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Social Media Use and Its Link to Physical Health Indicators

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Abstract

Social media use has become an integral part of many young adults' daily lives. Although much research has examined how social media use relates to psychological well-being, little is known about how it relates to physical health. To address this knowledge gap, the present research investigated how the amount of social media people use relates to various indices of physical health. Young adults provided a blood sample that was analyzed for C-reactive protein (CRP), a marker of chronic inflammation. They also completed self-report measures of social media use, somatic symptoms, illness-related physician or health center visits, and whether they sought medical care for infection-related illnesses in the last 3 months. Social media use was positively correlated with higher levels of CRP, more somatic symptoms, and more visits to the doctor or health centers for an illness. Although directionally consistent, the correlation with likelihood of seeking medical care for infection-related illnesses was nonsignificant ($p = 0.061$). All of these results held after controlling for factors such as sociodemographic information and depressive symptoms. Given the prevalence of social media use in daily life, these findings underscore the need for more research examining how social media use relates to physical health.

Keywords: social media use, physical health, somatic symptoms, C-reactive protein, inflammation, social integration

Introduction

Social media use has become an integral part of many people's daily lives. A recent survey indicates that Americans average about 144 minutes per day on social media[1]; more time than they spend exercising, directly socializing with others, or eating.[2] Social media usage is particularly high among *Generation Z* (i.e., people born in the late 1990s and early 2000s) who spend about 6 hours a day texting, online, and on social media[3] and report being online on a ''near-constant'' basis.[4]

The past decade has seen an explosion of studies examining the impact of social media use on psychological well-being.[5–9] However, little research has examined how social media use is related to *physical* health. This is surprising given the prevalence of social media in daily lives, and the close link between psychological well-being and physical health.[10]

Nevertheless, a small number of recent studies suggest a link between social media use and physical health.[11–14] For example, Xue and colleagues (2018) found that excessive use of WeChat (the most popular social media platform in China) was associated with lower self-reported health. More recently, Lee and Way (2021) discovered that among older adults with low self-esteem, social media use predicted higher levels of C-reactive protein (CRP) and interleukin (IL)-6—biomarkers of chronic inflammation.

While the above studies provide initial evidence, they have some limitations. First, some studies measured social media use in a single platform (e.g., WeChat) despite evidence that most people use multiple social media platforms.[15] Thus, it is unlikely that these studies fully captured the total amount of people's social media use.

Second, prior work has mostly used self-report measures of physical health, which can be vulnerable to demand characteristics and biases. Although a few studies have used

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biological measures, it is unclear to what extent the elevated levels of biological markers (e.g., cortisol, IL-6) reflect current health status. Thus, our goal was to extend prior work by examining how social media use across *several* platforms is associated with physical health outcomes measured at *multiple* levels (i.e., biological, behavioral, self-report).

How might social media use relate to physical health? One potential pathway might be through altering health behaviors. Several studies indicate that high levels of social media use or screen time may reduce users' amount and quality of sleep.[16,17] This may be particularly the case for those who use social media excessively—addictive social media or mobile phone use can lead to reduced sleep quality and insomnia.[18,19] A substantial body of evidence indicates that lower quality or quantity of sleep is linked to poorer physical health,[20–22] including elevated risks for cardiovascular disease,[23] hypertension,[24] and early mortality.[25] This perspective aligns with the displacement hypothesis, which posits that time spent on social media may have detrimental effects by displacing activities that are beneficial to well-being and health—for example, sleep, exercise, or face-to-face interactions.[7,26]

Second, several scholars contend that hyperconnectivity—the permanent availability of and connectivity to peers, media content, and online services through social media—can increase stress.[17,27,28] For example, new communication norms and demands arising from hyperconnectivity (e.g., the need to check or respond to social media posts constantly) can lead to communication overload and higher levels of stress.[28–30] Stress can undermine health in many ways, for example, by increasing the number and severity of somatic symptoms,[31] the probability of infection and the severity of symptoms following exposure to a cold virus,[32] and systemic inflammation.[33] Collectively, these perspectives suggest that high levels of social media use may relate to worse physical health.

