Journal of Computer-Mediated Communication

The Impact of Internet and Social Media Use on Well-Being: A Longitudinal Analysis of Adolescents Across Nine Years

Christian Schemer ,[1] Philipp K. Masur ,[2] Stefan Geiß ,[3] Philipp Müller ,[4] & Svenja Schäfer [5]

[1] Department of Communication, Johannes Gutenberg University in Mainz, 55128 Mainz, Germany

[2] Department of Communication Science, Vrije Universiteit Amsterdam (VU), 1081 HV Amsterdam, The Netherlands

[3] Department of Sociology and Political Science, Norwegian University of Science and Technology (NTNU), 7491 Trondheim, Norway

[4] Institute for Media and Communication Studies, University of Mannheim, 68159 Mannheim, Germany

[5] Department of Communication Science, University of Vienna, 1090 Vienna, Austria

The present research examines the longitudinal average impact of frequency of use of Internet and social networking sites (SNS) on subjective well-being of adolescents in Germany. Based on five-wave panel data that cover a period of nine years, we disentangle between-person and within-person effects of media use on depressive symptomatology and life satisfaction as indicators of subjective well-being. Additionally, we control for confounders such as TV use, self-esteem, and satisfaction with friends. We found that frequency of Internet use in general and use of SNS in particular is not substantially related subjective well-being. The explanatory power of general Internet use or SNS use to predict between-person differences or within-person change in subjective well-being is close to zero. TV use, a potentially confounding variable, is negatively related to satisfaction with life, but it does not affect depressive symptomatology. However, this effect is too small to be of practical relevance.

Keywords: Social Networking Sites (SNS), Internet, Television, Media Use, Subjective Well-being, Life Satisfaction, Depressive Symptomatology, Longitudinal Analysis, Adolescents

doi:10.1093/jcmc/zmaa014

With the increasing proliferation of electronic devices and social networking sites (SNS) in the daily life, there are growing concerns that the increased time spent online could harm the well-being of adolescents. Yet, answering this question has proven difficult. Numerous studies found that frequency of use of Internet applications, e.g., SNS diminished well-being. However, the effect sizes are mostly small (for reviews, see Appel, Marker, & Gnambs, 2020; Steers, 2015). Other studies demonstrated that online communication or specific features of SNS can increase well-being (for a review, see Valkenburg & Peter, 2011). A large-scale survey found that the relationship

Corresponding author: Christian Schemer; e-mail: schemer@uni-mainz.de

between technology use and adolescents' life satisfaction is often inconsistent, mostly weak, and dependent on analytical decisions (Orben & Przybylski, 2019). Meta-analyses also corroborate the heterogeneity of effects, suggesting on average a negative, yet comparatively small relationship between media use and of well-being (Huang, 2017; Liu, Ainsworth, & Baumeister, 2016). Appel et al. (2020) doubt that "social media use has (. . .) severe detrimental consequences." This assessment predominantly draws on evidence from cross-sectional surveys. Such research designs cannot determine the direction of causality between media use and changes in well-being. Neither can cross-sectional surveys rule out that unknown third variables jointly affect media use and well-being, producing a spurious correlation. In addition to cross-sectional research, longitudinal studies are needed because they allow to disentangle between-person relationships (i.e., between-person differences in Internet use are related to between-person *differences* in well-being) from within-person effects (i.e., more frequent Internet use is related to within-person *changes* in well-being). In particular, scholars have pointed out a scarcity of longitudinal studies that cover longer periods to disentangle between-person and within-person effects (Orben, Dienlin, & Przybylski, 2019; Whitlock & Masur, 2019).

Additionally, observational studies frequently suffer from omission bias. Most studies assessed general Internet use or the use of specific Internet applications without considering other media (e.g., TV use) or non-media factors (e.g., personality, social support) that may also affect well-being. Such variables are potential confounders since they can be related to well-being. Not considering potential confounders can result in biased estimates of media effects of interest. For instance, the debate as to whether the use of SNS is good or bad for society reminds us of the discussion related to the detrimental effects of TV (Kubey & Csikszentmihalyi, 1990). Similar to the effects of Internet or SNS use, research indicates that frequent exposure to TV can negatively affect well-being (Booker, Skew, Kelly, & Sacker, 2015; Primack, Swanier, Georgiopoulos, Land, & Fine, 2009). To date, Internet communication has not yet replaced TV use. Therefore, research on the impact of new forms of communication should also consider the impact of traditional media as one potential confounder. Other potential confounders like self-esteem (a central personality factor) or perceived quality of social relations (as a proxy for social factors) that can affect adolescents' subjective well-being should also be controlled for.

The present study addresses these shortcomings by investigating the impact of Internet use in general and SNS use in particular on adolescents' subjective well-being over a period of nine years using bi-annual repeated-measures panel data. We unscramble between- and within-person effects, consider the impact of TV use as an additional predictor, and control for central factors outside the domain of media use. This methodological approach complements the existing research as it offers a broader and long-term oriented view on adolescents' media use and well-being which is unique to the research landscape to date.

Media effects on subjective well-being

Facets of subjective well-being

Subjective well-being refers to an individual's cognitive and affective evaluation of one's own life (Diener, 2009). The term *subjective* indicates that well-being is an individual perception of life conditions and consists of both cognitive (such as general satisfaction with life) and affective components (such as negative moods or emotions; Reinecke & Oliver, 2017). Scholars have investigated different types of indicators for well-being. Originally, many communication scholars studied media effects on mental disorders (e.g., depression). Individuals who perceive their subjective states as negative over longer periods of time show indication of depressive symptoms (Krohne, Schmukle, Spaderna, & Spielberger, 2002). However, with the emergence of positive psychology, the focus moved from pathology to human strengths and positive experiences (Seligman & Csikszentmihalyi, 2000). An individual therefore has a high subjective well-being if she is generally satisfied with her life (cognitive), rarely experiences unpleasant emotions (negative affect) and frequently experiences pleasant emotional states (positive affect). In this study, we focus on life satisfaction and depressive symptomatology as two related, yet distinct indicators of subjective well-being. Both have a high stability and are thus suitable to study long-term effects of media use. In the following, we discuss research on the relationships of Internet and SNS with subjective well-being. We thereby emphasize the differences between findings from cross-sectional (between-person) and longitudinal designs (within-person).

Unpacking the relationships between Internet use, SNS use, and subjective well-being

With the diffusion of Internet applications, research on detrimental effects on well-being has skyrocketed. First, some scholars argue that Internet or SNS use leads to *lower* well-being because investments in online relations go at the expense of offline relations and other activities, which makes people more dissatisfied (Kraut et al., 1998; Lin et al., 2016). Second, online media use can lower well-being because potentially detrimental social comparisons become more likely. Specifically, on SNS individuals are often exposed to idealized depictions of others and engage in upward comparisons which may produce envy (Krasnova, Wenninger, Widjaja, & Buxmann, 2013), lower perceived attractiveness (Haferkamp & Krämer, 2011), or decreased self-esteem (Schmuck, Karsay, Matthes, & Stevic, 2019). Third, users may perceive passive browsing as less pleasant relative to active searching (Escobar-Viera et al., 2018; Verduyn et al., 2015). Fourth, online media use increases the likelihood of being exposed to mental health risks, such as cyberbullying. Users may often receive negative feedback which can decrease well-being (Valkenburg, Peter, & Schouten, 2006). A substantial body of evidence supports these lines of argumentation. Cross-sectional surveys found that frequent use of SNS was negatively related to happiness in the U.K. (Booker et al., 2015) and U.S. adolescents (Lin et al., 2016). An early longitudinal study found that frequent Internet users more often suffered from loneliness and depressive symptoms than low-frequency users (Kraut et al., 1998). Kraut et al. (2002) later found that hours spent online at home increased depression in the first study period, but reduced depression and increased positive affect in the second. A time diary study of more than 6,000 U.S.-Americans demonstrated that time spent online at home reduced the time people spent with friends and thereby increased loneliness (Nie, Hillygus, & Erbring, 2002). A two-wave panel analysis of 1,012 U.S.-Americans failed to find any relationship between general Internet use and depression in the period of six to eight months (Bessière, Kiesler, Kraut, & Boneva, 2008). An experience sampling study revealed that increased Facebook use reduced subjective well-being and satisfaction with life within 14 days (Kross et al., 2013). A survey of 663 Dutch students found that frequency of instant messaging (IM) increased depressive symptoms six months later (Van den Eijnden & Meerkerk, 2008). Finally, a two-wave panel survey of 431 Austrians demonstrated that Facebook use harmed well-being through negative social comparison within three months (Schmuck et al., 2019).

