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Social Media Use as a Predictor of Higher Body Mass Index in Persons living with HIV

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Abstract

Social media tools have been touted as an approach to bring more democratic, and effective, communication networks to health care and to improve the experiences of those either receiving or delivering it. At the same time there are risks associated with social media use. We conducted a multi-site cross-sectional study among persons living with HIV (PLWH) to understand their social media use. We conducted a secondary analysis of data collected from the parent study to understand technology use among PLWH in the US and the association between social media use and body-mass index (BMI). Our primary predictor variable was social media use. Our primary outcome was BMI measured through height and weight during the study visit. Descriptive statistics were used to describe the demographic profiles of the study participants and linear regression models were used to analyze associations between the outcome and predictor variables controlling for demographic characteristics. Study participants (N=606) across 6 study sites in the United States (US) were predominately 50–74 years old (67%). 33% of study participants had a normal weight (BMI 18.5–25), 33% were overweight (BMI 25–30), and 32% were obese

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Conflict of interest
All authors declare that they have no conflict of interest.

Ethical Approval
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.

Informed Consent
Informed consent was obtained from all individual participants included in the study.

Research Involved in Animal Rights
This article does not contain any studies with animals performed by any of the authors.

(BMI>30). Participants used several social media sites with Facebook (45.6%) predominating with more than five-times as many people using this site than Google+ (8.4%) and Instagram (6.1%). Social media use was associated with higher BMI in study participants ($p<.001$) and this effect persisted, although not as strongly, when limiting the analysis to those who only used Facebook ($p=.03$) or only used other social media sites (not including Facebook) ($p=.03$). Further consideration of social factors that can be ameliorated to improve health outcomes are timely and needed.

Introduction

With about 200 million active websites on the world wide web,(Netcraft Ltd, 2018) the Internet has become a common source of health information for people living with chronic illnesses. This is especially relevant for HIV, which has now largely become a chronic illness for those in the US who are living with the disease. It is widely accepted that technology access and smartphone ownership are now almost universal among all Americans, yet little is known about PLWH's social media use. In fact, extensive studies have been conducted on persons at risk for HIV infection and their use of social media for meeting sex partners,(Beymer et al., 2014; Grov, Crow, & Prevention, 2012; Rendina et al., 2014; Rice et al., 2012) but few investigators have explored PLWH's use of social media and whether there is a relationship between social media use and health outcomes.

Social media tools have been touted as an approach to bring more democratic, and to improve the experiences of those either receiving or delivering health care.(Hawn, 2009) At the same time there are risks associated with social media use in the delivery of healthcare. For example, issues related to patient privacy and the potential for diagnostic errors.(Kane & Sands, 1998) Outside the context of healthcare delivery, negative effects of social media use have been described. For example, the American Heart Association has implicated social media use as a contributor to childhood obesity.(Li Jennifer, Barnett Tracie, Goodman, Wasserman Richard, & Kemper Alex, 2013) In another study, Facebook was identified as having a negative impact on young women's body image and mood.(Fardouly, Diedrichs, Vartanian, & Halliwell, 2015) Finally, social media tools, such as GRINDR, have been implicated in facilitating high-risk sexual partnering among young men.(Landovitz et al., 2013)

While technological capabilities advance, we are also experiencing national increases in obesity diabetes and high blood pressure. Obesity affects about 93.3 million US adults.(Hales, Carroll, Fryar, & Ogden, 2017) The obesity epidemic and its associated conditions is likewise highlighted in PLWH, such that up to 65% of PLWH in the US are overweight or obese.(Kim et al., 2012; Lakey, Yang, Yancy, Chow, & Hicks, 2013; Tate et al., 2012) and they are being diagnosed at the same or higher rates as their age-matched HIV-infected peers, with cardiovascular disease, renal disease, and diabetes.(Crum-Cianflone et al., 2010; Sullivan, Morrato, Ghushchyan, Wyatt, & Hill, 2005; Vinikoor et al., 2013; Worm et al., 2009) Social media use has been understudied in PLWH. Therefore, the purpose of this study among PLWH in the US was to: 1) describe their technology use and 2) assess the relationship between their BMI and social media use.

