Marketing Science Institute Working Paper Series 2021

Report No. 21-120

Social Media Use and Psychological Well-Being

Cammy Crolic, Peter Pal Zubcsek, Andrew T. Stephen, and Gillian Brooks

Social Media Use and Psychological Well-Being

Date of Submission: 24 March 2021

Cammy Crolic
Associate Professor of Marketing
Saïd Business School, University of Oxford
Park End St, Oxford OX1 1HP, United Kingdom
+44 (0)1865 288505
Cammy.Crolic@sbs.ox.ac.uk

Peter Pal Zubcsek
Senior Lecturer of Marketing
Coller School of Management, Tel Aviv University
Sderot Henry Gildred, Tel Aviv-Yafo, Israel
+972 36409564
PeterZ@tauex.tau.ac.il

Andrew T. Stephen
L'Oréal Professor of Marketing & Associate Dean of Research
Saïd Business School, University of Oxford
Park End St, Oxford OX1 1HP, United Kingdom
+44 (0)1865 614659
Andrew.Stephen@sbs.ox.ac.uk

Gillian Brooks
Assistant Professor of Strategic Marketing
King's Business School, King's College London
Bush House 30 Aldwych, London WC2B 4BG, United Kingdom
+44 (0)2078 483770
Gillian.Brooks@kcl.ac.uk

Cammy Crolic (cammy.crolic@sbs.ox.ac.uk) is an Associate Professor of Marketing at the Saïd Business School, University of Oxford; Peter Pal Zubcsek (peterz@tauex.tau.ac.il) is a Senior Lecturer of Marketing at the Coller School of Management, Tel Aviv University; Andrew T. Stephen (andrew.stephen@sbs.ox.ac.uk) is the L'Oreal Professor of Marketing and Associate Dean of Research at the Saïd Business School, University of Oxford; Gillian Brooks (gillian.brooks@kcl.ac.uk) is an Assistant Professor of Strategic Marketing at King's Business School, King's College London.
 This research was funded by the John Fell Fund at the University of Oxford, the Henry Crown Institute of Business Research in Israel at Tel Aviv University, the Marketing Science Institute, and internal research funds at the Saïd Business School, University of Oxford. Funds from corporations were not used for this research. The authors thank William Fritz for his help with data collection, Inyoung Chae, Felipe Thomaz and Jacob Goldenberg for their comments and suggestions, and seminar participants at Georgia University of Technology, Interdisciplinary Center, Singapore Management University, University of Oxford, and Warwick University.

Billions of people around the world use social media, which is broadly defined as the collection of digital services that facilitate ostensibly "social" communications for the purposes of sharing information, keeping in touch with friends and family, accessing news and entertainment, expressing oneself, and following interesting people and brands. Given its ubiquity in modern life, it is important to understand how using, or *consuming*, social media impacts people. In the current research, we specifically consider how using social media affects individuals' *psychological well-being*, which is a key component of mental health and a major contributor to overall well-being and life satisfaction (Windle and Woods 2004).

Findings from prior research into how social media use *psychologically* affects people are mixed. Some studies have suggested that social media use is linked to adverse psychological effects including depression (Appel, Gerlach, and Crusius 2016; Brooks and Longstreet 2015), envy (Krasnova, et al. 2013; Lin and Utz 2015), mental overload (Maier et al. 2012), feelings of social isolation (Primack et al. 2017), and lower happiness (Brooks 2015; Kross et al. 2013). Additionally, social media use has been shown to increase some negative behaviors such as impulse shopping (Zhang et al. 2018), diminished self-control (Wilcox and Stephen 2013), impaired non-verbal emotive skills (Uhls et al. 2014), and reduced focus and attention (Brooks 2015). Furthermore, research has said that using social media platforms, such as Facebook, predicts declines in well-being (Kross et al. 2013).

These negative impacts of social media use have received substantial attention in the popular press and media. Popular press articles have reported that social media has detrimental effects, claiming that, "Instagram is 'worst for young mental health'" (BBC News 2017), issuing warnings to, "Take Back Your Brain from Social Media" (Wall Street Journal; Fowler 2017), suggesting that, "An Instagram With No 'Likes' Could Have a Big Impact on Mental Health," (Huffpost; Wong 2019) and outlining, "Six Ways Social Media Negatively Affects your Mental Health" (The Independent; Barr 2018). As a result, Facebook, the world’s largest and most prominent social media company, now openly questions how the platform might psychologically affect their users (Ginsberg and Burke 2017).

Despite these negative findings and headlines, other research suggests a variety of positive consequences of spending time on social media. For example, social media use results in accumulating more and stronger social ties (Acquisti and Gross 2006; Ellison, Steinfield, and Lampe 2007; Reinecke and Trepte 2014; Utz 2015; Valkenburg, Peter, and Schouten 2006), building social capital (Valenzuela, Park, and Kee 2009), and having greater feelings of connectedness, social support, and belongingness to communities (Greene 2011; Kraut et al. 2002; Laroche et al. 2012; McAlexander, Schouten, and Koenig 2002; Merolli, Gray, and Martin-Sanchez 2013). Additionally, a study of teenagers in the U.K. found a weak positive link between their self-reported social media use and overall life satisfaction (Orban, Dielin, and Przybylski 2019).

Yet, very few of these studies have examined psychological well-being as an overall subjective and multi-faceted self-appraisal. Instead, most of the prior research has tended to look at specific correlates of psychological well-being (i.e., antecedents or consequences) instead of the general construct itself. Examining the general construct is admittedly not easy to do, given that psychological well-being is an overall appraisal that can be impacted by many facets of one’s life (e.g., social support, personal perspective, faith, work, physical activity, sleep, health, finances, family, and age). Because much of the prior research has not directly looked at psychological well-being, it is plausible that mixed findings are not necessarily conflicting, but rather that they are not readily comparable. Accordingly, it remains an open question whether consumption of social media is ultimately good or bad for people’s psychological well-being.

In an attempt to address this, we explored the association between time spent using social media and subsequent psychological well-being with two longitudinal studies of six and 3.5 months duration, respectively, and involving a combined total of 1,843 adult internet users who mostly lived in the U.K. or U.S. Our main hypothesis was that time spent using social media has a positive impact on subsequent psychological well-being. Yet, we expected this effect to be relatively small because psychological well-being is a general, multi-faceted self-appraisal that is influenced by a multitude of personal, social, and macro-environmental factors. We further predict that the mechanism driving this effect is the types of interactions people have on social media. Specifically, using social media in a *truly social* manner (i.e., actively interacting with meaningful social relations such as close friends and family members in a way that is similar to non-digital social interactions) was expected to be positively associated with psychological well-being since this type of social media use promotes meaningful social connectivity and social bonds, which should have positive psychological consequences. On the other hand, we expected using social media in a "less social" manner (e.g., passively following weakly connected others, celebrities, or strangers for entertainment purposes) to be psychologically inconsequential.

Conceptual Framework

Psychological Well-Being

Psychological well-being is a general, overall subjective self-appraisal. It is the combined cognitive and affective evaluation of one's life (Diener, Diener, and Diener 1995; Dolan and Metcalfe 2012) including happiness, life satisfaction, and positive affect (Diener 1984). It is composed of both top-down (i.e., happy people frame experiences more positively and thus experience greater well-being) and bottom-up effects (i.e., the presence of happy events and absence of unhappy events equates to greater well-being; Brief et al. 1993; Diener and Larson 1993).

Psychological well-being is influenced by a variety of factors. Prior research has consistently shown that *social relationships* are an important part of normal psychological functioning. Social support is an important contributor to psychological well-being regardless of whether a person is currently experiencing life stress (e.g., personal or professional loss, health issues) or whether their life is currently normal and/or going well (Rook 1984; La Rocco and Jones 1978; Lin et al. 1979; Williams, Ware, and Donald 1981). Furthermore, the stronger the ties (i.e., closeness) in the social relationship, the better the related outcomes for those involved (Wellman and Wortley 1990).

Social relationships have important consequences for psychological well-being because of the collaborative and inherently social aspect of being human. Specifically, social relationships are a core part of our identity and sense of self (Gergen 1987; Powell 2009; Tomasello et al. 2012). Social relationships provide social support, defined as the feeling that one is loved and cared about, valued, and a member of a reciprocal network (Cobb 1976). Furthermore, social integration impacts well-being by dictating normative behavior (Cobb 1976). Social relationships predict how well one copes (Cobb 1976; Cobb 1979; House 1981; Mitchell, Billings, and Moos 1982) and mitigate some of the negative consequences of stressful life events such as the death of a loved one (Bunch 1972; Rook 1984), illness (Egbert et al. 1964), and job loss (Gore 1978). For example, Egbert (1964) found that patients assigned to a special supportive care relationship with a hospital worker required less medicine and were released from the hospital 2.7 days sooner than patients not assigned to a supportive relationship.

While social relationships are important, there is an expectedly long list of other factors that can also influence psychological well-being. Some of these include individuals' perspectives (e.g., optimism versus pessimism, hardiness, resilience, mental fortitude; Augusto-Landa, Pulido-Martos, and Lopez-Zafra 2011; Florian, Mikulincer, Taubman 1995;

Hajek and König 2019; Rutter 1987), faith (Green and Elliott 2010; Shams 1993), fulfilling work (Arnold et al. 2007; White and Dolan 2009), physical activity (Bray and Kwan 2006; Fox et al. 2000; Netz et al. 2005), sleep (Hamilton et al. 2007; Kalak et al. 2014; Steptoe et al. 2008), health (Boehm and Kubzansky 2012; Cummings 2002), and economic security (Adelmann 1987; Kaplan, Shema, and Leite 2008; Ullah 1990).

Thus, social relationships are an important factor, albeit by no means the only important factor, that tends to influence psychological well-being. While prior research on the importance of social relationships for well-being is relatively old and not focused on relationships built and maintained through social media, social media is a place where meaningful, strong social relationships can be developed and maintained. Hence, it is conceivable that certain kinds of social relationships occurring on social media platforms, such as having meaningful friendships and healthy relationships with family members, could have a positive effect on one's psychological well-being.

The Nature of Social Media Use

Using social media could have a variety of effects on an individual's state of mind, including their psychological well-being. As discussed earlier, prior research has documented a range of effects from positive to neutral to negative. Thus, it is likely that how social media is used (i.e., what people do on it) plays a role in the types of psychological effects that can arise as a consequence of time spent on social media. Therefore, the nature of social media use is likely an important factor when considering the extent to which spending time using social media can affect subsequent psychological well-being. Next, we discuss the different natures of social media use and explain why we believe that certain types of social media use can affect psychological well-being.

Social media use can involve several kinds of activities. The most common activity is viewing digital content in the form of posts that are displayed in a scrollable feed. Posts can include text, images, video, or a combination of these. Digital content can be posted by people or by other entities such as commercial businesses (e.g., brands, influencers), public figures (e.g., politicians, celebrities), and non-commercial organizations (e.g., educational institutions, charities). This array of sources varies from being *truly social*, such as friends and family members that are meaningful and relevant to the individual viewing their posts, to the other extreme of being entirely non-social (e.g., posts from brands).

The other activities that social media users can undertake when spending time using social media are more interactive than merely viewing content from others. Typically, these involve posting content themselves (e.g., posting a photo on Instagram or writing a tweet on Twitter) and interactively engaging with content posted by others by, for example, commenting on it or reacting to it (e.g., "liking" a post). Notably, also, a mixture of all of these activities occurs in the case of messaging. In sum, social media usage can vary based on the social nature of the source and the activeness of the activity.

The diversity of source- and activity-related experiences means that time spent on social media platforms could involve a set of substantially different experiences. For example, one individual might focus their attention on a post from a *truly social* source, such as a close friend, who has shared a photo album of her new baby. The user looks through the photos, "likes" a couple of them, and reads the many positive comments, including from other close friends, before adding a comment of his own. Another individual might passively check her social feed and see a series of posts from people she followed in the past but does not know particularly well. These *somewhat* social, but not *truly* social, sources are sharing information that is not relevant or interesting to her. Yet another individual might come across posts in his feed talking about a contentious topic (e.g., politics) and see some tense, even inflammatory, posts and comments from a variety of sources, perhaps from some people he knows but also from complete strangers as well as non-social sources such as news outlets and companies. Finally, another person may see a series of posts from brands and glamorous social media influencers promoting various products.

