Multi-Platform Social Media Use and Well-Being: Evidence on Usage Variety and Intensity From the General Social Survey

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Abstract

Social media have become a near-ubiquitous part of our lives. The growing concern that their use may alter our well-being has been met with elusive scientific evidence, in part because appropriate data are lacking. Existing literature often simplifies social media use as a homogeneous process. In reality, social media use and functions vary widely depending on platform and the demographic characteristics of users. Using data from the General Social Survey, a source essentially untapped for this purpose, we characterize intensive social media users and examine how differential platform use impacts well-being. We first document substantial heterogeneity in the demography of users and show how intensive users differ from lower-intensity users. In a next step, we examine how the intensity of social media use is associated with various well-being indicators through analyzing the number of used platforms and their interaction with age, the analysis of single specific platforms, and propensity-score adjustment. The results show that multi-platform use seems largely unrelated to well-being in both unadjusted and propensity-score adjusted models, but among middle-aged and older adults, it is slightly associated with depressive symptoms. We discuss how our methods improve on previous studies and situate our results in the larger literature on social media and well-being. Our initial findings indicate that social media has changed the surface form of communication rather than its function.

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Introduction and Background

Social media seem near-ubiquitous today, but were nearly unknown 15 years ago. Social media now play a major role in many areas of public and private life, including in how we get information, keep in touch with our social contacts, and meet new people. In a short period of time, a large fraction of the US population has begun using a large variety of social media platforms: For example, 69% of the US population uses Facebook, 28% use Pinterest, while Instagram use recently reached 37% (Perrin & Anderson, 2019). Facebook, which started as a network for ivy-league college students, is now the most widely used social network and has been adopted by people of all ages and education levels; in general, social media use is now widespread across demographic characteristics. Similar trends have occurred globally, and an estimated 2.8 billion people worldwide use some form of social media (eMarketer, 2018).

The rapid and widespread adoption of social media can therefore be seen as a transformational process: On the one hand, it represents a change in form, by changing the medium through which we communicate. On the other hand, the change may go beyond form and additionally affect function by changing the quality of our interactions, the social support we receive from our networks, and subsequently our well-being. In this work, we provide a new perspective on the under-studied implications of social media use for well-being, a topic that has drawn controversies in existing research and that has often not been examined in a nuanced way. In particular, it is so far unclear whether there is a negative, positive, or null effect of social media use intensity on well-being because of conflicting results and varying operationalizations. In the present analysis, we examine a nationally representative data source, a larger variety of social media platforms than most previous studies have considered, and a larger variety of well-being indicators than most previous studies have considered.

Existing literature often simplifies internet use and social media use as homogeneous processes, in part because of the available data which are often simple aggregate measures of whether a person uses any social media platform or how much time they spend online. Social media use and functions, however, vary widely depending on the platform and the socio-economic/demographic characteristics of users. For instance, in contrast to some studies showing negative effects on well-being, multiple studies have found that social media use can instead enhance the well-being of young populations by fostering social support and social inclusion, including in Turkish high school students (Doğan, 2016), Korean college students (Park et al., 2009), and US young adults (Hardy & Castonguay, 2018). The current literature shows a gap in investigations into the associations between multi-platform social media use and well-being across demographic groups, which are still poorly understood. One of the contributions of this paper is to close this gap by evaluating how heterogeneous use of social media, including intensity of multi-platform social media use, differentially affects the well-being of different demographic groups.

In particular, we are focusing on the number of social media platforms that are being used because this variable can indicate how strong the presence of social media is in a given person's life and how many social and time stressors somebody is exposed to through social media. Despite this potential relevance, multi-platform use has drawn comparatively little research attention to date. A person who has a Facebook account to keep in touch with family and a LinkedIn profile to connect with colleagues interacts with social media in fewer parts of their life than somebody who is on Facebook for family, LinkedIn for work, Instagram for food blogging, Twitter for news, Pinterest for cooking inspiration, and Snapchat for contact with friends. In addition, the former person may experience fewer time conflicts because they are likely spending less time on social media overall. Finally, the former person may be exposed to fewer social conflicts, upsetting news, and posts about others' successes that elicit social comparison processes. Assuming that social conflicts (Abbey, Abramis, & Caplan, 1985; Lepore, 1992), upsetting news (Szabo & Hopkinson, 2007; Veitch & Griffitt, 1976), and upward social comparisons (H. Appel, Gerlach, & Crusius, 2016; Gerber, Wheeler, & Suls, 2018; Myers & Crowther, 2009) make people less satisfied with their lives, we could expect higher well-being for those who use fewer social media platforms than for those who use many. Past literature does suggest that multi-platform use may be linked to stronger symptoms of depression and anxiety (Hardy & Castonguay, 2018; Primack et al., 2017; Vannucci, Ohannessian, & Gagnon, 2019), but overall few studies have investigated the impact of multi-platform social media use.

Alternatively, however, the use of social media platforms may matter less than what they are used for (e.g., Bessière, Pressman, Kiesler, & Kraut, 2010; Park, Kee, & Valenzuela, 2009; Rae & Lonborg, 2015; Valkenburg, Peter, & Schouten, 2006). In offline life, an extroverted person may form large social networks, an introverted person may have fewer social contacts and perhaps spend more time reading the news instead, and another person might spend a lot of time watching TV. If those three people take to social media, they may continue the same activities, simply on another medium – for example, using Facebook to keep in touch with friends, to read and discuss news articles, or to watch videos, respectively. If, in this way, social media changes the surface form of activities more than the functions they fulfill, we would not expect consistent negative or positive effects on well-being. This account is supported by a number of studies and reviews that find null effects or only small effects (M. Appel, Marker, &

Gnambs, in press; see, e.g., a correlation of r = -.07 in a meta-analysis of the relation between time spent on social media and well-being, Huang, 2017; Orben, Dienlin, & Przybylski, 2019; Orben & Przybylski, 2019) of social media use on well-being, as well as by multiple studies that examine the direction of this association. Although it has often been argued that social media make people lonelier, more depressed, and less satisfied with their life (e.g., Kross et al., 2013; Twenge & Campbell, 2019), it could also be that lonely, depressed, and unhappy people (or people who are simply more introverted) are more likely to self-select into using social media as a means of forming new relationships, finding communities that provide social support, and coping with negative affect (e.g., Fergie, Hunt, & Hilton, 2016; Gowen, Deschaine, Gruttadara, & Markey, 2012; K. M. Griffiths, Calear, & Banfield, 2009; Lee, Noh, & Koo, 2013). Despite the fact that these two processes are not mutually exclusive, mounting evidence suggests that this self-selection process may be playing a stronger role than the opposite causal pathway (Aalbers, McNally, Heeren, de Wit, & Fried, 2019; Song et al., 2014, a meta-analysis of 18 studies which examined introversion and loneliness simultaneously; van der Velden, Setti, van der Meulen, & Das, 2019). In that case, there may be no causal effect of social media use on well-being, or potentially even a positive effect if lonely people use social media to form new social ties or to strengthen existing ties, which is in turn associated with improved health (e.g., Berkman & Syme, 1979; Pinquart & Sörensen, 2000).

