



More than search? Informational and participatory eHealth behaviors



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ABSTRACT

Few studies in the eHealth literature have paid attention to participatory eHealth behaviors. Addressing this gap, the present study examines how informational and participatory eHealth behaviors are related to eHealth literacy, Internet use and Facebook interaction, as well as user characteristics. Drawing on a sample of college students ($N = 540$), results from Structural Equation Modeling (SEM) analysis show that eHealth literacy has a positive direct effect on informational eHealth behaviors. It also serves as a mediator suppressing the negative relationship between excellent mental health status and eHealth behaviors. While both instrumental Internet use and Facebook interaction are related to participatory eHealth behaviors, only instrumental Internet use is associated with informational eHealth behaviors. There are significant eHealth disparities by health status, gender, and class. Implications for health communication and promotion are discussed.

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1. Introduction

eHealth behaviors are multifaceted and may include using information and communication technologies to seek health information, communicate health issues, purchase medicine, or participate in online health support groups (Atkinson, Saperstein, & Pleis, 2009; Norman, 2011; Rice, 2006). A better understanding of people's eHealth behaviors helps to advance an emerging literature on how the Internet and social media can be leveraged for health communication, promotion, and intervention (Gold et al., 2012; Luca & Suggs, 2013; Oh, Rizo, Enkin, & Jadad, 2005; Stellefson et al., 2011).

Informational eHealth behaviors involve online health information search. About 72% of adult American Internet users searched health information online within the past year (Fox & Duggan, 2013). Since the mid-2000s, the rapid diffusion of social media, especially social networking sites (SNSs), has offered additional sources of health information and new venues for participatory eHealth behaviors such as using SNSs to post, share, or comment on health-related issues, join or develop online health communities, or maintain healthy lifestyles. A large-scale survey shows that 32% of Americans have used SNS for health-related activities (Thackeray, Crookston, & West, 2013). Another national survey suggests that about 11% of adult American Internet users have posted about health matters and 9% have started or joined a health-related group on SNSs (Fox, 2011).

Informational eHealth behaviors have been the center of an emerging literature on eHealth behaviors (Renahy, Parizot, & Chauvin, 2010). By contrast, participatory eHealth behaviors have been less studied (Stellefson et al., 2011; van der Vaart et al., 2011). Even studies that have examined individuals' social media use for health issues have focused on social media as a source for information rather than a new venue for participation (National Research Corporation, 2011; Thoren, Metzke, Bührer, & Garten, 2013). As importantly, there has been a lack of research that integrates insights from digital divides, eHealth disparities, and eHealth literacy literatures to examine how Internet and Facebook usage patterns, eHealth literacy, health status, and users' socio-demographic characteristics are related to eHealth behaviors. This study aims to address these critical knowledge gaps.

2. Literature review

The digital divide literature has focused on how users' socioeconomic status (SES) and socio-demographic characteristics shape their Internet access and use (Chen, 2013; DiMaggio, Hargittai, Neuman, & Robinson 2001; Hargittai & Hinnant, 2008). There has been a growing body of literature demonstrating eHealth behaviors can vary by SES and socio-demographic characteristics (Cotten & Gupta, 2004; Thoren et al., 2013). Furthermore, eHealth literacy has important implications for eHealth behaviors (Lustria, Smith, & Hinnant, 2011; Norman, 2011; Stellefson et al., 2011).

2.1. Usage patterns

General Internet use in terms of the year of Internet experience, the amount of time online, and the frequency of Internet activities

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was positively related to the likelihood or the frequency of online health information search (Rice, 2006). Yet, a recent study suggests that general Internet use is insignificant to online health information search (Mesch, Mano, & Tsamir, 2012). Given the rapid diffusion of the Internet and the evolving patterns and natures of Internet use, scholars have pointed out that specific Internet activities may have greater social implications than general Internet use (Hargittai & Hinnant, 2008). Accordingly, we focus on two specific usage patterns: instrumental Internet use and Facebook interaction.

