Social Media & Mental Health Data Analysis

How Does the Use of Different Social Media Applications Affect Mental Health?

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Introduction

We study the effect of usage of social media on short term mental health by using data from the 2016 General Social Survey. We use measures of poor mental health in the past 30 days and stress experienced at work in the past two weeks and find that Facebook, Instagram, and Snapchat all have significant correlations to higher levels of short term poor mental health.

Why do we care?

Over the past decade, the spread of social media has been a transformative phenomenon that has reached vast swaths of the population. A study in early 2018 by the Pew Research Center showed that 68% of Americans use Facebook.[1] Moreover, roughly three-quarters of Facebook users and around six-in-ten Snapchat users use their respective platform daily. With such widespread adoption, social media has become a central part of the lives of many and has indirectly affected many others as well. This leads us to ask the question of how has social media transformed the way Americans think and what effects it has on mental health?

What do we think the answer might be and why?

We hypothesize that there is a strong correlation between the state of one's mental health and how often they use social media and other apps. Additionally, we believe that some social media will have a more significant effect on mental health over others. This correlation may potentially be explained by how different stimuli from apps frequented may create different emotional responses that affect their mental state. For instance, people who read negative stories on Twitter or Facebook regularly may experience more feelings of sadness, anger, or frustration.

An additional explanation for a correlation between social media usage and mental health could be that social media usage indirectly affects other factors that correlate to mental health. For instance, people who engage in excessive online messaging as a replacement for in-person interactions that may develop anxiety.

Causality vs. Correlation

Our primary aim is to determine if there is a causal relationship between various social media usage behaviors and mental health. To do this, we will specifically examine social media mobile app usage. We will analyze this usage during fixed periods and determine their correlation to measures of mental health, such as feelings of anxiety or depression, in that same period.

While there is potential for causal relationships between Internet usage and mental health, we may not be able to adequately distinguish the effects of Internet usage on mental health due to confounding variables. Such confounding variables may include physical fitness, diet, sleep

[1] “10 facts about Americans and Facebook” by John Gramlich. Retrieved May 9, 2019 from www.pewresearch.org/fact-tank/2019/02/01/facts-about-americans-and-facebook

patterns, or predisposing conditions. While it may be possible to attempt to account for some of these variables by including fixed effects in the regression model, it will be hard to adequately control for the many aspects of an individual that contribute to their mental health given the limitations of our data.

Confounders

Although we hypothesize that web browsing alone has significant effects on mental health, other confounding variables might influence the correlation between mental health and social media usage. Namely, we believe some of these variables to be physical health, age, diet, sleep patterns, predisposing conditions, family history, socioeconomic status, substance abuse, relationships, and community engagement.

Some of these variables are associated with health, such as physical fitness, diet, and sleep patterns could also affect mental health separate from web browsing. For example, using social media for more extended periods may be associated with fewer hours of exercise in a day, which is seen to have adverse effects on mental health. However, the direction of causality between these two factors is unclear and exercise may be an intervening variable and would not be controlled for in the regression. Additionally, individuals with predisposing conditions may be associated with specific web browsing patterns. In this case, their social media usage and mental health both would be affected by an underlying condition.

Data

The dataset we have chosen to use is the 2016 results of the General Social Survey (referred to as the GSS hereafter). The primary purpose of the GSS is to gather empirical data on social change and development in American society. The data was collected and distributed publicly by NORC at the University of Chicago, which is an objective\ non-partisan research institution specializing in data analysis. The data from the GSS is used primarily for making policy, program and business decisions.

There are 2,867 observations in the 2016 GSS. Each of these observations represents an individual in the United States who voluntarily took part in the 2016 GSS and answered some of the survey questions. As questions could have been omitted or unanswered by the respondent, not all of our variables encompass the full sample of the survey. To prepare the data for the study, we omitted responses marked as non-applicable or no answer. These omitted observations were not systematically different except for age (see Statistical Tests for the relevant tests and analysis).