In this paper, we provide a new perspective on the relationship between social media and well-being using data from the General Social Survey (GSS), which provides a rich yet almost untapped resource for this purpose. To our knowledge, only one single paper previously used this data to examine well-being and social media use. However, that paper focused on only a third of the social media platforms and on only on one out of seven well-being variables that were available in the data (Hardy & Castonguay, 2018). With this article, we challenge some of the results previously shown in the literature by offering a more comprehensive picture of heterogeneous social media use, including an examination of number and types of multiple platforms and their relationship to socio-demographic characteristics, multiple indicators of well-being, and a more stringent adjustment for selection bias by using inverse-probability of treatment weighting (IPTW) to adjust for propensity scores.

Data

The 2016 wave of the GSS has, to date, been the only one to include a social media module and we therefore focus on 2016 data only. The GSS is the result of predominantly face-to-face interviews (English or Spanish) that were conducted between April and November of 2016, targeting adults living in households in the US (Smith, Davern, Freese, & Morgan, 2019). A total of N = 1371 respondents reported on their social media use as well as their well-being, but because not all questions were shown to all respondents, sample sizes for individual analyses may differ. The General Social Survey uses an area-probability cluster sample with two-stage sub-sampling for nonresponse and the results in this report are based on design-corrected standard errors that incorporate design weights and nonresponse weights (figures represent the raw data for ease of plotting).

Variables

Online activity. Respondents were asked whether they used each of the following platforms: Twitter, Facebook, Instagram, LinkedIn, Snapchat, Tumblr, Whatsapp, Google+, Pinterest, flickr, Vine, and Classmates, plus space for free-form responses. These variables were binary and by summing them, we derived a continuous index of multi-platform social media use. We also used variables in which respondents had indicated how many hours and minutes they used the internet (not just social media) on a typical weekday and a typical weekend day, a variable that indicated which social media platform the participant had joined first, and a variable that indicated when the respondent had joined this first platform. We used the latter variable to obtain the number of years for which the respondent had been using social media and to calculate the proportion of their life that they had spent using social media. These indices should be used as approximate indications of how long respondents had used social media, but not necessarily as accurate indices because retrospective recall of this sort appeared difficult and imprecise: A substantial number of respondents (n = 101) gave impossible responses, e.g., claiming to have been using Instagram (which launched in 2010) since 2006 or Facebook (which launched in 2004) since 1985 (these impossible responses were recoded to the launch date of the specific platform).

Offline social activity. The survey also asked how often respondents spent an evening with relatives, with friends, with neighbors, and in bars. The items were scored in such a way that they reflect the approximate weekly frequency (e.g., "several times a week" would be between 2 and 5 times a week, which on average would be 3.5 times a week; similar patterns occurred when using more liberal or more conservative ways of scoring the frequencies). The four items were summed up to create an overall index of offline social activity.

Personal Well-being variables. The survey further included several questions that could be used as indicators of well-being, one which measured general happiness, one which measured general health condition, and one which measured whether respondents perceived life as exciting or dull. Although these questions provide only a subjective assessment of health, prior research has found that subjective responses to such single-item questions are strongly predictive of mortality (see DeSalvo, Bloser, Reynolds, He, & Muntner, 2006, for a meta-analysis; and

Schnittker & Bacak, 2014, for an analysis of the GSS, specifically). One more question asked participants to rate their satisfaction with their financial situation. Although this index of course was associated with income, the correlation was not strong enough to see financial satisfaction as a mere proxy for income, $r = 0.35$. All items had three or four response options and were scored such that positive responses (e.g., *Excellent, Very happy)* received positive values, neutral or middle responses (e.g., *Fair, Pretty happy*) received a value of 0, and negative responses (e.g., *Poor, Not too happy*) received negative values.

Further, a 5-item version of the Center for Epidemiologic Studies Depression (CES-D) Scale (Radloff, 1977) was administered to measure depressive feelings (feeling depressed, happy, lonely, sad, and experiencing restless sleep) during the preceding week. The items ranged from 0 = *None or almost none of the time* to 3 = *All or almost all of the time* and formed an internally consistent index, Cronbach's $\alpha = 0.76$, and were thus averaged into a composite score.

Finally, one question asked whether the respondent had ever felt like they were going to have a mental breakdown, and one question asked respondents to indicate how many of the days in the past month their mental health had not been good. Closer examination of these two items, however, raises potential doubts about their validity. The item on breakdown propensity did not explain to respondents what a "mental breakdown" meant, likely leading to considerable variation in subjective definitions of a vague concept and the item referred to the respondents' entire lifespan, making it unfavorable for the analysis of recent phenomena (such as the widespread adoption of social media) and current well-being. In fact, this item showed only low-to-medium correlations with all other indicators of well-being in the survey, $r = -.14$ with happiness, $r = -.17$ with health, $r = .31$ with depression, and $r = .25$ with bad mental health days. The item on bad mental health days was noisy (e.g., several people rated themselves as "very happy" despite indicating that 30 out of the last 30 days had been bad mental health days for them) and difficult to validate. In fact, the number of bad mental health days seemed more closely related to self-rated physical health, $r = -0.32$, than to happiness, $r = -0.27$, whereas the CES-D depression scale (a well-validated and widely-used questionnaire) showed the opposite pattern. The items are still included in the analyses for completeness's sake and for comparison with a previous study of the breakdown variable (Hardy & Castonguay, 2018), but should be interpreted with caution.

Social well-being variables. Two questions asked about participants' happiness in their marriage (if they were married) or happiness in their relationship with their partner (if they had a partner). Because respondents answered at most one of these questions (none if they were single), we combined them into one index of relationship satisfaction. Respondents also indicated on three different items whether they considered people in general helpful vs. looking out for themselves, fair vs. likely to try and take advantage, and trustworthy vs. "can't be too careful". These items were averaged to obtain a composite index of social trust, Cronbach's $\alpha = 0.65$. Another set of 15 items asked respondents to rate their confidence in various social institutions, such as major companies, organized religion, education, television, the scientific community, or congress. These variables were moderately to strongly associated with each other and we averaged them to obtain a composite index of social confidence, Cronbach's $\alpha = 0.78$. The social well-being variables all had three response options and were scored such that the positive response received a value of 1, the neutral response received a value of 0, and the negative response received a value of -1.