Additionally, there is a large body of research arguing that some Internet applications can have *beneficial* effects on people's well-being (Valkenburg & Peter, 2007). First, Internet applications can increase social capital which, in turn, bolsters subjective well-being (Bessière et al., 2008; Valkenburg & Peter, 2011). Second, positive feedback from online interaction partners can improve well-being

(Valkenburg et al., 2006). Third, increased online communication enhances subjective well-being by expanding communication quantity and quality (Dienlin, Masur, & Trepte, 2017). Several studies support such positive effects. A cross-sectional survey of 1,210 Dutch teenagers found that more IM was associated with spending more time with friends, which, in turn, enhanced subjective well-being (Valkenburg et al., 2006). Longitudinal studies corroborate these beneficial effects of SNS. More precisely, time spent on Internet communication with relatives and friends decreased depression over time (Bessière et al., 2008). A longitudinal survey of 460 German SNS and IM users found that SNS communication was positively (but weakly) related to life satisfaction six months later (Dienlin et al., 2017). Unlike these findings, other longitudinal studies found no effect of SNS use on subjective well-being. For instance, research found no effect of SNS use on changes in depressive symptomatology among adolescents over six (Ferguson, Munoz, Garza, & Galindo, 2014) or 12 months (Scherr, Toma, & Schuster, 2019).

Taken together, previous studies are inconclusive with respect to the overall relationship between the frequency of Internet or SNS use and subjective well-being. Some Internet applications or modes of use may be beneficial while others may be detrimental. A look at reviews and meta-analysis that summarized the primarily cross-sectional evidence suggests that studies documenting negative relationships outweigh those that found positive relationships (Huang, 2010; Steers, 2015). This finding may reflect that passive use of Internet applications is dominant (Escobar-Viera et al., 2018; Verduyn et al., 2015) or that processes that are detrimental to subjective well-being (negative feedback, upward comparisons, displacement of offline relationships) occur more frequently than processes that produce positive outcomes (positive feedback, building social capital, engage in identity exploration) when using Internet application like SNS (de Vries & Kühne, 2015; Haferkamp & Krämer, 2011). Facing these negative net effects, the present study starts from the following between-person hypothesis:

H1:Frequency of: (a) Internet use in general; and (b) SNS use in particular are negatively related to subjective well-being (*between-person* correlation).

Longitudinal findings are similarly inconclusive. There are several explanations for this inconsistency. One account may be that differences in inter-panel intervals in these studies caused these inconsistencies. Most studies covered short periods ranging from one week to six months. Few studies examined longer periods (see Orben et al., 2019). Another explanation is that life satisfaction and depressive symptomatology exhibit high temporal stability (Eid & Diener, 2004). Given that well-being is more likely to be affected by monthly or yearly doses of exposure to Internet applications, researchers need to study their effects over considerably longer time spans (Huang, 2010). The present study addresses this gap by investigating the unique effects of the use of Internet and SNS on subjective well-being over a period of nine years. Based on previous research, we start from the following within-person hypotheses:

H2:Individuals using: (a) the Internet; and (b) SNS more frequently than usual will experience lower subjective well-being than usual (*within-person* correlation of deviations).

H3: Individuals using: (a) the Internet; and (b) SNS more frequently than usual will experience lower well-being than usual at a later point in time (time-lagged *within-person* correlation of deviations).

Controlling the effects of potentially confounding variables

Previous research frequently suffers from omission bias. Specifically, when studying the impact of Internet use researchers often focus on specific predictors of interest and do not account for the potential impact of others. The most immediately relevant factors are those for which similar theoretical arguments have been made regarding their effect on well-being, and for which empirical correlations have been observed. We separate *media-related factors*, e.g., TV use or other media use, *person-related factors*, such as self-esteem, and *social factors*, e.g., quality of social relations; of these, media-related factors are most immediately related to the variables of interest, Internet and SNS use as alternative types of media use. When extant studies suffer from omission bias, we cannot be sure that the effects of Internet or SNS use on well-being that are found are not due to omitting potentially confounding variables that might be the true causes of effects. For instance, Selfhout, Branje, Delsing, Bogt, and Meeus (2009) argued that the effect of frequency of use of IM on depression in Van den Eijnden et al. (2008) may have resulted from omission bias. Selfhout et al. (2009, p. 829) argue: "Effects of IM-ing on internalizing problems may be confounded with effects of surfing on internalizing problems, since adolescents who spend more time IM-ing also tend to spend more time surfing." The size and direction of this confounding influence due to omission, i.e., upward or downward bias, depends on the true effects of interest and the effect of the potential confounders on subjective well-being. Since these true effects are unknown, the safest way to reduce bias is to include potentially confounders as predictors.

Television use as a potentially confounding variable

The debate about benefits and risks of Internet use parallels the discussion about effects of TV viewing on well-being (Booker et al., 2015; Kubey & Csikszentmihalyi, 1990; Primack et al., 2009). For instance, a longitudinal panel study found that heavy use of TV in adolescence increased depression in early adulthood (Primack et al., 2009). Additionally, Booker et al.'s (2015) study of adolescents found that heavy TV users were less happy than light TV users. That study also found that frequent SNS use decreased happiness. The authors reasoned that screen-based media use in general is passive in nature and can reduce the time that adolescents spend on social activities or sports. This suggests that similar mechanisms (e.g., time displacement, passivity) underlie the effects of TV, Internet and SNS use on well-being. Still, the effects of TV use and of the use of Internet applications can occur independently (see, also Nie et al., 2002).

However, most studies on the impact of the Internet use or the use of specific applications fail to consider this TV effect (recent examples: Burke & Kraut, 2016; Lin et al., 2016; Schmuck et al., 2019). That is problematic since Internet use (including SNS) and TV use may be correlated positively (jointly representing individuals' extent of screen-media use) or negatively (when e.g., Internet use displaces TV use as they compete for individuals' limited leisure time); either way, they are inherently linked as media use behaviors. If TV and Internet applications exert independent effects on well-being observational studies should measure these different forms of screen-based media use to disentangle their unique effects. Otherwise, the omission of relevant predictors can severely bias the estimates of any regression (Wooldridge, 2010).

Potential person-related and social confounding variables

Omission bias can also occur when researchers mistake the impact of media use on subjective well-being for the effect of other non-media predictors that affect well-being (and are potentially correlated with media use), but are not observed in a study. Subjective well-being has multiple determinants.