Instrumental Internet use refers to online activities with “an active and purposive orientation” (Papacharissi & Rubin, 2000, p. 189). It may include online information search for education or employment, online banking, online rating and research, and online purchase of product and service. Instrumental Internet use often involves capital-enhancing Internet activities for political participation or career advancement (Hargittai & Hinnant, 2008).

In contrast to the rich literature on Internet use and informational eHealth behaviors, few studies have examined the implications of Facebook interaction for eHealth behaviors. We argue that Facebook interaction can affect eHealth behaviors for several reasons. First, Facebook has been widely adopted and used in the U.S. and beyond. About two-thirds of adult American Internet users use SNSs such as Facebook, LinkedIn or Google+ (Pew, 2012). According to one study, an average American user spends about 6.5 h monthly on Facebook (Nielsen, 2013). The average time American college students spends on Facebook ranges from about 0.5 h (monitored) to 2.5 h (self-reported) a day (Junco, 2013). The wide adoption and intensive use of Facebook has made it an integral part of everyday life, with significant impacts on users' identity and network building (Ellison, Steinfield, & Lampe, 2007) as well as on their psychological wellbeing (Chen & Lee, 2013; Nabi, Prestin, & So, 2013).

Second, allowing users to share information and emotions about their habits and lifestyles, SNSs, especially Facebook, can be a source of information and a venue of engagement. Among Americans who have used social media for health information, 94% of them have used Facebook for health information (National Research Corporation, 2011). Despite privacy concerns, people have used Facebook for sharing health information, even sensitive health information (Househ, 2011). Many people use Facebook to share health experience, ask health-related questions, or offer health-related help or support to their Facebook friends. Patients or their caregivers who deal with similar health conditions set up Facebook groups to share information and experience (Thoren et al., 2013). More importantly, as health behaviors spread across interpersonal networks, social reinforcement and social support enabled by SNSs can increase users' adoption of healthier behaviors (Centola, 2010).

Third, many health organizations have actively employed Facebook to raise health awareness, distribute health information, engage with stakeholders, or drive traffic to their main websites (Alas, Sajadi, Goldman, & Anger, 2013; Goldstein et al., 2013; Park, Rodgers, & Stemmler, 2011). Studies have demonstrated the growing usefulness of Facebook and other social media platforms in organ donor registration (Cameron et al., 2013) or recruiting participants for medical research (Parkinson & Bromfield, 2013).

However, few studies have examined how Facebook interaction such as posting, sharing, liking, or commenting on SNSs is related to eHealth behaviors. Building on existing studies on Internet use and informational eHealth behaviors as well as a well-established positive association between habitual use of a medium and its subsequent prevalence in users' life (Rubin, 1984), we hypothesize that

H1a. Non-health related instrumental Internet use is related to informational and participatory eHealth behaviors.

H1b. Facebook interaction is related to informational and participatory eHealth behaviors.

2.2. eHealth literacy

Health literacy, especially in early studies, was defined as individuals' reading, writing and numeracy skills in terms of accessing, processing, and utilizing health information, which contributes to healthier lifestyle, better stress coping, and a range of positive health outcomes (Berkman, Davis, & McCormack, 2010). The Internet allows unprecedented access to health information. However, people often have limited skills in searching and evaluating the relevance and trustworthiness of online information due to the vast amount, diverse sources, and varying quality. Norman and Skinner (2006) developed the eHEALS scale to capture eHealth literacy – people's “ability to seek, find, understand, and appraise health information from electronic sources and apply the knowledge gained to addressing or solving a health problem”.

Several empirical studies have identified a positive relationship between eHealth literacy on informational eHealth behaviors (for a review see Norman, 2011). For instance, female college students with greater eHealth literacy have more sophisticated informational eHealth behaviors: searching health information through multiple sources rather than solely depending on a search engine (Stellefson, Hanik, Chaney, & Tennant, 2012). By contrast, the research on the relationship between eHealth literacy and participatory eHealth behaviors has been thin.