Socio-demographic characteristics. Respondents indicated their gender, age (in years, but the oldest participants were grouped into *89 or older*, which was counted as 89 in the analyses), race (White, Black, Other) and ethnicity (Hispanic/Latino/Latina or not), household size, and number of children. They also indicated whether they had been born in the US, whether their parents had been born in the US (we coded whether at least one parent had been born abroad), and the number of grandparents that were born in the US. The interviewer coded the approximate size of the respondent's place of living. For indicators of socio-economic status (SES), respondents reported their subjective social rank (1 = *top* to 10 = *bottom*), their individual income (binned data, the bin midpoint was used in the analyses), their occupation (which was recoded into prestige codes based on the 2010 Census occupation classification using a modified threshold technique), employment status (we coded whether they were currently employed either full- or part-time and whether they were currently employed full-time), and their education (we coded whether they had a 4-year college degree or higher). Finally, respondents indicated how strongly they were affiliated with their religion, how often they attended religious services, how often they attended other religious events (we recoded both items into 0 = *never*, 1 = < *once a year to several times a year*, 2 = *about once a month to nearly every week*, and 3 = *every week to several times a day*), who they had voted for in the 2012 election (or, if they had not voted, who they would have voted for), and as how 1 = *liberal* to 7 = *conservative* they rated their political views.

Method

To compare intensive social media users with moderate social media users and non-users, we grouped respondents based on how many platforms they reported using (0, 1-5, 6+). For our initial comparison, we used t-tests that compared intensive users with everyone else. Following prior research, we examine the associations between social media use and well-being using correlations (for bivariate relations) and regression approaches (for multi-factor prediction). For better interpretability, outcomes and continuous predictors were standardized and we present standardized linear regression coefficients. Most indicators of well-being were only modestly correlated (typically $r = .10$ - $.30$) and we therefore analyze them separately, but in future analyses we will further examine the multivariate nature of well-being as it relates to social media use.

Results and Discussion

The Demography of Social Media Users

Prevalence. Social media use was highly prevalent in the 2016 GSS data and only 11% were not on social media (numbers are adjusted for design and non-response weights; rounding means estimates may not sum up to 100). Typically, respondents used between 1 and 5 different platforms, however, a minority of respondents reported using 6 platforms or more. We termed this group of respondents *intensive social media users* (6+ platforms; 11%) and used t-tests to evaluate which socio-demographic characteristics differentiate them from both *moderate users* (1-5 platforms; 79%) and *non-users* (0 platforms; 11%).

General characteristics. Consistent with prior findings (e.g., Perrin & Anderson, 2019), social media users in general tended to be younger than non-users, and intensive social media users were again younger than moderate users, $t(63) = -5.25$, $p < .001$ (for the comparison of intensive users versus everyone else; see Figure 1 for all patterns of means). Social media users in general were also substantially more likely to be female than non-users, and intensive social media users were marginally more likely to be female than everyone else, $t(63) = -1.87$, $p = .066$. Intensive social media users were more likely to identify as Black, $t(63) = 2.49$, $p = .015$, and correspondingly less likely to identify as White, $t(63) = -2.05$, $p = .045$. Further, intensive users were significantly more likely to live in a larger city than either non-users or moderate users, $t(63) = 2.34$, $p = .023$.

Further, intensive social media users scored higher on several measures of SES. They assigned themselves higher ranks in society, $t(63) = -2.39$, $p = .021$, reported higher incomes, $t(63) = 2.26$, $p = .027$, held marginally more prestigious occupations, $t(62) = 1.98$, $p = .052$, and were substantially more likely to hold a degree from a 4-year college, $t(63) = 4.02$, $p < .001$. Despite slight visual trends in the means, there were no significant differences for employment status, $t(63) = 1.65$, $p = .103$, or full-time employment, $t(63) = 0.57$, $p = .577$. Intensive users did not differ significantly from non-users and moderate users on religious or political characteristics, although the patterns of means showed trends towards more participation in religious services ($t(63) = 1.68$, $p = .099$) and events ($t(63) = 1.76$, $p = .083$) and towards a higher chance of having voted (or intended to vote) for Obama in 2012, $t(63) = 1.87$, $p = .067$.

Finally and as expected, intensive social media users had started using social media earlier both in absolute terms (year of start), $t(60) = -5.10$, $p < .001$, and in relative terms (proportion of life using social media), $t(60) = 5.26$, $p < .001$, compared to their more moderately-using counterparts. They also reported using the internet for almost an hour longer on both weekdays, $t(62) = 3.74$, $p < .001$, and weekend days, $t(62) = 3.34$, $p = .001$, than either non-users or moderate users.

Migration. Respondents' migration status did not make a difference for how many social media platforms they used, $t(63) = -1.16$, $p = .250$. In contrast, the results suggested potential effects on second-generation migrants (such that those with at least one foreign-born parent were more likely to be intensive users), $t(63) = 1.97$, $p = .053$, and possible but weak effects on thirdgeneration migrants (such that those with more foreign-born grandparents were slightly more likely to be intensive users), $t(63) = 1.70$, $p = .094$.

Fertility. Non-users and moderate social media users did not differ in their number of children, but intensive users had on average fewer children, $t(63) = -3.33$, $p = .001$. This effect can be partially attributed to the lower average age among the intensive users. Controlling for age differences, $b = 0.03$, $SE = 0.00$, $p < .001$, however, did not remove the effect, $b = -0.89$, $SE = 0.22$, $p < .001$, but rather yielded an interaction such that among younger adults (between approximately 18 and 40 years), intensive users had about half as many children as their peers who were non-users or moderate users, $b = 0.02$, $SE = 0.01$, $p = 0.002$ (Figure 2). There was no observed difference in fertility for those aged about 40-50 or older (but note that this latter group did not include many intensive users, $n = 55$). Despite this difference in number of children, there was no difference in overall household size, $t(63) = 0.41$, $p = 0.681$.

Social Media Use and Well-Being

Multi-platform use. We examined the association between intensity of social media use (number of used platforms) and well-being, and also compared these results with the relation between offline social contact and well-being for discriminant validity. Overall, there were no detrimental effects of social media use on various indicators of personal well-being including happiness, health, depression, or the number of bad mental health days (Table 1). More specialized forms of well-being such as financial satisfaction or excitement about life were also not decreased by social media use – in fact, rather than experiencing negative consequences, people who used more social media found their life slightly more exciting. The same effect, however, was observed for offline social contact and increased interest in one's own life may thus represent a consequence (or cause) of a more active social life rather than a feature that is specific to online media. The only well-being indicator that was negatively impacted by multi-platform social media use was the chance of ever in one's life having felt that one would have a mental breakdown, and it was this item that led Hardy and Castonguay (2018) to conclude that social media negatively affects well-being. As mentioned previously, however, the validity of this item is questionable because the concept of a mental breakdown was ill-defined and the item did not show strong concurrent validity with other indicators of well-being or mental health. Further, this item was the only one that referred to respondents' entire lifespan instead of current well-being. If the correlation between this item and social media use is seen as a valid and non-spurious result, it would therefore suggest reverse causation: If lifespan mental health relates to social media use but current mental health doesn't, the most likely explanation is that earlier mental health problems led people to self-select into social media instead of social media affecting well-being like Hardy and Castonguay claimed.

Intensity of social media use seemed similarly unrelated to social well-being, as there were no negative (or positive) effects on relationship satisfaction with respondents' romantic partners, social trust in people in general, or confidence in various social institutions. Finally, there was no evidence of a displacement effect for social support either, rather, online and offline social activity frequency were modestly positively correlated. In other words, people who used social media intensively did not compensate this by reducing their offline social contact. Instead, it appears likely that people high in extraversion would seek both online and offline social contact, thus producing the observed positive correlation.