METHODS

Study Design

We conducted a multi-site cross-sectional study to examine associations between physical activity and cardiorespiratory fitness patterns among PLWH.(Webel et al., 2018) We conducted a secondary analysis of data collected from the parent study to understand technology use among PLWH in the US and the association between social media use and BMI.

The multi-site study was overseen by the International Nursing Network for HIV Research..(Holzemer, 2007) Institutional Review Board (IRB) approval was obtained at the coordinating site Case Western Reserve University and at each of the local sites prior to the start of the study activities. .

Sample and Recruitment

To be eligible for participation in this study, participants had to be ≥18 years of age, have a confirmed HIV diagnosis and be able to understand English or Spanish. Exclusion criteria included: 1) medical contraindication for exercise determined by American Health Association criteria through self-report, or 2) inability to be physically active without an assistive device (i.e. wheelchair, walker, or cane). Participants were recruited by responding to study advertisements in clinic waiting rooms and community-based organizations. A research assistant conducted a screening with an IRB-approved script to describe the study purpose and determine whether candidates met eligibility criteria.

Procedures

Written informed consent was obtained prior to the start of all study procedures. Study activities were completed in the following order: anthropomorphic assessments (i.e., height, weight, waist and hip circumference), the 6-minute walk test, demographic questionnaire, the Stanford 7-day physical activity recall scale(Sarkin et al., 1997), and either consented for the study team to access their electronic medical chart or provided a print out of their medical record. All data were entered in a central RedCAP database(Harris et al., 2009). All study procedures for this analysis occurred between January 2016 and September 2017.

Measures

Demographic, Medical and Anthropomorphic Characteristics—All participants completed a self-reported demographic questionnaire on a private computer or tablet. Trained study staff measured height and weight, which were used to calculate BMI. Participants also consented to medical chart abstraction including the number of years a participant had been living with HIV, Current CD4+ T-cell count, current HIV Viral Load, current and past comorbid conditions, and current medication list.

6-minute walk test—Cardiorespiratory fitness was measured with the 6-minute walk test, (Ross et al., 2016) according to the American Thoracic Society guidelines. (“ATS Statement,” 2002)

Technology and Social Media Use—Technology and Social media use questions focused on frequency of use, most commonly used technologies and when participants started using the technology. The specific questions and answer choices are listed in Table 2.

Data Analysis

Descriptive statistics were used to describe the demographic characteristics and technology use of the study sample. All statistical analyses were conducted using SAS 9.4 and *p*-values <0.05 were considered statistically significant. We used linear regression to conduct a bivariate analysis of the relationship between BMI and each demographic, social media use, and cardiorespiratory measure. In our final model, we used linear regression to assess the relationship of BMI and social media use and controlled for the co-variates that were found to be significant in our bivariate model.

RESULTS

We enrolled 606 participants across 6 study sites in the US. The average age of our participants was 52 ± 10.76 years old, most were male (59%), not working (79%), and had an income <$1000/month (68%). Most participants had a viral load ≤50 copies (79%) and most used antiretroviral therapy (ART) (91%). Participants had an average (± standard deviation) BMI of 27.9 ± 6.7 and walked an average of 406 ±108 meters on the 6-minute walk test. Additional demographic characteristics of the sample can be found in Table 1.

Technology Use

Technology use is described in Table 2. Most of our study participants used some form of personal technology 60.8% of participants use an Android phone followed by 23.8% who use an iPhone. Location-based (GPS) apps were the most frequently (33%) used type of app followed by sharing data with personal connections (16.1%). Mood tracking (2.8%) and side effect tracking (2.8%) were the least frequently used type of app.

Predictors of BMI among PLWH:

Table 3 displays results of the bivariate analysis of demographic characteristics and BMI as an outcome. Study site was significantly related to BMI with participants from Texas and California having significantly lower BMI than participants from other sites. Females, Blacks, married persons, those with lower viral load and higher income were significantly more likely to have a higher BMI. Participants who used Facebook and multiple social media sites were significantly more likely to have a higher BMI.