As eHealth literacy is about users' ability to search and utilize online information for health problem-solving, we argue that such skills are likely to contribute to participatory eHealth behaviors such as posting or sharing health-related content on SNSs, joining or developing online communities of people with shared health issues, or utilizing SNSs for maintaining a healthy lifestyle. Thus,

H2. eHealth literacy is related to informational and participatory eHealth behaviors.

2.3. User characteristics: health status SES, gender, and race

Early research suggested that healthier and happier people were more likely to search health information online (Cotten & Gupta, 2004). However, some recent studies have shown that poor physical health is related with more frequent health information search online (Mesch et al., 2012; Renahy et al., 2010) or participation in online support groups (Chou, Hunt, Beckjord, Moser, & Hesse, 2009). People with chronic health conditions are more likely to consult online rankings or reviews of health professionals, organizations, or treatments (Thackeray et al., 2013). Yet, one study on college students shows no significant relation between general health status and using online health information (Dobransky & Hargittai, 2012). As to mental health, people with better mental health are less likely to search health information online (Powell & Clarke, 2006).

Early studies also revealed that SES (e.g., education and income), gender, and race/ethnicity were associated with the digital divides in general and eHealth disparities in specific (Rice, 2006; Skinner, Biscope, & Poland, 2003). Yet, the rapid diffusion of the Internet has narrowed many aspects of digital divides and eHealth disparities.

First, SES. More recent studies show no significant class difference or educational gap in online health information search (Dobransky & Hargittai, 2012; Renahy et al., 2010). One study even identifies a reversed educational gap: the better educated search health information online less frequently than the less educated (Mesch et al., 2012). Yet, people with lower levels of education

and income remain less likely to consult online rankings or reviews of health professionals, organizations, or treatments (Thackeray et al., 2013). As to more participatory eHealth behaviors, more affluent Americans are more likely to participate in online support groups (Atkinson et al., 2009).

Second, gender and race. Most research supports that women and racial/ethnic majorities remain more likely to search health information online than men and racial/ethnic minorities (Viswanath & Ackerson, 2011). For instance, women are more likely to consult online rankings or reviews of health professionals, organizations, or treatments as well as use SNSs for health-related activities than men (Thackeray et al., 2013). However, there is no significant gender gap in online health communication (Mesch et al., 2012).

Since the literature becomes inconsistent as the Internet and eHealth behaviors diffuse, a research question is developed:

RQ1: How do eHealth behaviors vary by health status, gender, class, and race?

3. Data and method

This research focused on college students as young people have led other age groups in Internet use and many aspects of eHealth behaviors (Fox, 2011). Nonetheless, there are great variations in eHealth disparities among this age group as many college students have difficulties in using online health tools (Dobransky & Hargitai, 2012; Stellefson et al., 2011). Data were drawn from a survey of students in two introductory courses at a big public university in Southwest U.S. A total of 594 students out of the 630 students enrolled answered the online survey from November 6 to December 10, 2011, yielding a response rate of 94% (AAPOR RR2). As 35 students failed to answer more than 50% of the questions, it lowered the response rate to 89% (AAPOR RR1). In this research, only respondents with valid answers on all variables involved in the analyses were included (N = 540). Missing value analysis suggested no systematic pattern of missing values. Common method biases were checked using Hartman's single-factor test and confirmatory factor analysis. Table 1 reported the descriptive statistics.

3.1. Dependent variables

3.1.1. Informational and participatory eHealth behaviors

Using items adapted from the Health Information National Trends Surveys (NIH, 2012) and the Pew surveys (Fox, 2011), respondents were asked whether they had engaged in a variety of online health activities (1 = yes and 0 = no).

Informational eHealth behaviors were measured by the sum score of eight items on whether the respondent had searched online: (1) a specific physical disease or medical problem, (2) depression, anxiety, stress, or mental health issues, (3) exercise, fitness, weight control or weight lost, (4) prescription, over-the-counter drugs, and a medical treatment or procedure including experimental or alternative treatments or medicines, (5) doctors, health professionals, hospitals or other medical facilities, (6) health insurance, including private insurance, Medicare, or Medicaid, (7) other health issue, or (8) got any health information on social networking sites (mean = 3.42, SD = 2.28).