The results did not change when comparing intensive social media users (6+ platforms) to more moderate and non-users, with two exceptions: Intensive users reported higher satisfaction with their romantic relationship and more confidence in social institutions than other respondents. Additionally, the previously discussed positive effect of social media users finding life more exciting than non-users (M = 0.51, 95% CI [0.37, 0.64]) appeared to be driven by intensive (M = 0.63, 95% CI [0.50, 0.76]), but not moderate users (M = 0.47, 95% CI [0.41, 0.53]).

Multi-platform use and interactions with age. Multi-platform use was substantially influenced by age and some prior literature has found interactions of multi-platform use with age (Hardy & Castonguay, 2018), and therefore we repeated these analyses including age as an additional predictor and a moderator. Out of the ten well-being variables we examined, there were eight for which social media use intensity was unrelated to well-being in interaction with age (ps = .16 - 96). One of these variables for which we found no such interaction (β = 0.06, SE = 0.04, p = .158) was whether respondents had ever felt like they were going to have a mental breakdown, which was the variable for which Hardy and Castonguay had reported an interaction (they used only four of the available social media platforms, whereas we used all available indicators of social media use). For depression, middle-aged to older adults (top three quartiles of age, everyone over 34) report marginally higher depression with higher social media use, r = -.09, p = .054, but for younger adults (lowest quartile, 34 and younger), depression and social media use were unrelated, r = .08, p = .152 (Figure 3; interaction β = 0.10, SE = 0.04, p = .017). For social trust, the top three age quartiles (>34) report higher social trust with higher social media use r = .09, p = .004, but young adults do not, r = -.01, p = .738 (interaction β = 0.06, SE = 0.03, p = .035). Three more variables showed no interaction between age and social media use, but social media use was a significant predictor of well-being after controlling for mean-centered age: These included ever having felt like one would have a breakdown (the same negative effect as in the bivariate results; β = 0.10, SE = 0.04, p = .018), finding one’s life exciting (the same positive effect as in the bivariate results; $\beta = 0.10$, $SE = 0.04$, $p = .020$), and confidence in social institutions (positive effect of social media use; $\beta = 0.06$, $SE = 0.03$, $p = .022$). After accounting for age, most results therefore did not change; the exceptions were the results for depression (negative effect of social media use on older, but not younger people), social trust (positive effect of social media use on younger, but not older people) and confidence in social institutions (positive effect).

Specific platform use. Finally, we analyzed if any specific social media platforms were associated with personal or social well-being. In general, almost all social media platforms were used more by younger than by older people, with the interesting exception of Classmates - a platform to connect with former peers from all stages of life (kindergarten to workplace), but especially focused on former high school peers. The site hosts a collection of online yearbooks with which former classmates can be found. This retrospective focus on connections that happened years or decades ago, combined with its very early founding date (1995) can explain why it is primarily older people who use Classmates. Because of these associations with age, we controlled for age in the subsequent models (Table 2).

Most platforms showed few negative relations to well-being. Facebook usage appeared to be associated with worse health and a higher chance of ever having felt like a mental breakdown was approaching when controlling for the effect of age and Tumblr users reported being unhappier, unhealthier, and less confident in social institutions than people who were not on Tumblr. Tumblr is known for an audience that partially consists of young adults with low well-being and an active community where health, especially mental health problems are prominently discussed or turned into communal coping humor. Pinterest use was associated with more happiness and more excitement about one's life, but also with a higher chance of ever having felt like having a mental breakdown. This inconsistent pattern could cast further doubt onto the validity of the breakdown variable as an indicator of well-being. Pinterest and Classmates users both reported spending fewer evenings in social situations.

All other observed associations were positive in nature, such as Twitter being associated with more social trust and lower chance of having felt like having a breakdown, Snapchat being associated with fewer bad mental health days, and LinkedIn being associated with most indicators of personal well-being. LinkedIn focuses especially on working-age adults in higher-paying positions, and people who cannot participate in the labor force (e.g., through severe health or mental health problems) will likely self-select out of the platform. Income predicts well-being and after controlling for income, the associations between LinkedIn use and happiness, excitement about life, and financial satisfaction became non-significant. Importantly, no indicator of social media use was associated with relationship satisfaction, again offering no support for a displacement theory according to which online activity should take a toll on the quality of offline social relationships.

Propensity-score adjustment. Many of the results we presented can reasonably be explained by selection effects in who decides to use social media, such as the finding that LinkedIn users report higher well-being. To reduce selection effects in our analyses and obtain less biased estimates of causal effects (to the extent possible in cross-sectional survey data), we used a propensity score adjustment procedure. In a first step, we calculated propensity scores by obtaining the fitted probabilities from a logistic regression in which binary indicators of social media use and intensive social media use were regressed on various socio-demographic variables - internet use start dat, region, hometown size category, hometown population, number of children, social class, self-rated social rank, age, gender, household income, job prestige, work status, full-time work status, race, Hispanic ethnicity, being born in the US vs. abroad, having vs. not having a foreign-born parent, number of foreign-born grandparents, religion, frequency of attending worship, frequency of attending other religious events, voting decision, political ideology, and highest education degree[1]. In a second step, we used these propensity scores as inverse-probability of treatment (IPTW) weights (Austin, 2011; Austin & Stuart, 2015) when regressing measures of well-being on the binary indicators of social media use. Following the recommendations of Ridgeway, Kovalchik, Griffin, and Kabeto (2015), we combined these newly-calculated weights with the GSS survey weights by multiplying them. To calculate standard errors and confidence intervals, this procedure was bootstrapped with 5000 replicates and we then computed bias-corrected and accelerated confidence intervals based on these results.

Overall, there was no evidence for an effect of either regular or intensive social media use on well-being (Table 3). Most effect sizes were small, all confidence intervals but one included zero, and there was no consistent pattern across the different indicators of well-being. The only effect for which zero is not included in the confidence interval is the association of social media use (vs. non-use) on health: Both before and after propensity adjustment, social media users on average report poorer health than non-users. This effect, however, does not extend to the intensity of social media use, where if anything, the tendency is for intensive users to report better health than moderate users and non-users combined. The effect of social media use (vs. non-use) on ever having felt like having a breakdown is substantially reduced when adjusting for the propensity score (on average, 13% of the range vs. 25% without adjustment) and in 20% of

[1] Religiosity and respondent income were not included in the list of covariates because of relatively high proportions of missing data; including these variables would have reduced the effective sample size from 873 to 450.

the bootstrap replicates, the effect is zero or smaller. After adjustment, intensive social media users on average were also more likely to report low financial satisfaction and high social trust compared to moderate users or non-users, but again the results were too variable to be considered reliable and both confidence intervals included zero. In sum, results from propensity adjustment thus supported the finding that effects of social media use on well-being tend to be small and inconsistent.