In the above example of social media use, across four distinct usage sessions, the people's experiences vary considerably. We posit that the subsequent impact of the kinds of experiences on psychological well-being is driven by whether or not the social media use is of a *truly social* nature. For example, the active engagement with positive content and comments from close friends could boost one's psychological well-being, since the content reinforces their feelings of connection and being meaningfully engaged with relevant others. That is, this kind of social media use involves active interactions with people that one is interested in and cares about, much like social interactions in non-digital settings (e.g., sharing a restaurant meal with a good friend). Alternatively, seeing posts from long-forgotten acquaintances might have a slightly positive impact (e.g., for nostalgia reasons), but more likely a neutral effect on psychological well-being since these interactions, albeit social, are more passive in that they do not involve others with whom one is presently meaningfully connected. Or, seeing contentious or even inflammatory content might stir up some feelings of anxiety or stress. Whether this has a negative impact on subsequent psychological well-being is unclear, but certainly possible, and might depend on other factors such as the extent to which the topics of the content are relevant to the person and if the source of the content is known or a stranger. Finally, commercial content from brands, public figures, and influencers conceivably could have a positive effect (e.g., if it is interesting or entertaining), neutral effect (e.g., if it is irrelevant and simply ignored), or negative effect (e.g., if it triggers an identity threat or results in unhealthy social comparisons).

How Might Time Using Social Media Affect Psychological Well-Being?

The above examples illustrate some of the many ways in which people consume social media and posit a variety of potential impacts on psychological well-being. While prior research has looked at some of these usage types and associated impacts, the research has often been narrowly focused. Consequently, the influence of social media use on psychological well-being as an important and general self-appraisal has not been directly empirically documented. The goal of the current research, therefore, is to directly test whether there is a positive association between time spent using social media and subsequent psychological well-being. Further, to the extent possible given practical and ethics-related constraints described later, we test whether this hypothesized positive effect of using social media on psychological well-being is driven by how much time spent using social media is of a *truly social* nature. *Truly social* interactions on social media platforms are similar to typical non-digital social interactions with personally important others.

Predicting how a person will be psychologically affected by their social media use is challenging. This is because it comes down to factors related to how the individual uses social media (including source and activity, as discussed and illustrated above). Despite this inherent complexity, we argue that, on average, time spent using social media can have a positive effect on a person's psychological well-being because social media's main function is to facilitate active social relationships (Acquisti and Gross 2006; Ellison, Steinfield, and Lampe 2007; Utz 2015; Valkenburg, Peter, and Schouten 2006).

Social media can facilitate active social relationships by increasing connections and engagement with others. Social media use can increase the number of social ties one has (Valkenburg, Peter, and Schouten 2006) and can help strengthen those ties (Acquisti and Gross 2006; Ellison, Steinfield, and Lampe 2007; Utz 2015). It also can help make relationships in digital contexts feel more genuine or "real" by facilitating authentic self-presentation and disclosure (Reinecke and Trepte 2014). Social media can strengthen communities by bringing together people suffering from loss or illness (Greene 2011; Laroche et al. 2012; McAlexander, Schouten, and Koenig 2002; Merolli, Gray, and Martin-

Sanchez 2013) and embedding people in their offline communities (Kraut et al. 2002). And more generally, social relationships and communities, digital or otherwise, are fundamental to psychological well-being because humans are inherently collaborative, social beings that need to belong (Bowlby 1969; Cobb 1976; Durkheim 1951; Faris 1934; Kahneman and Krueger 2006; Rook 1984).

These points support our belief that it is possible for time spent using social media to be positively associated with psychological well-being. We are cautious in making this claim, however, given the mixed empirical evidence discussed earlier. Nevertheless, if indeed there is an average positive effect of social media use on psychological well-being, we expect this effect to be relatively small. Psychological well-being is a general, multi-faceted self-appraisal influenced by a multitude of personal, social, and macro-environmental factors. Thus, social media use, even if it is prominent in a person's life (as is the case for millions, if not billions, of people around the world), is likely just one among a constellation of drivers of psychological well-being. For example, while social relationships are fundamental to psychological well-being, it is likely that only a fraction of the communication to build and maintain social relationships occurs digitally, with a majority of social relationships still occurring non-digitally. And of those digital communications, only a fraction occurs in a *truly social* manner with meaningful others (i.e., interacting with meaningful social relations such as close friends and family members in a way that is similar to non-digital social interactions).

Thus, while we predict a small but significant average positive impact of general social media use on psychological well-being in general, we believe that the majority of benefits of social media will be tied to the nature of the usage, with greater positive benefits conferred on people who use social media in a *truly social* manner. Put simply, we posit that the mechanism for the hypothesized positive effect of using social media on psychological well-being is related to whether or not the social media use is of a *truly social* nature. Prior research supports this notion (e.g., people were more likely to feel happy after reading a Facebook post written by a close friend or family member; Lin and Utz 2015). *Truly social* interactions, such as actively engaging with known others, maintaining relationships with friends and family, and being part of a meaningful community are healthy social behaviors that should foster psychological well-being. Healthy, *truly social* behaviors in this sense are rooted in interactions with meaningful social relations, or people with whom one is genuinely interested and positively socially invested. Examples of meaningful social relations include friends and family members, but not strangers, anonymous individuals, or public personalities or celebrities.

Indeed, decades of research on real-world social relationships demonstrates how meaningful relationships and socially engaging with others positively contributes to well-being (e.g., Bowlby 1969; Cohen 2004; Durkheim 1951; Faris 1934; Holt-Lunstad, Smith, and Layton 2010; House, Umberson, and Landis 1988; La Rocco and Jones 1978; Lin et al. 1979; Rook 1984; Vanderhorst and McLaren 2005; Williams, Ware, and Donald 1981). Being connected to others should help, not hinder, psychological well-being because relationships can provide social support, a sense of belonging and community, and feelings that one is cared about and valued (Cobb 1976; Laroche et al. 2012; McAlexander, Schouten, and Koenig 2002).

Overview of Studies

We investigated the association between of time spent using social media and subsequent psychological well-being with two longitudinal studies of six and 3.5 months duration, respectively, and a combined total of 1,843 internet-using adults, with most living in the U.K or U.S. In each study, we measured psychological well-being with a short survey pushed to the participants' mobile devices once every two weeks (i.e., biweekly). Social media use was continuously tracked—unobtrusively, automatically, ethically, and accurately—for each participant and measured as time spent using various social media applications (including messaging) on their mobile devices.

This design is important because a potential reason for the aforementioned mixed findings in prior research is arguably attributable to critical limitations of previously used research designs. In our studies, social media use was accurately and unobtrusively measured. Prior studies typically did not do this. Instead, they relied on participants' self-reports of their social media use (Brooks and Longstreet 2015; Brynjolfsson, Gannamaneni, and Eggers 2019; Hughes et al. 2011; Krasnova et al. 2013; Kross et al. 2013; Primack et al. 2017; Valkenburg, Peter, and Schouten 2006), which are inherently error-prone, unreliable, and subject to self-presentational concerns. Also, many prior studies' findings are based on small samples (Kross et al. 2013; Kushlev and Dunn 2015; Skiera, Hinz, and Spann 2015) and/or ones that are demographically very limited (e.g., undergraduates in a single location; Brooks and Longstreet 2015; Chou and Edge 2012; Hunt et al. 2018; Krasnova et al. 2013; Skiera, Hinz, and Spann 2015) and/or with data collected over extremely short observation periods (e.g., one-shot surveys; Brooks and Longstreet 2015; Burke, Marlow, and Lento 2010; Chou and Edge 2012; Oberst et al. 2016; Primack et al. 2017; Przybylski and Weinstein 2017; Valkenburg, Peter, and Schouten 2006).

Our studies were designed to overcome these kinds of research design limitations. Specifically, in the two studies reported next, we employed larger samples with greater demographic diversity. Our studies were also longitudinal, allowing us to examine temporal causation. Finally, as mentioned above, much of the prior research has looked at outcomes that may be correlates of, but are not the same as, psychological well-being, which makes it difficult to compare and integrate findings across studies. We instead measured psychological well-being itself, not its correlates.

To test the key predicted relationship between time spent using social media and psychological well-being and the moderating role of *truly social* social media use versus other kinds of social media use, we were unable, for privacy and research ethics reasons, to know what participants *actually did* on social media during the study. Instead, we only knew how much time each day they spent using social media applications on their phones. We exploited differences in the typical ways that different social media platforms are operated and the typical primary purposes for which people use them to distinguish, albeit as proxy, between *truly social* and other uses of social media.

With respect to the major platforms covered in our studies, we considered Facebook to be more likely to foster *meaningful social relations* due to the way in which the algorithm behind the news feed operated during the time of our studies. Facebook's algorithm was, and still is, designed such that users are more likely to see posts from other users in their network that have been classified by Facebook as "meaningful relations" (Mosseri 2018). We also deemed messaging (e.g., WhatsApp and Messenger) as more likely to foster meaningful social relations because people typically use messaging applications to actively communicate with individuals and groups they know well and likely care about more. On the other hand, mainstream follower-based social media, which includes, for example, Instagram and Twitter, were deemed less likely to engender meaningful social interactions. This is because people tend to use them to follow others, typically people who they do not necessarily know and do not actively socially interact with (e.g., celebrities, influencers, politicians) or to follow non-human entities (e.g., brands, governments).

Additionally, another way to think of this is to consider the nature of the social graphs underlying these platforms (i.e., with users as nodes and connections between users as ties).

Facebook and instant messaging apps typically are *undirected* graphs, meaning that users *i* and *j* must mutually agree to be connected for them to be able to communicate (e.g., a "friend request" must have been "accepted" in the past for two Facebook users to be able to communicate with each other on the platform). Thus, this link is a form of active connection requiring consent of both parties. The follower-based platforms, such as Instagram and Twitter, instead typically are *directed* graphs, meaning that user *i* can "follow," and therefore be exposed to communications/posts from, user *j* without mutual agreement (unless an account is "private") allowing much more passive connections. We are not saying that *all* ties in undirected social graphs are "strong" and represent active and meaningful social relations and, similarly, *all* ties in directed social graphs are "weak," passive, and not meaningful. However, we do assume that relations in undirected social graphs (i.e., those that required mutual agreement to establish) are more likely to be of a meaningful, *truly social* nature than relations in directed social graphs.

Study Design and Measurement

The two studies used the same basic design and approach for participant recruitment. We recruited participants from online panels, using Prolific Academic for Study 1 and Amazon Mechanical Turk for Study 2. We explained that, if they chose to participate, participants would be required to install an application on their mobile device that would track how much time they spent using each application on their device and that every two weeks they would be asked to complete a short survey for which they would receive a nominal payment. For technical reasons, our application was only available for Android (an iOS version was not possible due to how Apple prevents developer access to device and app usage time data, a restriction not imposed by Google on Android). Hence, all participants had to be using a mobile device running a recent version of Android. Specifically, the participants installed a mobile behavioral research platform *mLab* (Cooke and Zubcsek 2017; Cooke, Zubcsek, and Crolic 2018). *mLab* collected responses to surveys which we pushed to participants every two weeks and on-device application usage data which were collected unobtrusively and constantly.

Initial Recruitment and Survey

At the time of initial recruitment, participants read an overview of the study explaining that in addition to completing an initial survey (see below for details on the measures used) and installing *mLab*, they would be asked to continue participating over six (3.5) months for Study 1 (Study 2). Participants were told that the initial survey and *mLab* download and installation would take about 25 minutes and they would be paid £3 ($4). Then, over the next six (3.5) months, participants would receive a short three-minute survey request every two weeks. For every survey they completed, participants would be awarded additional payments of £0.75 ($1). Finally, participants confirmed they used an Android mobile device, gave informed consent, and provided their anonymized Prolific email address (MTurk Worker ID). At this initial stage, 1,293 individuals joined Study 1 (recruited during August and September 2017) and 1,019 individuals joined Study 2 (recruited during December 2017 and January 2018).

During the recruitment procedure, participants also completed the initial survey. In the initial survey we collected demographic and socio-economic information that we used as control variables in our analysis (age, sex, household income, employment status, marital status, education level, country of residence, and primary language). We also measured in this survey (and all subsequent biweekly surveys) our psychological well-being dependent variable using eight scale items (1 *strongly disagree* to 7 *strongly agree*).