Table I: Poor Mental Health Days Models

Poor Mental Health Days in the Past 30 Days							
	OLS				LPM		Probit
Variable	1	2	3	4	5	6	7
Uses Social Media							
Twitter	-0.506	-0.309	-0.325	-1.56	-0.073	-0.157	-0.356
Facebook	1.921 ***	0.757	1.96 *	6.109 *	0.107 **	0.364 *	0.815 **
Instagram	1.061 *	0.505	0.867	7.535 ***	0.066 *	0.357 ***	0.323 *
Snapchat	-1.388 **	-1.984 ***	-2.014 **	-4.273 *	-0.12 ***	-0.131	-0.608 **
Uses Internet on mobile device	0.652	-0.167	-0.207	(omitted)	0.025	(omitted)	0.109
Avg. Internet usage hrs. per week	0.315 ***	0.348 ***	0.345 ***	0.059	0.019 ***	0.028 *	0.078 ***
Age of respondent		0.044	0.032	13.429	0.001	0.9 *	0.025
Age squared		-0.001	-0.001	-0.296	0	-0.021 *	0
Male		-1.415 **	0.924	3.579	0.052	0.179	0.517
Household annual income		-0.16 ***	-0.167 ***	-0.144	-0.008 **	-0.007	-0.031 **
Respondent's level of education		0.017	0.012	-0.825	-0.002	-0.005	-0.006
Race of Respondent							
White		*Reference*	*Reference*	*Reference*	*Reference*	*Reference*	*Reference*
Black		-2.496 ***	-2.371 ***	-4.769 **	-0.091 **	-0.199 *	-0.402 *
Other		-0.182	-0.155	2.28	0.004	0.165	-0.033
Marital Status							
Married		*Reference*	*Reference*	*Reference*	*Reference*	*Reference*	*Reference*
Widowed		3.342 **	3.423 **		0.145 *		1.014 **
Divorced		2.524 ***	2.501 ***	1.99	0.094 **	0.563	-1.484 *
Separated		1.943	1.983	2.668	0.123	0.611 *	-2.437 **
Never married		1.371 *	1.376 *	4.293	0.068 *	0.181	-3.626 **
Closest relative commited suicide		0.58	0.577	3.746	0.043	0.151	0.235
2nd closest relative commited suicide		1.911 *	1.916 *	(omitted)	0.029	(omitted)	0.107
Male and uses Twitter			0.228	3.037	0.068	0.12	0.387
Male and uses Facebook			-2.452	-4.891	-0.127	-0.267	-0.855 *
Male and uses Instagram			-1.035	-3.182	-0.062	-0.073	-0.245
Male and uses Snapchat			0.037	-2.366	0.017	-0.086	-0.013
Constant	0.609	5.079	4.391	-142.367	0.151	-10.033 *	-2.896 ***
N	719	612	612	83	612	83	612
R^2 adjusted	0.027	0.085	0.084	0.218	0.081	0.266	---

Legend: * p<0.1; ** p<0.05; *** p<0.01

· Regressions 1- 4 use an OLS model
· Regression 4 is the same as 3 restricted to respondents ≤ 25 y.o.
· Regression 5 uses an LPM model where the dependent variable is experiencing more than 10 days of poor mental health in the previous 30
· Regression 6 is the same as 5 restricted to respondents ≤ 25 y.o.
· Regression 7 uses a probit model where reported coefficients are marginal effects

Regression Model: Poor Mental Health Days in the Past 30 Days

For specifications 1 through 4, we used the number of 'not good mental health days' experienced by individuals in the 30 days prior to their survey interview.[2] For specifications 5 through 7 we created a binary variable which equals 1 if the sample individual has experienced 10 or more mental health days in the 30 days prior to the survey. As such, if the use of one of the social media platforms have a bad effect, that is, an increase in the number of poor mental health days a month,one would see a positive coefficient which refers to the increase in the number of mental health days, or increase in the probability of having more than 10 mental health days a month.

[2] The definition of a "not good" mental health day according to the 2016 General Social Survey question includes feeling stressed, depressed, and having problems with emotions that day.