General Discussion

In sum, intensive users of social media tended to be young, female, more likely to be Black, higher-SES, and from larger cities compared to both non-users and moderate users. Intensive social media users in young and middle adulthood had on average fewer children, but this difference did not emerge for intensive users in middle to late adulthood. Multi-platform social media usage generally did not affect personal or social well-being of 2016 GSS respondents. When effects emerged, they either were positive in nature or most consistent with a self-selection effect of pre-existing differences (rather than a causal effect from social media to well-being), a result that was confirmed by models that adjusted for the propensity to use social media (or use it intensively) based on a variety of socio-demographic covariates. Symptoms of depression were the only exception; they were slightly higher with higher social media usage among middle-aged to older adults, but not for young to middle-aged adults (18-34). For individual social media platforms, there was no consistent pattern of effects either – some platforms’ users report lower well-being on some of the indicators (e.g., Facebook, Tumblr, Pinterest), whereas other platforms’ users report higher well-being on several indicators (e.g., Twitter, Snapchat, Pinterest, LinkedIn).

This overall absence of consistent effects on well-being is at odds with several publications that had argued for detrimental effects of social media use generally (e.g., Kross et al., 2013; Twenge & Campbell, 2019) and multi-platform social media use specifically (Hardy & Castonguay, 2018; Primack et al., 2017; Vannucci et al., 2019). It is, however, in line with a growing literature that suggests that effects of social media on well-being may be smaller than previously suggested (e.g., M. Appel et al., in press; Huang, 2017; Orben et al., 2019; Orben & Przybylski, 2019). Our analyses offer additional context for the findings of Hardy and Castonguay (2018) who, using the same dataset, found detrimental effects of multi-platform use on the chance of ever having felt like a mental breakdown was imminent, more so for older than for younger adults: Examining a larger number of social media platforms, a larger number of well-being indicators, and more stringent adjustment for selection bias, we were not able to replicate their findings for any variable except for symptoms of depression. Several influential publications that cautioned against social media use were specifically concerned about youth (Balbo, 2018; e.g., Kross et al., 2013; Twenge & Campbell, 2019). The 2016 GSS data do not support these concerns. If anything, the patterns indicated that comparatively older adults (35+) may be more at risk of experiencing depressive symptoms when they are also using many social media platforms (Figure 3), whereas we observed no such risk for younger adults.

The findings from this research can be useful first for those who seek to understand who is using social media more versus less intensively. If future research uncovers effects of intensive social media use on other health variables that have so far remained unexamined, the characterization of intensive users in the present work can help to identify groups that are at particularly high (or low) risk. Second, this work contributes to the ongoing discussion on whether social media use is overall harmful, helpful, or neutral for the well-being of populations in the digital age. The results from the 2016 GSS overall suggest that social media use does not have strong implications for either personal or social measures of well-being, and that specific patterns of usage (e.g., specific platforms, or usage in specific age groups) can have harmful and helpful effects alike. Social media has undeniably changed people's lives by offering a completely new form of infrastructure with which people can and do obtain information, share their opinions, and communicate with others. Now that this new infrastructure exists, however, using it versus not using it may not have strong effects on well-being. The current results thus support the idea that social media has changed the surface form of communication rather than both form and function – just as with offline interactions, well-being may depend more on what, specifically, happens in an interaction (e.g., Bessière et al., 2010; Park et al., 2009; Rae & Lonborg, 2015; Valkenburg et al., 2006) rather than on the medium of communication. In the early days of internet research, after initial concerns about detrimental effects on well-being, many studies found small, null, or even positive effects and the internet appeared as "a new way of doing old things" (Tyler, 2002); it is possible that social media research is heading in a similar direction.

Third, our findings may be of interest to health and mental health professionals. For example, there have been calls for clinicians to ask their clients about their social media use, and, if the client is using many social media platforms, to treat this as a warning sign for mental health problems or dysfunctional behavior. Our results caution against using multi-platform social media use as such a warning sign to avoid over-pathologizing commonplace and potentially harmless behaviors such as social media use. Instead, our results can offer more specific guidance for clinicians: Ask for more details about how, how much, and for which purposes clients are using social media to determine whether a problem exists and if so, where it lies, familiarize yourself with the characteristics of different social media platforms and their associated risk factors and protective factors, and be aware that older people may be at higher risk of depression than younger people when they are heavy users of social media.

Because the social media module was included in the GSS only once to date, this dataset offers only a cross-sectional snapshot of a single time point. It is possible that on the macro-level, population well-being changed when social media first reached widespread popularity, but such a historical analysis is beyond the scope of this current paper. Even though our findings in this work thus cannot speak to historical developments, they offer relevant and timely information going forward: With social media already a ubiquitous part of societal functioning and interpersonal communication patterns, should people avoid social media to overall improve population health? The present results suggest that this step may not be necessary because the intensity of social media use is not consistently related to poorer or better well-being. This dataset also includes only US residents and how transferable the results are to other structural and cultural contexts is an empirical question that should be examined by future work. The answer will likely depend on the purposes for which social media are being used in other countries. Finally, our results are not meant to indicate that problematic social media use does not exist. Like any other activity, social media use can become dysfunctional if it consumes excessive amounts of time and if users no longer feel like they can control their social media use (Andreassen, 2015; M. D. Griffiths, 2013; LaRose, Connolly, Lee, Li, & Hales, 2014), or if it is used in ways that reinforce harmful attitudes (e.g., radicalization of political attitudes, Grover & Mark, 2019; or potentially unhealthy views on body image, Holland & Tiggemann, 2016) or behaviors (e.g., by normalizing or encouraging behaviors such as disordered eating, Branley &

Covey, 2017; or self-harm, Dyson et al., 2016). On average, however, it appears that people use social media in ways that do not pose such problems.

To conclude, the 2016 wave of the General Social Survey offers nationally representative data on social media use and well-being in the United States. We offer a socio-demographic characterization of intensive social media users who have profiles on a multitude of social media platforms and find few detrimental as well as few positive effects of intensive social media use on both personal mental health and the quality of offline social relationships. These findings contribute to a growing literature on the transformative effects of the digital revolution and suggest that for typical patterns of usage, social media may change the form of social activities more than their function.