The scale items, which were a subset of eight measures from 24 measures of subjective feelings of psychological well-being categories including self-acceptance, positive relations with others, autonomy, environmental mastery, purpose in life, and personal growth (Ryff 1989), included “I feel supported by others”, “I am pleased with where my life is headed” and “I lead a purposeful and meaningful life” (see the Appendix 3 for all items). We used eight items to keep the measurement short because we believed that a longer scale would increase the attrition rate (α = .95 for Study 1 and .94 for Study 2; see Appendix 1 for the eight-item scale). These items were selected in a pretest and based on having high (> .70) commonalities in a principal component analysis (i.e., the items used for our shorter scale for measuring psychological well-being were those that loaded more strongly on the underlying latent factor).

Additionally, in the initial survey and all subsequent biweekly surveys we captured data on other well-being dimensions that might be correlated with psychological well-being and therefore should be controlled for in our analysis. First, we measured the commonly used “subjective well-being scale” or “Cantril Life Ladder” (0-10 scale; Cantril 1965; Diener et al. 1999; Helliwell et al. 2020). This scale is usually used as a single-item holistic measure of overall happiness or satisfaction with life, which is likely to be correlated with the more specific self-appraisal of psychological well-being. Second, we measured two other types of well-being: physiological (11 items, 1-7 scales; e.g., “I have had a lot more energy of late” and “I consider myself to be in good health”; α = .85 for Study 1 and .87 for Study 2) and financial (9 items, 1-7 scales; e.g., “I am satisfied with my current level of income” and “I am satisfied with my standard of living”; α = .91 for Study 1 and .92 for Study 2; see Appendix 2 for both scales). As with overall subjective well-being, we expected physiological and financial well-being to be associated with psychological well-being. In essence, all of these well-being dimensions are intertwined, so we measured them to allow us to control for them in our empirical analysis. Additional scale development details are provided in Appendix 4.

Biweekly Follow-Up Surveys

Every two weeks participants received a follow-up survey asking them to appraise their current well-being. Each participant had a new follow-up survey activated every two weeks, exactly twenty minutes before the day and time of the week that they completed the initial survey (for practical purposes, this was the case if the time was between 8 A.M. and 6 P.M. in the participant's time zone, or otherwise 8 A.M. the next morning). After the activation of a new survey, the *mLab* system sent a push notification to the participant's phone every two hours between 8 A.M. and 6 P.M. (in the participant's time zone) until the survey was completed or until a total of 25 notifications were sent. Participants could configure their notification preferences in the *mLab* app by restricting notifications to certain hours on certain days of the week and/or by holding all notifications for up to an hour (e.g., to prevent dangerous situations like being distracted by a notification while driving).

On each follow-up survey participants responded to the exact same set of well-being measures used in the initial survey. We also asked if participants had recently experienced a major life change since the last survey and two demographic measures that we had previously collected (i.e., gender, age). The demographic measures were taken to allow for us to check consistency across surveys, assuming that gender would not change and age would either not change or only go up by one once during the study. Where there were impossible deviations, we removed those participants as we suspected they were being misleading. This resulted in two and eleven participants being dropped from Studies 1 and 2 respectively.

This procedure was followed for the twelve (Study 1) and seven (Study 2) follow-up surveys. We only deviated from the procedure during Study 1 in an attempt midway through the study to reduce the attrition rate. The measures and base payments were unchanged;

however, we did slightly alter the email communication to participants to say that we would offer an extra incentive to remain in Study 1 until the end. Specifically, after survey 7 in Study 1 (i.e., the initial survey plus six follow-up surveys) participants who had completed all surveys so far were notified via email that if they completed every remaining survey in the study, they would receive a £3 bonus payment. Ultimately, after attrition, 1,046 participants fully completed Study 1 (18.98% attrition) and 797 participants fully completed Study 2 (20.93% attrition).

Unobtrusive Collection of Application Usage Times

The *mLab* app attempted to collect application usage data from the application usage logs created by the Android OS on each participant's mobile device. This was done unobtrusively, meaning that participants did not have to do anything to activate this data-capture process and they were not notified of it happening (they were, of course, aware of this because it was explained to them initially and they consented to this). Typically, *mLab* attempted to collect the usage data (aggregated by the Android OS to the last 24 hours) once every 15 (60) minutes per participant in Study 1 (2). We reduced the data collection/transmission frequency from every 15 minutes in Study 1 to every 60 minutes in Study 2 because we learned through conducting Study 1 that a 60-minute frequency was sufficient. This allowed us to make the data transmission more efficient in Study 2.

For a given participant, the raw application usage data collected each time was a record of the amount of time (in milliseconds) that each application spent in the "CPU foreground" (i.e., open on the screen and being used) in a preceding measurement interval, which we scaled to always be on a 24-hour basis (e.g., if a report of 30 minutes usage for a preceding 36-hour interval was given we rescaled that to be 20 minutes usage over a 24-hour basis). In addition, we discarded observations that we classified to be affected by technical errors. Specifically, we discarded observations reporting more than eight hours of CPU foreground time for a single application in a 24-hour interval, indicating it was actively used for a third of the day, which seemed very likely to be inaccurate and more likely a result of a technical error. Altogether, less than 0.4% of app usage observations were dropped in each of the two studies based on this criterion. We also performed the analysis with alternative exclusion criteria. Specifically, in Appendix 5, we report the results after excluding observations wherein a single application was reported to have been in the foreground over six or ten hours, respectively, in a 24-hour interval. Results are largely unchanged irrespective of the exclusion criteria used.

The application usage data, after the above-described cleaning, included 30,268 unique mobile applications. We categorized the most-used ones for the purposes of this research, but not all observed applications were categorized. To categorize a given application name, we performed an Internet search to look up its name and then, based on the description, assigned it to one of the categories listed in Table 1. A total of 1,700 apps, accounting for around 7-9% of all observed applications but around 90% of all device usage time in each study, were categorized. Importantly, social media applications in the dataset were Facebook, Facebook Messenger, Instagram, Reddit, Pinterest, Snapchat, Tumblr, Twitter, and WhatsApp.

Application-level usage data was also transformed into category-level usage data by summing—within participant—the times spent in each application within each category in the same time period. In our analysis, we selected a maximal set of non-overlapping app usage observations (to avoid double-counting) and calculated, for each category the average daily application/category usage time during the seven days before each biweekly survey (see Figure 1).

Model Analysis and Results

Analysis

The variables used in our analysis are listed in Table 2. To analyze the data, we estimated the same family of time series regression models in each study. In the first set of models (1-4), we regressed the natural log of psychological well-being measured in survey *t* on the natural log of average time spent using social media (combined) in the week *prior* to survey *t*. Additionally, the following control variables were included in the regression: (1) the natural log of psychological well-being measured in the previous survey (*t –1*) to allow for psychological well-being to carry-over between surveys (each model); (2) the natural log of the financial, physiological, and subjective well-being measures from survey *t - 1* (Models 1, 3, and 4); (3) average total daily time spent on the mobile device during the week preceding survey *t* (Models 2-4); (4) demographic and socio-economic control variables that could contribute to psychological well-being (age, sex, household income, employment status, marital status, education level, country of residence, and primary language, Models 2-4); and (5) indicators of positive and negative major life events reported by participants in surveys *t* and *t - 1* (four variables, with one variable of each type per survey, Model 4; for life event coding and frequency see Appendix 6). To ensure that the natural logarithm was defined for each variable in our analysis, we increased each of the subjective well-being and all device (including social media) use variables by one unit, respectively.

In the second set of models, we attempted to find some support for our mechanism-related hypothesis that a positive effect of social media use on psychological well-being is most likely to occur if the use involves interactions with meaningfully relevant others such as friends and family. This was not straightforward because our dataset did not include any information on what participants did when using social media and asking them would be subject to the same self-reporting concerns we have with prior research. In line with our earlier discussion about *truly social* uses of social media, we disaggregated the single measure of social media use into two separate social media use variables by types of app: *truly social* social media use where users have a higher likelihood of exposure to meaningful ties and *other* social media use.

To classify the social media platforms into these two groups we used our knowledge of these platforms (i.e., whether they most resembled undirected or directed graphs) as well as a market research study conducted by Kantar (see Appendix 7 for details) that asked social media users what they used different social media platforms for, including if they used it to communicate with friends and family (i.e., meaningfully relevant others). To the *truly social* group we assigned Facebook and the messaging apps Facebook Messenger and WhatsApp. Importantly, Facebook during the time of this study had implemented changes to its news feed algorithm that made it more likely for users to see content from meaningful ties such as close friends, and family members. Thus, during this study our participants would have been more likely to get exposed to content in their news feeds from meaningful ties (Mosseri 2018). To the other group we assigned Twitter, Instagram, Pinterest, Reddit, Tumblr, and Snapchat.

The second set of models (5-8) matched Models 1-4, respectively, but instead with two lagged social media use variables, one for social media use that was likely to be *truly social* with meaningful ties and one for everything else.

In all models, we controlled for common seasonal shocks via survey number dummy variables (i.e., time fixed effects). In addition, to control for time-invariant respondent heterogeneity, we included normally distributed respondent random effects into our models, which we estimated using the maximum likelihood method.

Results

Study 1. Our results are presented in Table 3. Below, we discuss the results of our regressions featuring all control variables (i.e., Models 4 and 8 – as Table 3 shows, our main results are identical across Models 1-4 and 5-8, respectively). Taking all social media together (Model 4), we found a significant positive effect of prior-period social media use on current-period psychological well-being (B = .0039, SE = .0014, $p = .004$). Not surprisingly, there was a strong positive carry-over effect of lagged psychological well-being on current psychological well-being (B = .7637, SE = .0083, $p < .001$). Also, lagged financial well-being significantly positively affected current psychological well-being (B = .0415, SE = .0069, $p < .001$), as did lagged overall subjective well-being (B = .0647, SE = .0091, $p < .001$). Lagged physiological well-being, however, did not significantly affect current psychological well-being (B = .0058, SE = .0082, $p = .480$).

Estimating separate coefficients for the impact of meaningful *truly social* and other social media use (Model 8), we found a significant positive effect of prior-period *truly social* social media use on current psychological well-being (B = .0087, SE = .0016, $p < .001$). However, the effect of prior-period *other* social media use on current psychological well-being was not significant (B = -.0001, SE = .0014, $p = .962$). Additionally, as before, there was a strong positive carry-over effect of lagged psychological well-being on current psychological well-being (B = .7577, SE = .0083, $p < .001$), lagged financial well-being again significantly positively affected current psychological well-being (B = .0411, SE = .0069, $p < .001$), lagged overall subjective well-being again also had a positive effect (B = .0632, SE = .0092, $p < .001$), and, as before, lagged physiological well-being did not have a significant effect (B = .0076, SE = .0082, $p = .354$).

Study 2. Our results are presented in Table 4. For brevity, we once again restrict our attention to Models 4 and 8. Taking all social media combined (Model 4), we found a significant positive effect of prior-period social media use on current psychological well-being (B = .0064, SE = .0023, p = .005). Just as in Study 1, there was a strong positive carry-over effect of lagged psychological well-being on current psychological well-being (B = .6597, SE = .0141, p < .001). Also, lagged financial well-being significantly positively affected current psychological well-being (B = .0419, SE = .0116, p < .001), as did lagged overall subjective well-being (B = .0724, SE = .0127, p < .001). Finally, unlike in Study 1, physiological well-being was also shown to have significantly affected current psychological well-being (B = .0475, SE = .0135, p < .001).

Estimating the different impacts of *truly social* versus *other* social media, we found a significant positive effect of prior-period *truly social* social media use on current psychological well-being (B = .0045, SE = .0023, p = .046). We note, however, that this effect was not significant in Models 6 (B = .0035, SE = .0023, p = *.133*) and 7 (B = .0045, SE = .0023, p = *.050*). We note that this may be because of omitted variable bias, as this effect is significant in the more-complete Model 8, which nests Models 6 and 7 plus controls for major life events. The effect of prior-period *other* social media use on current psychological well-being was, however, not significant (B = .0030, SE = .0022, p = .185). Additionally, similar to Model 4, there was a strong positive carry-over effect of lagged psychological well-being on current psychological well-being (B = .6609, SE = .0141, p < .001), and we documented significant positive effects for lagged financial well-being on psychological well-being (B = .0419, SE = .0116, p < .001), lagged physiological well-being on psychological well-being (B = .0467, SE = .0135, p < .001), and overall subjective well-being on psychological well-being (B = .0717, SE = .0127, p < .001).

