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Social Media Use and Adolescents' Well-Being: Developing a Typology of Person-Specific Effect Patterns

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Abstract

This study investigated the effects of active private, passive private, and passive public social media use on adolescents' affective well-being. Intensive longitudinal data (34,930 assessments in total) were collected through a preregistered three-week experience sampling method study among 387 adolescents. $N = 1$ time series were investigated, using Dynamic Structural Equation Modeling. Findings showed that different types of social media use very rarely yielded different effects within one and the same adolescent: 45% of adolescents experienced no changes in well-being due to any of the three types of social media use, 28% only experienced declines in well-being, and 26% only experienced increases in well-being. Only one adolescent experienced the theoretically expected effect pattern of a positive effect of active private and passive private use and negative effect of passive public use. Together, the findings suggest that the active–passive use dichotomy in social media research is less clear-cut than it might seem.

Keywords

DSEM, experience sampling, idiographic approach, social media, well-being

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Over the past decade, dozens of empirical studies have investigated the effect of social media on adolescents' well-being (e.g., Coyne et al., 2020; Jensen et al., 2019). Several recent reviews have attempted to organize and integrate the results of these empirical studies (e.g., Dienlin & Johannes, 2020; Orben, 2020; Verduyn et al., 2017). All of these reviews agree that there is a small positive effect of *active* social media use (typically defined as posting) and a small negative effect of *passive* social media use (typically defined as browsing) on well-being. In line with the results of these reviews, a recent experience sampling (ESM) study among adolescents confirmed the small overall positive effect of *active* social media use on well-being (Beyens et al., 2020). However, the negative effect of *passive* use on well-being only held for 10% of adolescents. The remaining adolescents either experienced a positive effect (46%) or no effect (44%) of passive social media use on well-being (Beyens et al., 2020).

The aim of the current study is to build on previous studies in three ways. First, it aims to extend previous studies by investigating the unique effects of private versus public forms of social media use. While most studies have conceptualized social media use as *public* use (e.g., posting or browsing), adolescents typically use social media in both public and private ways (van Driel et al., 2019). In this vein, researchers have pointed at the distinction between private and public forms of active social media use (e.g., Frison & Eggermont, 2020). After all, the affordances of active *private* (i.e., sending direct messages) and active *public* use (i.e., posting, broadcasting) differ in many respects. For instance, active private use is more synchronous and more intimate than active public use and typically involves more dynamic interactions (Bazarova et al., 2015; Waterloo et al., 2018). This intimate form of interpersonal communication is believed to increase one's well-being (Frison & Eggermont, 2020). Active public use, however, is more asynchronous and has a wider reach. This type of social media use is also assumed to enhance well-being (Frison & Eggermont, 2020), but occurs much less frequently than other forms of use (Frison & Eggermont, 2020; van Driel et al., 2019).

While studies have paid attention to the distinction between *active* private and public social media use (e.g., Frison & Eggermont, 2020), to our knowledge, no earlier studies have distinguished between *passive* private (i.e., reading direct messages) and public (i.e., browsing) social media use. However, it is conceivable that both types of passive use yield different or even opposite effects on well-being. In fact, the negative effects for passive use reported in earlier reviews (e.g., Verduyn et al., 2017) are due to passive *public* use, as most empirical studies focused on passive *public* use. Such use may reduce well-being, because it mainly involves browsing content of less intimate others, such as actors, influencers, and other celebrities (Frison & Eggermont, 2017). In contrast, passive *private* use may enhance well-being, because it entails communication among intimate others, such as close friends or family members (Valkenburg & Peter, 2007; van Driel et al., 2019). Therefore, the first aim of the current study is to investigate the overall within-person effects of private and public forms of social media use on adolescents' well-being.

A second extension of earlier studies is the focus on person-specific susceptibility to the effects of different types of social media use on well-being. Most earlier studies have reported across-the-board effects of social media use on well-being among groups or subgroups of adolescents (for a review, see Verduyn et al., 2017). However, both theory (Valkenburg & Peter, 2013) and empirical research (Beyens et al., 2020) suggest that the effects of social media use on well-being may differ from adolescent to adolescent. Investigating such person-specific social media effects on well-being is the second aim of this study.

A third extension of existing research is to investigate how the effects of different types of social media use co-occur within each individual adolescent. Virtually all adolescents regularly engage in different types of social media use (van Driel et al., 2019). In accordance with earlier theories and research (Verduyn et al., 2017), an adolescent may be *negatively* affected by passive public use, but *positively* affected by passive private and active private use. However, because the effects may vary from adolescent to adolescent (Beyens et al., 2020), the co-occurrence of the effects of different types of social media use may also differ from adolescent to adolescent. Some adolescents may indeed experience negative effects when engaging in passive public use and positive effects when engaging in passive and active private use. However, other adolescents may experience *positive* effects when engaging in passive public use and *negative* effects when engaging in private use, and yet other adolescents may experience only positive effects, only negative effects, or no effects at all. To unravel these within-person effect patterns, the third and final aim of the current study is to investigate how many adolescents experience a mix of positive and negative effects, and how many experience only positive effects, only negative effects, or no effects at all.

To address the three aims of this study, we conducted a three-week experience sampling (ESM) study among 387 middle adolescents. We adopted a person-specific approach to investigate the effects of active private, passive private, and passive public social media use on each individual adolescent's momentary affective well-being, defined as an adolescent's current feelings of happiness (Tov, 2018; henceforth referred to as well-being). We did not focus on active *public* social media use, such as posting a picture or sharing a story on Instagram, because the majority of adolescents do not engage in active public use frequently enough to measure it several times per day in an ESM study and to investigate its (person-specific) effects based on a three-week study (van Driel et al., 2019). To investigate the person-specific effects, we used Dynamic Structural Equation Modeling (DSEM), an advanced modeling technique that combines $N=1$ time-series modeling, multilevel modeling, and structural equation modeling (Asparouhov et al., 2018; McNeish & Hamaker, 2020).

The Effects of Social Media Use on Well-Being

Several studies have investigated whether different types of social media use have different effects on well-being. Most of these studies distinguished between active and passive social media use (for recent reviews, see for example Dienlin & Johannes, 2020; Orben, 2020; Verduyn et al., 2017). Some other studies used a more nuanced distinction, for example between private and public forms of *active* social media use. For instance, Frison and Eggermont (2020) distinguished between active *private* (i.e., sending private messages on Facebook) and active *public* Facebook use (i.e., posting on one's own Facebook feed) in addition to passive Facebook use (i.e., browsing through others' Facebook feed). Among a sample of Belgian adolescents, they found that *passive* Facebook use was indirectly associated with *lower* levels of well-being (i.e., increased depressed mood) 6 months later, whereas active private and active public Facebook use were indirectly associated with *higher* levels of well-being (i.e., decreased depressed mood).