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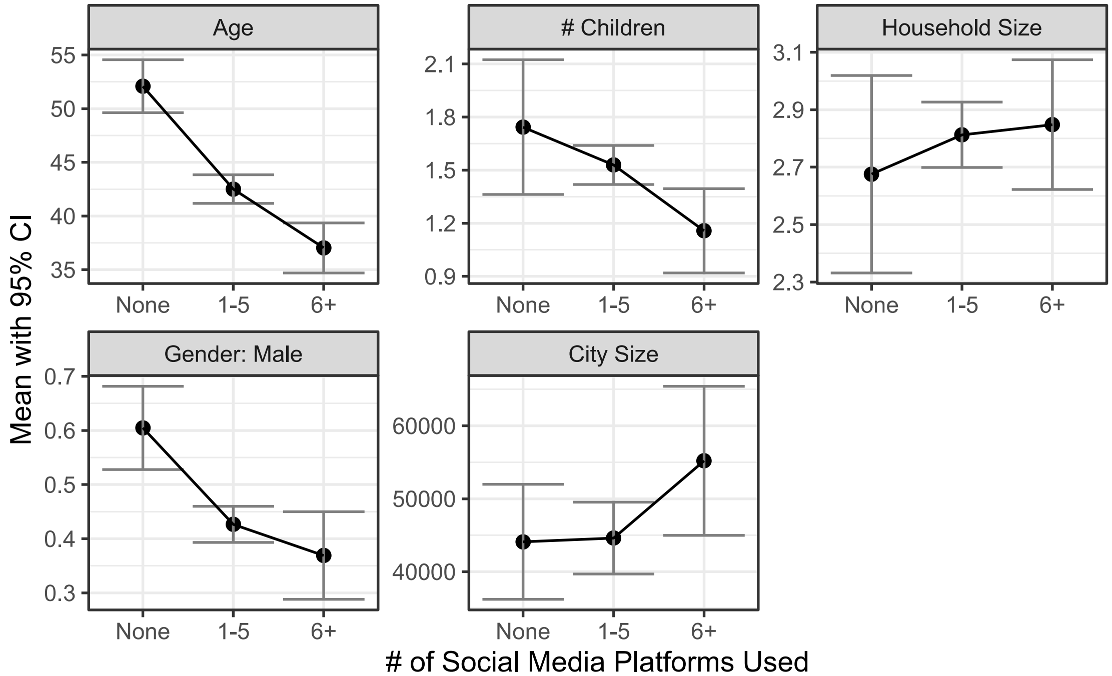
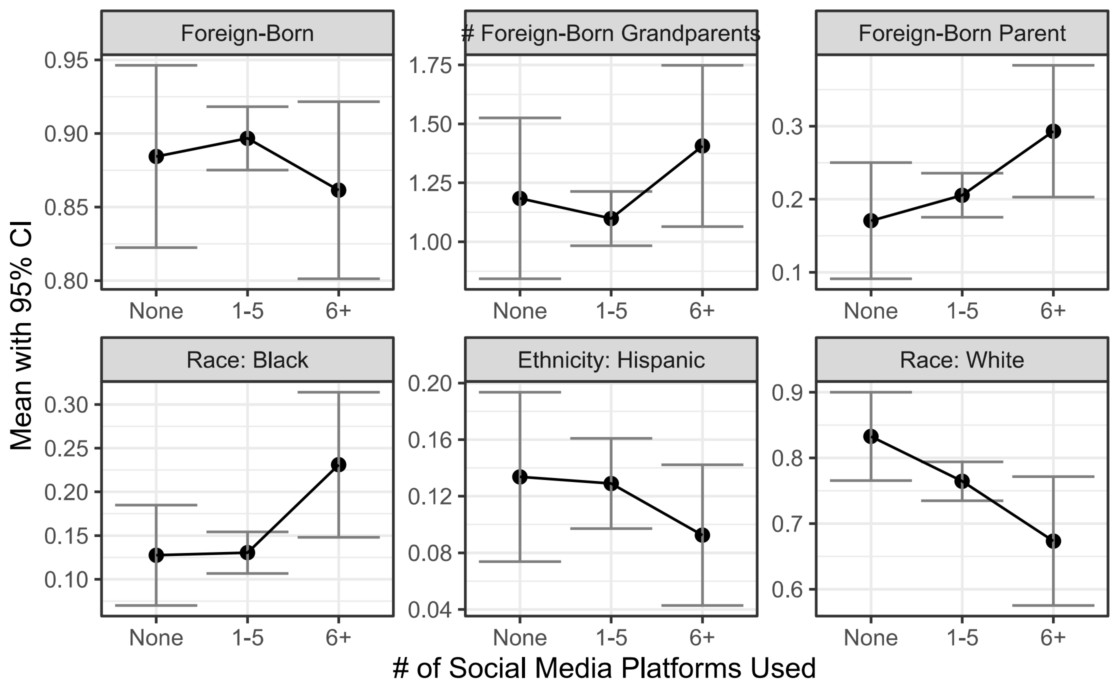
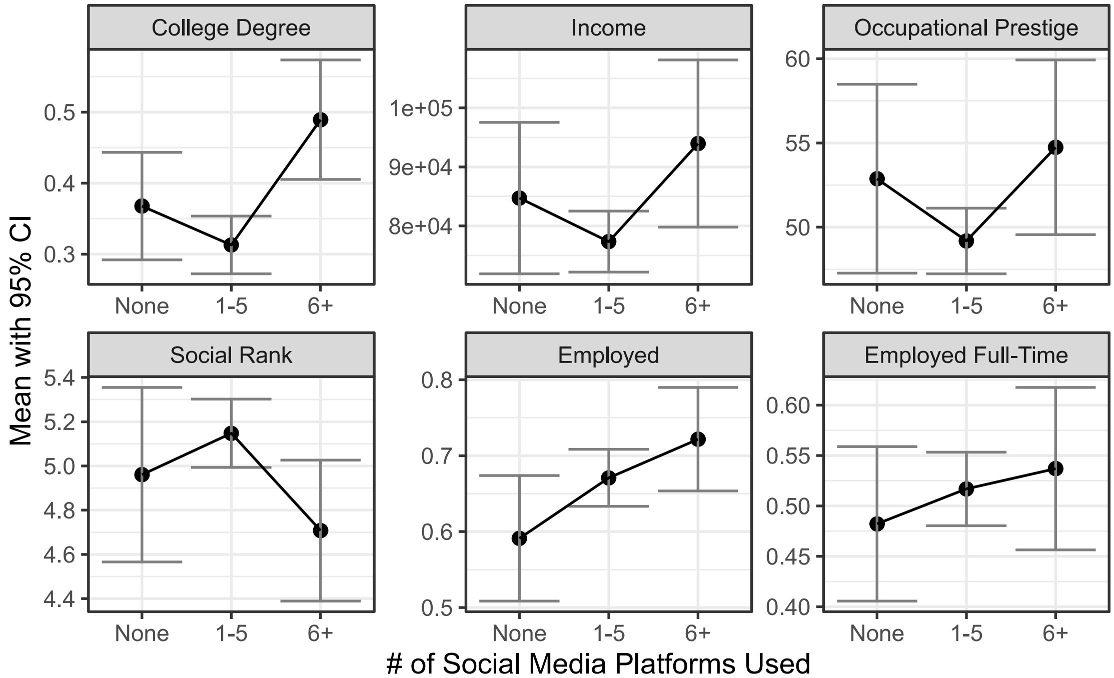
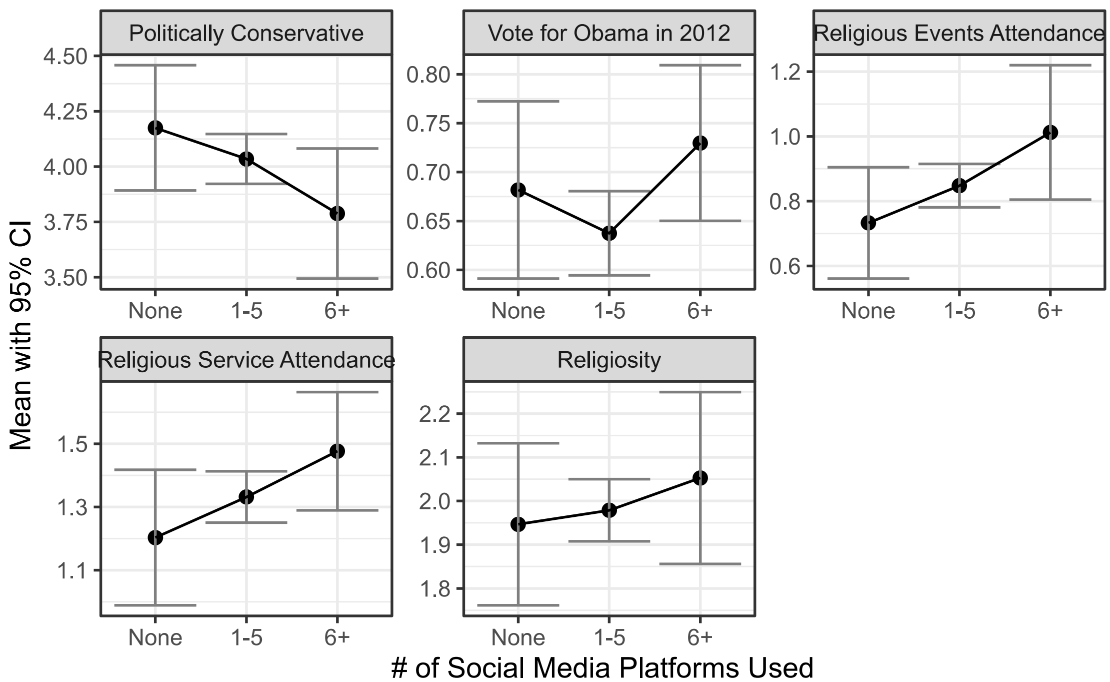