Discussion

Based on the findings from both studies, it appears that there is a small, yet significant, positive effect of using social media on subsequent psychological well-being. This is consistent with our hypothesis. Also, consistent with our theory, the analyses that split social media use into the use of *truly social* platforms versus *other* platforms provided evidence in support of the notion that when social media use has a positive impact on psychological well-being it is likely due to social media being used in a *truly social* manner to interact with meaningful social relations.

However, it is important to put these findings in context. While we believe there is evidence in support of a positive effect of time spent using social media on subsequent psychological well-being, these effects are small. This was unsurprising since other drivers of psychological well-being (which we controlled for) should be—and indeed are—important for one's psychological well-being. For instance, daily activities, such as working or sleeping, make up large portions of the day (typically eight and over six hours, respectively) and have been shown to influence psychological well-being. Further, as one would expect, things like being married and being employed are stronger positive contributors to psychological well-being than time spent using social media. Finally, major life events tend to be bigger "shocks" to psychological well-being, a pattern both documented in the literature (Kettlewell et al. 2020), and also evidenced by the substantial improvement in the fit statistics for our model specifications that included the major life event variables; i.e., in Study 1, LR(Model 4 vs. Model 3) = $\chi^2(4) = 73.01$, $p < .001$ and LR(Model 8 vs. Model 7) = $\chi^2(4) = 72.56$, $p < .001$, and in Study 2, LR(Model 4 vs. Model 3) = $\chi^2(4) = 62.09$, $p < .001$ and LR(Model 8 vs. Model 7) = $\chi^2(4) = 61.89$, $p < .001$.

General Discussion

To address prior mixed findings, with some academic studies and popular press articles reporting a detrimental effect of social media use and others reporting positive psychological consequences, we explored the association between time spent using social media and subsequent psychological well-being. Two large longitudinal studies, one lasting six months and the other lasting 3.5 months with a combined 1,843 participants, were conducted. We found a small, significant positive impact of time spent using social media on subsequent psychological well-being. Importantly, this effect is contingent on the type of interactions people have on social media. When people use social media in a *truly social* manner (i.e., actively interacting with meaningful social relations in a way akin to in-person social interactions) it was positively associated with psychological well-being. We propose this is because *truly social* usage promotes meaningful social relations, which result in positive psychological consequences such as reinforcing one's identity, feeling valued, and mitigating stressful situations. Yet, when people use social media in other ways (e.g., passively engaging with weakly connected others, celebrities, brands, companies, or strangers typically for entertainment purposes) it does not influence psychological well-being. Therefore, how and how much people use social media has implications for their psychological health.

Due to the ubiquity of social media in modern life, it is important to understand how consuming social media impacts individuals' psychological well-being. Literally billions of people use platforms such as Facebook, Instagram, Twitter, as well as various social messaging apps, every single day. This is where we go to socialize, stay in touch with family members, browse and shop for products, share opinions, get news, and much more. Social media has become ingrained in the fabric of modern life. Thus, understanding how spending time using social media is associated with our psychological well-being is important, especially given that prior findings have been mixed. This understanding is relevant to three key stakeholders: (1) marketers who use social media for advertising and other digital marketing activities, (2) social media companies, and (3) policymakers in the digital media and advertising domains.

In terms of marketers, our findings suggest that it is not necessarily irresponsible to make use of social media platforms for advertising and other marketing purposes. To some extent, people have argued against marketing on social media platforms because these platforms are “dangerous” to users, including from a well-being or mental health perspective. Our findings at least suggest that spending time using platforms such as Facebook are unlikely, on average, to be psychologically harmful to users. In fact, depending on how they are used, they may offer some positive psychological benefits. Brands could even be more conscientious about using social media for advertising and other marketing purposes, based on our findings. Instead of just “doing no harm” as our evidence suggests is the case, they could actively use social media to foster closer brand relationships and promote social relations. For example, by creating a dialogue directly with the customer, the customer could benefit from the stronger social tie (i.e., strong customer-brand link). Alternatively, the brand could promote dialogue and positive connections between customers, allowing customers to connect with one another (i.e., strong customer-customer link) to create meaningful social relationships.

Our findings also have important implications for the social media platforms themselves. As Facebook and other social media platforms grapple with concerns about how their digital services impact their users, our research suggests that fears of causing psychological harm may be overblown. Nevertheless, social media platforms must continue to work on finding ways to keep their users safe and on identifying ways that their services can positively impact people’s lives. Redesigning the platforms to facilitate more *truly social* interactions and foster closer connections is a viable way to pursue this goal. For example, Facebook should continue to train their feed algorithms to prioritize content from family members and close friends over acquaintances, influencers, celebrities, or politicians to ensure that their users focus a majority of their usage time on *truly social* interactions. Similarly, to have a "healthier" platform, Twitter could prioritize posts from users that engage in positive conversations (i.e., comment and retweet) with each other and deprioritize negative conversations and "Twitter battles" between distal users. Implementing these content prioritization strategies built into their feed algorithms, social media platforms could be more pro-social by promoting greater psychological well-being among users.

From a public policy standpoint, the social media industry will continue to attract attention from governments and regulators around the world. This represents, in our view, legitimate scrutiny of a relatively recent form of mass media. Concerningly, the policy debate thus far has not been sufficiently informed by strong empirical findings. As noted earlier, prior research suffers from serious design flaws or limitations. Yet, it has had disproportionate influence on policy. Our findings suggest to policymakers that concerns about general psychological harm associated with social media use may be overstated and that the average user experience did not result in detectable reductions in psychological well-being. Although social media platforms contain some harmful content, either users are not as affected by it as policymakers think or the prevalence of exposure is low. Our research cannot speak directly to this since we did not observe what participants actually saw or did when using social media. However, our findings do suggest that policy-related concerns about the safety of adult use of social media could be somewhat more balanced.

Limitations

We acknowledge that our research has two important limitations. The first limitation to our research is that we did not explicitly measure how people used social media (i.e., if they used it in a *truly social* manner or not). Due to participant privacy, we tracked mobile device app usage but were unable to track what the users did while using those apps.

Therefore, while we attempted to infer which apps were more likely to be used in what ways (i.e., made inferences about how *truly social* behavior was at an app level) we were unable to get a more fine-grained measure of specific behaviors.

The second limitation of our research is that we were unable to account for total social media usage or social media usage that occurred on other devices such as laptops, desktops, and additional mobile devices not registered with our surveys (i.e., if a participant registered their mobile phone but also used a tablet). Therefore, it is possible that some participants are heavy users of social media on their laptop and light users of social media on their mobile device, which would lead us to an inaccurate understanding of their total social media usage. However, mobile devices are primarily how users access social media (Villanti et al. 2017) and there is a correlation between how people use mobile devices and how they use laptops and desktops (Kane et al. 2009). We contend that social media usage on the registered device is an acceptable proxy for a participant's relative social media usage even if it is not an accurate measure of their total social media usage. Because our research and findings rely on relative differences in social media usage and not on absolute measures, our conclusions are still valid.

Future Research

One avenue for future research is to directly examine the process driving the effect. Future studies could directly manipulate how people use social media, asking participants to either increase or decrease the time spent in a *truly social* way on social media, holding overall usage constant, and measure the subsequent impacts to psychological well-being. Furthermore, more direct measures could test how the changes in social media usage impact psychological well-being through the proposed mechanism of social connections. Thus, while past research is very clear that social connections and close relationships positively impact psychological well-being by reinforcing one's identity, increasing feelings of value, and providing social support during stressful situations, it is still important to explore if the positive benefits of social media operates through the same process.

Another direction for future research would be to expand on the meaning of *truly social* and its operationalization. For example, we conflate the type of activity (e.g., actively engaging in conversation, passively viewing photos, information, or microblogs, sharing personal content) with who the activity involves (e.g., family, close friend, brands or companies, acquaintances, celebrities). Future research could disentangle the two to determine if it is the type of activity or who the activity involves that is responsible for social media use’s impact on social well-being. Furthermore, it could be that the impact is additive, with more social (versus less social) activities (e.g., conversation) and more social (versus less social) partners (e.g., close friends) both having a distinct, positive impact on psychological well-being. Or it could be that the impact is interactive, requiring both a more social activity type and more social partner to result in positive psychological well-being.

One additional question that deserves future attention is the impact of social media usage in the context of daily life. For example, when we concluded that social media consumption of a *truly social* nature has a positive impact on psychological well-being, we did not consider what the time spent on social media is taking away from, specifically the type of alternative activities. Therefore, future research can show how the positive effect of social media usage compares to other activities including in-person socialization, sports and physical activity, hobbies, and work. Because we found a relatively small effect of social media usage on psychological well-being, it stands to reason that if social media usage is taking away from activities with a stronger impact, such as in-person socializing, time spent on social media could be determined to still have a negative influence of psychological health. Yet, if social media usage is more likely to cannibalize more passive forms of entertainment, such as television watching, it could be that increasing social media usage would confer even greater benefits.

APPENDIX 1

EIGHT-ITEM PSYCHOLOGICAL WELL-BEING SCALE

I am satisfied with the quality of my close relationships (e.g., friends, significant other, family)

I feel supported by others

I feel that my close relationships generally involve mutual respect, trust, and support

I am pleased with where my life is headed

I am satisfied with my growth as a person

I lead a purposeful and meaningful life

My social relationships are supportive and rewarding

I am satisfied with my life as a whole these days

APPENDIX 2

OTHER WELL-BEING SCALES

Financial

I am satisfied with my current level of income

I am satisfied with my current amount of savings

I am satisfied with the amount of money I spend on unplanned purchases

I am satisfied with my current level of financial security

I am satisfied with the stability of my regular income (e.g., job security)

I am satisfied with my standard of living

I am satisfied with my control over impulse spending

I am satisfied with how in control I am of my debt/bills

I am satisfied with my ability to achieve my financial goals

Physiological

I have been having trouble falling asleep

I have been sleeping well lately

I have recently felt more tired than I normally feel

I have had a lot more energy of late

I have spent less time engaging in exercise recently than I normally do

I have worried more about my weight recently than I normally do

I have recently gained weight

I consider myself to be in good health

I have been less healthy recently than I normally am

I have been feeling rundown

I have been sick a lot lately

APPENDIX 3

FULL SET OF PRETESTED PSYCHOLOGICAL ITEMS

Ryff's (1989) Scale of Psychological Well-Being

Self-Acceptance

1. I am satisfied with who I am as a person
2. I accept myself for who I am
3. I am a good person and live a good life

Positive Relations with Others

4. I am satisfied with the quality of my close relationships (e.g., friends, significant other, family)
5. I feel supported by others
6. I feel that my close relationships generally involve mutual respect, trust, and support
7. My social relationships are supportive and rewarding
8. I actively contribute to the happiness and well-being of others

Autonomy

9. I am satisfied with my level of independence
10. I am satisfied with the control I have over my life
11. I am able to resist social pressures to think and act in certain ways

Environmental Mastery

12. I am satisfied with my level of proficiency of my daily tasks (e.g., work, school, home)
13. I am satisfied with my ability to overcome challenges
14. I have a sense of competence in managing my environment
15. I have difficulty managing my everyday affairs *(Reverse Coded)*
16. I am engaged and interested in my daily activities

Purpose in Life

17. I am pleased with where my life is headed
18. I lead a purposeful and meaningful life
19. I am satisfied with my life as a whole these days
20. I am satisfied with the goals I have set for myself

Personal Growth

21. I am satisfied with my growth as a person
22. I am satisfied with the personal improvements I am making
23. I have a sense of realizing my potential
24. I am bored and uninterested in life *(Reverse Coded)*

APPENDIX 4

SCALE DEVELOPMENT

Procedure. Four hundred seventy-eight Prolific Academic workers were recruited in exchange for payment. Participants responded to their overall subjective wellbeing, “Please imagine a ladder, with steps numbered from 0 at the bottom to 10 at the top. The top (10) of the ladder represents the best possible life for you. The bottom (0) of the ladder represents the worst possible life for you. On which step of the ladder would you say you personally feel you stand at this time?” (10 = Best possible life, 0 = Worst possible life; Cantril Life Ladder; Cantril 1965; Diener et al. 1999; Helliwell et al. 2020). Participants then reported measures designed to assess their current situation regarding their financial, psychological, and physiological wellbeing in random order. Specifically, participants answered seven questions assessing their subjective feelings of financial wellbeing developed from OECD Guidelines for Measuring Subjective Well-Being (Durand 2015). Participants responded to 24 measures of their subjective feelings of psychological wellbeing developed from scales of psychological wellbeing categories including self-acceptance, positive relations with others, autonomy, environmental mastery, purpose in life, and personal growth (Ryff 1989). Participants answered nine measures of their physiological wellbeing developed from The Goldberg Depression Questionnaire (Goldberg and Hillier 1979) and Social Indicators of Well-Being (Andrews and Withey 2012). Finally, participants answered a series of demographic questions before being thanked and paid.

