 Internet user sub-sample ($N = 1,887$).

Dependent variable and path	b	*SE*	B	p-*Value*
ACCESSBB				
EDU → ACCESSBB	.101	.057	.099	.076
HHINC → ACCESSBB	.001	.037	.001	.987
PLACES				
EDU → PLACES	.249***	.044	.218	.000
HHINC → PLACES	.101**	.039	.119	.009
HISSE				
PLACES → HISSE	.101	.054	.115	.061
ACCESSBB → HISSE	−.012	.052	−.012	.817
EDU → HISSE	.061	.037	.060	.101
HHINC → HISSE	.085*	.033	.114	.010
TRUST				
HISSE → TRUST	.241***	.052	.229	.000
PLACES → TRUST	−.087	.054	−.094	.109
ACCESSBB → TRUST	.162**	.060	.156	.007
EDU → TRUST	−.020	.042	−.019	.640
HHINC → TRUST	−.012	.034	−.016	.711
HSE				
HISSE → HSE	.395***	.046	.375	.000
EDU → HSE	.007	.043	.007	.871
HHINC → HSE	−.020	.036	−.025	.583
HB				
HSE → HB	.218***	.043	.228	.000
HISSE → HB	−.039	.044	−.039	.376
EDU → HB	.130**	.037	.129	.001
HHINC → HB	.031	.036	.042	.389
SRH				
HB → SRH	.247***	.040	.216	.000
HSE → SRH	.429***	.055	.394	.000
HISSE → SRH	−.030	.037	−.026	.422
EDU → SRH	.117*	.052	.101	.023
HHINC → SRH	.122***	.034	.143	.000
OHRA				
SRH → OHRA	.013	.041	.014	.746
HB → OHRA	.093**	.030	.086	.002
HSE → OHRA	−.085*	.039	−.082	.031

Continued

TABLE 2 Continued

Dependent variable and path	b	*SE*	B	p-*Value*
TRUST → OHRA	.113**	.041	.110	.006
HISSE → OHRA	−.032	.041	−.029	.435
PLACES → OHRA	.153***	.036	.161	.000
ACCESSBB → OHRA	.143**	.052	.134	.005
EDU → OHRA	.127**	.043	.116	.003
HHINC → OHRA	−.007	.037	−.008	.855

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

additional support for positive effects between social status, health behaviors, and OHRA predicted by the health lifestyle framework. Education (EDU) has a positive direct effect on health behavior (HB) ($b = .130$, $p < .010$) and health self-efficacy (HSE) is positively associated with health behavior (HB) ($b = .218$, $p < .001$). However, neither measure of SES (i.e. education (EDU) or household income (HHINC)) has a significant relationship to health self-efficacy (HSE).

Education (EDU) is positively associated with OHRA ($b = .127$, $p < .010$). Both measures of SES are positively associated with the number of places a person uses the Internet (PLACES) (EDU $b = .249$, $p < .001$; HHINC $b = .101$, $p < .010$). Both education (EDU) and household income (HHINC) have a significant indirect effect through the number of places a person uses the Internet (PLACES) (EDU $b = .035$, $p < .010$; HHINC $b = .015$, $p < .050$). Additionally, household income (HHINC) has a positive direct effect on health information seeking self–efficacy (HISSE) ($b = .085$, $p <$ 050) and a small, but significant positive indirect effect on OHRA via HISSE and trust of online health information (TRUST) ($b = .026$, $p < .050$).

As predicted by the digital inequality framework, Internet access is a relatively strong predictor of trust of online health information (TRUST) and OHRA. Broadband access (ACCESSBB) is positively related to trust of online health information (TRUST, $b = .162$, $p < .010$). Both measures of Internet access have a positive, direct relationship to OHRA (ACCESSBB $b = .143$, $p < .010$; PLACES $b = .153$, $p < .001$). In addition, broadband access (ACCESSBB) has a very small, but significant positive indirect effect on OHRA through trust on online health information (TRUST) ($b = .018$, $p < .050$) for a total positive effect of $b = .161$ ($p < .050$). Although the strength of this indirect effect is small, the direct effects along the path are in the hypothesized direction and provide general support that Internet access is related to more positive attitudes and to greater use of the Internet for health-related activities.