Participatory eHealth behaviors were measured by the sum score of six items on whether the respondent had (1) posted a review online of doctors, health providers, hospitals or other medical facilities, (2) shared photos, videos, or audio files online about health or medical issues, (3) gone online to find others who might have similar health concerns, (4) tracked his or her weight, diet, exercise routine, or other health indicators online, (5) started or joined a health-related group on a SNS, or (6) followed his or her friends' personal health experiences or updates on a SNS. The distribution of the sum score was positively skewed and only 12% of the respondents conducted three or more types of participatory eHealth behaviors. Thus, respondents with three or more types of participatory eHealth behaviors were combined into one single category (mean = .91, SD = 1.04).

3.2. Independent and control variables

Two latent variables instrumental Internet use and Facebook interaction measured usage patterns. Respondents were asked about 16 types of Internet activities in the past 30 days via a 7-point scale (1 = never to 7 = a few times an hour). After conducting confirmatory factor analysis (CFA) for construct validity and reliability, six items with high factor loadings were included: (1) search for job information online, (2) look for information from local, state, or federal government websites, (3) bank online, (4) buy something online, (5) rate a product or service online, and (6) research a product or service online. The Cronbach's alpha of the six items was .74 (mean = 17.59, SD = 5.07).

Facebook interaction was measured by eight items on the frequency of Facebook use in the past 30 days via a 7-point scale (1 = never and 7 = a few times an hour). After conducting CFA, seven items with high factor loadings were included: (1) update status, (2) upload and share photos, (3) share web links, news stories, blog posts, and notes, (4) "like" or comment on Facebook pages of groups, events, organizations, or companies, (5) click the

Table 1
Summary of descriptive statistics and bivariate correlations.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
(1) Informational eHealth	–									
(2) Participatory eHealth	.459***	–								
(3) Instrumental Internet use	.163***	.224***	–							
(4) Facebook interaction	.091*	.194***	.384***	–						
(5) eHealth literacy	.241***	.099*	.079	.026	–					
(6) Physical health status	–.016	.065	–.008	–.045	.049	–				
(7) Mental health status	–.090*	–.091*	–.005	.026	.192***	–.072	–			
(8) Class	.006	.061	–.083	–.105*	–.022	.062	.091*	–		
(9) Gender	.122**	.092*	–.123**	–.006	.064	–.055	–.005	–.036	–	
(10) Race	–.072	–.028	–.160***	–.150**	.021	.084	–.012	.331***	.017	–
Means	3.422	.913	17.594	19.938	11.328	.472	.594	3.326	.504	.628
S.D.	2.283	1.038	5.072	7.036	2.298	.500	.491	.888	.500	.484
Cronbach's alpha	–	–	.744	.844	.839	–	–	–	–	–

*** p < .001.

** p < .01.

* p < .05.

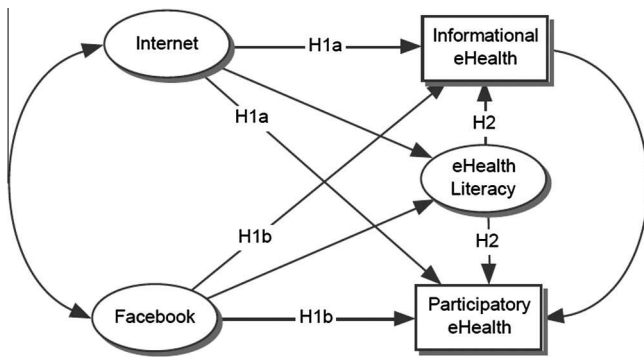


Fig. 1. Hypothesized model of Internet and Facebook use on eHealth behaviors.