Scale Development. We ran a PCA on all the component measures. Six factors emerged, the first one corresponding mostly to psychological, the second one mostly to physiological, and the third one mostly to financial wellbeing variables. The psychological measures were determined to have a sufficiently high Cronbach’s alpha (α = .94) to warrant creating a single measure. However, we wanted to create a short follow-up survey (i.e., fewer questions that took less time) to reduce attrition in the longitudinal studies. Therefore, we reduced the number of psychological measures from 24 by using a predetermined cutoff point (i.e., above .7) for the commonalities method. The resulting eight measures were used in the longitudinal studies (see Appendix B). The financial measures were determined to have a high enough Cronbach’s alpha (α = .83) and sufficiently short. However, two additional questions about their satisfaction with their level of debt/bills (Lange and Byrd 1998; O’Neill et al. 2006) and ability to achieve their financial goals (Sheldon and Elliot 1999) were added to provide a more complete financial picture of the construct and reflect recent research, which brought the total to eleven. The physiological measures were also determined to have a sufficiently enough Cronbach’s alpha (α = .87) to warrant a single measure. Like the financial wellbeing measure, two additional questions about their current feelings of health were added to bring the total to eleven.

References:

Andrews, Frank M. and Stephen B. Withey (2012), *Social Indicators of Well-Being*, Boston, MA: Springer.

Durand, Martine (2015), “The OECD Better Life Initiative: How's Life? and the Measurement of Well-Being,” *The Review of Income and Wealth*,” 61 (1), 4–17.

Goldberg, David P. and Valerie F. Hillier (1979), “A Scaled Version of the General Health Questionnaire,” *Psychological Medicine*, 9, 139–45.

Lange, Clare and Mark Byrd (1998), “The Relationship Between Perceptions of Financial Distress and Feelings of Psychological Well-Being in New Zealand University Students,” *International Journal of Adolescence and Youth*, 7 (3), 193–209.

O’Neill, Barbara, Aimee Prawitz, Benoit Sorhaindo, Jinhee Kim, E. Thomas Garman (2006), “Changes in Health, Negative Financial Events, and Financial Distress/Financial Well-Being for Debt Management Program Clients,” *Journal of Financial Counseling and Planning*, 17 (2), 46–63.

Sheldon, Kennon M. and Andrew J. Elliot (1999), “Goal Striving, Need Satisfaction, and Longitudinal Well-Being: The Self-Concordance Model,” *Journal of Personality and Social Psychology*, 76 (3), 482–97.

APPENDIX 5

TESTING THE ROBUSTNESS OF OUR RESULTS TO FILTERING THE APP USAGE DATA USING ALTERNATIVE CUTOFF CRITERIA

In our empirical studies, we defined social media usage levels as daily averages during the week preceding the given survey. To this end, we relied on the app usage logs collected by the Android operating system, sent to our server several times each day, and for each device, we extracted non-overlapping reports corresponding to 24-hour intervals during the given week.

As we noted in the paper, this process occasionally (in less than 0.4% of the cases) resulted in observations that we deemed to have resulted from a technical error. In particular, we discarded observations reporting more than eight hours of CPU foreground time for a single application in a 24-hour interval, indicating it was actively used for a third of the day. Below, we report results testing the robustness of this cut-off criterion. Table and Table show the results for study 1 using cutoffs of six and ten hours, respectively, while Table and Table do the same for study 2.

It is clear that all of our results are essentially identical to those reported in Table 3 and Table 4 in our paper. We conclude that setting the cutoff at eight hours per day did not affect the validity of our results.

APPENDIX 6

CODING FOR LIFE EVENTS

TABLE WA 1 - SUMMARY OF SELF-REPORTED "MAJOR LIFE EVENTS"

Variable	Coding	Frequency		Description
		Study 1	Study 2	
Romantic Relationship				
Negative	-1	.61%	1.11%	Negative event in their romantic relationship. Includes divorce
Positive	+1	.30%	.65%	Positive event in their romantic relationship. Includes weddings and engagements
Job				
Self Loss	-1	1.15%	.84%	Job loss, pay cut, or demotion for self
Self Gain	+1	.66%	.84%	Job found or started, raise, or promotion for self
Other Loss	-1	.08%	.16%	Job loss, pay cut, or demotion for family or friend
Other Gain	+1	.02%	.05%	Job found or started, raise, or promotion for family or friend
Health				
Self Negative	-1	2.94%	2.50%	Temporary deterioration in health, including mental health
Self Positive	+1	.22%	.22%	Improvement in health. Includes reports of going back to the gym
Other Negative	-1	.66%	.79%	Temporary deterioration in health for family or friend
Other Positive	+1	.05%	.03%	Improvement in health for family or friend
Family and Friends				
Pregnancy Negative	-1	.19%	.14%	Own/partner's pregnancy. Includes unwanted pregnancy, severe complications, or miscarriage
Pregnancy Positive	+1	1.18%	1.17%	Own/partner's pregnancy without negative context
Birth	+1	.14%	.19%	Recent birth of child
Death	-1	.68%	.68%	Death of a close friend or relative
Pet				
Negative	-1	.13%	.24%	Negative event about their pet. Includes death or medical issues.
Positive	+1	.02%	.03%	Positive event about their pet. Includes obtaining one or having their pet's medical condition improve
Holiday				
Birthday	+1	.04%	.08%	Recent birthday without negative context
Christmas	+1	.07%	0%	Christmas without negative context
Disaster				
Accident	-1	.14%	.08%	Car accident or some injury with no underlying health condition
Natural Disaster	-1	.10%	.05%	Includes hurricanes, earthquakes, and fire
Miscellaneous				
Negative	-1	1.21%	1.52%	Other negative events. Includes financial hardship or stress
Positive	+1	.54%	.93%	Other positive events. Includes financial windfall or returning to school

APPENDIX 7

TABLE REPRODUCED FROM CONNECTED LIFE 2017-2018 COUNTRY REPORT UK: MARKET RESEARCH FROM KANTAR

Understand What It Is Used For					
	Connecting with Close Family and Friends	**Following Famous People and Online Celebrities**	**Keeping Up with News and Live Events**	**Sharing Opinions**	**Sharing Moments as They Happen**
Facebook	Strong Positive	Weak Positive	Weak Positive	Strong Positive	Weak Positive
WhatsApp	Strong Positive	Negative	Negative	Negative	Negative
YouTube	Negative	Negative	Negative	Negative	Negative
Facebook Messenger	Negative	Negative	Negative	Negative	Negative
Twitter	Negative	Strong Positive	Strong Positive	Strong Positive	Weak Positive
Instagram	Negative	Strong Positive	Negative	Neutral	Weak Positive
Snapchat	Negative	Weak Positive	Negative	Negative	Strong Positive
Skype	Strong Positive	Negative	Negative	Negative	Negative
Pinterest	Negative	Negative	Negative	Negative	Negative

This table was reproduced with permission from Kantar's Connected Life.

Note from the authors: Facebook Messenger was an anomaly in that it was negative for all five of the "Understand What It Is Used For" category questions and the four "Provide Best-Fit Brand Services" category questions (Finding Information, Buy or Sell Goods or Services, Customer Service, Finding Out About New Products and Services), the five "Identify Perceptions" category questions (I Trust it with my Data, Cutting-Edge, It has Information I Can Trust, Cool, For Younger People), and the five "Create Appropriate Content" category questions (Videos, Funny and Light-Hearted, Inspiration, Entertaining, Help Make Decisions) that we do not reproduce in this table. Thus, we classified Facebook Messenger (direct messaging system of Facebook) with WhatsApp because we thought that was the most conceptually consistent.

REFERENCES

Acquisti, Alessandro and Ralph Gross (2006), "Imagined Communities: Awareness, Information Sharing, and Privacy on the Facebook," in *Privacy Enhancing Technologies*, ed. Danezis G. Golle, Berlin, Heidelberg: Springer, 36–58.

Adelmann, Pamela K. (1987), "Occupational Complexity, Control, and Personal Income: Their Relation to Psychological Well-Being in Men and Women," *Journal of Applied Psychology*, 72 (4), 529–37.

Andrews, Frank M. and Stephen B. Withey (1976), *Social Indicators of Well-Being: Americans' Perceptions of Life Quality*, New York, NY: Plenium Press.

Appel, Helmut, Alexander L. Gerlach, and Jan Crusius (2016), "The Interplay between Facebook Use, Social Comparison, Envy, and Depression," *Current Opinion in Psychology*, 9, 44–9.

Arnold, Kara A., Nick Turner, Julian Barling, E. Kevin Kelloway, and Margaret C. McKee (2007), "Transformational Leadership and Psychological Well-Being: The Mediating Role of Meaningful Work," *Journal of Occupational Health Psychology*, 12 (3), 193–203.

Augusto-Landa, José M., Manuel Pulido-Martos, and Esther Lopez-Zafra (2011), "Does Perceived Emotional Intelligence and Optimism/Pessimism Predict Psychological Well-Being?," *Journal of Happiness Studies*, 12 (3), 463–74.

Barr, Sabrina (2019), "Six Ways Social Media Negatively Affects Your Mental Health without You Even Knowing," *The Independent*, October 10, https://www.independent.co.uk/life-style/health-and-families/social-media-mental-health-negative-effects-depression-anxiety-addiction-memory-a8307196.html.

Boehm, Julia K. and Laura D. Kubzansky (2012), "The Heart's Content: The Association between Positive Psychological Well-Being and Cardiovascular Health," *Psychological Bulletin*, 138 (4), 655–91.

Bowlby, John (1969), *Attachment and Loss,* Vol. 1, New York, NY: Basic Books.

Bray, Steven R. and Matthew Y. W. Kwan (2006), "Physical Activity Is Associated with Better Health and Psychological Well-Being During Transition to University Life," *Journal of American College Health*, 55 (2), 77–82.

Brief, Arthur P., Ann H. Butcher, Jennifer M. George, and Karen E. Link (1993), "Integrating Bottom-Up and Top-Down Theories of Subjective Well-Being: The Case of Health," *Journal of Personality and Social Psychology,* 64 (4), 646–53.

Brooks, Stoney (2015), "Does Personal Social Media Usage Affect Efficiency and Well-Being?" *Computers in Human Behavior*. 46 (May), 26–37.

Brooks, Stoney and Phil Longstreet (2015), "Social Networking's Peril: Cognitive Absorption, Social Networking Usage, and Depression," *Cyberpsychology: Journal of Psychosocial Research on Cyberspace*, 9 (4) article 5.

Brynjolfsson, Erik, Avinash Gannamaneni, and Felix Eggers (2019), "Using Massive Online Choice Experiments to Measure Changes in Well-Being," *Proceedings of the National Academy of Science*, 116 (15) 7250–5.

Bunch, Jane (1972), "Recent Bereavement in Relation to Suicide," *Journal of Psychosomatic Research*, 16 (5), 361–6.

Burke, Moira, Cameron Marlow, and Thomas Lento (2010), "Social Network Activity and Social Well-Being," in Proceedings of the SIGCHI Conference on Human Factors in Computing Systems, Atlanta, GA: Association for Computing Machinery, 1909–12.

Cantril, Hadley (1965), *The Patterns of Human Concern*, New Brunswick, NJ: Rutgers University Press.

Chou, Hui-Tzu Grace and Nicholas Edge (2012), "'They Are Happier and Having Better Lives than I Am': The Impact of Using Facebook on Perceptions of Others' Lives," *Cyberpsychology, Behavior, and Social Networking*, 15(2), 117–21.

Cobb, Sidney (1976), "Social Support as a Moderator of Life Stress," *Psychosomatic Medicine*, 38 (5), 300–14.

Cobb, Sidney (1979), "Social Support and Health through the Life Course," in *Aging from Birth to Death: Interdisciplinary Perspectives*, ed. M. W. Riley, Boulder, CO: Westview Press, 93–106. Cohen, Sheldon (2004), "Social Relationships and Health," *American Psychologist*, 59 (8), 676–84.

Cohen, Sheldon (2004), "Social Relationships and Health," *American Psychologist*, 59 (8), 676–84.