Previous theorizing suggests that self-esteem and perceived social relations are among the most important sources of subjective well-being (Dumont & Provost, 1999; Shortt & Spence, 2006). Specifically, a sense of self-worth and self-acceptance is "a central characteristic of positive psychological functioning" (Ryff, 1989, p. 1071) and, therefore, a basic determinant of subjective well-being. Self-esteem is a pivotal factor for successfully coping with stressors (Shortt & Spence, 2006). Thus, individuals high in self-esteem are happier and experience more subjective well-being than individuals low in self-esteem (Ryff, 1989).

Another important set of predictors for subjective well-being are positive social relations (Ryff, 1989). Across adolescence, individuals experience an increase of stressful life events caused by interpersonal conflicts with peers or girl- or boyfriends (Burke & Kraut, 2016). While conflicts among friends are social stressors that reduce adolescents' well-being social bonding with friends supports well-being (Dumont & Provost, 1999). Most studies investigating the impact of Internet or SNS use did not account for these important determinants of subjective well-being (e.g., Scherr et al., 2019; Van den Eijnden & Meerkerk, 2008; but see Burke & Kraut, 2016 who study the role of critical life events). Some studies demonstrated that online social contacts with friends increased well-being among teenagers (Valkenburg et al., 2006). Since these studies did not assess the perceived quality of offline social relations, it is unclear whether the findings were due to social bonding online and not the effect of unobserved offline social relations. Thus, just like ignoring traditional media use, not accounting for self-esteem or quality of social relations offline as determinants of subjective well-being can induce omission bias. To account for confounding influence of TV use, self-esteem, and quality of social relations, we formulate the following research question:

> RQ1: Do between- and within-person effects of the frequency of: (a) Internet; and (b) SNS use change after controlling for the frequency of TV use, self-esteem, and quality of social relations?

Method

Sampling and survey design

The data originate from the German Family Panel Study (Brüderl et al., 2019; Huinink et al., 2011). The present analyses[1] are based on a random sample of the German population born in 1991–1993. In 2008, 4,338 adolescents were interviewed (age $M = 16.00$, $SD = .82$; 49.3% female; 97% still in school). We used five of the nine waves of the panel study (2008–2016), because only waves 1, 3, 5, 7, and 9 included media use (overall Internet use, SNS and TV use). Thus, the temporal spacing between panel waves was two years. For the analyses, we used all valid responses that participants gave. Thus, the data base also includes incomplete cases (see Table S2).[2]

Measures

For the present study, we predicted subjective well-being by using frequency of Internet, TV, and SNS use as independent variables. We relied on additional control variables which included the lagged dependent variable (for zero-order-correlation, see Table S1: https://osf.io/yvng6/; for descriptive statistics, see Table S2: https://osf.io/cgs8h/).

Subjective well-being

Two measures assessed subjective well-being: depressive symptomatology and satisfaction with life. First, the State-Trait Depression Scale (Krohne et al., 2002) was used to gauge depressive symptomatology in waves 2 to 9. Respondents rated ten items referring to their mood in general (1 = *almost never* to 4 = *almost always*). Five items referred to negative mood (e.g., *I am depressed* or *I feel sad*), five items to positive mood (e.g., *I feel good* or *I am happy*; see the OSF page for details on unidimensionality tests; reliability: McDonald's hierarchical ω ranging between .84 and .91). Second, satisfaction with life was assessed in all waves using a single item (*Now I would like to ask about your general satisfaction with life. All in all, how satisfied are you with your life at the moment?* 0 = *very dissatisfied*, 10 = *very satisfied)*. Test–retest correlations ranged from r=.431 to r=.547.

Media use

Frequency of Internet, TV, and SNS use were assessed every second wave (T1, T3, T5, T7, T9). Internet use was assessed using an item that asked for total hours spent on the Internet last week. Participants also reported the hours per week that they had watched TV. SNS use was assessed by asking whether respondents had a profile on a SNS, e.g., SchuelerVZ, Facebook, or Myspace (1 = *yes*, 2 = *no*). Participants with a profile reported their activity on other people's profile pages (6 = *several times a day*, 5 = *daily*, 4 = *3–5 days a week*, 3 = *1–2 days a week*, 2 = *every few weeks*, 1 = *more seldom*). For the analysis, we used this frequency measure. Respondents without any use of the respective media or without SNS profile were scored "0."[3]

Control and potentially confounding variables

Respondents' gender (0 = *male*, 1 = *female*) and age were assessed with single items (we did not include education because most respondents were still in school when the study started). As an indicator of self-worth, self-esteem was assessed in all panel waves using three items from the Rosenberg Self-esteem Scale (Rosenberg, 1965), e.g., *sometimes I believe that I'm worthless* (reverse-coded, scale ranging from 1 = *does not apply at all* to 5 = *completely applies*, reliability across waves: hierarchical ω=.68–.77). The items were summed up to form a composite score with high values denoting high self-esteem. To measure the perceived quality of social relations, satisfaction with friends (0 = *very unsatisfied*; 10 = *very satisfied*) was assessed with a single item. This measurement is guided by the assumption that relations to one's close social contacts become more important in adolescence and that satisfaction with peer relations is a good proxy for the quality of social relations.

Variable coding, statistical modeling, and power considerations

The data were analyzed using a random-effect within-between model (Bell, Fairbrother, & Jones, 2019), which allows to distinguish between- and within-person variance. To ease interpretation, the variables depressive symptoms, satisfaction with life, and self-esteem were rescaled to range from 1 to 10. Person-means (between-person variance of the variables) and age were grand-mean centered. The tests of the hypotheses were conducted separately for depressive symptomatology and satisfaction with life (Tables 1 and 2). For each dependent variable, we computed five models: Model 1 includes SNS and Internet use as predictors. Model 2 adds TV use to reduce bias stemming from the omission of traditional media use. Model 3 further includes age, gender as control variables and self-esteem and satisfaction with friends to control for potential non-media confounders. Model 4 adds time to account for common time trends that are independent of the predictors. Time squared captures non-linear time trends. Finally, Model 5 adds the lagged dependent variable, which represents the impact of the dependent variable in a preceding measurement occasion on the dependent variable in the current measurement occasion.[4]

Table 1 Media Effects on Depressive Symptomatology

	M1	M2	M3	M4	M5
Intercept	3.443 (0.026)*	3.450 (0.027)*	3.302 (0.025)*	3.154 (0.131)*	4.580 (0.466)*
Internet Use					
Between (H1a)	0.005 (0.003)*	0.005 (0.003)	0.005 (0.002)*	0.005 (0.002)*	0.004 (0.002)*
Within (H2a)	0.005 (0.001)*	0.004 (0.001)	0.002 (0.001)	0.002 (0.001)	0.004 (0.001)
Lagged within (H3a)	0.001 (0.001)	0.001 (0.001)	0.001 (0.001)	0.001 (0.001)	0.001 (0.001)
SNS Use					
Between (H1b)	0.021 (0.019)	0.020 (0.019)	–0.005 (0.013)	–0.003 (0.013)	–0.014 (0.013)
Within (H2b)	0.015 (0.011)	0.019 (0.011)	0.019 (0.009)	0.018 (0.009)	0.013 (0.012)
Lagged within (H3b)	0.020 (0.010)	0.009 (0.010)	–0.005 (0.009)	0.001 (0.009)	0.003 (0.012)
TV Use (RQ1)					
Between		0.004 (0.004)	0.0002 (0.003)	–0.0002 (0.003)	–0.002 (0.003)
Within		0.004 (0.002)	0.005 (0.002)	0.004 (0.002)	0.005 (0.002)
Lagged within		–0.001 (0.002)	0.001 (0.002)	–0.0002 (0.002)	–0.003 (0.002)
Control Variables					
Age (in Years)			0.010 (0.023)	0.010 (0.021)	–0.014 (0.021)
Gender (1 = female)			0.121 (0.039)*	0.123 (0.036)*	–0.001 (0.036)
Sat. with Friends			–0.154 (0.010)*	–0.165 (0.010)*	–0.159 (0.011)*
Self-Esteem			–0.484 (0.009)*	–0.484 (0.008)*	–0.445 (0.010)*
Time				0.116 (0.081)	–0.910 (0.243)*
Time (quadratic)				–0.034 (0.012)	0.097 (0.030)*
Lagged Depression (T–1)					0.221 (0.011)*
Var: Person|Intercept	1.359	1.361	0.477	0.473	0.177
AIC	26,640.09	26,356.74	22,773.91	22,747.69	14,516.57
BIC	26,702.43	26,439.72	22,884.47	22,872.08	14,639.94
Log-Likelihood	–13,311.47	–13,166.37	–11,370.95	–11,355.85.	–7239.28
R^2 (between-person level)	.00	.00	.65	.65	.87
R^2 (within-person level)	.02	.03	.27	.28	.23