While distinguishing between the effects of active private and active public social media use is an important extension of the literature, a recent survey among Dutch adolescents also recommends distinguishing between *passive* public and *passive* private social media use (van Driel et al., 2019). To date, studies that found a negative association between passive use and well-being operationalized passive use as browsing (e.g., Frison & Eggermont, 2020; Verduyn et al., 2015). While browsing, which can be considered passive *public* use, is indeed one of the most popular passive social media activities among adolescents, passive *private* use is at least as popular (van Driel et al., 2019; Weinstein, 2018). For instance, van Driel et al. (2019) found that 72% of Dutch adolescents reported to engage in passive *public* use on a daily basis (i.e., browsing through Instagram posts of others), whereas 90% reported to engage in passive *private* use daily (i.e., reading WhatsApp messages of others).

Distinguishing between passive *public* and passive *private* social media use is also theoretically warranted, because the two types of social media use may yield different or even opposite effects on well-being. Overall, evidence shows that passive use, often implicitly or explicitly defined as passive *public* use, has a negative effect on well-being (Dienlin & Johannes, 2020; Verduyn et al., 2017). This negative effect has been explained by the positivity bias on social media, that is, the tendency to share more positive than negative information on social media (Waterloo et al., 2018). Because, according to social comparison theory (Festinger, 1954), people tend to compare themselves with others, and passive social media use often leads to upward social comparison (Hu & Liu, 2020), this positivity bias is believed to elicit envy and reduce well-being (Verduyn et al., 2017).

However, the negative effect of passive public use may not hold for passive private and active private use. While public social media use typically involves asynchronous interactions, private social media use is typically more synchronous and dynamic, which may result in a stronger sense of belonging and relatedness (Hall, 2018; Steele et al., 2020). In addition, private social media use generally encourages more "honest" interactions than public social media use, such that it is more normative to share both positive and negative emotions in private use than in public use (Waterloo et al., 2018). This enhanced sharing of positive and negative emotions may bring more connectedness among both passive private and active private users (Valkenburg & Peter, 2009), which may, in turn, enhance adolescents' well-being (Verduyn et al., 2017). Altogether, investigating the differential effects of active private, passive private, and passive public social media use on well-being seems both relevant and opportune. We predict the following overall within-person effects:

H1: The time adolescents spend using social media in an *active private* way positively affects their momentary well-being.
H2: The time adolescents spend using social media in a *passive private* way positively affects their momentary well-being.
H3: The time adolescents spend using social media in a *passive public* way negatively affects their momentary well-being.

The Person-Specific Effects of Social Media Use on Well-Being

Besides investigating the overall differential effects of active private, passive private, and passive public social media use on adolescents' well-being, the current study investigates potential differences in adolescents' susceptibility to the effects of social media. Media effects theories and models such as the Differential Susceptibility to Media Effects Model (DSMM; Valkenburg & Peter, 2013) posit that each adolescent has a unique susceptibility to the effects of social media. While social media use may enhance some adolescents' well-being, it may undermine others' well-being, and it may not affect yet others' well-being.

To investigate the assumption that each adolescent may be affected by social media in a unique way, a person-specific media effects approach is warranted (Odgers & Jensen, 2020). Such person-specific or idiographic approach (Molenaar, 2004; Molenaar & Campbell, 2009) estimates the effects of social media on each *individual* adolescent's well-being, and goes beyond estimating one overall effect that is assumed to apply to *all* adolescents (i.e., nomothetic approach) or specific *groups* of adolescents (i.e., group-differential approach). Hence, in line with the propositions of the DSMM (Valkenburg & Peter, 2013) and the assumptions of person-specific media effects, we hypothesize:

H4: The effects of active private, passive private, and passive public social media use on momentary well-being differ from adolescent to adolescent.

Person-Specific Social Media Effect Patterns

To truly understand the differential effects of active private, passive private, and passive public social media use on adolescents' well-being, we need to understand how these effects co-occur within the same individual. After all, since active private, passive private, and passive public social media use may yield different or even opposite effects on well-being, it is likely that an adolescent experiences positive as well as negative effects, depending on the type of use. By gaining insight into the person-specific effect patterns, we will be able to understand for each single adolescent what type of social media use elicits positive effects on his/her well-being, what type elicits negative effects, and what type elicits no effects. Such insights will help clarify whether different types of social media use yield different effects, as theory suggests.

An important question that then arises is whether there are subgroups of adolescents whose well-being is affected by social media in comparable ways. The study by

Beyens et al. (2020) found that one group of adolescents experienced a positive effect of passive social media use on well-being, another group a negative effect, and yet another group no effects. However, these groups were distinguished based on adolescents' differential susceptibility to *one* type of social media use. Since most adolescents engage in active private, passive private, as well as passive public social media use (van Driel et al., 2019), the picture may be more complex. Therefore, we will explore how many adolescents experience a mix of positive and negative effects, and how many experience only positive effects, only negative effects, or no effects at all. Hence, we posit the following question:

> *RQ1*: How do the effects of active private, passive private, and passive public social media use on momentary well-being co-occur within single adolescents?

Method

The current preregistered study is part of a larger longitudinal project that examines the psychosocial consequences of social media use among adolescents. The larger project comprises a measurement burst design (Nesselroade, 1991), which combines longitudinal data obtained at closely spaced intervals (e.g., hours, days) and longitudinal data obtained at widely spaced intervals (e.g., months, years). The design and sampling plan of the project were preregistered at the Open Science Framework (OSF; https://osf.io/327cx/) prior to data collection. The hypotheses and analysis plan of the current study were preregistered prior to analyzing the data (https://osf.io/692h7/). The current study uses data from the first measurement burst of the project, obtained through a three-week experience sampling method (ESM) study conducted in December 2019.

Participants

Participants were recruited from a secondary school (grades 8 and 9) in the Netherlands to participate in the larger project. In total, 387 middle adolescents (M_{age} = 14.11, SD = 0.69; 54% girls) participated in the first ESM wave of the project. All participants and their parents provided active consent to participate. Most participants (96%) self-identified as Dutch and were born in the Netherlands. Participants were enrolled in different educational levels: 44% in prevocational secondary education, 31% in intermediate general secondary education, and 26% in academic preparatory education. The sample was representative of adolescents in the south of the Netherlands in terms of educational level, sex, and ethnic background (Statistics Netherlands, 2020). In addition, the sample's social media habits were comparable to the habits found in a national survey study among Dutch adolescents (van Driel et al., 2019). A priori power analyses using Monte Carlo simulations in Mplus for sample size estimation (see https://osf.io/ar4vm/) indicated that a sample size of 300 participants would be sufficient to reliably detect small effects and variance around these effects with a minimum power of 80% and significance level of .05. As a result, with 387 participants, the study was sufficiently powered.