In this study, we examined whether social media use would be correlated with worse physical health indicators (i.e., higher levels of chronic inflammation, more frequent somatic symptoms, and more visits to health clinics). We tested this hypothesis in a college student sample because it is the age group most actively engaged with social media.[34]

Our physical health indicators consisted of three measures: (a) CRP, a biological marker of chronic inflammation in the blood; (b) self-report of somatic symptoms; and (c) illness-related physician or health center visits. Chronic inflammation is a potent driver of disease.[35] In particular, elevated levels of CRP are associated with increased risk for chronic diseases, including cardiovascular disease, cancers, and depression.[36,37] We also assessed somatic symptoms (e.g., headaches, chest or back pains), which are the leading cause of outpatient medical visits and associated with substantial functional impairment, disability, and health care usage. Such reports also predict future chronic illnesses[38] and thus serve as a good indicator of physical health.[39,40] Finally, as a broader behavioral marker of physical health, we assessed illness-related physician and health center visits.[41]

Methods

Participants and procedure

Data collection for this study occurred between October, 2018 and February, 2019. Two hundred and fifty-one undergraduate students (123 females; $M_{age} = 19.40$, $SD_{age} = 2.23$; 60.8 percent White, 27.7 percent Asian/Pacific Islander, 5.8 percent African American, 3.5 percent Hispanic/Latin American, 2.2 percent Other) at a large Midwestern university participated in a study of ''how people use social media'' for course credit.

In the absence of an established literature on social media use and physical health, we estimated effect size from the related literature on social media use and psychological well-being.[7,42] A power analysis using G*Power based on a small-to-medium effect size ($f^2 = 0.09$) between social media use and each of our dependent variables indicated that a sample size of 200 provides 90 percent power ($\alpha = 0.05$) to detect a significant effect; we intentionally oversampled and aimed to recruit 250 participants to account for participants who opt out of providing blood samples. All analyses were conducted after data collection was completed.

Participants were escorted to a laboratory where a trained research assistant collected blood samples through finger sticks to be assayed for CRP. Participants could opt out of providing their blood samples without losing their compensation. Twenty-eight (11 percent) opted out; these participants were excluded whenever we conducted analyses with the CRP variable, but were included for other analyses.[a] Participants then completed a battery of questionnaires in a separate room. To ensure validity of questionnaire responses, at the end of the study, participants were instructed to report the extent to which they took the study seriously (1 = *not at all seriously*, 5 = *very seriously*). Before data collection, we decided to exclude participants who responded ''not at all seriously.''

The Institutional Review Board at authors' university approved all research reported in this article. All participants provided informed consent.

Measures

Social media use. Participants indicated how much time they spend on each of four social media platforms (i.e., Snapchat, Instagram, Twitter, and Facebook) on average each day (1 = *10 minutes or less*, 2 = *11–30 minutes*, 3 = *31–60 minutes*, 4 = *1–2 hours*, 5 = *>2 hours*). We measured social media use across these four platforms for two reasons. First, according to the PEW Research Center, they are the most commonly used social media platforms among U.S. adults from ages 18–24.[34] Second, emerging work recommends measuring social media use across multiple platforms because people use them for different purposes and in different amounts.[43] Thus, we averaged the four items to create a composite *social media use* variable ($\alpha = 0.57$, mean [M] = 2.37, standard deviation [SD] = 0.85).[b]

C-reactive protein. CRP, our biological indicator of physical health, was assayed from dried blood spots with a protocol slightly modified from prior research.[44] In brief, the participant's finger was swabbed with alcohol and then pricked with an 18-gauge needle (Owen Mumford Unistick 3). Blood drops were collected on a Whatman 903 Protein Saver Card and left to dry for 24 hours at room temperature. Samples were then punched using a 3 mm Biopsy Punch (Henry Schein) and stored in microcentrifuge tubes at –80°C until assay.

For assay, a single 3 mm punch was thawed and 200 μL of buffer (phosphate-buffered saline with 0.1 percent Tween 20) was added followed by overnight ($\sim$16 hours) incubation at 4°C while shaking at 60 rpm. The following morning, eluate was diluted 1:10 and CRP was assayed according to the manufacturer's instructions using the Meso Scale Delivery Vplex Plus Kits (K151STG). The assay coefficient of variation (CV) was 2.05 percent and interassay CV was 4.94 percent ($M = 1.73$, $SD = 4.25$).

Somatic symptoms. For our subjective health indicator, participants indicated how frequently they experienced somatic symptoms (e.g., chest pain, headaches) in the past month by completing the Patient Health Questionnaire (PHQ-15; $\alpha = 0.90$, $M = 2.03$, $SD = 0.72$).[39] Because over half of our sample comprised male participants, we dropped one item that measured menstrual cramps from analyses. Including this item in the analyses did not alter the results. Because values for PHQ-15 were highly skewed, they were log-transformed to achieve a normal distribution.