Social Media Use and BMI:

In our full regression model (Table 4), we assessed the relationship between social media and BMI as our outcome and controlled for those demographic and cardio-metabolic variables that were significant in our bivariate analysis We observed that Facebook users were more likely to have a higher BMI than persons who did not use any social media ($p=.03$).

DISCUSSION

In this multi-site study of PLWH, we found that almost 85% of our study population are smartphone owners. The latest national statistics from 2016 indicate that 72% of all adults across the U.S. own a smartphone, which is consistent with our study sample. (Poushter, 2016) Further, our findings are consistent with national trends of Android ownership exceeding iPhone ownership.(Smith, 2013)

Overall participants had low uptake of apps. Notably location-based tools were the most commonly used app which may be attributable to usefulness of the technology for this purpose. Interestingly, study participants rarely used apps to track their side effects or to manage their medications, despite other PLWH reporting using apps for this purpose and finding them to be useful (Beauchemin, Gradilla, Baik, Cho, & Schnall, 2019; Cho, Porras, Baik, Beauchemin, & Schnall, 2018; Stonbraker, Cho, Hermosi, Pichon, & Schnall, 2018) and potentially efficacious at improving health outcomes;(Schnall, Cho, Mangone, Pichon, & Jia, 2018) this may be partially explained by concerns around privacy and confidentiality(Schnall, Higgins, Brown, Carballo-Dieguez, & Bakken, 2015).

A wider range of app choices (including but not limited to games, news, and media apps) might have illustrated a greater uptake in app usage.The associations observed between demographic characteristics and BMI in our study sample was expected and is consistent with previous research demonstrating that females, Blacks, and married persons are the most likely to have higher BMIs (Ogden et al., 2006; Tate et al., 2012) Age was not a significant predictor of BMI in our sample, despite previous research demonstrating that older persons are more likely to have a higher BMI.

There are several limitations of this study. First, this was a cross-sectional study design. Second, the questionnaires had limited response options that may not have fully captured the frequency or duration of use of the social media. Frequency of use of social media sites may have a greater influence on outcomes than type of social media outlet. Finally, it the use of technology, social media use, and apps will continually change with the times and so the implications of the timing of these findings should be considered in future work.

Conclusion

Social media use was associated with higher BMI in study participants and this effect persisted, although not as strongly, when limiting the analysis to those who only used Facebook or only used other social media sites. These findings are novel and important considering the current HIV and obesity epidemics in the US. The American Heart Association statement on the effects of social media use on children is laudable but leaves unaddressed the potentially negative effects of social media use on adults, and those living with a chronic illness such as HIV. As PLWH age, pronounced cardiovascular effects of living with the disease have become evident, further consideration of social factors that can be ameliorated to improve health outcomes are timely and needed.

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Table 1:

Demographic Characteristics of Sample of PLWH

Characteristics (N = 606)	N (%)
Mean age in year (SD)	52 (10.76)
Age	
20–34	60 (10)
35–49	132 (22)
50–74	411 (67)
75+	2 (1)
Gender	
Male	361 (59)
Female	222 (37)
Transgender Male	5 (1)
Transgender Female	15 (2)
Genderqueer	2 (1)
Sex at Birth	
Male	381 (63)
Female	224 (37)
Race	
African-American	316 (52)
White/Anglo	149 (25)
Other	140 (23)
Hispanic/Latino	
No	445 (74)
Yes	156 (26)
Marital Status	
Married/Partnered	113 (19)
Single	338 (56)
Other	153 (25)
Highest Level of Education Completed	
High school/GED or less	307 (51)
More than high school/GED	295 (49)
Monthly Income	
No monthly income	67 (11)
Less than $200	29 (5)
$200-$599	69 (11)
$600-$799	126 (21)
$800-$999	120 (20)
$1,000 or more	191 (32)
Health Insurance	
Medicaid	253 (42)
Medicare	130 (22)