(*Continued*)

Table 1 (continued)

	M1	M2	M3	M4	M5
Total: Observations	7530	7441	7409	7409	4881
Total N	2898	2876	2865	2865	2246
Adj. sig. level (between)	.041	.042	.042	.042	.068
Adj. sig. level (within)	.002	.002	.002	.002	.010

Note: Unstandardized regression coefficients, standard errors in parentheses. Random effects within-between model. Between-effects mean that differences between individuals in one variable are related to differences between individuals in another. Within-effects mean the impact of within-person change in one variable from T1 to T2 (or later periods) on within-person change in the same period. Lagged within-effects mean effects of within-person change of one variable in a given period on within-person changes in another variable in a subsequent period.

*$p <$ adjusted significance level (*between* and *within*; see two last rows of the table)

Table 2 Media Effects on Satisfaction With Life

	M1	M2	M3	M4	M5
Intercept	7.940 (0.021)*	7.925 (0.021)*	7.972 (0.023)*	8.766 (0.132)*	7.477 (0.163)*
Internet Use					
Between (H1a)	–0.010 (0.002)*	–0.008 (0.002)*	–0.005 (0.002)*	–0.005 (0.002)*	–0.004 (0.002)*
Within (H2a)	–0.005 (0.001)*	–0.003 (0.001)	–0.002 (0.001)	–0.002 (0.001)	–0.002 (0.001)
Lagged within (H3a)	0.0004 (0.001)	0.001 (0.001)	0.002 (0.001)	0.002 (0.001)	0.003 (0.001)
SNS Use					
Between (H1b)	0.018 (0.015)	0.018 (0.015)	0.022 (0.012)	0.021 (0.012)	0.018 (0.011)
Within (H2b)	–0.012 (0.010)	–0.015 (0.010)	–0.015 (0.009)	–0.008 (0.009)	–0.008 (0.010)
Lagged within (H3b)	–0.012 (0.010)	–0.016 (0.010)	–0.005 (0.009)	–0.001 (0.009)	–0.0004 (0.009)
TV Use (RQ1)					
Between		–0.014 (0.003)*	–0.012 (0.002)*	–0.012 (0.002)*	–0.010 (0.002)*
Within		–0.009 (0.002)*	–0.009 (0.002)*	–0.008 (0.002)*	–0.009 (0.002)*
Lagged within		–0.004 (0.002)	–0.005 (0.002)	–0.005 (0.002)	–0.004 (0.002)
Control Variables					
Age (in Years)			–0.016 (0.020)	–0.017 (0.020)	–0.007 (0.018)
Gender (1 = female)			0.038 (0.034)	0.037 (0.034)	0.060 (0.030)
Sat. with Friends			0.194 (0.009)*	0.194 (0.009)*	0.188 (0.009)*
Self-Esteem			0.283 (0.008)*	0.283 (0.008)*	0.262 (0.008)*
Time				–0.521 (0.082)*	–0.462 (0.085)*
Time (quadratic)				0.077 (0.012)*	0.071 (0.012)*
Lagged Satisfaction with Life (T-1)					0.145 (0.010)*
Var: Person|Intercept	0.750	0.734	0.335	0.336	0.169
AIC	25,737.82	25,396.69	23,302.98	23,278.39	23,162.48
BIC	25,800.43	25,480.02	23,413.94	23,403.23	23,294.25
Log-Likelihood	–12,859.91	–12,686.35	–11,635.49	–11,621.20	–11,562.24

(*Continued*)

Table 2 (continued)

	M1	M2	M3	M4	M5
R^2 (between-person level)	–.08	–.06	.52	.52	.76
R^2 (within-person level)	.14	.15	.24	.25	.18
Total: Observations	7756	7661	7597	7597	7594
Total N	2960	2937	2912	2912	2912
Adjusted alpha (between)	.040	.040	.041	.041	.041
Adjusted alpha (within)	.001	.002	.002	.002	.002

Note: Unstandardized regression coefficients, standard errors in parentheses. Random effects within-between model.
*$p <$ adjusted significance level (*between* and *within*; see two last rows of the table).

Based on the large sample size, we decided to adapt our alpha level using a balanced alpha-beta approach. The smallest, yet still significant effect in the literature was *beta*=.07 (Dienlin et al., 2017). We hence set r=.07 as our smallest effect size of interest (SESOI; Lakens et al., 2018). For the between-person relationship of Internet use (SNS use) and depression, such a SESOI equals an *unstandardized* effect size of $b = 0.009$ ($b = 0.007$). For the between-person relationship between Internet use (SNS use) and life satisfaction it equals $b = 0.007$ (b=.005). This implies, for example, that if a 1-hour between-person difference in Internet use per week is related to a 0.009 points between-person difference on the 10-point depression scale (or lower), we deem this effect irrelevant. To put things into perspective, a one scale point higher depression score would equal 111 hours more Internet use per week. We used the same SESOI for the within-person level (e.g., an unstandardized effect size of $b = 0.006$ for the within-person relationship between deviations in Internet use and deviations in depression). Given that we had sample sizes between 2,246 and 2,960 on the between level and 4,881 and 7,756 on the within-level, the balanced alpha and beta margins were between .040 and .042 on the between-level and .001 and .010 on the within-person level for our two-tailed hypothesis tests (see Tables 1 and 2, last two rows). We used R (Version 3.6.1; R Core Team, 2017) and the packages *lme4* (Bates, Mächler, Bolker, & Walker, 2015), and *tidyverse* (Version 1.2.1; Wickham, 2017) for the analysis.