Health care usage. Finally, for our behavioral health indicator, participants reported how many times they visited the health center or doctor's office for an illness in the last 3 months (Medical visits; $M = 0.79$, $SD = 1.53$, range = 0–15) and whether they sought medical care for any sort of cold, flu, or infection in the last 3 months (0 = *no*, 1 = *yes* [$n = 80$]). Because values for the health center visits were highly skewed, they were log-transformed.

Covariates. Based on prior work,[12,45,46] we controlled for extraneous factors associated with inflammation. Sociodemographic covariates were age, gender, household income, and highest level of education completed by father and mother (1 = *some high school*, 5 = *graduate school*; $M = 3.60$, $SD = 1.02$). Health behavior covariates included body mass index (BMI; $M = 23.46$, $SD = 4.80$), cigarette smoking (i.e., number of cigarettes smoked per day on average; 1 = *none*, 2 = *1 to 10*, 3 = *11–20*, 4 = *21–30*, 5 = *31 or more*; $M = 1.10$, $SD = 0.31$), alcohol consumption frequency (1 = *4 or more times a week*, 2 = *2–3 times a week*, 3 = *2–4 times a month*, 4 = *monthly*, 5 = *never*; $M = 3.43$, $SD = 1.19$), and frequency of aerobic exercise (1 = *once a week*, 7 = *7 times a week*; $M = 3.08$, $SD = 1.73$).

We also controlled for depressive symptoms using the Center for Epidemiological Studies Depression Scale ($\alpha = 0.93$, $M = 1.05$, $SD = 0.69$)[47] and birth control pill use (0 = *no*, 1 = *yes* [$n = 58$]), as they can influence inflammation levels.[45,48]

Results

First, individuals with CRP values over 10 μg/mL ($n = 5$; < 2 percent) were excluded because these values may indicate the presence of an acute infection.[49] Then, CRP was log-transformed to achieve a normal distribution. Second, two participants who indicated at the end of the study that they "did not take the study seriously at all" were excluded. Including all excluded participants in the analyses did not substantively change any results. Table 1 presents zero-order correlations among all key variables.

TABLE 1. MEANS, STANDARD DEVIATIONS, AND ZERO-ORDER CORRELATIONS FOR MAIN VARIABLES

Variables	M	SD	*1*	*2*	*3*	*4*	*5*	*6*	*7*	*8*	*9*	*10*	*11*	*12*
1. SNS use	2.37	0.85	—											
2. CRP (log)	−0.38	0.68	0.21**	—										
3. PHQ (log)	0.28	0.15	0.24***	0.09	—									
4. Med visits (log)	0.18	0.24	0.21**	0.09	0.35***	—								
5. Med care	—	—	0.15*	0.05	0.18**	0.51***	—							
6. Depres	2.29	0.69	0.12†	−0.08	0.50***	0.19**	−0.05	—						
7. Gender	—	—	0.20**	0.08	0.26***	0.21**	0.20**	0.10	—					
8. Age	19.40	2.22	−0.02	0.08	0.01	−0.10	−0.11†	0.03	−0.08	—				
9. Edu (M)	3.52	1.12	−0.11†	0.09	−0.05	0.04	0.06	−0.19**	−0.05	−0.16*	—			
10. Edu (F)	3.67	1.20	−0.15*	0.06	−0.08	0.03	0.06	−0.18**	−0.10	−0.19**	0.55***	—		
11. Income	5.80	2.72	−0.20**	−0.04	−0.20**	0.05	−0.07	−0.21**	−0.09	−0.16*	0.31***	0.43***	—	
12. BMI	23.46	4.80	0.04	0.22**	0.01	−0.12†	−0.06	0.10	−0.14*	0.16*	−0.07	−0.10	−0.26***	—

Notes: $n = 249$ except when correlated with CRP ($n = 219$).
†$p \leq 0.10$. *$p \leq 0.05$. **$p \leq 0.01$. ***$p \leq 0.001$ (two-tailed).
BMI, body mass index; CRP, C-reactive protein; depress, depressive symptoms; Edu (M), highest degree obtained by mother; Edu (F), highest degree obtained by father; Income, family annual income; *M*, mean; PHQ, Patient Health Questionnaire; *SD*, standard deviation; SNS use, social media use.

Is social media use associated with CRP?