Characteristics (N = 606)	N (%)
ADAP	25 (4)
Veteran's Benefits	11 (2)
Private, provided by work	29 (5)
Private, not provided by work	15 (2)
Ryan White Care Act	25 (4)
Obamacare/ACA/Marketplace	28 (5)
Multiple Public Mechanisms	56 (9)
No insurance	32 (5)
Employment	
Working	124 (21)
Other (Not working)	480 (79)
Viral Load	
≤ 50 IU/mL	406 (79)
> 50 IU/mL	110 (21)
ART Use	
Yes	526 (91)
No	49 (9)
Sites	
Case Western Reserve University, Cleveland OH	116 (19)
Columbia University, NY & Rutgers, NJ	165 (27)
Texas A&M, Corpus Christi, TX	175 (29)
University of California, San Francisco CA	91 (15)
Old Dominion University, Norfolk, VA	59 (10)
Mean BMI (SD)	27.9 (6.7)
BMI – Clinical Cut-Off Points	
Underweight (<18.5)	16 (2)
Normal Range (18.5<25)	189 (33)
Overweight (25<30)	189 (33)
Obese (≥30)	183 (32)
Do you use any of the following Social Media Sites?	
None	214 (36)
Facebook only	226 (38)
Twitter only	15 (3)
Other only (Linkedin, Pinterest, Google Plus+, Tumblr, Instagram, Flickr, POZ)	86 (14)
Multiple social media sites	57 (10)
6-Minute Walk Test – Total Distance, mean, meters (SD)	406 (108)

Table 2.

Study Participant Use of Technology

	N(%)
How often do you use a desktop or laptop computer?	
Never	183 (30.1)
Once/ month or less often	90 (14.8)
Several Times/ Month	51 (8.4)
Several Time/ week	61 (10.0)
Once/ Day	56 (9.2)
Several times every day	166 (27.3)
When did you start using a desktop or laptop computer?	
Never	145 (23.9)
In the past 6 months	35 (5.77)
In the past year	45 (7.4)
In the past two years	26 (4.3)
More than two years	356 (58.6)
How often do you use a mobile device (e.g. Smartphone, tablet, cellphone)?	
Several times every day	429 (70.7)
Once a day	61 (10.0)
Several times per week	51(8.4)
Several times per month	17 (2.8)
Once a month or less often	15 (2.5)
Never	34 (5.6)
When did you start using a mobile device (e.g. Smartphone, tablet, cellphone)?	
I don't use a mobile device	31 (5.13)
In the past six months	33 (5.46)
In the past year	40 (6.6)
In the past two years	52 (8.6)
More than two years	448 (74.2)
Which type of mobile device do you use most frequently?	
I don't use a mobile phone	8 (1.4)
Android phone	368 (60.8)
iPhone	144 (23.8)
Tablet (e.g. ipad)	37 (6.1)
Netbook	6 (1.0)
Other	42 (6.9)
When did you start sending text messages/ SMS?	
I don't send texts.	88 (14.5)
In the past six months	40 (6.6)
In the past year	46 (7.6)

	N(%)
In the past two years	53 (8.7)
More than two years	379 (62.5)
About how many texts do you send per day?	
0–10	336 (55.4)
10–50	168 (27.7)
50–100	64 (10.5)
100–200	18 (3.0)
More than 200	21 (3.5)
Social networking Sites Ever Used by Participants (more than one selection is allowed)	
Facebook	277 (45.6)
Twitter	30 (4.9)
Linkedin	26 (4.3)
Pinterest	24 (4.0)
Google Plus+	51 (8.4)
Tumblr	14 (2.3)
Instagram	37 (6.1)
Flickr	6 (1.0)
POZ	5 (0.8)
Other	35 (5.8)
Types of apps used by participants (more than one selection is allowed)	
Location-Based Tools (GPS)	202 (33)
Sharing Data with HealthCare Providers	98 (16.1)
Sharing Data with Personal Connections (Family, Loved Ones)	150 (24.7)
Motivational Messaging	91 (15)
Adherence Progress Tracking	25 (4.1)
App Locking (Password Protection)	105 (17.3)
Mood Tracking (Journaling)	17 (2.8)
Personal Notes (For reflection, correlation, Identifying behavior triggers)	58 (9.6)
Side Effect Tracking	17 (2.8)
Educational Information Repository	59 (9.7)
Peer Support	67 (11.0)