Procedure

The project was approved by the Ethics Review Board of the Faculty of Social and Behavioral Sciences at the University of Amsterdam. The study procedure, sampling scheme, and ESM measures were successfully pilot tested (see Beyens et al., 2020). One week before the start of the ESM study, participants participated in a baseline session at school during school hours and completed a baseline survey. Upon completion of the baseline survey, participants were provided with instructions for completing the ESM study and installed the ESM software application (Ethica Data) on their own mobile phone. After installing the software, participants completed a set of questions to try out the ESM application and to indicate which social media they used more than once a week. Responses to the latter question were used to select the social media about which adolescents received questions in the ESM surveys.

During the three-week ESM study, six 2-minute surveys per day were sent to each participant. As such, each participant received a total of 126 ESM surveys (21 days × 6 surveys per day). The number of ESM surveys was determined based on the recommendation to aim for a minimum of 50 to 100 assessments per participant to be able to conduct $N=1$ analyses (Chatfield, 2016; Voelkle et al., 2012). To account for potential low compliance, we took a more conservative approach and scheduled for a total of 126 ESM surveys per participant. Altogether, a total of 48,762 ESM surveys were sent (i.e., 387 participants × 126 surveys). A small proportion of these surveys (<2%) was not received by participants, due to unforeseen technical issues within the ESM software. Of the 47,900 surveys that participants received, participants completed 34,930 surveys. This resulted in a net compliance rate of 73%, which is good compared with previous ESM studies among adolescents (van Roekel et al., 2019). On average, participants completed 90.26 ESM surveys each ($SD=23.84$; range 10–124; $Mdn=95$), with 93% of participants completing at least 50 surveys. Thus, the requirement to conduct $N=1$ analyses was met.

The ESM surveys were sent to each participant's mobile phone at random time points within fixed intervals. The sampling scheme was tailored to the school's schedule and participants' weekday and weekend routines, so that participants did not receive surveys during class hours and while sleeping in on the weekends. The notification scheme with an overview of all ESM survey notifications is available at OSF (https://osf.io/tbdjq/). A beep prompt on their mobile phone notified participants when a new survey was available. Five to ten minutes later, an automatic reminder was sent if participants had not yet completed the survey. A 30-minute response window was provided to complete each survey. This time window was extended to 1 hour for the first survey (morning) and 2 hours for the final survey (evening) of the day to account for travel time to school and time spent on evening activities, respectively.

Each ESM survey consisted of 23 questions, which assessed participants' social media use and well-being, along with other concepts included in the larger project. The first and last ESM survey of each day contained 24 questions. The questions about social media use were tailored to each participant's own social media use, based on the responses provided during the baseline session. Each participant received questions about three social media platforms. A participant received questions about the time spent using Instagram, WhatsApp, and Snapchat if the participant had indicated in the baseline session that s/he used these platforms more than once a week. If a participant did not use any of these platforms more than once a week, s/he received questions about YouTube and/or gaming. If a participant did not use YouTube or did not game either, s/he received alternative questions. This procedure was designed to ensure that each participant received the same number of questions. A total of 375 (97%) participants received questions about WhatsApp, 345 participants (89%) about Instagram, and 285 (74%) about Snapchat.

During the three-week ESM period, researchers monitored participant compliance to encourage participants to complete as many ESM surveys as possible and to check whether any assistance was needed with technical or other issues. Adolescents received a small gadget for participating in the baseline session and a compensation of €0.30 for completing an ESM survey, with a maximum compensation of €37.80 for completing all ESM surveys. In addition, each day, all participants who had completed all six ESM surveys the day before were entered into a raffle to receive one of four €25 cash prizes.

Measures

Social media use. To measure adolescents' social media use, we developed the ESM Social Media Use Questionnaire (E-SMUQ), generated explicitly for ESM studies. The E-SMUQ consists of ten items that each measure the amount of time spent using a particular social media platform in a specific way (see Appendix A). Based on a national survey among Dutch 14- and 15-year-olds (van Driel et al., 2019), we selected the three most frequently used social media platforms: Instagram, WhatsApp, and Snapchat. Next, we selected the most popular activities on these platforms, taking into account the feasibility of each activity to be measured in an ESM study. That is, the activity had to be performed frequently enough to be measured multiple times per day, allowing for sufficient within-person variance. Therefore, an activity was selected if at least one third of adolescents performed the activity at least daily. This resulted in a list of ten different activities across the three different platforms.

In each ESM survey, participants were asked to indicate how much time in the past hour they had spent on each of the ten social media activities. Response options ranged from 0 to 60 minutes, with 1-minute intervals. The current study used the active private, passive private, and passive public subscales of the E-SMUQ: "How much time in the past hour have you spent sending direct messages on Instagram," "sending snaps on Snapchat," and "sending messages on WhatsApp" (active private use); "reading direct messages on Instagram," "viewing snaps of others on Snapchat," and "reading messages on WhatsApp" (passive private use); and "viewing posts/stories of others on Instagram" and "viewing stories of others on Snapchat" (passive public use). The passive public subscale comprises Instagram and Snapchat, but not WhatsApp, because the passive public component of WhatsApp (WhatsApp Status) is hardly being used. Active public use (e.g., time spent posting a picture or story on Instagram) was not included in the E-SMUQ, because adolescents do not engage in this behavior frequently enough to assess it multiple times per day (van Driel et al., 2019). For each subscale, the items were summed. Sum scores exceeding 60 minutes (i.e., less than 2.5% of all occasions per subscale) were recoded to 60 minutes.

Well-being. We measured momentary affective well-being using one item. In each ESM survey, adolescents were asked to respond to the question "How happy do you feel right now?" using a 7-point scale ranging from 0 (*not at all*) to 6 (*completely*), with 3 (*a little*) as the midpoint. This single-item instrument has been reliably used in previous ESM studies and has high convergent validity, as indicated by the strong associations with positive and negative affect (see Beyens et al., 2020).

Statistical Analyses

Following the preregistered plan of analysis (https://osf.io/692h7/), we investigated the within-person effects of active private (H1), passive private (H2), and passive public (H3) social media use and between-person differences (i.e., variance) in these effects (H4) by means of Dynamic Structural Equation Modeling (DSEM) for intensive longitudinal data in Mplus Version 8.4 (Asparouhov et al., 2018). DSEM combines $N=1$ time-series modeling, multilevel modeling, and structural equation modeling (Asparouhov et al., 2018; McNeish & Hamaker, 2020). $N=1$ time-series modeling allows to investigate the effects of the three types of social media use on well-being for a single individual, and includes the lagged (i.e., autoregressive) effects, such that an individual's well-being is not only regressed on his/her social media use, but also on his/her well-being at the previous measurement occasion. This way, the effects can be interpreted as within-person *changes* in well-being due to social media use. In addition, the DSEM analyses automatically control for all time-invariant third variables (e.g., socio-demographics) by design. The multilevel part of DSEM allows to simultaneously model the time series of multiple individuals while allowing to investigate between-person differences in the time series.

