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Bidirectional Associations Between Smartphone Usage and Momentary Well-Being in Young Adults: Tackling Methodological Challenges by Combining Experience Sampling Methods With Passive Smartphone Data

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Given the pervasive role of smartphones in modern life, research into their impact on well-being has flourished. This study addresses existing methodological shortcomings using smartphone log data and experience sampling methods (ESM) to explore the bidirectional within-person relationship between smartphone usage and momentary well-being variables (i.e., affect valence, loneliness, positive affect, and negative affect). We further examine different categories of smartphone usage, namely, communication, social media, and other apps. We analyze three samples ($N_1 = 225$, $N_2 = 17$, $N_3 = 13$; with $T_1 = 7{,}874$, $T_2 = 2{,}566$, $T_3 = 1{,}533$ ESM reports) with multilevel models to test our preregistered hypotheses. Data for Sample I were collected in Spain in 2022 (82% female; $M_{\text{age}} = 23.1$). Samples II and III (80% female; $M_{\text{age}} = 21.6$) were collected in the Netherlands between 2021 and 2022. Our results suggest that smartphone usage within an hour before ESM assessment, especially using social media apps, is associated with reduced affect valence and increased loneliness on a within-person level. Loneliness was associated with more smartphone usage than usual, particularly the use of social media apps, within the hour following ESM assessments. However, overall, our findings indicate weak bidirectional associations between smartphone usage and indicators of momentary well-being (range standardized β = .00–.08). On the between-person level, those individuals generally high in loneliness were more affected in their momentary loneliness by prior social media use, suggesting a heightened social media sensitivity. The interplay between social media use and momentary loneliness should be studied in more detail, including contextual factors and experimental designs.

Keywords: smartphone usage, well-being, digital trace data, ecological momentary assessment, social media

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Recent years have seen a significant increase in the use of smartphones, which have become an indispensable part of daily life for many people (e.g., Vanden Abeele et al., 2018). The widespread use of smartphones in everyday life has led to a growing body of research examining the effects of smartphone usage on various aspects of human behavior and well-being (e.g., Bayer et al., 2023; Große Deters & Schoedel, 2024; Marciano et al., 2022; Roos & Wrzus, 2023; Ross & Campbell, 2021; Schenkel et al., 2024; Vahedi & Saiphoo, 2018).

While there has been much scholarly debate about the positive and negative psychological effects of frequent smartphone usage (Orben & Przybylski, 2019; Twenge, 2020), it remains unclear to what extent the time spent on the smartphone is predictive of (decreased) well-being given the current state of mixed findings (i.e., some studies report negative effects, while others show no effect; Große Deters & Schoedel, 2024; Krämer et al., 2024; Lin & Lachman, 2021; Marciano et al., 2022; Orben, 2020). Much of this debate has been focused on four method-related aspects that require further attention in the process of understanding how smartphone usage affects well-being: (a) how to measure smartphone usage, (b) how to measure immediate changes in well-being (directly after smartphone usage), (c) the directionality of effects, and (d) the content of smartphone usage (see also Bradley & Howard, 2023; Krämer et al., 2024; Kushlev & Leitao, 2020; Parry et al., 2022). We address these methodological challenges by combining experience sampling methods (ESM) with passive smartphone data, which enable us to examine bidirectional associations between objective smartphone usage and momentary well-being.

How to Measure Smartphone Usage

Previous research mainly used self-reported measures of smartphone usage duration (e.g., "How much time in the past hour have you spent reading/writing messages on WhatsApp?"; Pouwels et al., 2021) and frequency (e.g., "How often do you check social media apps?" from "never" to "all the time"; Marty-Dugas & Smilek, 2020). These measures may be subject to memory- and judgment-related biases (Trull & Ebner-Priemer, 2014; Wrzus & Mehl, 2015). As such, participants are often inaccurate in their self-estimations of smartphone or internet use (for a recent meta-analysis, see Parry et al., 2021). Additionally, relying only on self-report data for key study variables may lead to inflated estimates of effect sizes due to common method bias (Podsakoff et al., 2003): If self-reported ratings about the predictor (smartphone usage) and outcome (well-being) come from the same person, the measurement errors may be systematically correlated (e.g., due to desirability biases) and thus can lead to an overestimation of the statistical association.