From Table 1, we see a number of interesting results of our main explanatory variables as well as some of our controls. Specifications 1 through 4 use an OLS model to estimate the effect of certain controls on the number of days an individual suffers a mental health day, with specification 4 restricting the sample to individuals between 18 and 25 years old. Specifications 5 and 6 utilize a Linear Probability Model that estimates the associated increases in the likelihood of an individual experiencing 10 or more days of poor mental health. Along the same lines, we use a probit model to estimate the associated marginal effects of the explanatory variables on the probability of a person having 10 or more mental health days a month. In the columns that we restrict our sample to those between 18 and 25 years old, we believe that we find significant results that are representative of the effects social media and other variables have on young adults' mental health. The thought process behind this restriction was due to the higher penetration of these platforms in the younger cohort relative to the others in the sample. We decided to focus on the 18-24 age cohort due to the fact that nearly three-quarters of chronic mental illness begins by age 24.[3] This, compounded with the fact that this age cohort 3 is likely to use social media more frequently meant that we wanted to examine the effects on this group more closely by restricting our regression sample.

OLS Model

In the third specification, we find a statistically significant result, that a one hour increase in average internet usage per week is associated with an increase in the number of bad mental health days a month of 0.345 days at a 1% significance level, holding all else equal. This is aligned with our initial hypothesis, that the more hours a person uses the internet a week the higher the impact on one's mental health inducing stress, depression, or other emotional problems. Besides Snapchat, which will be discussed further, other significant effects in this model were as expected. In our age restricted OLS model (specification 4), we find statistically significant effects for three out of the four social media platforms usage variables - Facebook, Instagram, and Snapchat. Out of these, Instagram has the largest and most significant effect with an increase in mental health days of approximately 7.5 days a month for those who use the platform under 25 relative to those who don't use the platform, holding all else equal. This result was much larger than expected, and offers interesting implications. Facebook also had a large associated increase in poor mental health days for under 25s of approximately 6.1 days relative to non-users, holding all else equal, however, this result was only statistically significant at a 10% level.

While we saw these large positive effects of Facebook and Instagram on mental health days, we found an intriguing negative effect of Snapchat on its' users' reported mental health days, which was consistently statistically significant for both the unrestricted and age-restricted

[3] Kessler, R.C., et al. (2005). Prevalence, Severity, and Comorbidity of 12-Month DSM-IV Disorders in the National Comorbidity Survey Replication. Archives of General Psychiatry , 62 (6), 593–602. Retrieved January 16, 2015, from http://archpsyc.jamanetwork.com/article.aspx?articleid=208671

samples. This result was against our initial intuition and existing literature[4] that Snapchat, similar to other photo-sharing social media platforms, would induce feelings of depression, anxiety, self-consciousness, or fear of missing out and as such increase the number of mental health days a month. One solution perhaps might be that the estimate for Snapchat is capturing the effect of how social an individual is. Moreover, Snapchat is primarily used to communicate among individuals while Instagram and Facebook can generally be used alone and might be used more frequently for longer periods of time. In the same way, we also did not find significant effects for the interactions between gender and the social media variables which, again, is against our original hypothesis that the effect of social media differs between genders.

Linear Probability Model

In our linear probability models, we transformed our continuous variable for poor mental health days into a binary variable. In this case, our dependent variable represents the likelihood of having at least 10 days of poor mental health. The significance of this cutoff is that the likelihood of 10 or more days of poor mental health acts as an indicator for a prevailing mental health problem. If an individual experiences 14 or more consecutive days of poor mental health, an individual is likely to have a prevailing mental health condition and is advised to reach out to a professional for help.[5]

Our fifth specification estimates that both Instagram and Facebook have significant positive effects on the likelihood of having 10 or more poor mental health days, 11% and 7% respectively, all else equal, compared to those not using the platforms. The largest absolute and significant effect out of all social media platforms is Snapchat. Our model predicts that, holding all else equal, someone who uses Snapchat is 12% less likely to have 10 or more poor mental health days in a month, compared to someone who doesn't use Snapchat. This is an unconventional and intriguing result. The coefficient on Snapchat is consistently negative in all specifications, and continuously significant in 6 out of 7 of our specifications. Again, we support this result with the rationale that the Snapchat platform facilitates direct user-to-user communication, while the other platforms we examined emphasize browsing other user's photos and profiles for longer periods of time. An interesting component of Snapchat is that, unlike the other platforms, all content posted by a user is erased within 24 hours. This effectively serves as a blank slate for users and their "friends" on the app. Since content is temporary, users are not prone to browse other user's content retrospectively and compare one's life and activities to another's. There is also no concept of "likes" on Snapchat. The only way to express one's favor of another user's activities is to directly message or "snap" them. This eliminates passivity and directly influences user-to-user communication. These previously stated factors could eliminate the adverse mental health effects that other social media platforms creates. A combination of all

[4] Snapchat Depression. (2018, April 16). Retrieved May 5, 2019, from https://now.tufts.edu/articles/snapchat-depression
[5] Kennedy S. H. (2008). Core symptoms of major depressive disorder: relevance to diagnosis and treatment. Dialogues in clinical neuroscience , 10 (3), 271–277.

of these factors could be at play, resulting in the consistently negative and statistically significant coefficients.