We estimated three two-level autoregressive lag-1 models with well-being as the outcome and active private (Model 1), passive private (Model 2), and passive public (Model 3) social media use as the predictor. In each model, at the within-person level (level 1), we specified social media use as the time-varying covariate (i.e., predictor; to investigate H1-H3) and the autoregressive effect of well-being (i.e., well-being predicted by lag-1 well-being). Latent person-mean centering was used to center the variables. At the between-person level (level 2), we included the latent person-mean level of well-being, the latent person-mean of active private (Model 1), passive private (Model 2), and passive public (Model 3) social media use, and the correlation between these mean levels, as well as the between-person variance around the within-person effect of active private (Model 1), passive private (Model 2), and passive public (Model 3) social media use on well-being (i.e., random within-person effect of social media use on well-being; to investigate H4) and the between-person variance around the autoregressive effect (i.e., random autoregressive effect). Correlations between all random factors were included in the models to obtain more stable estimates.

Before estimating the models, we tested the required assumption of stationarity, by investigating whether the mean of well-being did not systematically change over the course of the study (McNeish & Hamaker, 2020). To that end, we compared a two-level fixed effect model including day of the study as predictor of well-being with an intercept-only model (i.e., a model with a random intercept for well-being, but without predictors). The assumption of stationarity was confirmed, since day of the study explained only 0.2% of the within-person variance in well-being.

We followed our preregistered plan of analysis (https://osf.io/692h7/) to run the DSEM models. By default, DSEM uses Bayesian Markov Chain Monte Carlo (MCMC) for model estimation. We ran each DSEM model with a minimum of 5,000 iterations and default maximum of 50,000 iterations of the MCMC algorithm, and 2-hour time intervals. Before interpreting the estimates, we checked whether the model converged, following the procedure of Hamaker et al. (2018). Model convergence is considered successful when the Potential Scale Reduction (PSR) values are very close to 1 (Gelman & Rubin, 1992) and the trace plots for each parameter do not contain trends, spikes, or other irregularities (i.e., they should look like fat caterpillars). We interpreted the parameter estimates with the Bayesian credible intervals (CIs), as well as the Bayesian *p*-values. If the 95% CIs for the within-person effects of social media use on well-being (within-level; H1-H3) do not include 0, the effects can be considered to be significantly different from 0.

We interpreted the effect sizes by assessing the standardized effects (STDYX standardization). Following the guidelines of Adachi and Willoughby (2015) for interpreting effects in longitudinal autoregressive models, we considered an effect size of $\beta = .05$ as the smallest effect size of interest (SESOI; Lakens et al., 2018). A recent meta-review on the effects of social media on well-being indicates that an effect size of $\beta = .05$ reflects the effect sizes reported in the literature (Meier & Reinecke, 2020). We considered all effects smaller than the SESOI as non-existent to very small effects ($-.05 < \beta < .05$), all effects with a size of $\beta \geq .05$ as positive effects, and all effects with a size of $\beta \leq -.05$ as negative effects.

To investigate the co-occurrence of the person-specific social media effects within each adolescent (RQ1), we looked at each adolescent's person-specific effect for active private, passive private, and passive public social media use. Adolescents were considered to experience (1) no effects when all three types of use yielded non-existent or very small effects; (2) negative effects when all three types yielded negative effects, or when one or two types yielded negative effects while the other type(s) yielded no effects; (3) positive effects when all three types yielded positive effects, or when one or two types yielded positive effects while the other type(s) yielded no effects; and (4) mixed effects when at least two types of use yielded opposite effects (i.e., positive and negative effects).

Data Availability

The anonymous data set underlying this study is available in Figshare at https://doi.org/10.21942/uva.14557902. The analysis scripts and materials belonging to this article are available at OSF (https://osf.io/nf32w/).

Table 1. Descriptive Statistics and Within-Person, Between-Person, and Intraclass Correlations for All Study Variables.

	1	2	3	4
1. Affective Well-Being	—	−.01	−.01	−.01*
2. Active Private Social Media Use	−.11*	—	.87***	.67***
3. Passive Private Social Media Use	−.12*	.99***	—	.71***
4. Passive Public Social Media Use	−.11*	.93***	.94***	—
M	4.46	7.61	8.43	6.71
SD	1.06	9.39	9.30	7.89
Range	0–6	0–60	0–60	0–60
ICC	.46	.50	.48	.46

Note. Mean scores for social media use reflect the average number of minutes spent using social media in the past hour. Correlations below the diagonal line represent between-person correlations, correlations above the diagonal line represent within-person correlations. ICC = intraclass correlation.
*p <.05. **p <.01. ***p <.001.

Results

Descriptive Statistics and Correlations

Table 1 presents the means, standard deviations, and the within-person, between-person, and intraclass correlations (ICCs) for well-being and the time spent using social media in an active private, passive private, and passive public way. The average level of well-being was high (M=4.46, SD=1.06). Most participants used social media in an active private (99%), passive private (99%), as well as passive public way (91%). On average, participants had spent almost 8 minutes using social media in an active private way in the hour before each measurement occasion, 8 minutes in a passive private way, and 7 minutes in a passive public way.

The ICCs indicated that (almost) half of the variance in well-being (46%), active private (50%), passive private (48%), and passive public (46%) social media use was explained by differences between adolescents (i.e., between-person variance). These ICCs confirm that the sampling scheme of six ESM surveys per day was appropriate for capturing within-person fluctuations in well-being and in the different types of social media use, and that the measures had sufficient within-person variance to conduct DSEM analyses.

At the between-person level, all three types of social media use were significantly negatively associated with well-being. This indicates that adolescents who spent more time (over the three-week period) than their peers using social media in an active private, passive private, or passive public way felt worse than their peers. The within-person correlations between social media use and well-being were very close to zero for all three types of use (r=−.01). Thus, on average, adolescents' momentary levels of well-being were unrelated to the time they had spent on each of the three types of social media use in the hour before.

Active private, passive private, and passive public social media use were strongly correlated at the between-person level ($r \geq .93$). This indicates that adolescents who spent more time (over the three-week period) on one type of social media use than other adolescents, also spent more time on the other two types of social media use. The different types of social media use were also strongly correlated at the within-person level ($r \geq .67$). This indicates that the more time an adolescent had spent on one type of social media use at a certain moment, the more time s/he had also spent on the other two types of social media use at that moment.