Results

Tables 1 and 2 illustrate the results of the tests (based on the adjusted alpha levels, see last two rows in the tables) and show the impact of the control and potentially confounding variables. Looking at the change of the models (M) 1 to 5 in both tables we observe that the overall predictive power increases (i.e., larger R^2) and fit improves (e.g., decrease in Log-Likelihood). Overall, the models explained nearly 90% (76%) of the variance of depressive symptomatology (satisfaction with life) between individuals and 28% (25%) of the variance of depressive symptoms (satisfaction with life) at the within-person level. The largest part of the variance was explained by including self-esteem and satisfaction with friends (M3-M5). Specifically, higher satisfaction with friends and higher self-esteem was associated with lower depressive symptoms (Table 1, M5: b_{sat}=–0.159, $SE = 0.011$, p<.001; b_{self}=–0.445, $SE = 0.010$, p<.001) and higher satisfaction with life (Table 2, M5: b_{sat}=0.188, $SE = 0.009$, p<.001; b_{self}=0.262, $SE = 0.008$, p<.001). Boys were less likely to experience depressive symptoms (Table 1, M4: $b = 0.121$, $SE = 0.034$, p=.001). This relation however vanished once we considered the lagged-dependent variable that already captures the gender effect. The significant time trends indicate that depressive symptomatology (Table 1, M5: b=–0.910, $SE = 0.243$, p<.001) and life satisfaction (Table 2, M5: b=–0.462, $SE = 0.085$, p<.001) decreased over time. However, the quadratic time trend suggests that this decrease slowed down over time (M5 in both tables: b_{depr}=0.097, $SE = 0.030$, p=.001; b_{sat}=0.071, $SE = 0.012$, p<.001).

H1 postulated negative between-person relationships between subjective well-being and: (a) Internet use; and (b) SNS use, respectively. Inter-individual differences in Internet use were positively related to inter-individual differences in depressive symptomatology (Table 1, M4: $b = 0.005$, $SE = 0.002$, p=.009). A similar between-level relation was uncovered for satisfaction with life (Table 2, M4: b=–0.005, SE=.002, p=.001). However, both effect sizes were smaller than the postulated SESOIs. The impact of Internet use on depressive symptoms (b=.005) has only half the size of the postulated SESOI (b=.009). This effect means that a between-person difference of around 100 hours of Internet use is related to a between-person difference of less than half a scale point on the depression scale. There were only between 0.1% and 0.8% of the participants at each wave with more than 100 hours of Internet use per week in the sample. The explanatory power of Internet use was close to zero (between-person R^2, M1 & 2 in the tables). These results do not support H1a. The findings are also inconsistent with H1b since there was no between-person relation between SNS use and depressive symptoms.

H2 stated that a within-person change in the frequency of: (a) Internet; and (b) SNS use should be negatively related to intra-individual changes in subjective well-being. We found a positive within-person effect of Internet use on depression (Table 1, M1: $b = 0.005$, $SE = 0.001$, $p = .036$). Similarly, there was a negative within-person effect of Internet use on life satisfaction (Table 2, M1: $b = -0.005$, $SE = 0.001$, $p < .001$). However, these effects vanished once control variables are included. For SNS use, there were no significant within-person relations. Intra-individual changes of overall Internet use or SNS use were not related to changes in well-being. H2a and H2b are rejected.

According to H3, a higher frequency of: (a) Internet; and (b) SNS use than usual should correspond to a lower subjective well-being than usual at a later point in time (lagged within-person effect). Results in both tables indicated no lagged within-person effects of Internet use on depressive symptoms or life satisfaction. Similarly, intra-individual change of SNS use did not affect later intra-individual change of depressive symptoms or life satisfaction. Thus, H3 was not supported.

RQ1 asked whether controlling for potential confounding variables would change the effects of Internet use or SNS use on subjective well-being. First, we focus on TV use. TV use was generally unrelated to depressive symptomatology both at the between- and the within-person level (Table 1). The estimates in Table 2, however, indicate that frequency of TV viewing is negatively related to life satisfaction (between-person level effect, M5: $b = -0.010$, $SE = 0.002$, $p < .001$) and affects intra-individual changes in satisfaction with life (within-person level effect, M5: $b = -0.009$, $SE = 0.002$, $p < .001$). Thus, adolescents who watch more TV than others are also less satisfied with their life than others. Similarly, an over-time increase in frequency of TV use is positively related to over-time reduction of life satisfaction. These latter effects correspond to an increase in explained variance of 1% (within-person R^2). Yet, these effect sizes are small, albeit larger than those related to SNS or Internet use: To reduce life satisfaction by one scale point adolescents would need to watch more than 100 hours more TV per week. The share of adolescents watching more than 100 hours of TV in the past week was below 0.01%. The inclusion of frequency of TV use finally reduced the coefficients of Internet and SNS use most of the time, in some cases to non-significance, i.e., the within-person effect of Internet use on depression (Table 1, M1 & M2 compared) or on lift satisfaction (Table 2, M1 & M2 compared). Next, we examine to what extent self-esteem and satisfaction with friends—the variables that explained most variance—affect the impact of Internet and SNS use on well-being. A comparison of M3 and 4 in both tables demonstrates that the between- and within-effects of Internet and SNS use on subjective well-being remain unchanged once self-esteem and satisfaction with friends are included in the model. Thus, these variables do not act as confounders.

Discussion

The present study demonstrates that the frequency of Internet use in general or SNS use in particular is neither harmful nor beneficial to the subjective well-being of adolescents in the long run. Although some statistically significant results were obtained, the effect sizes were generally too small to represent a substantial impact. The results relating to between-level effects align with findings from other large-scale studies (Orben & Przybylski, 2019) and are also consistent with recent meta-analytical research concluding that observed correlations between SNS use and well-being are too small to suggest any substantial detrimental effects (e.g., Appel et al., 2020). The findings on within-person effects likewise replicate results from other longitudinal studies (Ferguson et al., 2014; Orben et al., 2019). Changes in overall Internet use or SNS use are not related to concurrent or subsequent changes in adolescents' well-being once potentially confounding variables are considered. These results demonstrate that there are no harmful and no beneficial long-term average effects of frequency of Internet or SNS use on adolescents' well-being or change thereof.

It is also important to consider the results for TV use in this context. They are striking for two reasons: First, in line with previous studies (Booker et al., 2015) the present study shows that changes in TV use were related to a reduction in satisfaction with life, but, inconsistently with previous research (Primack et al., 2009), change in TV use was not related to change of depressive symptoms. Despite the relatively added explanatory power of this effect (approximately 1%), this indicates that detrimental effects of generalized electronic media use can be captured by the rather coarse-grained measures that were used in the present data set. Second, controlling frequency of TV use affected the effects of Internet and SNS use. Thus, not considering frequency of TV use would have resulted in an omission bias, i.e., an overestimation of other effects. Yet, this would not have changed the conclusions of the present study because most effects are below the postulated SESOI. In previous studies with smaller samples, this omission bias may have been more consequential since smaller sample sizes produce less precise estimates which are then more vulnerable to bias. Therefore, studies focusing on the impact of Internet or SNS use also need to consider other forms of media use. The same holds true for other potential confounders, e.g., self-esteem or satisfaction with friends that are important predictors of our criterion variables (Dumont & Provost, 1999; Shortt & Spence, 2006).

Taken together, the present evidence goes beyond findings from previous research because the results jointly: (a) generalize to longer periods of time; (b) are truly representative of the population of adolescents; (c) are robust against the influence of potentially confounding variables; (d) converge for two important indicators of subjective well-being; and (e) present a showcase for the distinction of between- and within-effects. First, the present study covers a period of nine years with five measurement occasions and the findings inform us on how general Internet use and SNS use affect individuals through the whole process of adolescence. Most previous longitudinal studies examined periods of two years or less, and were based on three of fewer measurement occasions. Therefore, previous studies give only snapshots of a longer ongoing process in which frequency of Internet and SNS use can affect subjective well-being. Discovering beneficial or harmful effects of Internet or SNS use in snapshot-studies cannot be generalized to longer periods that are not observed. Second, the present findings generalize to the population of adolescents since the data come from a probability sample of adolescents in Germany. Previous studies relied on non-probability samples or convenience samples. Therefore, it is unclear to what populations findings from these studies can be generalized. Third, we emphasized the role of potentially confounding variables that other studies may have overlooked. Including the level of TV viewing into our equations allows putting the results for Internet use and SNS use into perspective. We demonstrated that media-related confounders, i.e., frequency of TV use, played a role, but the effects were too small to be of practical relevance. Self-esteem and satisfaction with friends were important determinants of subjective well-being. However, these variables did not act as confounders, i.e., their inclusion did not meaningfully change the effects of Internet and SNS use on subjective well-being. Fourth, the null-effects that were found were similar for depressive symptomatology and satisfaction with life as two important indicators of subjective well-being that are widely used in previous research. This correspondence of results lends credence to the robustness of the findings.