“like” or “share” button on a non-Facebook website to share it on Facebook, (6) play social games (e.g. Farmville, Mafia Wars, etc.), and (7) share location using Facebook places. The Cronbach’s alpha of the six items was .84 (mean = 19.94, SD = 7.04).

eHealth literacy was measured through four items via a 5-point scale (1 = strongly disagree to 5 = strongly agree), adapted from eHEALS (Norman & Skinner, 2006). Respondents were asked how much they agreed with the following four statements: (1) I know where to find helpful health resources on the Internet, (2) I know how to use the health information I find on the Internet to help me, (3) I feel confident in using information from the Internet to make health decisions, and (4) Sometimes it’s difficult to tell high quality health resources from low quality health resources on the Internet. After conducting CFA for construct validity and reliability, Item (4) was excluded for low factor loading. The Cronbach’s alpha of the three items was .84 (mean = 11.33, SD = 2.30).

Physical and mental health status was measured by a 5-point scale respectively (1 = poor, 2 = fair, 3 = good, 4 = very good, 5 = excellent). As the distribution is skewed, we followed existing studies (Dobrany & Hargittai, 2012) and constructed two binary variables, with 1 indicating very good or excellent physical or mental health status and 0 otherwise (physical: mean = .47, SD = .50; mental: mean = .59, SD = .49).

User characteristics included *class*, *race*, and *gender*. Class was measured by a 5-point scale (1 = lower class to 5 = upper class; mean = 3.33, SD = .89). Gender and race were binary (1 = female and 0 = male; 1 = white and 0 = nonwhite). About fifty percent of the sample were female (female = 50.4%, male = 49.6%) and 62.8% were white students (nonwhite = 37.2%).

4. Results

We used Structural Equation Modeling (SEM) in Mplus 6.12 to test the hypothesized model (Fig. 1). Our analysis followed the two-step procedure: the measurement model and the structural model (Kline, 2011). The measurement model performed a CFA to examine whether individual items in a scale were good indicators of a latent construct. As discussed above, three latent constructs were included in the measurement model: instrumental Internet use, Facebook interaction, and eHealth literacy.

The structural model was consisted of three sets of regressions (Fig. 1). First, informational and participatory eHealth behaviors were regressed on instrumental Internet use, Facebook interaction, and eHealth literacy. In addition, as informational eHealth behaviors remained more prevalent than participatory eHealth behaviors (Fox, 2011; Fox & Duggan, 2013; Thackeray et al., 2013), the latter were regressed on the former. Second, eHealth literacy was regressed on Internet use and Facebook interaction. We also included a correlation between instrumental Internet use and Facebook

interaction as Internet and Facebook use were found to be related in the existing literature (Brenner, 2013; Ellison et al., 2007; Hunt, Atkin, & Krishnan, 2012). Physical and mental health status, class, gender, and race were controlled in the structural model as they were known factors related to eHealth behaviors, eHealth literacy, and Internet and Facebook use. As both types of eHealth behaviors were categorical, the mean- and variance-adjusted robust weighted least squares (WLSMV) estimation was used.

4.1. The measurement model

As shown in Model (a) in Table 2, the Chi-square for the measurement model was significant ($\chi^2 = 209.769$, $df = 97$, $p < .001$), indicating an inadequate fit. Since the Chi-square statistics were sensitive to sample size (Kline, 2011), other model fit indices were considered. The Bentler Comparative Fit Index (CFI) was .964, the Tucker-Lewis Index (TLI) was .956, and the Root Mean Square Error of Approximation (RMSEA) was .045, all indicating an adequate model fit based on the thresholds of acceptable fit ($CFI \geq .90$, $TLI \geq .90$, $RMSEA \leq .05$, see Bollen, 1989; Hu & Bentler, 1999). Thus, the measurement model adequately measured the latent constructs in the data.

4.2. The hypothesized model

Although the Chi-square of the hypothesized model was significant ($\chi^2 = 334.834$, $df = 192$, $p < .001$, see Model (b) in Table 2), other fit statistics supported an adequate model fit ($CFI = .934$, $TLI = .916$, $RMSEA = .037$).