Cooke, Alan D. J., and Peter P. Zubcsek (2017), "The Connected Consumer: Connected Devices and the Evolution of Customer Intelligence" *Journal of the Association for Consumer Research*, 2 (2), 164–78.

Cooke, Alan D. J., Peter P. Zubcsek, and Cammy Crolic (2018), "Push and Pull: Using Mobile Platforms for Consumer Research," working paper, University of Florida, Gainesville, FL 32611.

Cummings, Sherry M. (2002), "Predictors of Psychological Well-Being among Assisted-Living Residents," *Health & Social Work*, 27 (4), 293–302.

Diener, Ed (1984), "Subjective Well-Being," *Psychological Bulletin*, 95 (3), 542–75.

Diener, Ed and Larsen, Randy J. (1993), "The Subjective Experience of Emotional Well-Being: Stability in Global Assessment of Emotion," in *Handbook of Emotion*, ed. M. Lewis and J. M. Haviland.

Diener, Ed, Marissa Diener, and Carol Diener (1995), "Factors Predicting the Subjective Well-Being of Nations," *Journal of Personality and Social Psychology*, 69 (5), 851–64.

Diener, Ed, Eunkook M. Suh, Richard E. Lucas, and Heidi L. Smith (1999), "Subjective Well-Being: Three Decades of Progress," *Psychological Bulletin*, 125 (2), 276–302.

Dolan, Paul and Robert Metcalfe (2012), "Measuring Subjective Wellbeing: Recommendations on Measures for Use by National Governments," *Journal of Social Policy*, 41 (2), 409–27.

Durkheim, Émile (1951), *Suicide: A Study in Sociology*, New York, NY: Free Press.

Egbert, Lawrence D., George E. Battit, Claude E. Welch, Marshall K. Bartlett (1964), "Reduction of Post-Operative Pain by Encouragement and Instruction of Patients – A Study of Doctor-Patient Rapport," *New England Journal of Medicine*, 270, 825–7.

Ellison, Nicole B., Charles Steinfield, and Cliff Lampe (2007), "The Benefits of Facebook 'Friends': Social Capital and College Students' Use of Online Social Network Sites," *Journal of Computer-Mediated Communication*, 12 (4), 1143–68.

Faris, Robert L. (1934). "Cultural Isolation and Schizophrenic Personality," *American Journal of Sociology*, 40, 156–64.

Florian, Victor, Mario Mikulincer, and Orit Taubman (1995), "Does Hardiness Contribute to Mental Health During a Stressful Real-Life Situation? The Roles of Appraisal and Coping," *Journal of Personality and Social Psychology*, 68 (4), 687–95.

Fowler, Geoffrey A. (2017), "Take Back Your Brain From Social Media," *Wall Street Journal*, February 1, https://www.wsj.com/articles/take-back-your-brain-from-social-media-1485968678.

Fox, Kenneth R., Stephen H. Boutcher, Guy E. Faulkner, and Stuart J. H. Biddle (2000), "The Case for Exercise in the Promotion of Mental Health and Psychological Well-Being," in *Physical Activity and Psychological Well-Being*, ed. Stuart J. H. Biddle, Kenneth R. Fox, and Stephen H. Boutcher, London: Routledge, 1–9.

Gergen, Kenneth J. (1987), "Toward Self as Relationship," in *Self and Identity: Psychosocial Perspectives*, ed. K. Yardley and T. Honess, New York: Wiley, 53–63.

Ginsberg, David and Moira Burke (2017), "Hard Questions: Is Spending Time on Social Media Bad for Us?," *About Facebook*, https://about.fb.com/news/2017/12/hard-questions-is-spending-time-on-social-media-bad-for-us/.

Gore, Susan (1978), "The Effect of Social Support in Moderating the Health Consequences of Unemployment," *Journal of Health and Social Behavior*, 19 (2), 157–65.

Green, Morgan and Marta Elliott (2010), "Religion, Health, and Psychological Well-Being," *Journal of Religion and Health*, 49, 149–63.

Greene, Jeremy A., Niteesh K. Choudry, Elaine Kilabuk and William H. Shrank (2011), "Online Social Networking by Patients with Diabetes: A Qualitative Evaluation of Communication with Facebook," *Journal of General Internal Medicine*, 26, 287–92.

Hajek, André and Hans-Helmut König (2019), "The Role of Optimism, Self-Esteem, and Self-Efficacy in Moderating the Relation between Health Comparisons and Subjective Well-Being: Results of a Nationally Representative Longitudinal Study among Older Adults," *British Journal of Health Psychology*, 24 (3), 547–70.

Hamilton, Nancy A., Christy A. Nelson, Natalie Stevens, and Heather Kitzman (2007), "Sleep and Psychological Well-Being," *Social Indicators Research*, 82 (1), 147–63.

Helliwell, John F., Haifang Huang, Shun Wang, Max Norton (2020), "Social Environments for World Happiness," in *World Happiness Report 2020*, ed. John Helliwell, Richard Layard, Jeffrey D. Sachs, and Jan Emmanuel De Neve, New York, NY: Sustainable Development Solutions Network, 17–50.

Holt-Lunstad, Julianne, Timothy B. Smith, and J. Bradley Layton (2010), "Social Relationships and Mortality Risk: A Meta-Analytic Review," *Public Library of Science Medicine*, 7 (7), 1–20.

House, James S. (1981), *Work Stress and Social Support*, Reading, MA: Addison-Wesley

House, James S., Debra Umberson, and Karl R. Landis (1988), "Structures and Processes of Social Support," *Annual Review of Sociology*, 14, 293–318.

Hughes, David John, Moss Rowe, Mark Batey, and Andrew Lee (2011), "A Tale of Two Sites: Twitter vs. Facebook and the Personality Predictors of Social Media Usage," *Computers in Human Behavior*, 28 (March), 561–9.

Hunt, Melissa G., Rachel Marx, Courtney Lipson, and Jordyn Young (2018), "No More FOMO: Limiting Social Media Decreases Loneliness and Depression," *Journal of Social & Clinical Psychology*, 37 (10), 751–68.

"Instagram 'Worst for Young Mental Health'" (2017), *BBC News*, May 19, https://www.bbc.com/news/health-39955295.

Kahneman, Daniel and Alan B. Krueger (2006), "Developments in the Measurement of Subjective Well-Being," *Journal of Economic Perspectives*, 20 (1), 3–24.

Kalak, Nadeem, Sakari Lemola, Serge Brand, Edith Holsboer-Trachsler, and Alexander Grob (2014), "Sleep Duration and Subjective Psychological Well-Being in Adolescence: A Longitudinal Study in Switzerland and Norway," *Neuropsychiatric Disease and Treatment*, 10, 1199–207.

Kane Shaun K., Amy K. Karlson, Brian R. Meyers, Paul Johns, Andy Jacobs, and Greg Smith (2009), "Exploring Cross-Device Web Use on PCs and Mobile Devices," in *Human-Computer Interaction – INTERACT 2009*, ed. T. Gross, J. Gulliksen, P. Kotzé, L. Oestreicher, P. Palanque, R. O. Prates, M. Winckler, Heidelberg: Springer Berlin, 722–35.

Kaplan, George A., Sarah J. Shema, and Cláudia Maria A. Leite (2008), "Socioeconomic Determinants of Psychological Well-Being: The Role of Income, Income Change, and

Income Sources During the Course of 29 Years," *Annals of Epidemiology*, 18 (7), 531–7.

Kettlewell, Nathan, Richard W. Morris, Nick Ho, Deborah A. Cobb-Clark, Sally Cripps, and Nick Glozier (2020), "The Differential Impact of Major Life Events on Cognitive and Affective Wellbeing," *SSM-Population Health*, 10, 100533.

Krasnova, Hanna, Helena Wenningger, Thomas Widjaja, and Peter Buxmann (2013), "Envy on Facebook: A Hidden Threat to Users' Life Satisfaction?" paper presented at the *11th International Conference on Wirtschaftsinformatik*, Leipzig, Germany.

Kraut, Robert, Sara Kiesler, Bonka Boneva, Jonathon Cummings, Vicki Helgeson, and Anne Crawford (2002), "Internet Paradox Revisited," *Journal of Social Issues*, 58 (1), 49–74.

Kross, Ethan, Philippe Verduyn, Emre Demiralp, Jiyoung Park, David Seungjae Lee, Natalie Lin, Holly Shablack, John Jonides, and Oscar Ybarra (2013), "Facebook Use Predicts Declines in Subjective Well-Being in Young Adults," *Public Library of Science One*, 8 (8), 1–6.

Kushlev, Kostadin and Elizabeth W. Dunn (2015), "Checking Email Less Frequently Reduces Stress," *Computers in Human Behavior*, 43 (February), 220–8.

La Rocco, James M. and Allan P. Jones (1978), "Co-Worker and Leader Support as Moderators of Stress-Strain Relationships in Work Situations," *Journal of Applied Psychology,* 63 (5), 629–34.

Laroche, Michel, Mohammad Reza Habibi, Marie-Odile Richard, and Ramesh Sankaranarayanan (2012), "The Effects of Social Media Based Brand Communities on Brand Community Markers, Value Creation Practices, Brand Trust and Brand Loyalty," *Computers in Human Behavior*, 28 (September), 1755–67.

Lin, Nan, Walter M. Ensel, Ronald S. Simeone, and Wen Kuo (1979), “Social Support, Stressful Life Events, and Illness: A Model and an Empirical Test,” *Journal of Health and Social Behavior*, 20, 108-19.

Lin, Ruoyun and Sonja Utz (2015), “The Emotional Responses of Browsing Facebook: Happiness, Envy, and the Role of Tie Strength,” *Computers in Human Behavior*, 52 (November), 29–38.

Maier, Christian, Sven Laumer, Andreas Eckhardt, and Tim Weitzel (2012), “Online Social Networks as a Source and Symbol of Stress: An Empirical Analysis,” in Proceedings of the International Conference on Information Systems, Orlando, FL: Association for Information Systems, 1–19.

McAlexander, James H., John W. Schouten, and Harold F. Koenig (2002), “Building Brand Community,” *Journal of Marketing*, 66 (1), 38–54.

Merolli, Mark, Kathleen Gray, and Fernando Martin-Sanchez (2013), “Health Outcomes and Related Effects of Using Social Media in Chronic Disease Management: A Literature Review and Analysis of Affordances,” *Journal of Biomedical Informatics*, 46 (6), 957–69.

Mitchell, Roger E., Andrew G. Billings, and Rudolf H. Moos (1982), “Social Support and Well-Being: Implications for Prevention Programs,” *Journal of Primary Prevention*, 3 (2), 77–98.

Mosseri, Adam (2018), “Bringing People Closer Together,” *Facebook Newsroom*, January 11, https://about.fb.com/news/2018/01/news-feed-fyi-bringing-people-closer-together/

Netz, Yael, Meng-Jia Wu, Betsy Becker, and Gershon Tenenbaum (2005), “Physical Activity and Psychological Well-Being in Advanced Age: A Meta-Analysis of Intervention Studies,” *Psychology and Aging*, 20 (2), 272–84.

Oberst, Ursula, Elisa Wegmann, Benjamin Stodt, Matthias Brand, and Andrés Chamarro (2017), "Negative Consequences from Heavy Social Networking in Adolescents: The Mediating Role of Fear of Missing Out," *Journal of Adolescence*, 55 (February), 51–60.

Orban, Amy, Tobias Dielin, and Andrew K. Przybylski (2019), Social Media's Enduring Effect on Adolescent Life Satisfaction," *Proceedings of the National Academy of Science*, 116 (21) 10226–8.

Powell, Katherine C. (2009), "The Role of Concept of Self and Societal Expectations in Academic and Career Achievement," *Journal of Adult Education*, 38 (2), 32–40.

Primack, Brian A., Ariel Shensa, Jaime E. Sidani, Erin O. Whaite, Liu yi Lin, Daniel Rosen, Jason B. Colditz, Ana Radovic, and Elizabeth Miller (2017), "Social Media Use and Perceived Social Isolation among Young Adults in the US," *American Journal of Preventive Medicine*, 53 (1), 1–18.

Przybylski, Andrew K. and Netta Weinstein (2017), "A Large-Scale Test of the Goldilocks Hypothesis: Quantifying the Relations between Digital-Screen Use and the Mental Well-Being of Adolescents," *Psychological Science*, 28 (2), 204–15.