Other significant coefficients within our LPM regressions are those on our controls. Being widowed, divorced or never married all predicted a higher likelihood of having 10+ poor mental health days, compared to those that are married, holding all else constant. This is an unsurprising result but one that changes in the next LPM regression. We believe this is because we focus exclusively on the cohort aged 18 to 25 in specification 6. It is unlikely that many in this group were ever married or feel the social pressure of being married, therefore these coefficients become insignificant, aside from being separated. This could reflect the struggles of new marriages for young people. Additionally, the coefficient on being black is significantly negative in all LPM and other regressions. This is an unconventional and interesting trend that is addressed further in our Limitations of Approach section. The coefficient on income delivers an expected result in specification 5. It predicts that moving up an additional income bracket decreases the likelihood of having 10+ poor mental health days by almost 1%, all else held constant. This may go against conventional thinking that more income makes a drastic difference in mental health outcomes, however this should be explored further. In our LPM model focusing on the 18-24 age cohort, income becomes insignificant. This may be due to the fact that most in this age cohort are attending universities and are unlikely to have a stable income of their own.

The negative effect of Snapchat on poor mental health, in specification 6, is not significant in the 18-25 age cohort. This may signify that the Snapchat has no significant effect on the likelihood of having 10+ poor mental health days, although the OLS estimate does deliver significant results for the effect of Snapchat on poor mental health days in this age group. As a result this calls into question whether the estimate is imprecise due to the smaller sample size and the exclusion of unobserved characteristics, which will be discussed in the Limitations of Approach discussion.

The greatest limitation of our results in LPM regressions are the predicted values we receive when calculating the predicted probabilities using the mean value of each variable. We find that some of these predicted values are below 0 which, in the case of probability, is nonsensical. This is a common issue with the LPM model, and calls into question whether our estimates are imprecise or unreliable. As such, we attempt to remedy this issue by estimating the same model using a probit regression.

Probit Model

Similar to our LPM models, our probit model relies on the continuous variable for poor mental health days being transformed into a binary dependent variable. Here, our regression tests the likelihood of one reporting ten or more poor mental health days in the past month. Again, the exigence of this lies in the fact that those who exceed ten days of poor mental health a month are nearing, or have already reached, the clinical determination of major depressive disorder (defined above as 14 or more consecutive days of poor mental health in one month).

One result which differs from our other models was the estimated significant effect of the interaction between Facebook and gender. This negative coefficient, significant at a 10% level, suggests that there are different associated effects of Facebook on males and females. This estimate in combination with the coefficients on Male and Facebook, leads us to believe that the overall effect of Facebook on males is approximately 0. However, for women who use Facebook, the probability of experiencing ten or more days of poor mental health increases by 81.5 percentage points relative to women who aren't members of Facebook, holding all else constant. Nonetheless, we do not find significant differences in the effects for males and females who use any of the other platforms.

Additionally, both Instagram and Snapchat have positive associated effects at varying levels of statistical significance, demonstrating that Instagram and Snapchat play a significant role in predicting one's likelihood of experiencing ten or more poor mental health days a month. As with all other regressions included in Table 1, Twitter had a significant effect of decreasing the likelihood of having poor mental health days, which highlights that there are more positive impacts of Twitter than there are negative. The self-reported weekly internet usage average, however, shows that each additional hour browsing the internet increases the likelihood of suffering 10 or more poor mental health days by approximately 8 percentage points, at a 1% significance level. This estimate is significant to our question, as the average internet user today spends a third of their browsing time on social media (2.25 hours a day, on average)[6]. Further research should be done to assess the breakdown of individuals' internet usage variable, potentially incorporating these questions into future GSS surveys.