A better way of examining the association between smartphone usage and well-being is to deploy a multimethod approach in which common method biases are reduced, and smartphone usage is assessed via passive sensing methods (i.e., smartphone log data). Smartphone log data have the advantage that they are more objective than participants' self-report of smartphone usage (Ellis et al., 2019; Parry et al., 2021). In addition, smartphone log data allow us to match the objective information on how the smartphone was used to the timing of momentary well-being measures.

How to Measure Immediate Changes in Well-Being

A second method-related aspect is the widespread use of global measures of well-being (e.g., a satisfaction with life scale; Horwood & Anglim, 2019). Global well-being measures may not capture individuals' experiences as they go about their daily lives (e.g., Kahneman et al., 2004; Valkenburg, 2022). More beneficial would be to study the level of *momentary* well-being immediately after the use of the smartphone to get a direct estimate of the short-term effects of smartphone usage. While the study of long-term media effects is worthwhile (e.g., Shehata et al., 2021), our study focuses on the short-term effects (Potter, 2011): If the underlying theoretical process is that there is a moment-to-moment relationship between smartphone use and well-being (Vanden Abeele, 2021), we need to examine momentary well-being right after smartphone use. ESM are ideal to study these short-term patterns in daily life settings.

ESM involve frequently collecting self-reported data on individuals' experiences and behaviors in daily life settings (Trull & Ebner-Priemer, 2014), thus providing a detailed and nuanced picture of individuals' emotional states. Because these data are collected repeatedly, they can capture fluctuations and changes in well-being that may be missed by global measures of well-being.

Using ESM, we can thus measure the immediate affective responses to smartphone usage. By collecting fine-grained smartphone log data and momentary well-being with ESM, there is no delay between the measure of smartphone usage (via smartphone log data) and the measure of well-being outcomes, which can provide a better understanding of the short-term temporal relations between the two.

Repeated observations of smartphone usage and momentary well-being further allow us to differentiate between within- and between-person effects (Bolger & Laurenceau, 2013). Within-person effects capture how an individual's *own* responses vary over time, while between-person effects capture how individuals differ from each other in their average responses. In the context of this study, within-person effects would reflect how an individual's smartphone usage and momentary well-being fluctuate within the same person, while between-person effects would reflect how individuals differ in their average smartphone usage and momentary well-being across the whole study period (Bolger & Laurenceau, 2013). For example, a negative within-person effect of smartphone usage on momentary well-being would indicate that momentary well-being is lower after a period in which a participant uses the smartphone more than usual (i.e., comparing smartphone usage to one's own mean smartphone usage). Examining within-person effects, in which we compare measures with how the *same* participant usually behaves, can help us better understand the underlying microlevel processes of the relationship between smartphone usage and momentary well-being (Krämer et al., 2024; Lin & Lachman, 2021). The three studies that investigate the association between the duration of smartphone usage and momentary well-being on a within-person level show mixed evidence for the presence of such effects. First, Große Deters and Schoedel (2024) reported no significant within-person associations between smartphone use and ESM-based well-being measures in a general adult population sample. Second, Krämer et al. (2024) showed in an exploratory analysis of an adult sample that the duration of communication app usage was related to negative affect on a within-person level, but not to positive affect. Moreover, social media app use was not associated with positive or negative affect on a within-person level. Third, the study by Marciano et al. (2022) suggested that prior-day smartphone use is positively associated with well-being on current day in an adolescent sample. Our analyses aim to extend these findings to the population of young adults, who are particularly strongly affected by the omnipresence of the smartphone and increased levels of negative well-being markers, such as loneliness (Bayer et al., 2023; Nicolaisen & Thorsen, 2014; Trepte et al., 2018).