Table 3:

Linear Regression Models of Bivariate Analysis with BMI Outcome

Demographic Variables	Intercept	Parameter Estimate[g]	p-value
Age	28.69	−0.01 (−0.06, 0.04)	0.57
Site[a]	28.21		<.0001
New York & New Jersey		0.18 (−1.46, 1.82)	0.83
Texas		−0.81 (−2.37, 0.75)	0.31
California		−1.55 (−3.37, 0.27)	0.09
Virginia		1.73 (−0.35, 3.81)	0.10
Education	28.14	−0.32 (−1.41, 0.77)	0.56
Gender[b]	26.74		<.0001
Female		3.22 (2.06, 4.37)	<.0001
Transman		3.00 (−2.76, 8.75)	0.31
Transwoman		0.82 (−2.55, 4.20)	0.63
Genderqueer		−3.84 (−12.90, 5.21)	0.41
Other		−0.13 (−1.40, 1.14)	0.84
Sex at Birth	26.77	3.11 (2.01, 4.20)	<.0001
Race[c]	26.96		<.0001
Black		1.52 (0.44, 2.60)	0.006
Other		0.79 (−0.45, 2.03)	0.21
Viral Load	28.40	−1.66 (−3.13, −0.19)	0.03
Hispanic/Latino	27.92	0.26 (−0.91, 1.49)	0.68
Monthly Income[d]	27.08		<.0001
Less than $200		−1.61 (−1.65, 1.53)	0.29
$200-$399		1.03 (−1.65, 3.71)	0.45
$400-$599		1.11 (−1.71, 3.93)	0.44
$600-$799		1.61 (−0.38, 3.59)	0.11
$800-$999		1.87 (−0.14, 3.89)	0.07
$1,000 or more		0.38 (−1.49, 2.25)	0.69
Marital Status[e]	27.66		<.0001
Married		0.33 (−1.12, 1.78)	0.65
Other		0.88 (−0.42, 2.78)	0.19
Employment	28.17	−0.30 (−1.65, 1.05)	0.67
Social Media Use[f]	27.09		<.0001
Facebook only		1.20 (−0.04, 2.43)	0.06
Twitter only		−0.53 (−4.06, 3.00)	0.77
Other sites only		0.75 (−0.97, 2.48)	0.39
Multiple sites		2.75 (0.77, 4.74)	0.01

Demographic Variables	Intercept	Parameter Estimate[g]	p-value
6-Minute Walk Test Total Distance	31.81	−0.0097 (−0.015, −0.005)	0.0001

[a]Reference value is "Ohio";

[b]Reference value is "Male";

[c]Reference value is "White/Anglo";

[d]Reference value is "No monthly income";

[e]Reference value is "Single";

[f]Reference value is "No social media sites";

[g]Includes 95% Confidence Interval

Social Media Use and BMI

Table 4:

Generalized Linear Models of Social Media Variables with BMI Outcome

Social Media Variable[a]	Intercept	Parameter Estimate[c]	p-value
Facebook only[b]	27.42	1.55 (0.14, 2.96)	0.03
Twitter only[b]	27.42	−0.41 (−4.12, 3.30)	0.83
Other sites only[b]	27.42	2.08 (0.25, 3.90)	0.03
Multiple sites[b]	27.42	4.19 (1.93, 6.46)	0.0003

[a]Reference value is "No social media use";

[b]Adjusted for race, viral load, 6 minute walk test total distance (physical activity measure), sex at birth, study site, and monthly income;

[c]Includes 95% Confidence Interval