Level of Stress at Work

In addition to the regressions performed with days of poor mental health, we also looked at another variable, stress at work in the past two weeks, as another measure of mental health. This variable is not as directly related to mental illness, but is still useful as a proxy measure of mental health so we expected similar results to the prior regressions. We defined a binary dependent of experiencing at least some stress in the past two weeks at work and used both an LPM and probit models. We did not run any of the specifications restricted to individuals age 25 and younger due to insufficient sample size in that range.

Overall in both specifications we found the results for Instagram usage to be similar to the poor mental health days regressions where there was consistently a statistically significant increase in likelihood of experiencing stress for Instagram users. The effect is an increase of 7.1 to 11 percentage points when accounting for all controls depending on which model is used.

The results for the remaining social media platforms are less conclusive in this set of regressions with statistically insignificant results for Facebook and Snapchat under the LPM model and significant but very small (less than 1 percentage point marginal effect) coefficients under the probit model. Interestingly, Twitter appears to be associated with a reduction in stress. However, when comparing the magnitudes of the effects between the LPM model and the probit model there is a disparity of over 10 percentage points (-13.3 compared to -1.1) and this leads us to conclude that the results are not very robust for Twitter.

[6] Kemp, Simon. "Digital 2019: Global Internet Use Accelerates." GlobalWebIndex, 30 Jan. 2019

Table II: Modelling Stress at Work in the Past Two Weeks

Stress at Work in the Past 2 Weeks				
	LPM			Probit
Variable	1	2	3	4
Uses Social Media				
Twitter	-0.198	-0.079 *	-0.133 *	-0.011 **
Facebook	0.526 ***	-0.042	-0.075	-0.004 **
Instagram	0.326 **	0.076 *	0.11 *	0.071 ***
Snapchat	-0.364 **	-0.012	0.008	0.009 ***
Uses Internet on mobile device	0.295	0.096	0.094	0.003
Avg. Internet usage hrs. per week	0.065 ***	0.007	0.007	0
Age of respondent		-0.015 *	-0.016 **	0 **
Age squared		0 *	0 **	0 **
Male		-0.057	-0.097	-0.222 ***
Household annual income		0.005	0.004	0
Respondent's level of education		0.004	0.005	0
Race of Respondent				
White		*Reference*	*Reference*	*Reference*
Black		-0.067	-0.074	-0.001
Other		-0.016	-0.028	-0.002
Marital Status				
Married		*Reference*	*Reference*	*Reference*
Widowed		-0.133	-0.134	-0.001 *
Divorced		-0.025	-0.025	0.001 *
Separated		-0.016	-0.015	0.001
Never married		-0.043	-0.04	0.023 *
Closest relative commited suicide		0.041	0.039	0
2nd closest relative commited suicide		-0.01	-0.012	0
Male and uses Twitter			0.096	0
Male and uses Facebook			0.064	0.083 **
Male and uses Instagram			-0.071	-0.923
Male and uses Snapchat			-0.047	-0.94
Constant	-2.038 ***	1.1 **	1.153 ***	
N		246	246	
R^2 adjusted		0.011	0.003	

legend: * p<.1; ** p<.05; *** p<.01

· Regressions 1- 3 use an LPM model where the dependent variable is experiencing at least some stress at work

· Regression 4 uses a probit model where reported coefficients are marginal effects

Conclusions & Discussion

Throughout our analysis we have found compelling evidence on the associated effects of social media usage on the reported mental health of individuals. Of these associated effects for the total sample, we found that the usage of Facebook and Instagram and and the average number of hours they use the internet in a week are correlated with a decrease in an individual's mental health (as measured by an increase in the individual's reported poor mental health days). One of the most largest effects was the association of Instagram usage with an increase of 7.5 days of poor mental health for individuals under the age of 25. With a mental health issue being medically defined as experiencing "symptoms of depression and other emotional states for more than 2 weeks," the magnitude of this effect is considerable.[7] An interesting result observed was that Snapchat usage is associated with a statistically significant improvement in mental health. This result is potentially due to the timing of the data, which is from 2016 when Snapchat was only 4 years old and did not have as many advertisers and influencers as well as the ephemeral nature of interactions on Snapchat as discussed above; as such the effects on mental health that are seen in our models based on 2016 data might be different to the current effects on mental health that incorporate these aspects.