Directionality of Effects

A third aspect is the predominant use of unidirectional analysis strategies in existing research, in which only the effect of smartphone use on well-being is examined (i.e., media effects), but not how well-being is associated with subsequent smartphone use (i.e., media selection effects). Such a differentiation is not possible with cross-sectional designs, which are frequently used in studies on smartphone usage and indicators of well-being (e.g., Horwood & Anglim, 2019; Marty-Dugas & Smilek, 2020; Orben & Przybylski, 2019; Wolniewicz et al., 2018). Although, in recent years, it has become more common to deploy longitudinal designs to investigate the relationship between smartphone use and well-being (e.g., Große Deters & Schoedel, 2024; Kroencke et al., 2023; Vaid et al., 2024), only Marciano et al. (2022) had examined the association bidirectionally in daily life. However, due to sampling momentary well-being only once in the evening, their data do not capture the fine-grained changes in momentary well-being that happen during a day. Hence, the potential *bidirectional* nature of the relationship between smartphone usage and momentary well-being has not been fully examined, and it is still unclear whether smartphone usage is an antecedent or consequence of (lower) well-being (Parry et al., 2022).

Uses and gratifications theory (Katz et al., 1973; Ruggiero, 2000) has been extensively used to investigate the benefits individuals obtain from engaging with different media (i.e., media effects) and the motivations behind engaging with media (i.e., media selection effects). According to uses and gratifications theory, psychological and social needs drive the gratifications individuals seek through media consumption, for instance, in the context of smartphone usage. This approach distinguishes between gratifications sought, which motivate specific uses of smartphone, and gratifications obtained, which evaluate whether using the smartphone successfully satisfied the individuals' needs. While theoretical mechanisms about the media effects of smartphone use on well-being have been frequently discussed (e.g., Kushlev & Leitao, 2020), media selection effects—the effects of well-being on smartphone use—have received less theoretical and empirical attention.

A theory that may help to explain media selection effects specifically is mood management theory (Knobloch-Westerwick, 2006; Zillmann, 1988). According to mood management theory, individuals consciously and subconsciously select media content, including smartphone apps, that aligns with their desired mood states. For example, during periods of elevated negative affect or loneliness, individuals may turn to social media platforms on their smartphones to seek social connection and alleviate negative emotions. Existing research, indeed, suggests that when people are feeling lonely, anxious, or bored, they may turn to their smartphones as a way of avoiding facing these negative emotions (Elhai et al., 2016) or coping with the situation with distraction (Siebers et al., 2022; Stevic & Matthes, 2023; Wolfers & Utz, 2022). In turn, one might feel guilty for having procrastinated using the smartphone, which may lead to more negative emotions (Meier, 2022).

These two processes together potentially create a feedback loop, where increased smartphone usage leads to negative emotional states, which in turn may lead to more smartphone usage (Aalbers et al., 2022). Over time, this can become a habitual pattern of behavior that is difficult to break (Ross & Campbell, 2021). By understanding the bidirectional mechanisms between smartphone usage and momentary measures of well-being, it is possible to identify whether there is a feedback loop mechanism, which may help provide information about mechanisms to promote healthy smartphone usage and well-being (Vanden Abeele, 2021).

Content of Smartphone Usage

It has been suggested that the specific activities individuals engage in on their smartphones, rather than the total duration of usage, may be crucial in understanding the relationship between smartphone usage and well-being (e.g., Bradley & Howard, 2023; Büchi, 2021). For example, calling a friend for emotional support and scrolling through Instagram represent two distinct behaviors, each likely having different effects on momentary well-being. Despite these differences, research on smartphone usage and momentary well-being has not yet focused extensively on specific smartphone activities. To our knowledge, only the study by Krämer et al. (2024) addressed this gap, concluding from an exploratory analysis that using communication apps is associated with subsequently higher levels of negative affect at the within-person level.

To examine specific smartphone usage behaviors in more detail, we separately examine three categories of smartphone apps: communication, social media, and other. In addition to the general smartphone usage, we thus examine whether the amount of time spent on communication apps versus social media apps versus all other apps is differently related to subsequent momentary well-being and whether momentary well-being indicators differently predict the time spent on these categories of apps.