The Associations of Social Media Use With Well-Being

Table 2 presents the results of the DSEM analyses with well-being as outcome and active private (Model 1), passive private (Model 2), and passive public (Model 3) social media use as predictors. All three DSEM models converged well and before 5,000 iterations: The Potential Scale Reduction (PSR) convergence criteria were all very close to 1 (PSR = 1.007; 1.011; and 1.011, respectively), the density plots looked smooth, and the trace plots did not contain trends, spikes, or other irregularities. After doubling the number of iterations (to 10,000 iterations) to exclude the possibility that the PSR values were close to 1 by chance (i.e., premature stoppage problem; Schultzberg & Muthén, 2018), the PSR values were still very close to 1 (PSR = 1.003; 1.002; and 1.004, respectively). The results corresponded to those of the models with 5,000 iterations.

The Between-Person Associations of Social Media Use With Well-Being

In addition to testing the preregistered hypotheses regarding the within-person effects of the three types of social media use on well-being (H1-H3; see below), we assessed the between-person associations of each type of social media use with well-being. All three types of use were negatively associated with well-being at the between-person level (see Table 2). This indicates that adolescents who had spent more time than their peers (across the three-week ESM study) using social media in an active private ($\beta = -.118$), passive private ($\beta = -.122$), or passive public ($\beta = -.122$) way, reported lower levels of well-being than their peers.

The Average Within-Person Effects of Social Media Use on Well-Being

Our first hypothesis (H1) predicted that *active private* social media use would have an overall positive within-person effect on well-being. The hypothesis was not supported, as the average within-person effect was not significant ($\beta = -.002$; see Model 1 in Table 2). Our second hypothesis (H2) predicted that *passive private* social media use would have an overall positive within-person effect on well-being. Again, despite sufficient statistical power, the hypothesis was not supported ($\beta = -.002$; see Model 2 in Table 2). Finally, our third hypothesis (H3) predicted that *passive public* social media use would have an overall negative within-person effect on well-being. Again, the

Table 2. DSEM Estimates and 95% Bayesian Credible Intervals for the Within-Person Effects, Between-Person Associations, Random Effects, and Variances of the Time Spent Using Social Media (SMU) in an Active Private, Passive Private, and Passive Public Way, and Affective Well-Being (AWB).

	Active Private SMU Model 1				Passive Private SMU Model 2				Passive Public SMU Model 3			
	B	β	*p*	95% CI	*B*	β	*p*	95% CI	*B*	β	*p*	95% CI
Within-Person Effects												
SMU → AWB [H1/2/3; beta] beta]	−0.001	−.002	.435	[−.020, .015]	−0.002	−.002	.405	[−.019, .013]	−0.007	−.004	.326	[−.022, .014]
AWB (t-1) → AWB (t)	0.274	.274	.000	[.260, .288]	0.273	.273	.000	[.259, .287]	0.275	.275	.000	[.261, .289]
Between-Person Associations												
SMU & AWB	−0.117	−.118	.013	[−.215, −.015]	−0.120	−.122	.011	[−.218, −.018]	−0.102	−.122	.015	[−.229, −.013]
SMU & beta[a]	−0.005	−.039	.297	[−.184, .107]	−0.007	−.059	.213	[−.207, .090]	−0.003	−.020	.393	[−.162, .119]
AWB & beta[a]	−0.029	−.200	.010	[−.346, −.040]	−0.031	−.246	.002	[−.396, −.086]	−0.035	−.205	.027	[−.369, .002]
	σ^2		*p*	95% CI	σ^2		*p*	95% CI	σ^2		*p*	95% CI
Random Effects												
SMU → AWB [H4][b]	0.019		.000	[0.012, 0.029]	0.014		.000	[0.009, 0.024]	0.027		.000	[0.015, .041]
AWB (t-1) → AWB (t)	0.051		.000	[0.042, 0.061]	0.051		.000	[0.042, 0.062]	0.050		.000	[0.042, .061]
Other Variances												
SMU (within-person)	0.858		.000	[0.846, 0.871]	0.920		.000	[0.907, 0.934]	0.716		.000	[0.705, 0.727]
SMU (between-person)	0.891		.000	[0.775, 1.035]	0.874		.000	[0.761, 1.015]	0.631		.000	[0.543, 0.737]
AWB (within-person)	1.081		.000	[1.064, 1.097]	1.082		.000	[1.065, 1.099]	1.077		.000	[1.061, 1.094]
AWB (between-person)	1.116		.000	[0.965, 1.300]	1.116		.000	[0.966, 1.301]	1.118		.000	[0.966, 1.299]

Note. SMU = social media use; AWB = affective well-being; βs are standardized using the STDYX Standardization in Mplus. *p*-values are one-tailed Bayesian *p*-values (see McNeish & Hamaker, 2020).

[a]beta reflects the within-person effect of active private (H1; Model 1), passive private (H2; Model 2), and passive public (H3; Model 3) social media use on affective well-being. The between-person associations between SMU & beta and AWB & beta reflect the extent to which the within-person effect of active private (Model 1), passive private (Model 2), and passive public (Model 3) social media use on affective well-being depends on adolescents' average level of social media use (SMU & beta) and on adolescents' average level of affective well-being (AWB & beta). [b]The random within-person effect of social media use on affective well-being (H4) reflects the between-person variance around the within-person effect of active private (Model 1), passive private (Model 2), and passive public (Model 3) social media use on affective well-being.

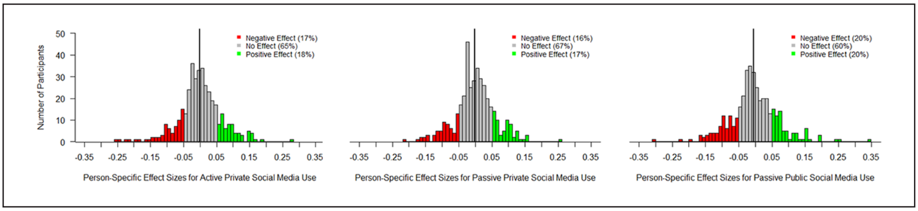

Figure 1. Distribution of the Person-Specific Standardized Effect Sizes Across the Sample for the Effects of Active Private, Passive Private, and Passive Public Social Media Use on Affective Well-Being.

Note. Standardized effect sizes are displayed on the *x*-axes, number of participants are displayed on the *y*-axes. The left panel shows the distribution of the person-specific effect sizes of active private social media use on affective well-being (range: $\beta = -.253$ to $\beta = +0.275$). The middle panel shows the distribution of the person-specific effect sizes of passive private social media use on affective well-being (range: $\beta = -.218$ to $\beta = +.256$). The right panel shows the distribution of the person-specific effect sizes of passive public social media use on affective well-being (range: $\beta = -.301$ to $\beta = +.348$). Vertical black lines represent the average of the person-specific effects (i.e., overall within-person effect: $\beta = -.002$ for active private use; $\beta = -.002$ for passive private use; and $\beta = -.004$ for passive public use).

hypothesis was not supported ($\beta = -.004$; see Model 3 in Table 2). Altogether, the findings indicate that, on average, the time adolescents spent using social media in an active private (H1), passive private (H2), or passive public (H3) way in the previous hour did not affect their momentary well-being.