Discussion

The first important finding is that social and structural conditions (i.e. SES, quality of Internet access) influence Internet–related attitudes and behaviors. This finding highlights the importance of examining how social and structural conditions shape people's experiences using information and communication technologies (ICT) and the development of distinct, status–based differences in Internet usage – an Internet habitus. The finding that SES is significantly related to OHRA, even after controlling for differences in Internet access, health status, and demographics, is consistent with findings in digital inequality literature, showing that SES is associated with greater use of the Internet for information gathering activities (Zillien & Hargittai 2009). Quality of Internet access is an important element of structural conditions, or to use Weber's concept 'life chances', that enable or constrain people's choices and shape the development of distinct Internet and informational habitus (Robinson 2009). The findings presented in this paper show that differences in the quality of Internet access influences information seeking self–efficacy and trust of online sources that in turn, predict health-related Internet use.

The findings also add to our knowledge of how social inequalities shape the distribution of health information and knowledge that may contribute to persistent health disparities – a topic of research that is currently underdeveloped (Link 2008). Social inequalities are understood to be a 'fundamental cause' of persistent, status–based health disparities (Link & Phelan 1995). Link and Phelan (1995) argue that in 'a dynamic system with changes in diseases, risks, and knowledge of risks' (p. 87) the persistent relationship between disadvantaged groups and poor health outcomes is not due to any one specific mechanism, but due to status–related differences in the ability to access and effectively use a range of resources that benefit health and improve longevity.

The Internet is an important new resource for health information and health care services that has the potential to alleviate social health disparities (Cotten 2001; Viswanath & Kreuter 2007). Unfortunately, socially disadvantaged groups, who could most benefit from online health resources are also those most likely to have limited Internet access. This creates the potential for what Merton (1988) termed the 'Matthew Effect', in which initial social advantages and disadvantages accumulate and accentuate social inequalities. Similarly, Link and Phelan (2000) note that 'when innovations beneficial to health are developed, their implementation necessarily occurs within the social context of existing inequalities in knowledge, money, power, prestige, and social connections' (p. 40). Thus, people who have limited access to the Internet are less likely to develop a range of health–related values, skills, and knowledge that are important to maintaining their health and participating in decisions regarding their medical treatment if they become ill (Abel 2007).

The second important finding is that there is some evidence to suggest that OHRA are part of a broader set of status–based health behaviors that represent health lifestyle. Three findings support this conclusion. First, OHRA were not significantly related to health status, as one might expect if OHRA was motived by poor health or a medical condition. Second, people who engaged in a greater number of health behaviors also made greater use of the Internet for health-related activities. Third, social and structural conditions were significant factors predicting OHRA and intervening Internet–related attitudes. Taken all together, these findings provide evidence that OHRA are part of a broader set of status–based health behaviors that represent health lifestyle.

This finding is important, because it extends the conceptualization of health behaviors that comprise health lifestyles to include using the Internet for a variety of health–related purposes. The Internet is increasingly understood to be a part of many people's everyday routines and a necessity to access a variety of services and to fully participate in society (Hargittai 2008). Therefore, it is important to understand how new forms of technology mediated health behaviors are being incorporated into people's daily lives and may contribute to the social reproduction of health disparities. The concept of health lifestyle highlights that these choices are not strictly individual choices, but are collectively patterned due to the close linkage between a person's social status background and the internalization of social conditions as habitus: attitudes, beliefs, and preferences to act in routine and habitual ways (Cockerham 2005).