The Present Study

In this study, we investigate the bidirectional relationship between smartphone usage and momentary well-being by taking a multimethod approach in which smartphone usage is assessed via passively collected smartphone log data and momentary well-being is measured using ESM questionnaires multiple times per day. Momentary well-being is assessed via a range of constructs (i.e., affect valence, loneliness, positive affect, and negative affect). While most studies on this topic focus on general well-being measures or affect, we additionally examine loneliness, further reflecting a feeling that is related to social experiences (Peplau & Perlman, 1982). We specifically examine two sets of preregistered hypotheses (Open Science Framework [OSF] preregistration form[1]: https://osf.io/w5kx6; Elmer, Fernández, et al., 2023). The first hypothesis concerns media effects and examines within-person association between smartphone usage and subsequent well-being:

[1] Given that the present study reports results from a secondary analysis, it is important to mention that the person who conceptualized the hypotheses and conducted the analyses (i.e., the first author) did not have access to the data prior to the submission of the preregistration.

Hypothesis 1: The duration of smartphone usage 60 min preceding an ESM assessment correlates negatively with momentary well-being measures.[2]

Given that 60 min is not a theoretically informed time interval and that the chosen time interval for aggregating app usage may have an impact on the results (Langener, Stulp, et al., 2024), we also examine 30-min and 90-min intervals in robustness analyses. In addition to this hypothesis, we explore whether the usage of the three different app categories (communication, social media, and other) is associated with subsequent momentary well-being.

The second hypothesis concerns media selection effects and examines the within-person association between momentary well-being measures and subsequent smartphone usage:

Hypothesis 2: Momentary well-being correlates negatively with smartphone usage in the subsequent hour (see footnote 2).

In addition to this hypothesis, we examine in exploratory analyses whether momentary well-being is associated with the subsequent use of different app categories (communication, social media, and other). As robustness analyses, we also examine 30-min and 90-min intervals.

To examine these hypotheses and preregistered exploratory analyses, we use three different samples. All three samples contain digital trace data from participants' smartphones in combination with momentary measures of well-being. Sample I entails T_1 = 7,874 reports of N_1 = 225 young adults, including ESM measures of affect valence and loneliness as markers of momentary well-being. Samples II and III contain T_2 = 2,566 of N_2 = 17 students and T_3 = 1,533 of N_3 = 13 students, including markers of positive and negative affect as indicators of momentary well-being. Samples II and III are reported and analyzed in a combined way, as the outcomes (positive and negative affect) are measured identically and the study population and design are similar.

Method

Participants

Sample I

Participants were mostly female (*N* = 184, 82%) and, on average, 23.1 (*SD* = 1.90) years old. Moreover, 1% of the participants (*N* = 3) categorized themselves as lower socioeconomic class, 30% (*N* = 68) in lower middle, 58% (*N* = 131) in middle, and 10% (*N* = 23) in upper middle. Forty-five percent of the participants (*N* = 101) were single, while 55% (*N* = 124) were in a relationship or married, of them, 33% (*N* = 41) were living together, and 67% (*N* = 83) were living either with their family, sharing a flat, or alone. Furthermore, 37% of the participants (*N* = 84) were only studying, while 21% (*N* = 47) were studying and working, and the remaining 42% (*N* = 94) were working, looking for a job, or in other situations.

Samples II and III

The majority of participants were female (*N* = 24, 80%). On average, participants were 21.6 years old (*SD* = 3.63, min = 17, max = 35). Most of the participants obtained a high school diploma (*N* = 18, 60%), followed by a bachelor's degree (*N* = 10, 33%). Two participants obtained a master's degree. The majority of participants were single (*N* = 20, 66%), seven (23%) were in a relationship or married and living apart, and three (10%) were in a relationship or married and living with their partner.

Procedure

Sample I

The recruitment was conducted in early 2022 via Netquest (https://www.netquest.com). Participants who met the inclusion criteria (aged 18–25, owned an Android smartphone, and reside in Spain) were provided with a link to a webpage with detailed instructions to download the Ethica app (Ethica Data Services Inc.), which was used to answer the questionnaires. On the same webpage, detailed study instructions were provided without any additional training sessions. Participants gave their informed consent through Netquest.