From these results we cannot conclude that there is a causal relationship between increased social media use and poor mental health status due to limitations of our sample. Our analysis only focused on short term mental health indicators and did not account for the timing of usage of social media with respect to the occurrence of poor mental health symptoms. Thus, we cannot rule out reverse causality effects. Additionally, the data is self-reported which is prone to high measurement error.However, we do have sufficient evidence to affirm that there is a strong correlation between the two factors, with the most interesting correlations found when restricting our sample to a younger cohort. There should be further research conducted on the effects of social media on younger age groups, to test if these significant associated effects hold.

There are many possible effects occurring that our models potentially reflect. There could be a true effect of certain platforms on well-being, where users are prone to making comparisons between their own lives and others, leading to adverse effects on their mental health. There is also an argument for reverse causality where it may be that people use social media as a coping mechanism when experiencing stress or poor mental health, and thus increased negative emotions are associated with increased use of social media. Further research and academic discussion should be focused on examining these effects and distinguishing the direction of the causal effect.

Limitations of Our Approach

Our model is the best estimate of the relationship between mental health and social media/apps usage, given the nature of our data. The data we use comes from the 2016 GSS,

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[7] Mental Health Diagnosis. (2018, October 3). Retrieved May 6, 2019, from nhs.uk website: https://www.nhs.uk/conditions/clinical-depression/diagnosis/

where all measures are based on self-reported information. Due to this, our model is prone to measurement error. Some of our control variables (age, sex, race, income) are less prone to such error because they can be verified by the interviewer or through a search of public records. Another control (family mental health history) cannot be confirmed, but we assume the observed respondents were not inclined to be dishonest concerning this metric, as they were afforded the opportunity to omit this question. If these metrics are inaccurate, measurement error would be present in the coefficients of our control variables.

Our continuous explanatory variable (average hours per day on the Internet) is also prone to measurement error. Respondents most likely provided a close estimate, rather than a precise measure, concerning their average minutes per day. We cannot confirm otherwise. This may generate attenuation bias in the coefficients on our explanatory variables. Most of our other explanatory variables were less prone to measurement error due to the straightforward nature of the "Yes or No" questions. We assume the observed respondents were not inclined to be dishonest concerning this metric, as they were afforded the opportunity to omit this question. However, this is not the case for the continuous variable of average hours per day on APPS. This metric was originally reported by respondents in average minutes per day on APPS. It is likely that respondents either over-reported or under-reported their minutes per day on APPS, due to rounding or plain uncertainty. It is difficult to sign the direction of this bias because it could be either that our coefficients overpredict or underpredict the actual effect of hours per day on mental health, given the measurement error present.

It should also be recognized that there may be possible limitations to our controlling for family mental health history, where we wanted to capture the potential hereditary mental illnesses. We controlled for it by assigning a binary variable to whether or not a family member of the respondent has died of suicide. This is an extreme measure and does not account for more moderate cases of hereditary mental illness specifically. We believe that the effect of this variable on an individuals mental health is twofold - hereditary mental health issues and the effect of a significant life event. As a result, the coefficient estimate might be inflated due to it capturing both effects, and not putting as much weight on hereditary conditions such as chronic anxiety.[8] It is also true that not all suicides are linked to mental health conditions . For the previously stated reasoning, the predictions found in our regressions may not fully capture actual family mental health history.

Our dependent variables are prone to measurement error due to the introspective and personal nature of the measure (number of poor mental health days, feelings of loneliness/depression in the last week). These metrics are based solely on the respondents' feelings and cannot be confirmed externally in any way. Respondents most likely provided a close estimate, rather than a precise measure, concerning their number of days of poor mental health. We cannot confirm otherwise. It is likely that respondents might under-report these mental health indicators due to social stigma concerning mental health, especially as they were

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[8] Sanati A. (2009). Does suicide always indicate a mental illness?. London journal of primary care, 2(2), 93–94.

surveyed in a face-to-face interview in-person. This type of measurement error should not create bias in coefficients, but might reduce the precision of the coefficient estimates due to larger errors in the model.

There are potential confounders which may affect the coefficient estimates in our models. For instance, how social someone is, would be positively correlated with their use of social media platforms and affect one's mental health. Throughout our analysis we have found that this is difficult to control for, and as such were not able to include in our regression. However, this should be accounted for in further studies, potentially by instrumenting for it.