Finally, the Internet and related technology is widely understood to be transforming the culture of medicine – a new era of eHealth. Eysenbach (2001) defined eHealth as:

> [A]n emerging field in the intersection of medical informatics, public health and business, referring to health services and information delivered or enhanced through the Internet and related technologies. In a broader sense, the term characterized not only a technical development, but also a state-of-mind, a way of thinking, an attitude, and a commitment for networked, global thinking, to improve health care locally, regionally, and worldwide by using information and communication technology. (p. 1)

What is important about this definition is that it highlights that the Internet is instrumental in generating a new 'state–of–mind, a way of thinking, an attitude' (Eysenbach 2001, p. 1), a new culture of health and health care. Health lifestyles are embedded in larger social and cultural contexts (Cockerham 2005) and provide a sense of social identity and status (Giddens 1991) to individuals. The utopian discourse surrounding ICT and the Internet is derived from a broader set of cultural values of individualization, personal empowerment and actualization, egalitarianism, and the emphasis on freedom of speech and access to information (Turner 2006). Thus, the findings from this paper are an important step toward understanding how technology enabled health behaviors and more traditionally studied health behaviors coalesce as health lifestyles and contribute to the construction of social identities.

Limitations

This paper has contributed to a clearer understanding of the factors associated with OHRA using a nationally representative sample of adults collected in 2007. However, there are limitations to this research that should be noted. First, the over–all survey response rate is relatively low (31 percent). This raises the possibility of nonresponse bias in estimates to the extent that key variables of interest are correlated with the likelihood of persons not responding to the survey (Groves 2006). The response rate, however is similar to the response rate of other nationally representative surveys, such as the 2007 Behavior Risk Factor Surveillance System (33.5 percent) (Centers for Disease Control and Prevention 2008), and higher than data from the Pew Internet & American Life Project in 2006 (27.1 percent) (Fox 2006).

Second, the variables measuring OHRA do not account for frequency or duration of uses, but only having participated in an activity during the past 12 months. This provides a rather limited measure of people's online activities. Variables that take into account frequency and duration of time spent participating in OHRA would capture to greater extent, behaviors that are routine and habitual choices.

Third, the data is relatively old for studying emerging trends in Internet usage and does not contain information on the use of mobile devices or mobile health applications. In 2007, cell phones had relatively few features and high-speed cellular service was not widely available. More powerful mobile devices were just beginning to become available, when this data was collected. For example, the Apple iPhone was released in June 2007 and marked the beginning of the widespread adoption of 'smartphones' capable of wireless Internet browsing and running a variety of health-related applications. Future research should focus on the use of mobile devices, health applications, and various digital health and fitness devices, as the convenience and portability of this technology is likely to contribute to more frequent use and the incorporation into daily routines that comprise health lifestyles.

Conclusion

Using the Internet for health-related purposes may be more closely associated with health lifestyle choices today than in the past. The Internet can no longer be considered a luxury, but has become a central component to our social infrastructure and participation in society (Hargittai 2008). In an era that places greater responsibility upon individuals to manage their health and be informed medical consumers (Conrad 2005; Crawford 2006) – the Internet has become a key structural resource people may use to find health information, communicate with others, and garner social support (Drentea & Moren-Cross 2005) and foster participation in health promoting behaviors (Ayers & Kronenfeld 2007; Webb *et al*. 2010).

The findings in this paper highlight the importance of social conditions to influence Internet habitus or status–specific patterns of Internet use. Perhaps, the most important contribution of this paper is to demonstrate that online health behaviors can be usefully conceptualized as part of much broader set of health behaviors that represent health lifestyle. The combination of health lifestyle and digital inequality provides a broader theoretical framework that highlights the importance of social conditions to shape distinct, status-specific patterns of attitudes and behaviors that are important for maintaining health and the effective use of health care services, if they become ill. Thus, it provides a useful tool for future research investigating persistent social disparities in health and ways to leverage new technology to narrow gaps in digital inequality and in health disparities.

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Note

1 Details regarding the computation of the sample and replicate weights can be found in the *2007 HINTS Final Report* by Cantor *et al*. (2009). Recommendations about the use of weights and the appropriate syntax for use with a variety of statistical packages is provided with the dataset available at http://hints.cancer.gov.

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