Following a baseline assessment of stable participant characteristics (e.g., demographic variables), a 28-day ESM period started, during which participants responded to five semirandom signal-contingent ESM prompts per day. Participants were prompted at semirandom signal-contingent scheme five times per day (prompts between 9:00–10:38, 11:48–13:26, 14:36–16:14, 17:24–19:02, and 20:12–21:50). As this was part of an experimental study including an antiphubbing intervention from day 11 onward, only data from the first 10 days were included, so that the intervention does not affect our results. Participants' smartphone use was logged through the Ethica app. The application recorded the timing and usage of various apps. Smartphone use was quantified by tallying the minutes spent on all apps within the hour preceding and following the completion of the ESM questionnaire.

Participants received a monetary reward proportionally to their participation rate in the ESM surveys, with a maximum reward equivalent to €55 in products. More details on the study procedure can be found on the OSF (https://osf.io/q6d3n) page of the data collection. The ethics committee of the University of Navarra reviewed and approved this procedure (project number: 2021.191).

Samples II and III

Participants were recruited in 2021 (Sample II) and 2022 (Sample III) through a university-wide study-participation system that is primarily used by students. During the data collection in 2021, a number of COVID-19-related measures were in place.[3] After recruitment, they were invited to fill out an online baseline questionnaire that assessed demographic variables and covariates. Next, participants attended an instruction session that lasted approximately 1 hr. The session covered the study's procedures in detail, including the purpose of the study, the ESM surveys, and

[2] For negative well-being measures—such as loneliness and negative affect—the association is hypothesized to be positive.

[3] These measures included work from home, restrictions for entering public buildings for unvaccinated/untested individuals, early closing times of stores (20:00), restrictions on public events (maximum number of participants), end of events at 17:00, no sports classes, maximum group size of 75 people for educational events, maximally four visitors per day (see National Institute for Public Health and the Environment of the Netherlands at https://www.rivm.nl/gedragsonderzoek/tijdlijn-van-coronamaatregelen-2021).

the smartphone-sensing part of the study. Informed consent was obtained from all participants during this session.

After the baseline assessment, a 28-day ESM period started, in which participants received six (Sample II) or five (Sample III) prompts daily to measure momentary well-being and daily activities. Participants were prompted at semifixed (morning questionnaire, open from 6.00 a.m. to 10:30 a.m.; evening questionnaire, open from 9 p.m. to 4 a.m.) and random times within specific time intervals (Sample II: 10:30 a.m. to 12:30 p.m., 1–3 p.m., 3:30–5:30 p.m., 6–8 p.m.; Sample III: 11:30 a.m. to 1:30 p.m., 3–5 p.m., 6–8 p.m.). Moreover, participants in Sample II were asked to respond to an ESM survey after every social interaction that lasted longer than 5 min. ESM data were collected through the m-Path app (Mestdagh et al., 2023). For more details regarding the study procedures, see study description files on the OSF at https://osf.io/jqdr9.

Both data collections included a smartphone-sensing component, in which participants were asked to install the Behapp (https://www.behapp.com) app on their smartphones (Eskes et al., 2016; Jagesar et al., 2021; Jongs et al., 2020). The app measured which apps were used at what point in time. Smartphone usage was calculated based on the minutes spent on all apps within the last hour before and after the ESM questionnaire was completed.

Participants in Sample II were compensated with 60€ for their participation, while participants in Sample III received 90€. The ethics committee of the University of Groningen reviewed and approved this study (research codes: PSY-2021-S-0486 and PSY-2223-S-0018). More information about Samples II and III can be found on the OSF page of the project at https://osf.io/jqdr9.

Materials

Sample I

Affect Valence. A single item was used to measure affect valence. The item “How do you feel right now?” was rated on a scale from 1 (*very bad*) to 7 (*very good*). Single-item affect ratings generally provide good agreement with multiple-item scores of the same construct (Verster et al., 2021).

Loneliness. Loneliness was measured with the item “How lonely do you feel right now?” rated on a scale from 1 (*not at all*) to 7 (*very much*). Single measures of loneliness are frequently applied but tend to exhibit lower values than multi-item scales (Eccles et al., 2020; also see Mund et al., 2020).