The Person-Specific Effects of Social Media Use on Well-Being

Hypothesis 4 (H4) predicted that the within-person effects of active private, passive private, and passive public social media use on well-being would differ from adolescent to adolescent. This hypothesis was supported for all three types of social media use, as indicated by the significant random effects (see Table 2; random effects: $\sigma^2 = 0.019$ for active private, $\sigma^2 = 0.014$ for passive private, and $\sigma^2 = 0.027$ for passive public use). This means that there was significant variance across participants in the extent to which their social media use predicted changes in well-being. Figure 1 illustrates this heterogeneity, by showing the distribution of the person-specific standardized effect sizes across the sample for the effects of active private, passive private, and passive public social media use on well-being.

As Figure 1 shows, the effect sizes ranged from $\beta = -.253$ to $\beta = +.275$ for active private use, from $\beta = -.218$ to $\beta = +.256$ for passive private use, and from $\beta = -.301$ to $\beta = +.348$ for passive public use. Among 65% of participants, active private social media use had no or very small positive or negative effects on well-being ($-.05 < \beta < .05$). Among 18% of participants active private use had positive effects ($\beta \geq .05$), whereas among another 17% it had negative effects ($\beta \leq -.05$). Similar percentages were found for passive private (67% no effect; 17% positive effect; 16% negative effect) and passive public (60% no effect; 20% positive effect; 20% negative effect) social media use.

A Typology of Person-Specific Social Media Effects

Our research question (RQ1) asked how the effects of active private, passive private, and passive public social media use on momentary well-being would co-occur within each adolescent. We found that the person-specific effects of active private and passive private use ($r = .89$), passive private and passive public use ($r = .77$), and active private and passive public use ($r = .72$) were strongly correlated. Based on the co-occurrence of the effects of active private, passive private, and passive public social media use on well-being within each adolescent, we identified four groups (see Table 3). A first group, including 45% of participants, did not experience any effect of social media use on their well-being, irrespective of the type of use. A second group, consisting of 28% of participants, only experienced negative effects. Most adolescents in this group experienced a decline in well-being due to all three types of social media use. A third group, encompassing 26% of adolescents, only experienced positive effects of social media use on well-being. Most of them benefited from all three types of social media use. Finally, a fourth group constituted a cluster of only three adolescents (1%). They all experienced a combination of both positive and negative effects, depending on the type of social media use. The theoretically expected effect pattern of a positive effect of active private and passive private use and a negative effect of passive public use was found for only one participant (0.3%).

Figure 2 displays three $N = 1$ time-series plots for the effects of active private, passive private, and passive public social media use on well-being: One time-series plot for a negatively affected adolescent, one for a positively affected adolescent, and one for the adolescent who experienced all three hypothesized effects. All three time series show that adolescents' well-being regularly co-fluctuated with the time spent using social media in an active private, passive private, and passive public way. However, substantial differences exist: The well-being of the negatively affected adolescent regularly *decreased* when his/her active private, passive private, or passive public social media use *increased*, and vice versa. In contrast, the well-being of the positively affected adolescent regularly *increased* when his/her active private, passive private, or passive public social media use *increased*, and vice versa. And the well-being of the adolescent who experienced a mix of effects *increased* when his/her active private or passive private social media use *increased*, and vice versa, but *decreased* when his/her passive public social media use *increased*, and vice versa.

Sensitivity Analyses

As preregistered, we conducted three sets of sensitivity analyses to examine the robustness of the results. An overview of the sensitivity analyses and results can be found in Appendix B. All results remained virtually unchanged.

Exploratory Analyses

In addition to investigating the hypothesized within-person effects of active private, passive private, and passive public social media use on well-being (H1–H3)

Table 3. Effect Pattern Groups Based on the Person-Specific Effects of Active Private, Passive Private, and Passive Public Social Media Use on Affective Well-Being.

	Active Private SMU	*Passive Private SMU*	*Passive Public SMU*	n	%	*% Girls*	*Affective Well-Being M (SD)*	*Active Private SMU M (SD)*	*Passive Private SMU M (SD)*	*Passive Public SMU M (SD)*
No Effects	0	0	0	**175**	**45.22**	52.57	4.52 (1.02)	8.50 (10.70)	9.34 (10.63)	7.55 (9.00)
Negative Effects				**109**	**28.17**	61.47	4.36 (1.07)	7.12 (8.63)	8.08 (8.38)	6.20 (7.11)
	−	−	−	33	8.53					
	−	−	0	16	4.13					
	−	0	−	7	1.81					
	−	0	0	10	2.58					
	0	−	−	5	1.29					
	0	0	−	30	7.75					
	0	−	0	8	2.07					
Positive Effects				**100**	**25.84**	47.00	4.47 (1.10)	6.49 (7.55)	7.18 (7.58)	5.77 (6.50)
	+	+	+	43	11.11					
	+	+	0	12	3.10					
	+	0	+	3	0.78					
	+	0	0	9	2.33					
	0	+	+	5	1.29					
	0	0	+	25	6.46					
	0	+	0	3	0.78					
Mixed Effects				**3**	**0.78**	66.67	4.74 (1.74)	9.71 (5.01)	10.02 (6.41)	6.10 (4.49)
	+	+	−*	1	0.26					
	+	0	−	1	0.26					
	−	+	−	1	0.26					
Total				**387**	**100**	54	4.46 (1.06)	7.61 (9.39)	8.43 (9.30)	6.71 (7.89)

Note. SMU = social media use; 0 = no effect; + = positive effect; − = negative effect; *The theoretically assumed effect pattern.