Reinecke, Leonard and Sabine Trepte (2014), "Authenticity and Well-Being on Social Network Sites: A Two-Wave Longitudinal Study on the Effects of Online Authenticity and the Positivity Bias in SNS Communication," *Computers in Human Behavior*, 30 (January), 95–102.

Rook, Karen S. (1984), "The Negative Side of Social Interaction: Impact on Psychological Well-Being," *Journal of Personality and Social Psychology*, 46 (5), 1097–108.

Rutter, Michael (1987), "Psychosocial Resilience and Protective Mechanisms," *American Journal of Orthopsychiatry*, 57 (3), 316–31.

Ryff, Carol D. (1989), “Happiness is Everything, or Is It? Explorations on the Meaning of Psychological Well-Being,” *Journal of Personality and Social Psychology*, 57 (6), 1069–81.

Shams, Manfusa (1993), “Religiosity as a Predictor of Well-being and Moderator of the Psychological Impact of Unemployment,” *British Journal of Medical Psychology*, 66 (4), 341–52.

Skiera, Bernd, Oliver Hinz, and Martin Spann (2015), “Social Media and Academic Performance: Does the Intensity of Facebook Activity Relate to Good Grades?” *Schmalenbach Business Review*, 67 (1), 54–72.

Steptoe, Andrew, Katie O’Donnell, Michael Marmot, and Jane Wardle (2008), “Positive Affect, Psychological Well-Being, and Good Sleep,” *Journal of Psychosomatic Research*, 64 (4), 409–15.

Tomasello, Michael, Alicia P. Melis, Claudio Tennie, Emily Wyman, and Esther Herrmann (2012), “Two Key Steps in the Evolution of Human Cooperation: The Interdependence Hypothesis,” *Current Anthropology*, 53 (6), 673–92.

Uhls, Yalda T., Minas Michikyan, Jordan Morris, Debra Garcia, Gary W. Small, Eleni Zgourou, and Patricia M. Greenfield (2014), “Five Days at Outdoor Education Camp without Screens Improves Preteen Skills with Nonverbal Emotion Cues,” *Computers in Human Behavior*, 39 (October), 387–92.

Ullah, Philip (1990), “The Association between Income, Financial Strain and Psychological Well-Being among Unemployed Youths,” *Journal of Occupational Psychology*, 63 (4), 317–30.

Utz, Sonja (2015), “The Function of Self-Disclosure on Social Network Sites: Not Only Intimate, but also Positive and Entertaining Self-Disclosures Increase the Feeling of Connection,” *Computers in Human Behavior*, 45 (April), 1–10.

Valenzuela, Sebastián, Namsu Park, and Kerk F. Kee (2009), “Is There Social Capital in a Social Network Site?: Facebook Use and College Students' Life Satisfaction, Trust, and Participation,” *Journal of Computer-Mediated Communication*, 14 (4), 875–901.

Valkenburg, Patti M., Jochen Peter, and Alexander P. Schouten (2006), “Friend Networking Sites and their Relationship to Adolescents' Well-Being and Social Self Esteem,” *CyberPsychology & Behavior*, 9 (5), 584–90.

Vanderhorst, Rob K. and Suzanne McLaren (2005), “Social Relationships as Predictors of Depression and Suicidal Ideation in Older Adults,” *Aging & Mental Health*, 9 (6), 517–25.

Villanti, Andrea C., Amanda L. Johnson, Vinu Ilakkuvan, Megan A. Jacobs, Amanda L. Graham, Jessica M. Rath (2017), “Social Media Use and Access to Digital Technology in US Young Adults in 2016," *Journal Medical Internet Research*, 19 (6), e196.

Wellman, Barry and Scot Wortley (1990), “Different Strokes from Different Folks: Community Ties and Social Support,” *American Journal of Sociology*, 96 (3), 558–88.

White, Mathew P. and Paul Dolan (2009), “Accounting for the Richness of Daily Activities,” *Psychological Science*, 20 (8), 1000–8.

Wilcox, Keith and Andrew T. Stephen (2013), “Are Close Friends the Enemy? Online Social Networks, Self-Esteem, and Self-Control,” *Journal of Consumer Research*, 40 (1), 90–103.

Williams, Ann W., John E. Ware, and Cathy A. Donald (1981), “A Model of Mental Health, Life Events, and Social Supports Applicable to General Populations,” *Journal of Health and Social Behavior*, 22, 324–36.

Windle, Gill and Robert T. Woods (2004), “Variations in Subjective Wellbeing: The Mediating Role of a Psychological Resource,” *Ageing & Society*, 24 (4), 583–602.

Wong, Brittany (2019), "An Instagram With No 'Likes' Could Have A Big Impact On Mental Health," *HuffPost*, May 10, https://www.huffingtonpost.co.uk/entry/instagram-hiding-likes-mental-health_l_5cd092d3e4b0548b735e50bc.

Zhang, Kem Z. K., Haiqin Xu, Sesia Zhao, and Yugang Yu (2018), "Online Reviews and Impulse Buying Behavior: The Role of Browsing and Impulsiveness," *Internet Research*, 28 (3), 522–43.

TABLE 1

HIGH-LEVEL APP CATEGORIES AND SHARES OF USAGE

App Category	**Sample Members**	**Average share of device usage**	
		Study 1	**Study2**
Social Media (Truly Social)	Facebook, WhatsApp, Messenger	13.64%	11.90%
Social Media (Other)	Twitter, Instagram, Reddit, Pinterest, Tumblr, Snapchat	6.21%	6.60%
Retail & Entertainment	Games, YouTube, other on- and offline media, retailing apps	30.52%	32.50%
Information	Browser, News & Weather, Maps & Navigation, Search	16.02%	14.70%
Communication	Contact list managers, Dialer apps, Texting apps	4.70%	7.67%
Productivity	Office & Email apps	4.07%	4.17%
Miscellaneous	Home screen & other system apps, Finance & Banking, Antivirus, Health & Fitness apps	13.56%	12.47%
Uncategorized		11.29%	9.98%

TABLE 2

SUMMARY OF VARIABLES

Variable	Description		Study 1 M (S.D.)	Study 2 M (S.D.)
Well-Being				
PsyWB	Psychological well-being; eight-item subjective measure of one's personal situation		4.82 (1.30)	4.98 (1.32)
PhyWB	Physiological well-being; eleven-item subjective measure of one's health situation		4.07 (1.07)	4.26 (1.19)
FinWB	Financial well-being; nine-item subjective measure of one's financial situation		4.02 (1.34)	3.80 (1.43)
SWB	Subjective wellbeing; one-item Cantril Life Ladder measuring best to worst possible life (Worst = 0, Best = 10)		5.94 (1.84)	5.42 (2.05)
Social Media Use				
Truly Social SM Use	Time spent on Facebook, Facebook Messenger, and WhatsApp (in minutes)		43.60 (60.18)	40.44 (57.28)
Other SM Use	Time spent on Twitter, Instagram, Pinterest, Reddit, Tumblr, and Snapchat (in minutes)		19.44 (38.67)	22.18 (43.91)
Total SM Use	Total time spent on social media (in minutes)		63.05 (71.57)	62.62 (71.05)
Other				
Device Use	Total usage time (in minutes)		321.76 (275.96)	344.00 (290.57)
Positive Life Event	Positive life event		3.40%	3.63%
Negative Life Event	Negative life event		6.25%	6.93%
Individual Characteristics				
Age	Age (in years)		33.21 (9.56)	33.61 (8.91)
Gender	Female = 1, Male = 0		56.70%	54.64%
Education	Highest degree completed	1 = high school or less	15.38%	15.85%
		2 = some college or completed bachelors	69.52%	70.49%
		3 = masters or professional degree	13.68%	12.02%
		4 = PhD	1.42%	1.64%
Work	Employment status	1 = working	69.69%	74.86%
		2 = not working but searching	5.03%	8.20%
		3 = not working	14.72%	9.84%
		4 = student	1.49%	.55%
		5 = not specified	9.07%	6.56%
Relationship	Marital status	1 = married	32.76%	40.98%
		2 = widowed	.57%	.55%
		3 = divorced	3.70%	8.74%
		4 = separated	2.85%	3.83%
		5 = never married	59.54%	45.90%
		6 = prefer not to say	.57%	0%
Country	Country of residence	1 = U.K.	56.13%	2.19%
		2 = U.S.	30.20%	85.79%
		3 = neither	13.68%	12.02%
Income	Household income level (12 levels ranging from below $10,000 to greater than $150,000 (from below £10,000 to greater than £150,000 for U.K.-based participants)		4.38 (2.70)	4.68 (2.92)
Language	Primary spoken language (English = 1, Other = 0)		90.31%	92.35%

TABLE 3

ESTIMATION RESULTS FOR STUDY 1

Variable	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8
SWB (lagged)	.0656***		.0628***	.0644***	.0629***		.0616***	.0632***
	(.0088)		(.0091)	(.0091)	(.0089)		(.0092)	(.0092)
PsyWB (lagged)	.7781***	.8309***	.7628***	.7622***	.7721***	.8256***	.7582***	.7577***
	(.0080)	(.0061)	(.0083)	(.0083)	(.0081)	(.0061)	(.0084)	(.0083)
PhyWB (lagged)	-.0031		.0042	.0059	.0012		.0059	.0076
	(.0079)		(.0082)	(.0082)	(.0080)		(.0082)	(.0082)
FinWB (lagged)	.0430***		.0415***	.0413***	.0431***		.0413***	.0411***
	(.0067)		(.0070)	(.0069)	(.0067)		(.0070)	(.0069)
Total SM Use	.0046***	.0063***	.0061***	.0060***				
	(.0012)	(.0016)	(.0016)	(.0016)				
Truly Social SM Use					.0072***	.0093***	.0089***	.0087***
					(.0012)	(.0015)	(.0016)	(.0016)
Other SM Use					-.0012	-.0003	-.0001	-.0001
					(.0012)	(.0014)	(.0014)	(.0014)
Total Device Use		-.0053*	-.0047	-.0046		-.0065**	-.0058*	-.0058*
		(.0024)	(.0024)	(.0024)		(.0023)	(.0024)	(.0024)
Positive Life Event				.0613***				.0609***
				(.0119)				(.0119)
Positive Life Event				-.0415***				-.0414***
(lagged)				(.0125)				(.0124)
Negative Life Event				-.0507***				-.0506***
				(.0087)				(.0087)
Negative Life Event				.0387***				.0384***
(lagged)				(.0092)				(.0092)
Const.	.1413***	.2502***	.1637***	.1574***	.1473***	.2580***	.1707***	.1643***
	(.0150)	(.0244)	(.0274)	(.0273)	(.0149)	(.0245)	(.0274)	(.0274)
Demographic and Socio-economic Controls	No	Yes	Yes	Yes	No	Yes	Yes	Yes
Observations	8958	8958	8958	8958	8958	8958	8958	8958
Log Likelihood	2,108.87	2,073.84	2,135.82	2,172.32	2,120.10	2,084.48	2,145.52	2,181.80

Standard errors in parentheses.
**** p<.001, ** p<.01, * p<.05*

TABLE 4

ESTIMATION RESULTS FOR STUDY 2

Variable	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8
SWB (lagged)	.0745***		.0728***	.0719***	.0744***		.0727***	.0717***
	(.0122)		(.0127)	(.0127)	(.0122)		(.0127)	(.0127)
PsyWB (lagged)	.6709***	.7477***	.6598***	.6595***	.6714***	.7484***	.6611***	.6609***
	(.0139)	(.0111)	(.0142)	(.0141)	(.0140)	(.0111)	(.0142)	(.0141)
PhyWB (lagged)	.0339**		.0439**	.0473***	.0341**		.0433**	.0467***
	(.0132)		(.0136)	(.0135)	(.0132)		(.0136)	(.0135)
FinWB (lagged)	.0515***		.0457***	.0423***	.0512***		.0454***	.0419***
	(.0111)		(.0117)	(.0116)	(.0111)		(.0117)	(.0116)
Total SM Use	.0073***	.0062*	.0074**	.0077**				
	(.0020)	(.0025)	(.0025)	(.0025)				
Truly Social SM Use					.0060**	.0035	.0045	.0045*
					(.0020)	(.0023)	(.0023)	(.0023)
Other SM Use					.0015	.0026	.0027	.0030
					(.0020)	(.0023)	(.0023)	(.0022)
Total Device Use		-.0034	-.0024	-.0026		-.0020	-.0007	-.0009
		(.0045)	(.0045)	(.0045)		(.0045)	(.0045)	(.0044)
Positive Life Event				.0692***				.0698***
				(.0194)				(.0194)
Positive Life Event				.0131				.0127
(lagged)				(.0218)				(.0218)
Negative Life Event				-.0950***				-.0946***
				(.0143)				(.0143)
Negative Life Event				.0520***				.0523***
(lagged)				(.0159)				(.0159)
Const.	.2413***	.2945***	.1538*	.1534*	.2467***	.2930***	.1530*	.1525*
	(.0229)	(.0605)	(.0622)	(.0618)	(.0227)	(.0605)	(.0623)	(.0618)
Demographic and Socio-economic Controls	No	Yes	Yes	Yes	No	Yes	Yes	Yes
Observations	3778	3778	3778	3778	3778	3778	3778	3778
Log Likelihood	411.98	380.12	427.06	458.11	410.74	378.93	425.30	456.24