Smartphone Usage. Smartphone usage in the hour before and after the ESM assessment was measured with the smartphone log data captured by the Ethica app (https://avicennaresearch.com/).

App Type Usage. To explore how the relationship between momentary well-being and smartphone usage differs between different categories of smartphone applications, we differentiated between three categories: communication, social media, and other app usage. Because the Ethica app provided information on how much time participants spent on different apps (log data includes timestamp, app type, and duration), we could compute the time participants spent in these three categories. To determine which app belongs to which category, we used our modified version of the categorization scheme by Schoedel et al. (2022). We made some minor adjustments to Schoedel et al.’s (2022) categorization system because some apps from our samples were not categorized and some apps used for communication purposes were not classified as such (e.g., calling app).[4] The “other” category includes apps that did not fall into the communication or social media categories as defined by the modified Schoedel et al.’s (2022) classification scheme (for details, see Supplemental Materials). The other app categories mostly consisted of time spent on YouTube, Netflix, and the web browser Google Chrome. For an overview of the 10 most used apps per category in Sample I, see Supplemental Table S2. For each category, we computed the number of minutes in the hour before and after each ESM report to test our hypotheses.

Samples II and III

Positive Affect. Positive affect was measured at each ESM assessment with the mean of three items (“I feel happy”, “I feel energetic”, and “I feel relaxed”) on an 11-point Likert scale (0 = *strongly disagree* to 10 = *strongly agree*). The reliability of this scale was $\omega_{within} = .72$ on a within-person level and $\omega_{between} = .90$ on a between-person level in Sample II and $\omega_{within} = .69$, $\omega_{between} = .65$ in Sample III (see also Nezlek, 2017).

Negative Affect. Negative affect was assessed with the mean of four items (“I feel sad”, “I feel anxious”, “I feel stressed”, and “I feel irritated”), rated on an 11-point Likert scale (0 = *strongly disagree* to 10 = *strongly agree*). The reliability of this scale was estimated to be $\omega_{within} = .74$ on a within-person level and $\omega_{between} = .89$ on a between-person level in Sample II and $\omega_{within} = .75$, $\omega_{between} = .92$ in Sample III.

Smartphone Usage. Smartphone usage in the hour before and after the ESM assessment was measured with the smartphone log data captured by the Behapp app (log data includes timestamp, app type, and duration).

App Type Usage. The same categorization process as for Sample I was used to categorize apps into communication, social media, and other app usage. For a detailed list of apps and our categorization, refer to the OSF at https://osf.io/5yt8h; Elmer, Fernández, et al., 2023. Moreover, in Samples II and III, the most frequently used other apps were YouTube, Netflix, and Google Chrome. For an overview of the 10 most used apps per category in Samples II and III, see Supplemental Table S3.

Data Cleaning

Sample I

Participants with fewer than 10 ESM survey observations were removed from the analysis. In this step, we removed 11 individuals with 61 observations from Sample I. One ESM survey observation from Sample I was removed due to missing data on loneliness and affect. We additionally removed two individuals from Sample I with a variance of 0 in affect valence and loneliness measures or who always reported a value of 7 on affect valence and loneliness besides the first time point.

[4] For details on differences between our categorization and the one by Schoedel et al. (2022), refer to the OSF at https://osf.io/5yt8h or the Supplemental Materials.

Samples II and III

We excluded participants if less than 10 days of app usage data were available or if multiple phones were used during the study (Sample II: $n = 5$, Sample III: $n = 2$; see our preregistration for more details). Furthermore, we exclude observations with missing values for positive and negative affect. This resulted in a sample of $n = 17$ participants for Sample II ($N_{\text{obs}} = 2{,}984$) and $n = 15$ participants for Sample III ($N_{\text{obs}} = 1{,}542$). Because it is not possible to observe whether app usage data are missing because a participant did not use an app or because of a technical error, it is also common to exclude a participant's day of data if there was no app use for a certain number of hours (e.g., 12 or 18 hr; Langener, Stulp, et al., 2024). Following this procedure, we choose a time window of 18 hr to label missing values as described in our preregistration. That is, if no app use was recorded for 18 hr over the course of the day, app use for that day was considered missing rather than assuming that the participant did not use any apps. This resulted in the exclusion of 418 observations from Sample II and nine observations from Sample III[5] from 13 individuals.