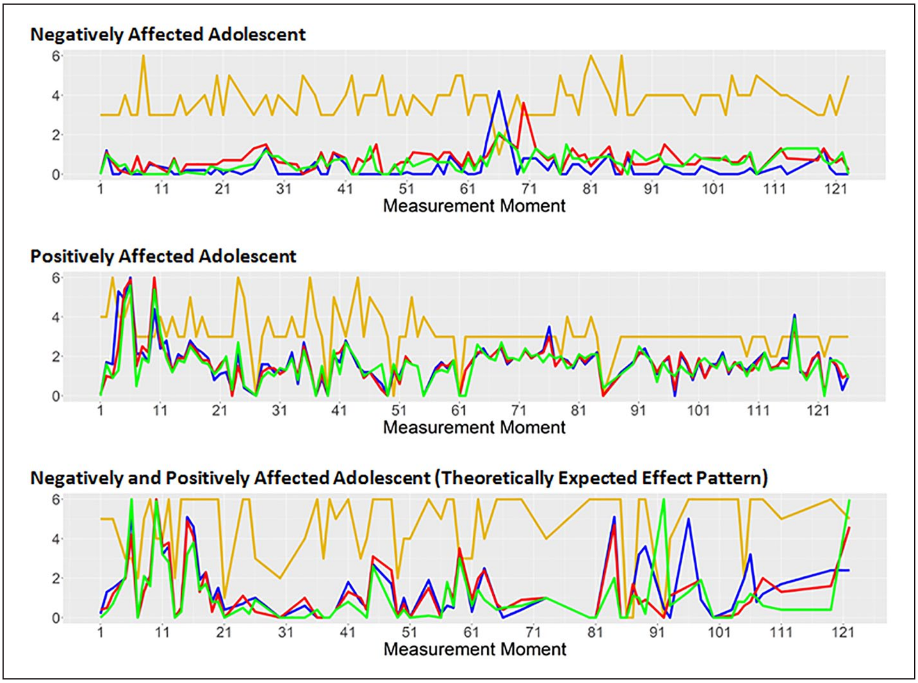

Figure 2. $N=1$ Time Series for the Effects of Active Private, Passive Private, and Passive Public Social Media Use on Affective Well-Being for a Negatively Affected Adolescent, a Positively Affected Adolescent, and an Adolescent Who Experienced Both Negative and Positive Effects.

Note. Measurement moments are displayed on the *x*-axes (range 1–126). The time spent using social media in an active private (blue lines), passive private (red lines), and passive public (green lines) way (0 = *0 minutes* to 6 = *60 minutes*), and state affective well-being (yellow lines; 0 = *not happy at all* to 6 = *completely happy*) are displayed on the *y*-axes. The top time-series plot belongs to an adolescent who experienced negative effects. The middle time-series plot belongs to an adolescent who experienced positive effects. The bottom time-series plot belongs to an adolescent who experienced the theoretically expected positive effect of active and passive private use and negative effect of passive public use.

and between-person differences in these effects (H4), we explored whether the effects differed according to adolescents' mean level of active private, passive private, and passive public social media use and mean level of well-being. As shown in Table 2, the cross-level interactions of adolescents' mean level of each of the three types of social media use with the within-person effect were not significant. However, the within-person effect of each type of social media use on well-being varied according to adolescents' mean level of well-being. Adolescents with lower mean levels of well-being tended to respond with stronger increases in their momentary well-being when they spent more time using social media in an active private, passive private, or passive public way than adolescents with higher mean levels of well-being.

Discussion

The current study investigated the effects of active private, passive private, and passive public social media use on adolescents' affective well-being, using intensive longitudinal data of a three-week experience sampling study (34,930 assessments). Based on theory and previous empirical studies, we assumed that different types of social media use would lead to different effects. Specifically, we hypothesized that active and passive private use (i.e., sending and reading direct messages) would enhance adolescents' well-being (H1-H2), whereas passive public use (i.e., browsing) would undermine adolescents' well-being (H3). These hypotheses were not confirmed: None of the overall (within-person) effects of the three types of social media use were significant. On average, sending or reading direct messages or browsing through others' social media posts did not affect adolescents' well-being.

However, in support of H4, the (within-person) effects of all three types of use differed from adolescent to adolescent. The theoretically assumed positive effect for active private social media use held for only 18% of adolescents. For the other 82%, the effect did not match expectation: 65% of adolescents experienced no or very small effects and 17% experienced an effect opposite of theoretical expectation, that is, a *negative* effect. Likewise, the theoretically assumed positive effect for passive private social media use was only confirmed for 17% of adolescents. Most adolescents did not match expectation, as 67% of adolescents experienced no effect and 16% experienced an effect opposite of expectation. Additionally, the expected negative effect of passive public social media use was found for only 20% of adolescents, while another 20% experienced an opposite effect, and 60% experienced no effect.

While differences exist between adolescents in the extent to which their well-being changes due to their active private, passive private, and passive public social media use, differences *within* adolescents in how different types of social media use affect them are exceptional. Looking at the co-occurrence of the effects of active private, passive private, and passive public social media use within each single adolescent (RQ1), our study showed that an adolescent either experienced positive, negative, or no effects when sending or reading private messages as well as when browsing through others' content. In fact, a large group of adolescents (45%) did not experience any effects: None of the three types of social media use led to changes in their well-being. Another group of adolescents (28%) only experienced negative effects, whereas a group of similar size (26%) only experienced positive effects. Only a very small group (1%) experienced both positive and negative effects.

Different Adolescents, Different Effects

There are at least three potential explanations as to why different adolescents experience different effects of social media use on well-being. First, how adolescents respond to social media may differ. For instance, private social media use may enhance relational closeness and connectedness among those who experience positive effects. However, among those who experience negative effects, private use may create feelings of disconnection, insecurity about peer relationships, social approval anxiety and distress about others' reactions, as well as availability stress (Steele et al., 2020). And while passive public use may undermine some adolescents' well-being, for instance because they feel worse off than others, it may enhance other adolescents' well-being, for instance because it leads to inspiration (Meier et al., 2020; Weinstein, 2018).

A second explanation for adolescents' differential susceptibility to the effects of social media may be that different adolescents send, receive, or browse through different content. Adolescents who experience negative effects due to passive public use may browse through posts that contain more idealized content (e.g., unrealistic appearance ideals) than the posts that are viewed by adolescents who experience positive effects. And adolescents who experience positive effects may browse, share, and receive more positive content (e.g., funny posts, memes). Likewise, the private interactions of adolescents who experience negative effects may be more negative than those of adolescents who experience positive effects. These private interactions may mirror adolescents' offline peer relationships. According to the poor-get-poorer and rich-get-richer hypotheses (Kraut et al., 2002), adolescents who have low-quality offline relationships may also have low-quality social media interactions, and, consequently, they may become unhappier, whereas adolescents with high-quality offline relationships may have more high-quality private social media exchanges and therefore become happier. Research is needed that investigates whether between-person differences in the effects of active private, passive private, and passive public social media use on adolescents' well-being can be explained by differences in what adolescents send, receive, and browse through on social media. Therefore, there is a dire need for studies that focus on the content of adolescents' social media use, for instance by tracking such content.

A third explanation for the between-person differences in susceptibility may be that adolescents' motivations for using social media differ. For instance, passive public use may not only comprise mindless browsing, but also intentional, interest-driven browsing (Trieu & Ellison, 2018). Although both types of browsing can be considered passive public use, their implications for adolescents' well-being may differ. For instance, adolescents who browse others' posts intentionally, driven by social interest (e.g., to learn more about their peers), may use this information to connect and interact with others, which may improve their connectedness with others and enhance their well-being. For adolescents who do not have such motivations, but who engage in mindless browsing, reading or watching others' posts may elicit insecurities, which may undermine their well-being. Research is needed that investigates adolescents' motivations behind social media browsing, in order to understand whether certain types of browsing enhance adolescents' well-being, whereas other types undermine their well-being.