Finally, it is important to disentangle between-effects of media use from within-effects. Although in the present case we found neither, there may be instances where this distinction can become important. Most longitudinal studies to date that demonstrate detrimental or beneficial effects of SNS use on subjective well-being fail to disentangle between- from within-effects. This distinction is important because these effects have different meanings and change the interpretation of findings. Between-effects indicate that inter-individual differences in SNS use correlate with inter-individual differences in well-being while within-effects point to correlated change of both variables. Discovering only between-effects would prompt researchers to infer that there is a correlation of SNS use and subjective well-being, but this is insufficient evidence that the former caused the latter. The same holds true for within-effects that indicate that both variables change concurrently. From lagged within-effects researchers may infer temporal precedence in change, a necessary indication of causality. The distinction of between- and within-effects can also inspire theorizing since it forces researchers to be more specific in the formulation of hypotheses.

Limitations

Several limitations should be acknowledged when interpreting the results. The first refers to the measurement of media use. As a secondary analysis, the present study had to rely on a rather coarse-grained self-report measurement of Internet, SNS, and TV use. This comes at the price of potential issues in terms of validity and reliability. For instance, individuals are generally not very good at estimating the frequency of their media use (Scharkow, 2016), which may result in under- or overestimation. Recent research suggests that closed-ended questions result in more accurate responses as compared to open-ended questions (Ernala, Burke, Leavitt, & Ellison, 2020). If this is true, then the measure of SNS use in the present study should be more precise than the assessment of weekly hours spent using the Internet and TV which might have been an alternative way of measuring use. A comparison with previous research shows that studies using similar single-items measures with similar test–retest reliability (range of correlations between adjacent measurement occasions ranged from r=.311–.437 for Internet use and r=.344–.548 for SNS use in the present study) found effects of SNS or Internet use on subjective well-being in some cases (Kraut et al., 1998; Schmuck et al., 2019), but not in others (Kraut et al., 2002; Scherr et al., 2019). Therefore, it is unlikely that the present findings on media effects are due to the specific measurement of media use. It should be noted that test–retest reliability is problematic in a variable that is subject to true change—while test–retest reliability interprets instability as a sign of lack of reliability, it may very well result from substantial change that is measured reliably. Still, we are convinced that the use of more fine-grained and more reliable measures of media use results in more precise estimates of media effects on subjective well-being (Huang, 2010). In terms of validity, the use of these measures also prevented us from examining the effects of specific Internet applications or specific functions, e.g., active or passive use. For instance, we do not know how many participants engaged in active or passive use, compared upwards or downwards, or received positive or negative feedback while using SNS. Therefore, we were unable to undertake a fine-grained analysis of the effects of specific applications, specific content that the survey participants were exposed to, or the processes that are conducive to the effects observed in this study. If, however, individuals engage in harmful use of electronic media that have more long-lasting effects, then even general measures of media use should capture a portion of this form of media use and help reveal negative outcomes for subjective well-being. Future research should consider ways to overcome these limitations of self-reported media use by exploring the potential to log individuals' media use and combine digital trace data with self-reported media use to check validity and increase the precision of estimates.

Second, the study covered a period of nine years, but assessed media use only on five measurement occasions. Thus, the present study design with an inter-panel interval of two years cannot uncover short-term effects that occurred within these intervals, but vanished prior to the subsequent wave. Since other studies with inter-panel intervals of six (Ferguson et al., 2014) or 12 months (Scherr et al., 2019) did not find effects of SNS use on subjective well-being, but studies looking at shorter periods did (14 days in the study by Kross et al., 2013, 3 months in Schmuck et al., 2019), it seems advisable to design longitudinal studies that incorporate measures with short periods repeated over periods with longer temporal spacing. For instance, in measurement burst designs (Stawski, MacDonald, & Sliwinski, 2015), researchers can combine experience sampling and classic survey research at fixed intervals. This can also help specify how long media applications take to exert causal effects on well-being. Without knowing the answer to that question, the choice of measurement intervals in longitudinal survey studies will remain arbitrary.

Finally, this study only deals with net or average effects of Internet use or SNS use on adolescents' well-being. The absence of meaningful average or net effect of Internet or SNS use on subjective well-being in the present study does not mean that there are no vulnerable sub-groups in the population that may have experienced adverse outcomes that go unnoticed in an analysis of net effects. Additionally, since we did not study the impact of specific applications, the present study cannot uncover potentially detrimental effects that are offset by positive effects due to the use of features that support individuals' subjective well-being.

Conclusion

In light of the present findings as well as the limitations of this research, we conclude that identifying the exact ways how the use of electronic media impacts adolescents' life is far more challenging than current (primarily cross-sectional, but also longitudinal) analyses suggest (also see, Whitlock & Masur, 2019). First, since average effects seem to be very small, researchers should investigate potentially vulnerable sub-groups of the population who are most likely to suffer from harmful electronic media use (e.g., individuals with extant familial or social problems, low-self-esteem). Second, future research should consider the many different facets of Internet use that could be harmful to subjective well-being, such as IM (Van den Eijnden & Meerkerk, 2008), or Internet communication with strangers (Valkenburg & Peter, 2007) and that these negative effects can be offset by the use of application that support subjective well-being (e.g., receive positive feedback, engage in identity exploration, or stay in touch with close friends; de Vries & Kühne, 2015; Haferkamp & Krämer, 2011). Third, scholars should consider potential confounding variables, among them other forms of media use, but also personality-related and social influence confounding variables. Fourth, researchers should be specific about between- and within-effects of media technology use both in theorizing as well as in statistical modeling. Finally, the timing of measurement should enable future research to examine short-term situational effects that can occur within days or weeks. Future studies should thereby aim to identify contextual (e.g., where, with whom, under what circumstances) and situational factors (e.g., current mood, motivations, goals, duration of exposure) that could substantially shape the ways in which Internet and particularly SNS use affect adolescents' well-being and thereby estimate the longevity of such effects and potential long-term benefits or harms over months or years.

Supporting information

The following supporting information is available for this article:

Table S1. Zero-Order Correlations.

Table S2. Means and Standard Deviations of all Variables.

Additional Supporting Information may be found in the online version of this article.

Acknowledgements

This article uses data from the German Family Panel pairfam, coordinated by Josef Brüderl, Karsten Hank, Johannes Huinink, Bernhard Nauck, Franz Neyer, and Sabine Walper. pairfam is funded as a long-term project by the German Research Foundation (DFG). More information about the study and access to the data can be found here: https://www.pairfam.de/.