Following prior work, we conducted a series of multiple regression analyses with social media use as a predictor of CRP.[12,46] The models sequentially controlled for the following covariates: (a) sociodemographic factors, (b) health behaviors, (c) depressive symptoms, and (d) birth control pill use. Consistent with our hypothesis, social media use was associated with elevated levels of CRP in Model 1 ($\beta = 0.20$, $p = 0.007$), Model 2 ($\beta = 0.17$, $p = 0.023$), Model 3 ($\beta = 0.19$, $p = 0.011$), and Model 4 ($\beta = 0.17$, $p = 0.019$). The results of these analyses are summarized in Table 2.

Is social media use associated with somatic symptoms?

Next, we conducted multiple regression analyses to examine the link between social media use and self-reports of somatic symptoms. Controlling for sociodemographic factors, as predicted, social media use was associated with more frequent somatic symptoms experienced in the past month ($\beta = 0.18$, $p = 0.006$, 95 percent confidence interval [CI] = 0.05–0.30). Adjusting for depressive symptoms did not substantively change the results ($p = 0.01$).

Is social media use associated with health care usage?

Consistent with our hypothesis, multiple regression analyses indicated that social media use was positively associated with more visits to the health center or doctor's office for an illness in the past 3 months ($\beta = 0.19$, $p = 0.005$, 95 percent CI = 0.06–0.32). Controlling for depressive symptoms did not alter our results ($p = 0.007$). In addition, a logistic regression analysis revealed a nonsignificant, but directionally consistent link between social media use and seeking medical care for any sort of cold, flu, or infection in the last 3 months (Wald coefficient = 3.50, odds ratio = 1.38, 95 percent CI = 0.99–1.77, $p = 0.061$). Controlling for depressive symptoms did not substantively change the results ($p = 0.054$).

Discussion

The current research examined whether social media use is associated with various physical health indicators among college students. Social media use was correlated with higher levels of CRP—a biomarker of chronic inflammation that is associated with chronic illnesses such as cardiovascular diseases and cancers. Social media use was also related to experiencing more frequent somatic symptoms, and to behavioral health indices such as more visits to the doctor or health centers for an illness. The pattern of results remained the same even after adjusting for various factors, such as gender and depressive symptoms.

Our findings make several novel contributions. To our knowledge, this is the first study to demonstrate the association of social media use across several platforms with CRP, a chronic inflammatory and health marker, in a college sample. Importantly, the use of a biological marker as a key health indicator is a strength of this study given that prior studies on social media use have primarily relied on self-report well-being measures, which can be vulnerable to demand characteristics. Furthermore, by measuring college students' social media use across several platforms (vs. one

Table 2. Coefficients from Linear Regression Models Predicting C-Reactive Protein

Model 1				Model 2				Model 3				Model 4			
Predictor	β	p	95 percent CI	Predictor	β	p	95 percent CI	Predictor	β	p	95 percent CI	Predictor	β	p	95 percent CI
Sex	0.07	0.32	−0.07–0.21	Sex	0.11	0.12	−0.03–0.25	Sex	0.12	0.10	−0.02–0.26	Sex	−0.05	0.57	−0.21 to 0.11
Age	0.10	0.15	−0.04–0.24	Age	0.07	0.30	−0.07–0.21	Age	0.07	0.32	−0.07–0.20	Age	0.10	0.15	−0.03 to 0.23
Edu (M)	0.09	0.28	−0.07–0.25	Edu (M)	0.07	39	−0.11–0.23	Edu (M)	0.06	0.48	−0.11–0.22	Edu (M)	0.06	0.44	−0.09 to 0.21
Edu (F)	0.09	0.31	−0.08–0.26	Edu (F)	0.06	0.47	−0.09–0.23	Edu (F)	0.06	0.52	−0.10–0.21	Edu (F)	0.03	0.71	−0.13 to 0.19
Income	−0.06	0.48	−0.21–0.10	Income	0.01	0.87	−0.15–0.18	Income	−0.01	0.97	−0.17–0.16	Income	0.03	0.73	−0.13 to 0.19
SNS use	0.20	0.007	0.06–0.34	BMI	0.23	0.001	0.09–0.37	BMI	0.25	0.001	0.10–0.38	BMI	0.25	<0.001	0.11 to 0.38
				Smoking	0.06	0.44	−0.09–0.20	Smoking	0.06	0.38	−0.08–0.20	Smoking	0.09	0.20	−0.05 to 0.23
				Alcohol	−0.06	0.43	−0.21–0.09	Alcohol	−0.04	0.59	−0.19–0.11	Alcohol	0.01	0.98	−0.15 to 0.15
				Exercise	−0.07	0.32	−0.20–0.07	Exercise	−0.09	0.19	−0.23–0.05	Exercise	−0.11	0.11	−0.24 to 0.03
				SNS use	0.17	0.023	0.02–0.32	Depres	−0.14	0.06	−0.28–0.01	Depres	−0.18	0.014	−0.31 to −0.04
								SNS use	0.19	0.011	0.04–0.35	BirthCon	0.31	<0.001	0.14 to 0.46
												SNS use	0.17	0.019	0.03 to 0.32
R^2		0.07 (0.04)				0.13 (0.10)				0.14 (0.11)				0.20 (0.18)	