Age
Children
Household Size
Gender: Male
City Size
Mean with 95% CI
None
1-5
6+
# of Social Media Platforms Used


Foreign-Born
Foreign-Born Grandparents
Foreign-Born Parent
Race: Black
Ethnicity: Hispanic
Race: White
Mean with 95% CI
None
1-5
6+
# of Social Media Platforms Used


College Degree
Income
Occupational Prestige
Social Rank
Employed
Employed Full-Time
Mean with 95% CI
None
1-5
6+
0.3
0.4
0.5
8e+04
9e+04
1e+05
50
55
60
4.4
4.6
4.8
5.0
5.2
5.4
0.5
0.6
0.7
0.8
0.40
0.45
0.50
0.55
0.60
# of Social Media Platforms Used


Politically Conservative
Vote for Obama in 2012
Religious Events Attendance
Religious Service Attendance
Religiosity
Mean with 95% CI
None
1-5
6+
3.50
3.75
4.00
4.25
4.50
0.60
0.65
0.70
0.75
0.80
0.6
0.8
1.0
1.2
1.1
1.3
1.5
1.8
1.9
2.0
2.1
2.2
# of Social Media Platforms Used

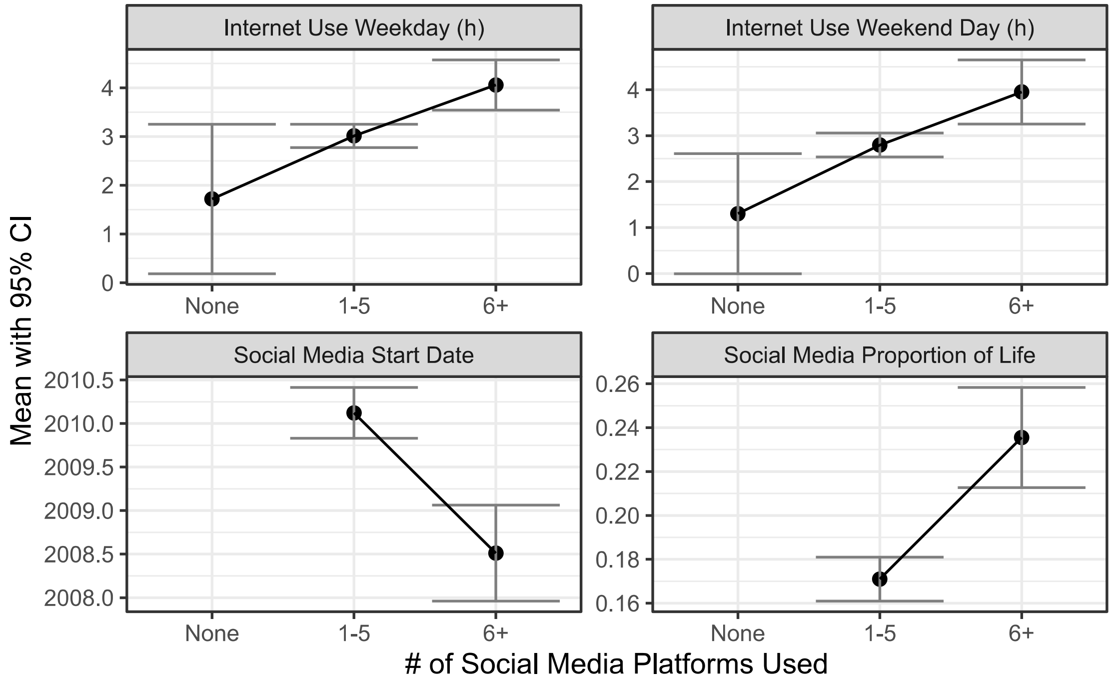


Figure 1. Means and 95% confidence intervals of socio-demographic characteristics across categories of social media usage intensity.

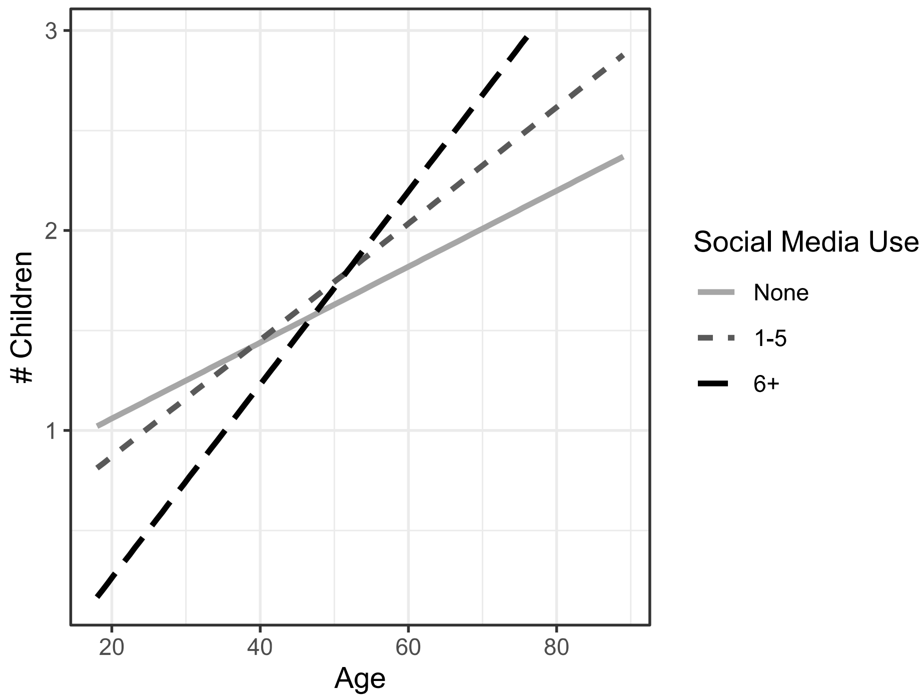


Figure 2. Linear regression for the interaction of age and social media usage intensity on number of children. Social media use was measured by the number of platforms that respondents were using.