Preregistered Analytical Strategy

We used multilevel modeling (Snijders & Bosker, 1999) to analyze the relationships between smartphone usage and momentary well-being. Multilevel models allow us to account for the nesting of observations (i.e., individual responses to the ESM surveys) within individuals and can be used to estimate both fixed and random effects. We used the lme4 package (Bates et al., 2015) in R to estimate the multilevel models with restricted maximum likelihood. To facilitate the interpretation of the estimated coefficients, we computed the standardized coefficients (β) for the relevant within- and between-person effects using the method proposed by Hoffman (2014). Marginal R^2, representing the explained variance attributed to the fixed effects alone, and conditional R^2, representing the explained variance attributed to the fixed and random effects, were computed using the method by Nakagawa and Schielzeth (2013).

Media Effects of Smartphone Usage on Momentary Well-Being (Hypothesis 1)

To test Hypothesis 1, we estimated a multilevel model for each of the four dependent variables (affect valence, loneliness, negative affect, and positive affect). The main independent variable of interest was smartphone usage within the last hour, which was measured through the Ethica app (Sample I) or the Behapp app (Samples II and III). From the smartphone log data of app usage, we derived a measure that represents how many minutes of the past hour participants spend on apps. From this variable, we created (a) a person-mean centered variable, which captures the hypothesized (Hypothesis 1) within-person effect, and (b) a person-mean variable, which captures the between-person effects. Additionally, we controlled for the gender of the participant. In the analyses on Samples II and III, a dummy-coded variable was used to indicate from which sample the respective data point is.[6] We further specified a random intercept term and a random slope for the within-person-centered smartphone usage variable.

For the result interpretation, we used one-sided p values with Bonferroni-corrected α values within each research question ($\alpha/4 = .0125$; corrected for the four momentary well-being variables) and discuss the size of the effect.

Media Selection Effects of Momentary Well-Being on Smartphone Usage (Hypothesis 2)

In the analyses testing Hypothesis 2, the time spent on the smartphone in the hour *after* the ESM assessment was used as the dependent variable. We used person-mean-centered predictors and person-mean predictors of the respective momentary well-being measures as independent variables—affect valence and loneliness in Sample I and positive and negative affect in Samples II and III. In addition, we controlled for the gender of the participant and individual-level heterogeneity of smartphone usage (i.e., a random intercept and random slope term). In the analyses on Samples II and III, a dummy-coded variable was used to indicate from which sample the respective data point is.[3] For the result interpretation, we used one-sided p values with Bonferroni-corrected α values within each research question ($\alpha/4 = .0125$; corrected for the four momentary well-being variables) and discuss the size of the effect.

App Type Usage

We additionally examined how the usage of different types of apps (communication, social media, other) is correlated differently with (subsequent and previous) momentary well-being. The same analyses as above were repeated to differentiate between the time spent on different types of apps. Instead of using a variable on the total time spent on the smartphone, three different variables were used: the amount of time spent on (a) communication apps, (b) social media apps, and (c) all other apps. These three variables constituted the independent variables in the analyses predicting momentary well-being (Hypothesis 1) and constituted dependent variables of separately estimated models in the analyses predicting smartphone usage (Hypothesis 2).

Preregistered Robustness Analyses

We conducted robustness analyses in which not only the smartphone usage of the past and subsequent hour was used but also 30-min and 90-min time windows. Additionally, we explored how smartphone usage is related to *changes* in affect valence and loneliness in Sample I by controlling for affect valence and loneliness from the previous time point (i.e., lag1). By modeling the change in momentary well-being variables, we can more conclusively attribute these changes to factors occurring between the two measurement time points, such as recent smartphone use.