Notes: Sex was coded with 1 (male) and 2 (female). BirthCon was coded with 0 (not currently taking birth control medication) and 1 (currently taking birth control medication). R^2 values reflect those with SNS use in the models. R^2 values in parentheses reflect those without SNS use in the models.

Alcohol, frequency of alcohol consumption; BirthCon, consumption of birth control medication; CI, confidence interval; Exercise, no. of times engaged in aerobic exercise per week; Smoking, no. of cigarettes smoked per day.

particular platform), our study captured social media usage in a more ecologically valid fashion[43]: By showing how this overall social media use variable was related to multiple health indicators, this study integrates and extends the nascent research on social media and physical health.

Broadly, our findings highlight the potential role of social media use in the context of social relationships and physical health research.[50,51] Although people can engage in ''nonsocial'' activities on social media (e.g., reading the news), much of what they do on social media involves efforts to initiate, maintain, and develop relationships with others. For example, similar to the traditional conceptualization of social integration,[52,53] people use social media platforms to have intimate conversations and exchange social support,[54] to participate in groups and organizations (e.g., Facebook groups), and to cultivate diverse types of relationships.

Thus, an interesting question is why social media use was not associated with better physical health in this study, especially given the salubrious health effects typically seen with traditional measures of social integration and interaction (e.g., Social Network Index).[53] Given the changing nature of social interactions and communication norms, it would be a timely and important endeavor to understand how social media use may contribute to social integration, which would have implications for research on social relationships and health.

In addition to the possibility that high social media usage leads to stress or displacement of health-promoting activities, problematic social media use (e.g., social networking site (SNS) addiction, social comparison) may trigger psychological processes or change in lifestyles that can undermine health.[55–57] For instance, SNS addiction (e.g., preoccupation with social media, excessive use) is associated with lower well-being and depression,[14,58] which can predict worse physical health.[59] Although it is unclear how much our participants engaged in problematic social media use in this study, future studies may directly assess social media addiction and examine its relation to physical health (e.g., Bergen Social Media Addiction Scale).[55]

Caveats and limitations

This study has some limitations. First, the cross-sectional design of this study limits our ability to make causal or temporal inferences about the relation between social media use and physical health. For example, we cannot rule out the possibility that people with undermined health may use social media more (e.g., to seek health information or distraction from their dysphoria). Thus, future research should consider using longitudinal or experimental designs to establish causal and temporal effects.

Second, the effect sizes found in this study are small ($0.17 < \beta s < 0.20$), although comparable to those typically found in studies on social media use and psychological well-being ($-0.05 < rs < -0.15$). Thus, it would be important to consider whether these effect sizes have clinical or practical significance.

Finally, this study documented an *aggregate* association between overall amount of social media use and physical health. Although focusing on the amount of social media use—the most commonly studied variable—allowed us to connect to extant literature, this broad metric does not provide any insight into *how* people use social media. Given that people use social media for a variety of reasons, and that the ways in which they use social media can also influence their well-being,[60,61] future research should examine how the types of social media use may relate to health.

Conclusion

The present study found that social media use is associated with multiple indicators of physical health. Given the prevalence of social media in daily lives and the importance of social relationships to physical health, we call for additional research to examine the relation between social media use and physical health by utilizing diverse methodologies.

Notes

a. Missing data analyses indicated that participants who opted in vs. out of the dried blood spotting procedure did not differ in terms of their gender, social media use, or any dependent variables.
b. While an average score of 2 on this measure can roughly be interpreted as spending about 44 minutes to 2 hours on social media daily, the nonlinear scale used in this measure warrants a cautious interpretation.

Author Disclosure Statement

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Supplementary Material

Supplementary Data

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