We reported both unstandardized and standardized coefficients in Fig. 2 and later in Fig. 3 but used the unstandardized coefficients when reporting the results in the text (Kline, 2011). H1a on a positive relationship between instrumental Internet use and eHealth behaviors was supported (informational: $b = .181$, $s.e. = .072$, $t = 2.510$, $p < .05$, participatory: $b = .189$, $s.e. = .071$, $t = 2.654$, $p < .01$). H1b on a positive relationship between Facebook interaction and eHealth behaviors was only supported with participatory eHealth behaviors ($b = .153$, $s.e. = .052$, $t = 2.943$, $p < .01$). H2 on a positive relationship between eHealth literacy and eHealth behaviors was only supported with informational eHealth behaviors ($b = .388$, $s.e. = .054$, $t = 7.151$, $p < .001$).

Physical health status was not significantly related to either type of eHealth behaviors. Mental health status was significantly and negatively related to informational eHealth behaviors ($b = -.321$, $s.e. = .090$, $t = -3.559$, $p < .001$). Women had more frequent informational eHealth behaviors than men ($b = .263$, $s.e. = .088$, $t = 2.969$, $p < .01$). There was a significant, positive relationship between class and participatory eHealth behaviors ($b = .126$, $s.e. = .049$, $t = 2.577$, $p < .05$). There were no significant differences in eHealth behaviors between whites and racial minorities.

4.3. The revised model

Fig. 2 showed that both instrumental Internet use and Facebook interaction were not significantly associated with eHealth literacy at $p < .05$. As importantly, the path between Facebook interaction and informational eHealth behaviors and the path between eHealth literacy and participatory eHealth behaviors were not statistically significant at $p < .05$. Thus, in a revised model, we excluded these insignificant paths to achieve a more parsimonious model.

Although the Chi-square was significant as shown in Model (c) in Table 2 ($\chi^2 = 301.422$, $df = 196$, $p < .001$), other fit statistics supported an adequate fit ($CFI = .951$, $TLI = .940$, $RMSEA = .032$). As the hypothesized and the revised models were nested, we conducted

Table 2
Summary of fit indicators.

Models	χ^2	df	p	CFI	TLI	RMSEA
(a) Measurement model	209.769	97	.000	.964	.956	.045
(b) Hypothesized structural model	334.834	192	.000	.934	.916	.037
(c) Revised structural model	301.422	196	.000	.951	.940	.032

Note: The control variables were not included in the test of the measurement model.

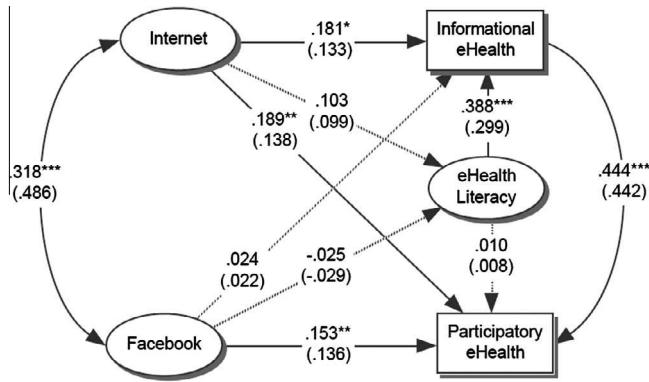


Fig. 2. Results for the test of the hypothesized model: Model (b).
Note: Standardized coefficients in parentheses and insignificant paths indicated with dotted lines.

the Chi-square difference test to examine whether the changes between the two models were significant. The difference in the Chi-square statistics between the two models was not statistically significant ($\Delta\chi^2 = 4.750$, $\Delta df = 4$, $p > .05$), indicating that the hypothesized model with more parameters did not significantly better explain the data than the revised model. Thus, the revised model was preferred as it was more parsimonious than the hypothesized model.

Fig. 3 reported results in the revised model and showed that instrumental Internet use was significantly and positively related to both informational and participatory eHealth behaviors while Facebook interaction was positively related to only participatory eHealth behaviors. eHealth literacy was significantly and positively associated with informational but not with participatory eHealth behaviors.