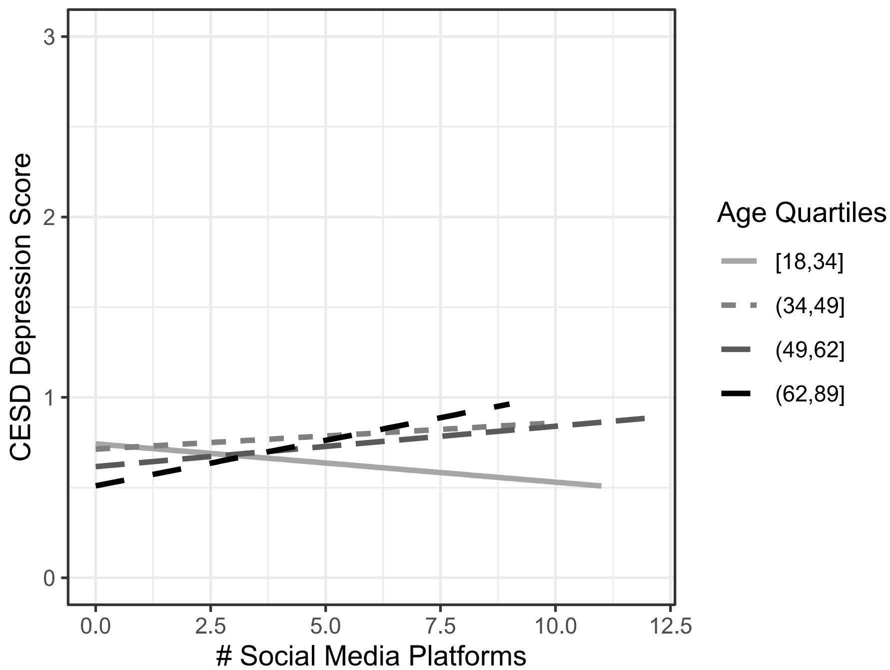


Figure 3. Linear regression lines for the interaction of social media usage intensity and age on symptoms of depression, plotted by age quartiles.

Table 1

Pearson correlations (r) of social media use, offline social contact, and personal and social well-being.

	Social media use	Offline social contact
Happiness	.01	.03
Health	.02	.06
Depression	.04	+
Bad mental health days	.07	.07
Ever feel like breakdown	.13*	.03
Exciting vs. dull life	.08*	.13*
Financial satisfaction	-.01	-.02
Relationship satisfaction	.06	.05
Social trust	-.01	-.12
Confidence in social institutions	.06	.06
Offline social contact	.13*	

* $p < .05$

+ could not be calculated because the variables were never administered in the same questionnaire

Table 2

Standardized linear regression coefficients (β) for predicting well-being from use of social media platforms, controlling for age (the effect of age is shown separately in the second column). Only β coefficients significant at p *< .05 are shown.*

Social Media Platform	*r* with age	Happi -ness	Health	Depre- ssion	Bad mental health days	Ever feel like break- down	Exciting vs. dull life	Financial satis- faction	Relation -ship satis- faction	Social trust	Confidence in soc. institutions	Offline social contacts
# platforms	-.30						.05			.04	.03	
Facebook	-.16		-.21			.27						
Twitter	-.22					-.22	.18	.22		.23	.22	
Tumblr	-.11	-.40	-.76								-.27	
Snapchat	-.42				-.17							.35
Vine	-.14											
Instagram	-.38											
Pinterest	-.03 (ns)	.13				.31	.16					-.19
flickr	.06 (ns)											
Classmates	.16											-.34
LinkedIn	.00 (ns)	.20	.40	-.24			.23	.19		.37		
Google+	-.02 (ns)										.14	

Table 3

Results of propensity-adjusted IPTW regressions of social media use on well-being. IPTW estimate represent means and 95% percentiles of 5000 bootstrapped samples. For comparison, the non-adjusted baseline regression coefficients are presented and the adjusted IPTW regression coefficients are additionally shown as percent of the variable's range.

Outcome	Outcome Range	Baseline *b*	IPTW average *b*	IPTW 95% CI	% of range
Social media users (1) vs. non-users (0)					
Happiness	-1 to 1	-0.09	-0.06	[-0.56, 0.15]	-3%
Health	-1 to 2	-0.31	-0.25	[-0.67, -0.03]	-8%
Depression	0 to 3	0.16	0.02	[-0.54, 0.20]	1%
Bad mental health days	0 to 30	0.48	0.26	[-5.84, 2.24]	1%
Ever feel like breakdown	0 to 1	0.25	0.13	[-0.37, 0.34]	13%
Exciting vs. dull life	-1 to 1	-0.07	0.01	[-0.28, 0.37]	1%
Financial satisfaction	-1 to 1	-0.18	0.02	[-0.49, 0.20]	1%
Relationship satisfaction	-1 to 1	-0.09	0.06	[-0.22, 0.47]	3%
Social trust	-1 to 1	0.04	0.07	[-0.26, 0.48]	4%
Confidence in social institutions	-1 to 1	0.05	0.07	[-0.02, 0.25]	4%
Intensive social media users (1; 6+ platforms) vs. moderate users and non-users (0; 0-5 platforms)					
Happiness	-1 to 1	-0.06	-0.11	[-0.48, 0.15]	-5%
Health	-1 to 2	0.04	0.24	[-0.07, 0.54]	8%
Depression	0 to 3	0.07	0.03	[-0.12, 0.24]	1%
Bad mental health days	0 to 30	1.59	-0.39	[-1.90, 2.61]	-1%
Ever feel like breakdown	0 to 1	0.02	0.01	[-0.20, 0.24]	1%
Exciting vs. dull life	-1 to 1	0.12	0.19	[-0.15, 0.39]	9%
Financial satisfaction	-1 to 1	-0.19	-0.30	[-0.58, 0.04]	-15%

Relationship satisfaction	-1 to 1	0.04	0.09	[-0.19, 0.28]	5%
Social trust	-1 to 1	0.09	0.20	[-0.07, 0.39]	10%
Confidence in social institutions	-1 to 1	0.05	0.02	[-0.15, 0.20]	1%