Standard errors in parentheses.
**** p<.001, ** p<.01, * p<.05*

FIGURE 1

MAPPING THE RAW APP USAGE LOGS COLLECTED FROM A PARTICIPANT'S MOBILE DEVICE TO THE USAGE INTENSITY VARIABLES USED IN OUR ANALYSIS

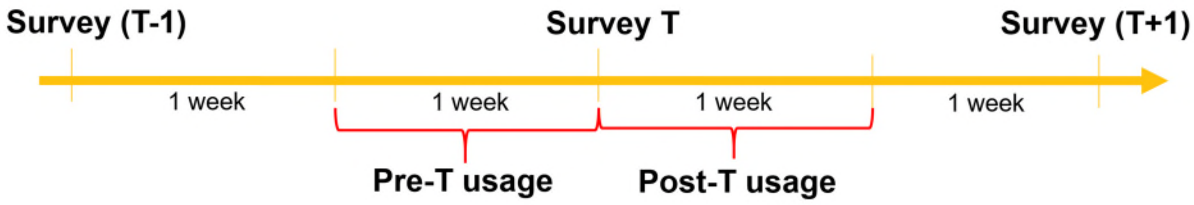

TABLE 5 - ESTIMATION RESULTS FOR STUDY 1 AFTER EXCLUDING APP USAGE OBSERVATIONS WITH MORE THAN 6H CPU FOREGROUND TIME IN 24 HOURS

Variable	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8
SWB (lagged)	.0656***		.0628***	.0644***	.0629***		.0615***	.0631***
	(.0088)		(.0091)	(.0091)	(.0089)		(.0092)	(.0092)
PsyWB (lagged)	.7779***	.8307***	.7627***	.7620***	.7720***	.8253***	.7581***	.7575***
	(.0080)	(.0061)	(.0083)	(.0083)	(.0081)	(.0061)	(.0084)	(.0083)
PhyWB (lagged)	-.0030		.0043	.0060	.0013		.0060	.0077
	(.0079)		(.0082)	(.0082)	(.0080)		(.0082)	(.0082)
FinWB (lagged)	.0430***		.0415***	.0413***	.0431***		.0412***	.0410***
	(.0067)		(.0070)	(.0069)	(.0067)		(.0070)	(.0069)
Total SM Use	.0047***	.0064***	.0061***	.0061***				
	(.0012)	(.0016)	(.0016)	(.0016)				
Truly Social SM Use					.0073***	.0094***	.0090***	.0089***
					(.0012)	(.0016)	(.0016)	(.0016)
Other SM Use					-.0012	-.0003	-.0001	-.0000
					(.0013)	(.0014)	(.0014)	(.0014)
Total Device Use		-.0053*	-.0046	-.0045		-.0065**	-.0058*	-.0057*
		(.0024)	(.0025)	(.0025)		(.0024)	(.0024)	(.0024)
Positive Life Event				.0614***				.0610***
				(.0119)				(.0119)
Positive Life Event				-.0414***				-.0415***
(lagged)				(.0125)				(.0124)
Negative Life Event				-.0507***				-.0506***
				(.0087)				(.0087)
Negative Life Event				.0387***				.0384***
(lagged)				(.0092)				(.0092)
Const.	.1413***	.2502***	.1631***	.1568***	.1474***	.2585***	.1707***	.1644***
	(.0150)	(.0245)	(.0275)	(.0274)	(.0149)	(.0246)	(.0275)	(.0275)
Demographic and Socio-economic Controls	No	Yes	Yes	Yes	No	Yes	Yes	Yes
Observations	8958	8958	8958	8958	8958	8958	8958	8958
Log Likelihood	2,109.03	2,073.86	2,135.79	2,172.31	2,120.30	2,084.63	2,145.54	2,181.87

Standard errors are in parentheses.
*** p<.001, ** p<.01, * p<.05

TABLE 6 - ESTIMATION RESULTS FOR STUDY 1 AFTER EXCLUDING ONLY APP USAGE OBSERVATIONS WITH MORE THAN 10H CPU FOREGROUND TIME IN 24 HOURS

Variable	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8
SWB (lagged)	.0656***		.0628***	.0644***	.0629***		.0615***	.0631***
	(.0088)		(.0091)	(.0091)	(.0089)		(.0092)	(.0092)
PsyWB (lagged)	.7781***	.8310***	.7629***	.7623***	.7722***	.8258***	.7584***	.7578***
	(.0080)	(.0061)	(.0083)	(.0083)	(.0081)	(.0061)	(.0083)	(.0083)
PhyWB (lagged)	-.0031		.0042	.0059	.0012		.0059	.0076
	(.0079)		(.0082)	(.0082)	(.0080)		(.0082)	(.0082)
FinWB (lagged)	.0430***		.0416***	.0414***	.0431***		.0413***	.0411***
	(.0067)		(.0070)	(.0069)	(.0067)		(.0070)	(.0069)
Total SM Use	.0046***	.0062***	.0059***	.0059***				
	(.0012)	(.0016)	(.0016)	(.0016)				
Truly Social SM Use					.0072***	.0091***	.0087***	.0086***
					(.0012)	(.0015)	(.0016)	(.0015)
Other SM Use					-.0012	-.0004	-.0001	-.0001
					(.0012)	(.0014)	(.0014)	(.0014)
Total Device Use		-.0050*	-.0045	-.0044		-.0062**	-.0056*	-.0055*
		(.0023)	(.0024)	(.0024)		(.0023)	(.0023)	(.0023)
Positive Life Event				.0613***				.0608***
				(.0119)				(.0119)
Positive Life Event				-.0414***				-.0414***
(lagged)				(.0125)				(.0124)
Negative Life Event				-.0507***				-.0507***
				(.0087)				(.0087)
Negative Life Event				.0386***				.0384***
(lagged)				(.0092)				(.0092)
Const.	.1413***	.2491***	.1627***	.1562***	.1473***	.2566***	.1695***	.1630***
	(.0150)	(.0244)	(.0273)	(.0273)	(.0149)	(.0245)	(.0274)	(.0273)
Demographic and Socio-economic Controls	No	Yes	Yes	Yes	No	Yes	Yes	Yes
Obs.	8958	8958	8958	8958	8958	8958	8958	8958
Log Likelihood	2,108.84	2,073.61	2,135.63	2,172.11	2,119.98	2,084.18	2,145.24	2,181.49

Standard errors are in parentheses.
*** *p<.001*, ** *p<.01*, * *p<.05*

TABLE 7 - ESTIMATION RESULTS FOR STUDY 2 AFTER EXCLUDING APP USAGE OBSERVATIONS WITH MORE THAN 6H CPU FOREGROUND TIME IN 24 HOURS

Variable	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8
SWB (lagged)	.0743***		.0728***	.0718***	.0743***		.0726***	.0717***
	(.0122)		(.0127)	(.0127)	(.0122)		(.0127)	(.0127)
PsyWB (lagged)	.6708***	.7475***	.6597***	.6594***	.6713***	.7483***	.6610***	.6608***
	(.0139)	(.0111)	(.0142)	(.0141)	(.0140)	(.0111)	(.0142)	(.0141)
PhyWB (lagged)	.0340**		.0439**	.0473***	.0342**		.0433**	.0467***
	(.0132)		(.0136)	(.0135)	(.0132)		(.0136)	(.0135)
FinWB (lagged)	.0515***		.0458***	.0423***	.0512***		.0454***	.0420***
	(.0111)		(.0117)	(.0116)	(.0111)		(.0117)	(.0116)
Total SM Use	.0074***	.0062*	.0074**	.0077**				
	(.0020)	(.0026)	(.0025)	(.0025)				
Truly Social SM Use					.0061**	.0035	.0045	.0045*
					(.0020)	(.0023)	(.0023)	(.0023)
Other SM Use					.0015	.0025	.0026	.0029
					(.0020)	(.0023)	(.0023)	(.0023)
Total Device Use		-.0030	-.0020	-.0023		-.0015	-.0002	-.0004
		(.0047)	(.0046)	(.0046)		(.0046)	(.0046)	(.0045)
Positive Life Event				.0692***				.0697***
				(.0194)				(.0194)
Positive Life Event				.0130				.0127
(lagged)				(.0218)				(.0218)
Negative Life Event				-.0950***				-.0946***
				(.0143)				(.0143)
Negative Life Event				.0520**				.0522***
(lagged)				(.0159)				(.0159)
Const.	.2413***	.2920***	.1516*	.1517*	.2468***	.2902***	.1504*	.1504*
	(.0228)	(.0606)	(.0623)	(.0619)	(.0227)	(.0606)	(.0624)	(.0619)
Demographic and Socio-economic Controls	No	Yes	Yes	Yes	No	Yes	Yes	Yes
Observations	3778	3778	3778	3778	3778	3778	3778	3778
Log Likelihood	412.13	380.19	427.14	458.19	410.87	378.97	425.36	456.30

Standard errors are in parentheses.
*** *p<.001, ** p<.01, * p<.05*

TABLE 8 - ESTIMATION RESULTS FOR STUDY 2 AFTER EXCLUDING ONLY APP USAGE OBSERVATIONS WITH MORE THAN 10H CPU FOREGROUND TIME IN 24 HOURS

Variable	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8
SWB (lagged)	.0745***		.0729***	.0720***	.0744***		.0727***	.0718***
	(.0122)		(.0127)	(.0127)	(.0122)		(.0127)	(.0127)
PsyWB (lagged)	.6708***	.7476***	.6597***	.6594***	.6713***	.7484***	.6610***	.6608***
	(.0139)	(.0111)	(.0142)	(.0141)	(.0140)	(.0111)	(.0142)	(.0141)
PhyWB (lagged)	.0340**		.0439**	.0473***	.0342***		.0433***	.0467***
	(.0132)		(.0136)	(.0135)	(.0132)		(.0136)	(.0135)
FinWB (lagged)	.0515***		.0457***	.0423***	.0512***		.0454***	.0419***
	(.0111)		(.0117)	(.0116)	(.0111)		(.0117)	(.0116)
Total SM Use	.0074***	.0062*	.0075**	.0077**				
	(.0020)	(.0025)	(.0025)	(.0025)				
Truly Social SM Use					.0060**	.0035	.0045*	.0046*
					(.0020)	(.0023)	(.0023)	(.0023)
Other SM Use					.0015	.0026	.0027	.0030
					(.0020)	(.0023)	(.0023)	(.0022)
Total Device Use		-.0032	-.0022	-.0024		-.0018	-.0006	-.0008
		(.0044)	(.0044)	(.0044)		(.0044)	(.0044)	(.0043)
Positive Life Event				.0692***				.0698***
				(.0194)				(.0194)
Positive Life Event				.0131				.0127
(lagged)				(.0218)				(.0218)
Negative Life Event				-.0951***				-.0946***
				(.0143)				(.0143)
Negative Life Event				.0520**				.0522***
(lagged)				(.0159)				(.0159)
Const.	.2411***	.2929***	.1523*	.1520*	.2466***	.2918***	.1520*	.1516*
	(.0229)	(.0603)	(.0621)	(.0616)	(.0227)	(.0604)	(.0621)	(.0616)
Demographic and Socio-economic Controls	No	Yes	Yes	Yes	No	Yes	Yes	Yes
Observations	3778	3778	3778	3778	3778	3778	3778	3778
Log Likelihood	412.14	380.20	427.21	458.26	410.86	378.99	425.39	456.34

Standard errors are in parentheses.
**** p<.001, ** p<.01, * p<.05*