In addition, mental health status was negatively related to informational eHealth behaviors ($b = -.327$, $s.e. = .090$, $t = -3.623$, $p < .001$). Women had more informational eHealth behaviors than men ($b = .271$, $s.e. = .089$, $t = 3.048$, $p < .01$). More privileged class background was related to more participatory eHealth behaviors ($b = .126$, $s.e. = .049$, $t = 2.575$, $p < .05$).

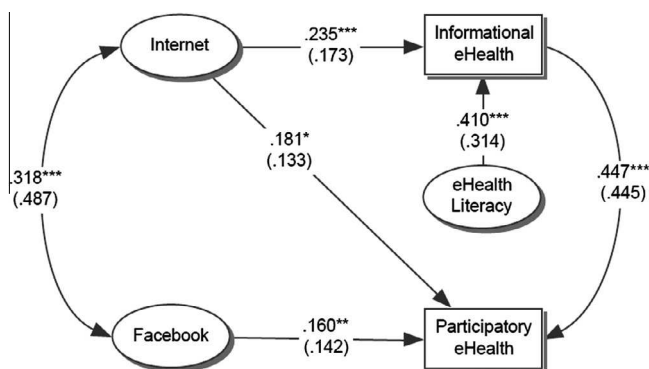


Fig. 3. Results for the test of the revised model: Model (c).
Note: Standardized coefficients in parentheses.

Table 3
Effect decomposition based on the revised model.

Predictor	Criterion	Direct effect	Indirect effect	Total effect
Mental health	Informational eHealth behavior	-.327*** (.090)	.136*** (.035)	-.191* (.092)
	Via eHealth literacy		.136*** (.035)	
Mental health	Participatory eHealth behavior	-.141 (.088)	-.086* (.041)	-.226 (.099)
	Via informational eHealth behavior		-.146*** (.041)	
	Via eHealth literacy and informational eHealth behavior		.061*** (.016)	

Note: Unstandardized coefficients with standard errors in parentheses.
* $p < .05$.
** $p < .01$.
*** $p < .001$.

4.4. Indirect effect

Besides the direct effect, we identified significant indirect effects (Table 3). First, excellent mental health status was indirectly associated with informational eHealth behaviors via eHealth literacy ($b = .136$, $s.e. = .035$, $t = 3.862$, $p < .001$).

Second, excellent mental health status was indirectly associated with participatory eHealth behaviors via two mediators: a negative indirect effect of informational eHealth behavior ($b = -.146$, $s.e. = .041$, $t = -3.550$, $p < .001$) and a positive indirect effect involving a two-step mediation via eHealth literacy and informational eHealth behaviors ($b = .061$, $s.e. = .016$, $t = 3.837$, $p < .001$). As the negative effect of the former was greater than the positive effect of the latter, the total negative effect of excellent mental health on participatory eHealth behaviors became statistically significant ($b = -.226$, $s.e. = .099$, $t = -2.284$, $p < .05$).

Overall, eHealth literacy served as a suppressor of the negative relationship between excellent mental health status and eHealth behaviors. Informational eHealth behaviors served as an enhancer of the negative relationship between excellent mental health and participatory eHealth behaviors.

5. Discussion and conclusion

Offering a more comprehensive understanding of eHealth behaviors, this research makes unique contributions to the existing eHealth literature in several aspects. First, it addresses one critical gap in the existing literature which has centered on informational eHealth behaviors (or online health information search) but paid limited attention to participatory forms of eHealth behaviors. Expanding the existing literature, this research examines both informational and participatory eHealth behaviors.

Second, integrating insights from digital divides, eHealth disparities, and eHealth literacy literatures, this research provides a refined analysis of factors and mechanisms related to informational and participatory eHealth behaviors. In particular, it takes

into account of eHealth literacy, usage patterns, physical and mental health status, and other user characteristics, while most existing studies only include some of these variables.