A result against our initial intuition which is consistently significant was the coefficients on race which predicted that, all else held constant, a black person has a decreased likelihood of having 10 or more poor mental health days, in comparison with their white counterparts. These results could be entirely valid and represent an interesting and unaddressed trend. There is compelling research that suggests that African Americans in the U.S have a higher likelihood of experiencing and developing mental health issues relative to other races. This is due to compounding cultural factors of racism, discimination, low-income and poor availability of mental health facilities. Studies show that not only do minorities have lower access to mental health resources, they are also likely to be treated differently by healthcare professionals and are more likely to have their issues neglected.[9] This would lead us to believe that, holding all else constant, African Americans would have an increased likelihood of having 10+ poor mental health days. Aside from this, there is substantial research showing that there is especially strong stigma against mental illness in black communities, and those experiencing mental illness often conceal their suffering and thus under-report the number of mental health days experienced.[10] Considering all of these factors, we can speculate a few phenomena that are occurring together or separately within our sample. It is possible that in face-to-face interviews, African Americans were systematically under-reporting their number of poor mental health days due to stigmatization they have experienced in the past, leading to results which underestimate the effect of race. It is also possible that our model does not encompass a representative sample of black individuals. Within the entire 2016 GSS sample, only 17% of respondents identified as black, approximately 490 individuals. It is possible that a representative sample of black individuals did not respond to the mental health, social media or other identifier questions during the survey. Considering that our regression samples only account for those who responded to all of these questions, it is possible that we are accounting for very few black individuals. Due to a small sample and underrepresentation of the racial group, there could be bias in our point estimates that underestimate the effect of race on mental health. These effects could be occurring simultaneously and influencing our interesting and unconventional results.

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[9] Office of the Surgeon General (US); Center for Mental Health Services (US); National Institute of Mental Health (US). Mental Health: Culture, Race, and Ethnicity: A Supplement to Mental Health: A Report of the Surgeon General. Rockville (MD): Substance Abuse and Mental Health Services Administration (US); 2001 Aug.

[10] Masuda, A., Anderson, P. L., & Edmonds, J. (2012). Help-seeking attitudes, mental health stigma, and self-concealment among African American college students. Journal of Black Studies, 43(7), 773-786.

Policy Relevance

While our results are only preliminary and further research must be done, there are a selection of policy implications that are worth discussing. This analysis adds to the growing and influential literature that highlights the negative relationship between social media usage and individuals' mental health, especially in young people. As these social media platforms have a growing presence in the lives of many, there are certain aspects that must be considered in policy moving forwards. Primarily, there ought to be discussion surrounding the responsibility of these platforms for their users and how their usage affects their mental health that can be tackled by creating a user friendly environment that promotes mental well-being while minimizing the negative effects. For example, in April 2019, CEO and co-founder of Instagram, Kevin Systrom, announced adjustments to the platform to support the mental health of its users and make it a welcoming place for self-expression and exploration.[11]One of these changes being removing likes on photos, which might remove the stress of posting online and facilitate more positive user contact. The change is currently being trialed in Canada and will possibly be expanded further in the future.[12] Furthermore, Facebook, in light of controversies over the past year, has announced its aim for significant changes to protect the safety of its users and foster more productive engagement. This includes making the platform group-oriented rather than the newsfeed style users currently experience on the site.[13] While these large corporations have announced these goals there is still much work to be done to decrease the social comparisons made by its users which are seen to significantly affect the mental health of their users.[14]

Additionally, we believe that the implications of literature should be incorporated into how mental health issues should be treated. For example, as of March 2019, the United Kingdom has mandated questions about screen use in the NHS psychiatric assessments for young people.[15] This enables the consideration of these effects in the treatment of young adults seeking help with conditions like anxiety, depression, and eating disorders which, potentially, could be causing or exacerbating their illness. Furthermore, there have been calls from healthcare professionals and policymakers to parents to limit screen time of their children which further emphasizes the growing awareness of these effects.[16] Mandates and policies such as these will become an ever growing part of the healthcare policy surrounding mental illnesses. There are a collection of policies in the U.S. targeting youths' mental health, but few target social media as a contributing factor. It would be in the public interest for U.S. policy makers to take on a proactive role in examining the contribution of screen usage on youth mental health.

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