Note

1. An OSF page provides analysis scripts (R code) and additional analyses: https://osf.io/fdp39/.
2. The sample size is decreasing over time due to attrition (see Table S2: https://osf.io/cgs8h/) and varies because individuals could skip an interview in one year, but participated again in later waves. We included all participants to bolster test power and precision of estimates. Considering only complete cases for all five panel waves (N=1,224) does not change the findings, but estimates become less precise, i.e., have larger standard errors.
3. In our study, the share of adolescents with a profile on SNS developed as follows: 2008: 85.3%; 2010: 87.1%; 2012: 89.0%; 2014: 87.7%; 2016: 85.1%. The present study does not assess the use of specific SNS platforms, but asks whether SNS are used at all. Other studies show that the platforms that participants used changed over time, as Facebook displaced formerly-popular SchuelerVZ (JIM, 2008, 2016). The content categories that adolescents actually use on SNS have remained remarkably stable (JIM, 2008, 2016).
4. The models were built stepwise to be transparent about the change in results as a function of model complexity. The inclusion of lagged dependent is controversial: Some argue they could bias estimates of variables of interest (e.g., Vaisey & Miles, 2017); others scholars advocate for including lagged dependent variables (e.g., Curran & Bollen, 2001). In response to this controversy, we decided to add the lagged dependent variable in the last step to avoid the danger of "polluting" all models with biased estimates while still exploring whether the model proves robust. The coefficients relevant for our hypotheses are not affected or only reduced in size, e.g., self-esteem, satisfaction with friends. The addition of the lagged dependent variable reduces the explanatory power of stable individual-difference variables such as gender, because the lagged dependent variable captures this effect.

References

Appel, M., Marker, C., & Gnambs, T. (2020). Are social media ruining our lives? A review of meta-analytic evidence. *Review of General Psychology, 24(1), 60–74.* doi: 10.1177/1089268019880891

Bates, D., Mächler, M., Bolker, B., & Walker, S. (2015). Fitting linear mixed-effects models using lme4. *Journal of Statistical Software*, 67(1), 1–48. doi:10.18637/jss.v067.i01

Bell, A., Fairbrother, M., & Jones, K. (2019). Fixed and random effects models: Making an informed choice. *Quality & Quantity*, 53, 1051–1074. doi:10.1007/s11135-018-0802-x

Bessière, K., Kiesler, S., Kraut, R., & Boneva, B. S. (2008). Effects of Internet use and social resources on changes in depression. *Information, Communication & Society*, 11(1), 47–70. doi: 10.1080/13691180701858851

Booker, C. L., Skew, A. J., Kelly, Y. J., & Sacker, A. (2015). Medie use, sports participation and well-being in adolescence: Cross-sectional findings from the UK household longitudinal study. *American Journal of Public Heath*, 105(1), 173–179. doi:10.2105/AJPH.2013.301783

Brüderl, J., Drobnič, S., Hank, K., , Nauck, B., Neyer, F. J., Walper, S., ... , . . . Wilhelm, B. (2019). *The German Family Panel (pairfam)*. GESIS Data Archive, Cologne. ZA5678 Data file Version 10.0.0. doi:10.4232/pairfam.5678.10.0.0

Burke, M., & Kraut, R. E. (2016). The relationship between Facebook use and well-being depends on communication type and tie strength. *Journal of Computer-Mediated Communication*, 21(4), 265–281. doi:10.1111/jcc4.12162

Curran, P. J., & Bollen, K. A. (2001). The best of both worlds. Combining autoregressive and latent curve models. In L. M. Collings & A. G. Sayer (Eds), *New methods for the analysis of change* (pp. 107–135). Washington, DC: APA.

de Vries, D. A., & Kühne, R. (2015). Facebook and self-perception: Individual susceptibility to negative social comparison on Facebook. *Personality and Individual Differences*, 86, 217–221. doi: 10.1016/j.paid.2015.05.029

Diener, E. (2009). Subjective well-being. In E. Diener (Ed.), *Social indicators research series* (Vol. 37, pp. 11–58). Dordrecht, the Netherlands: Springer.

Dienlin, T., Masur, P. K., & Trepte, S. (2017). Reinforcement or displacement? The reciprocity of FtF, IM, and SNS communication and their effects on loneliness and life satisfaction. *Journal of Computer-Mediated Communication*, 22(2), 71–87. doi:10.1111/jcc4.12183

Dumont, M., & Provost, M.A. (1999). Resilience in adolescents: Protective role of social support, coping strategies, self-esteem, and social activities on experience of stress and depression. *Journal of Youth and Adolescence*, 28(3), 343–363. doi:10.1023/A:1021637011732

Eid, M., & Diener, E. (2004). Global judgments of subjective well-being: Situational variability and long-term stability. *Social Indicators Research*, 65(3), 245–277. doi:10.1023/B: SOCI.0000003801.89195.bc

Ernala, S. K., Burke, M., Leavitt, A., & Ellison, N. B. (2020). *How Well Do People Report Time Spent on Facebook? An Evaluation of Established Survey Questions with Recommendations.* Proceedings of the 2020 CHI Conference on Human Factors in Computing Systems, April 2020. doi: 10.1145/3313831.3376435

Escobar-Viera, C. G., Shensa, A., Bowman, N. D., Sidani, J. E., Knight, J., James, E., & Primack, B. A. (2018). Passive and active social media use and depressive symptoms among United States Adults. *Cyberpsychology, Behavior and Social Networking*, 21(7), 437–443. doi:10.1089/cyber.2017.0668

Ferguson, C. J., Munoz, M. E., Garza, A., & Galindo, M. (2014). Concurrent and prospective analyses of peer, television and social media influences on body dissatisfaction, eating disorder symptoms and life satisfaction in adolescent girls. *Journal of Youth and Adolescence*, 43, 1–14. doi: 10.1007/s10964-012-9898-9

Haferkamp, N., & Krämer, N. C. (2011). Social comparison 2.0: Examining the effects of online profiles on social-networking sites. *Cyberpsychology, Behavior, and Social Networking*, 14(5), 309–314. doi: 10.1089/cyber.2010.0120

Huang, C. (2010). Internet use and psychological well-being: A meta-analysis. *Cyberpsychology, Behavior, and Social Networking*, 13(3), 241–249. doi:10.1089/cyber.2009.0217

Huang, C. (2017). Time spent on social network sites and psychological well-being: A meta-analysis. *Cyberpsychology, Behavior and Social Networking*, 20(6), 346–354. doi:10.1089/cyber.2016.0758

Huinink, J., Brüderl, J., Nauck, B., Walper, S., Castiglioni, L., & Feldhaus, M. (2011). Panel analysis of intimate relationships and family dynamics (pairfam): Conceptual framework and design. *Journal of Family Research*, 23(1), 77–100.

JIM (2008). *Jugend, Information, (Multi-) Media [Youth, Information, (Multi) Media].* Stuttgart, Germany: Medienpädagogischer Forschungsverbund Südwest. Retrieved from https://www.mpfs.de/fileadmin/files/Studien/JIM/2008/JIM_Studie_2008.pdf

JIM (2016). *Jugend, Information, (Multi-) Media [Youth, Information, (Multi) Media].* Stuttgart, Germany: Medienpädagogischer Forschungsverbund Südwest. Retrieved from https://www.mpfs.de/fileadmin/files/Studien/JIM/2016/JIM_Studie_2016.pdf

Krasnova, H., Wenninger, H., Widjaja, T., & Buxmann, P. (2013). *Envy on Facebook: A hidden threat to users' life satisfaction*. Paper presented at the 11th international conference on Wirtschaftsinformatik, Leipzig, Germany.