Third, this research offers of the similar and differential Internet and Facebook implications for eHealth behaviors. Instrumental Internet use – but not Facebook interaction – is related to informational eHealth behavior. The results support findings from national survey data that more than three-quarters health information seekers started their health information search with a search engine but only 1% started with a SNS site such as Facebook (Fox & Duggan, 2013). The results are in line with qualitative interviews that search engines and health websites were the most and social media the least important health information sources among college students (Zhang, 2013). By contrast, both instrumental Internet use and Facebook interaction are significant to participatory eHealth behaviors.

Fourth, moving beyond existing studies focusing on either physical or mental health, this research includes both physical and mental health status. It demonstrates that excellent mental health has a negative direct effect on informational eHealth behaviors. In comparison, physical health status is not significant to eHealth behaviors.

Fifth and most importantly, this research confirms the critical role of eHealth literacy in eHealth behaviors. It has a significant and positive direct effect on informational – but not on participatory – eHealth behaviors. Furthermore, it identifies eHealth literacy as a mediator suppressing the negative relationship between excellent mental health status and both informational and participatory eHealth behaviors.

Last but not least, although college students are often dubbed as the digital natives with an edge in using and benefiting from the latest technologies, this research reveals informational eHealth disparities by gender and participatory eHealth disparities by class. By contrast, this research finds no significant racial variations in eHealth behaviors. Our findings resonate with some existing studies on a significant gender gap in online health information search (Dobransky & Hargittai, 2012; Thackeray et al., 2013; Viswanath & Ackerson, 2011), an insignificant class difference in online health information search (Dobransky & Hargittai, 2012; Renahy et al., 2010), and a significant class gap in eHealth behaviors beyond information search (Atkinson et al., 2009; Beckjord et al., 2007). Our findings, however, contradict with some existing studies that women are less likely to engage eHealth behaviors beyond information search (Mesch et al., 2012; Stellefson et al., 2011) or a significant racial gap in eHealth behaviors (Viswanath & Ackerson, 2011).

These findings have scholarly and practical implications. First, improving eHealth literacy is critical to eHealth engagement due to its direct and mediating effects on eHealth behaviors. Suppressing the negative relationship between excellent mental health status and eHealth behaviors, greater eHealth literacy helps to promote eHealth behaviors beyond individual users' immediate health need. Our results further show that frequent instrumental Internet use and Facebook interaction do not necessarily lead to greater eHealth literacy. That is, boosting eHealth literacy requires targeted programs rather than leaving it to the users' own devices (Xie, 2011). Second, the differential eHealth implications of different usage patterns and user characteristics point to the importance of strategic allocation of eHealth resources. As eHealth disparities become more diversified along the fault lines of gender, class, and race, it is more effective for health professionals to develop and distribute customized health content.

This research has limitations that call for future research. First, the data are cross-sectional and the sample is limited to college students, which hinders the generalizability of the results. Future research needs to draw on longitudinal data from the general pop-

ulation to test the relationships and mechanisms identified in our research. Second, our measure of eHealth literacy is adapted from eHEALS, “developed at a time when the first generation of web tools gained prominence before the rise of social media” (Norman, 2011). This may partially contribute to the lack of a significant direct effect on participatory eHealth behaviors. As people's eHealth literacy and eHealth behaviors evolve over time due to personal, social, and technological changes, we need to update and develop a more comprehensive measure of eHealth literacy that conceptualizes users as both educated consumers and empowered citizens who not only consume but also create and promote health content by including more items on social media literacy (Chinn, 2011; Norman, 2011). Future research also needs to examine the presence and the magnitude of the gaps between self-reported and observed eHealth literacy (Stellefson et al., 2011) and eHealth behaviors (van der Vaart et al., 2011).

Despite these limitations, this research has greatly extended the existing studies on eHealth behaviors. It will inspire future research on the longitudinal relationship between a wide range of usage patterns of the Internet and social media, eHealth literacy, user characteristics, and informational and participatory eHealth behaviors in the general population, especially the mediating role of eHealth literacy which serves as a mechanism that links user characteristics and eHealth behaviors.

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