Same Adolescent, Same Effects

Based on theory and previous studies, we assumed that active and passive private use would have a *positive* effect on adolescents' well-being, whereas passive public use would have a *negative* effect. However, this pattern of effects held for only one adolescent. In fact, positive and negative effects co-occurred very rarely within the same adolescent, as only three participants experienced such opposite effects. Instead, browsing through others' content, sending private messages, and reading private messages all seemed to have similar effects on an adolescent's well-being. In fact, we found that almost half of the adolescents did not experience any effect at all due to the three types of use, whereas the other half consistently experienced either positive or negative effects.

Several explanations for this homogeneity of effects are conceivable. First, there might be certain traits that predict whether an adolescent experiences either positive, negative, or no effects of using social media, irrespective of whether it involves active private, passive private, or passive public use. Perhaps certain adolescents, such as those with low self-esteem, have a negativity bias for how they look at the world, attaching more weight to negative than positive experiences (Rozin & Royzman, 2001). These adolescents may have a more negative approach towards social media, developing insecurities and envy rather than inspiration, and seeking, consuming, and posting more negative content, and receiving more negative feedback from others (Ehrenreich & Underwood, 2016; Rideout & Robb, 2018).

A second explanation as to why there were almost no mixed effects patterns in the sample may be that the theoretical distinction between active and passive use cannot be empirically verified, at least not among adolescents. As our study showed, active private, passive private, and passive public social media use were all strongly correlated within adolescents. Active and passive private social media use in particular were highly correlated and had very similar effects on well-being. This is not surprising, since private social media use is a highly dynamic process, involving two-way interactions between sender and receiver, such that active private use (i.e., sending messages) likely elicits passive private use (i.e., receiving messages), and vice versa. Overall, the findings indicate that the active–passive use dichotomy may be an artificial distinction that does not provide a comprehensive picture of adolescents' actual patterns of social media use.

Similarly, the extremely high between-person correlations between the three types of social media use suggest that the distinction between active and passive use may have little value. Given these strong intercorrelations, it is not surprising that we found almost equally sized (negative) between-person associations of the three types of social media use with well-being. Adolescents who spent more time using social media than their peers felt unhappier than their peers, no matter whether it concerned active private, passive private, or passive public use. Altogether, the findings of the current study show that different types of social media use are related to an adolescent's well-being in very similar ways. These findings point at the need to move beyond the distinction between active and passive social media use and further refine the measurement of different types of social media use, as suggested by other scholars (e.g., Ellison et al., 2020).

Comparing Within- and Between-Person Associations

While adolescents who spent more time using social media than their peers reported lower levels of well-being than their peers (i.e., significant between-person associations), on average, adolescents' momentary well-being did not change as they spent more time using social media (i.e., nonsignificant average within-person associations). Although this may seem contradictory at first, it is important to realize that between-person (or group-level) associations are not necessarily generalizable or comparable to within-person (or individual-level) associations. Only when processes at the group level and individual level are ergodic (i.e., when the sample is homogenous and stationary), statistical findings at the group level generalize to the individual level (Molenaar, 2004; Molenaar & Campbell, 2009). However, in the social sciences, processes are very rarely ergodic, as individuals differ from each other and change over time (Howard & Hoffman, 2018; Schmiedek & Dirk, 2015). Therefore, it is not surprising that the within-person effects of social media use on well-being found in the current study are different than the between-person associations between social media use and well-being. Overall, the findings highlight the importance of disentangling within-person from between-person associations in media effects research and investigating media effects at the individual level.

Avenues for Future Research

An important question is why for so many adolescents their social media use does not lead to changes in well-being. While it is possible that social media use does not affect these adolescents' well-being at all, such conclusion may be premature. At least for some adolescents, the null effects may have resulted from a combination of increases and decreases in well-being, which likely cancel each other out. Although our study found that only very few adolescents experienced both positive and negative effects, it is possible that those who do not experience any effects also experience a mix of positive and negative effects, even from the same type of use. For instance, it is possible that browsing an Instagram feed elicits envy and undermines an adolescent's well-being at one moment, while it leads to inspiration and enhances that adolescent's well-being the next moment. Such pattern of positive and negative effects may ultimately result in an overall null effect.

Qualitative evidence indeed shows that adolescents have both positive and negative experiences when using social media. Even though the current study found that if adolescents experience any changes in well-being, these are either positive or negative, it is likely that adolescents experience both social media-induced ups and downs in their well-being. For instance, as illustrated in the time-series plot for the positively affected adolescent (see Figure 2), an adolescent who in general experiences positive effects of social media may, at least sometimes, also experience negative effects. To further understand the co-occurrence of positive and negative effects within one and the same adolescent, research is needed that investigates when social media use elicits positive effects, when negative effects, and when no effects within a single adolescent.

For a complete understanding of the effects of different types of social media use on well-being and a more comprehensive typology of person-specific effect patterns, studies should also investigate the effect of active public use, in addition to the effects of active private, passive private, and passive public use. However, it is doubtful whether this would meaningfully advance our understanding because, as previously suggested, the active versus passive use distinction is less clear-cut than it might seem, and not least because adolescents much less frequently engage in active public use than in other forms of use (Frison & Eggermont, 2020; van Driel et al., 2019). Since adolescents engage in active public use only about one to three times a month, on average (Frison & Eggermont, 2020), studies that aim to investigate its (person-specific) effects would have to follow adolescents across multiple months.

Another avenue for future research is to investigate the long-term consequences of different types of social media use for adolescents' well-being. Although our study did not provide evidence for differential within-person effects in the short term, it is possible that such evidence can be found in the long term. In addition, the question remains how the short-term effects develop at the long term, and whether adolescents who become (un)happier in the short term when they spend more time using social media, also become (un)happier in the long term. For instance, since short-term effects do not necessarily translate into identical long-term effects (Frijns et al., 2020; Keijsers & van Roekel, 2019), an adolescent who experiences immediate negative effects on his/her well-being may not necessarily develop long-term negative effects.

In addition, given the rapid developmental changes in adolescence, adolescents' susceptibility to the effects of social media may change over time. For instance, it is possible that some adolescents experienced negative effects in the past but learned to cope with these experiences and no longer experience effects or even positive effects. Conversely, it is possible that adolescents who did not experience changes in their well-being due to their social media use may become (more) susceptible to experience negative or positive effects in the future. This is quite likely, since adolescents' social media use may change over time (e.g., the content, the people they interact with), as well as contextual factors (e.g., important life events, breaking-up of friendships). A crucial next step for future research is to examine the long-term consequences of the short-term effects of social media use on adolescents' well-being, and to investigate why some adolescents may ultimately benefit from using social media, why others may suffer from using social media, and, equally important, why yet others are unaffected by using social media.

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Supplemental Material

Supplemental material for this article is available online.

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