Kraut, R., Kiesler, S., Boneva, B., Cummings, J., Helgeson, V., & Crawford, A. (2002). Internet paradox revisited. *Journal of Social Issues*, 58(1), 49–74. doi:10.1111/1540-4560.00248

Kraut, R., Patterson, M., Lundmark, V., Kiesler, S., Mukopahyay, T., & Scherlis, W. (1998). Internet paradox: A social technology that reduces social involvement and psychological well-being. *American Psychologist*, 53(9), 1017–1031. doi:10.1037/0003-066X.53.9.1017

Krohne, H. W., Schmukle, S. C., Spaderna, H., & Spielberger, C. D. (2002). The state-trait depression scales: An international comparison. *Anxiety, Stress & Coping*, 15(2), 105–122. doi:10.1080/10615800290028422

Kross, E., Verduyn, P., Demiralp, E., Park, J., Lee, D. S., Lin, N., . . . Ybarra, O. (2013). Facebook use predicts declines in subjective well-being in young adults. *PLoS One*, 8(8), e69841. doi:10.1371/journal.pone.0069841

Kubey, R. W., & Csikszentmihalyi, M. (1990). *Television and the quality of life: How viewing shapes everyday experience*. Hillsdale, NJ: Lawrence Erlbaum Associates.

Lakens, D., Adolfi, F. G., Albers, C. J., Anvari, F., Apps, M. A. J., Argamon, S. E., . . . Zwaan, R. A. (2018). Justify your alpha: A response to "Redefine statistical significance". *Nature Human Behavior*, 2, 168–171. doi:10.1038/s41562-018-0311-x

Lin, L. Y., Sidani, J. E., Shensa, A., Radovic, A., Miller, E., Colditz, J. B., . . . Primack, B. (2016). Association between social media use and depression among U.S. young adults. *Depression and Anxiety*, 33, 323–331. doi:10.1002/da.22466

Liu, D., Ainsworth, S. E., & Baumeister, R. F. (2016). A meta-analysis of social networking online and social capital. *Review of General Psychology*, 20(4), 369–391. doi:10.1037/gpr0000091

Nie, N. H., Hillygus, D. S., & Erbring, L. (2002). Internet use, interpersonal relations, and sociability: A time diary study. In B. Wellman & Haythornthwaite (Eds.), *The Internet in everyday life* (pp. 215–243). Malden, MA: Blackwell.

Orben, A., Dienlin, T., & Przybylski, A. K. (2019). Social media's enduring effect on adolescent life satisfaction. *Proceedings of the National Academy of Sciences of the United States of America*, 116(21), 10226–10228. doi:10.1073/pnas.1902058116

Orben, A., & Przybylski, A. K. (2019). The association between adolescent well-being and digital technology use. *Nature Human Behavior*, 3, 173–182. doi:10.1038/s41562-018-0506-1

Primack, B. A., Swanier, B., Georgiopoulos, A. M., Land, S. R., & Fine, M. J. (2009). Association between media use in adolescence and depression in young adulthood. *Archives of General Psychiatry*, 66(2), 181–188. doi:10.1001/archgenpsychiatry.2008.532

R Core Team (2017). *R: A language and environment for statistical computing*. Retrieved from https://www.R-project.org

Reinecke, L., & Oliver, M. B. (2017). Media use and well-being: Status quo and open questions. In L. Reinecke & M. B. Oliver (Eds.), *The Routledge handbook of media use and well-being* (pp. 3–13). New York: Routledge.

Rosenberg, M. (1965). *Society and the adolescent self-image*. Princeton, NJ: Princeton University Press.

Ryff, C. D. (1989). Happiness is everything, or is it? Explorations on the meaning of psychological well-being. *Journal of Personality and Social Psychology*, 57, 1069–1081. doi:10.1037/0022-3514.57.6.1069

Scharkow, M. (2016). The accuracy of self-reported Internet use. A validation study using client log data. *Communication Methods and Measures*, 10(1), 13–27. 10.1080/19312458.2015.1118446

Scherr, S., Toma, C. L., & Schuster, B. (2019). Depression as a predictor of Facebook surveillance and envy. *Journal of Media Psychology, 31(4), 196–202*. doi:10.1027/1864-1105/a000247

Schmuck, D., Karsay, K., Matthes, J., & Stevic, A. (2019). Looking up and feeling down. The influence of mobile social networking site use on upward social comparison, self-esteem and well-being of adult smartphone users. *Telematics and informatics*, 42, 1–12. doi:10.1016/j.tele.2019.101240

Selfhout, M. H. W., Branje, S. J. T., Delsing, M., Bogt, T. F. M., & Meeus, W. H. J. (2009). Different types of Internet use, depression, and social anxiety: The role of perceived friendship quality. *Journal of Adolescence*, 32(4), 819–833. doi:10.1016/j.adolescence.2008.10.011

Seligman, M. E. P., & Csikszentmihalyi, M. (2000). Positive psychology. *American Psychologist*, 55(1), 5–14. doi:10.1037//0003-066x.55.1.5

Shortt, A. L. & Spence, S H. (2006). Risk and protective factors for depression in youth. *Behaviour Change*, 23, 1–30. doi:10.1375/bech.23.1.1

Stawski, R. S., MacDonald, S. W. S., & Sliwinski, M. J. (2015). Measurement Burst Design. In S. K. Whitbourne (Ed.), *The Encyclopedia of Adulthood and Aging*. New York: Wiley. doi:10.1002/9781118521373.wbeaa313

Steers, M.-L. N. (2015). “It’s complicated”: Facebook’s relationship with the need to belong and depression. *Current Opinion in Psychology*, 9, 22–26. doi:10.1016/j.copsyc.2015.10.007

Vaisey, S., & Miles, A. (2017). What you can—and can’t—do with three-wave panel data. *Sociological Methods & Research*, 46(1), 44–67. doi:10.1177/0049124114547769

Valkenburg, P. M., & Peter, J. (2007). Internet communication and its relation to well-being: Identifying some underlying mechanisms. *Media Psychology*, 9(1), 43–58. doi:10.1080/15213260709336802

Valkenburg, P. M., & Peter, J. (2011). Online communication among adolescents: An integrated model of its attraction, opportunities, and risks. *Journal of Adolescent Health*, 48, 121–127. doi:10.1016/j.jadohealth.2010.08.020

Valkenburg, P. M., Peter, J., & Schouten, A. P. (2006). Friend networking sites and their relationship to adolescents’ well-being and social self-esteem. *CyberPsychology & Behavior*, 9(5), 584–590. doi:10.1089/cpb.2006.9.584

Van den Eijnden, R. J. J. M., & Meerkerk, G.-J. (2008). Online communication, compulsive Internet use, and psychosocial well-being among adolescents: A longitudinal study. *Developmental Psychology*, 44(3), 655–665. doi:10.1037/0012-1649.44.3.655

Verduyn, P., Lee, D. S., Park, J., Shablack, H., Orvell, A., Bayer, J., ... Kross, E. (2015). Passive Facebook usage undermines affective well-being: Experimental and longitudinal evidence. *Journal of Experimental Psychology: General*, 144(2), 480–488. doi:10.1037/xge0000057

Whitlock, J., & Masur, P. K. (2019). Disentangling the association of screen time with developmental outcomes and well-being. Problems, challenges, and opportunities. *JAMA Pediatrics, 173(11), 1021–1022*. doi:10.1001/jamapediatrics.2019.3191

Wickham, H. (2017). Tidyverse: Easily install and load the 'tidyverse'. Retrieved from https://CRAN.R-project.org/package=tidyverse

Wooldridge, J. M. (2010). *Econometric analysis of cross section and panel data*. Cambridge, MA: MIT Press.