Transparency and Openness

All data of Sample I, analysis code, and research materials are publicly available on the Open Science Framework at https://osf.io/5yt8h (Elmer, Fernández, et al., 2023). Data of Samples II and III cannot be shared publicly due to agreements with the local ethics committee. Throughout the article, we report all data exclusions, all

[5] Behapp was improved between the data collection of Samples II and III, resulting in fewer missing values.

[6] The presence of this dummy variable was not preregistered. All deviations from the preregistration are reported in Supplemental Table S4.

manipulations, and all measures in the study and where to find them on OSF. Sample size for Sample I was determined by budget restrictions. We studied emerging adults (ages 18–25; Arnett, 2000) given the pervasive role of smartphones in their lives (Irimiás et al., 2021). Sample size for Samples II and III was determined by standards for mixed-methods studies that include qualitative interviews (Braun & Clarke, 2006), which were also part of the data collection. Data were analyzed using R, Version 4.3.1 (R Core Team, 2021) and the packages *lme4* (Version 1.1-35.1; Bates et al., 2015) and *ggplot2* (Version 3.4.4; Wickham, 2016). This study's design and its analysis were preregistered (see https://osf.io/w5kx6). We deviated from the preregistration in two aspects (see Supplemental Table S4 for details). First, we made minor adjustments to the app categorization scheme by Schoedel et al. (2022), which are explained further in the Supplemental Materials. Second, we added a dummy variable to the models for Samples II and III, controlling for whether the data point stems from Sample II or Sample III.

During the preparation of this work, the authors used ChatGPT 3.5 to improve the readability of the text and to correct language errors. After using this tool, the authors reviewed and edited the content as needed and took full responsibility for the content of the publication.

Results

Before we turn to examining the two hypotheses, we present and discuss a selection of descriptive statistics. The mean response rates for the signal-contingent ESM reports were 70.0% (SD_1 = 19.7%), 81.0% (SD_2 = 11.0%), and 84.2% (SD_3 = 7.3%) for the three samples. Table 1 shows descriptive statistics of the key variables across the three samples. As the results of analyses of variance in Table 1 show, the three samples differed significantly regarding most variables—only the mean communication and other app use post-ESM assessment did not differ between the three samples.

Media Effects of Smartphone Usage on Momentary Well-Being (Hypothesis 1)

Figure 1 shows (a) the estimate of the fixed-effect slope as an orange line between smartphone usage within the 60 min prior to the ESM assessment and the four momentary well-being variables, (b) the estimates of each individual's slope as gray lines, and (c) the raw data points as blue dots. Detailed results of the multilevel models that were used to estimate the slopes in Figure 1 are reported in detail in Supplemental Tables S5 and S6. Our results show that, on a within-person level, smartphone usage within 60 min prior to ESM assessment was associated with lower subsequent affect valence, $b = -0.003$, $t(224) = -3.27$, $p = .001$, and higher loneliness, $b = 0.006$, $t(212) = 5.24$, $p = <.001$, in Sample I, but not with positive affect, $b = 0.001$, $t(17) = 0.20$, $p = .841$, and negative affect, $b = 0.002$, $t(17) = 0.65$, $p = .527$, in Samples II and III. The standardized effect size for the significant effect of prior smartphone usage on affect valence is $\beta = .04$ and $\beta = .08$ on loneliness. Putting the latter effect into context, using the smartphone for 1 min longer than usual was associated with an increase in loneliness of 0.006 points (on a scale from 1 to 7).

In between-person comparisons (i.e., using the person mean as an independent variable), smartphone usage was only associated with loneliness, $b = 0.09$, $\beta = .09$, $t(225) = 2.30$, $p = .021$, but not with affect valence, $b = -0.00$, $\beta = -.03$, $t(225) = -0.38$, $p = .707$; positive affect, $b = 0.04$, $\beta = .28$, $t(26) = 0.20$, $p = .165$; and negative affect, $b = 0.01$, $\beta = .06$, $t(26) = 0.29$, $p = .778$. In other words, those participants of Sample I who used the smartphone more reported greater loneliness overall. Together, the within- and the between-person effects of prior smartphone usage only explained a small proportion of the variance ($R^2_{\text{Affect}} = .001$, $R^2_{\text{Loneliness}} = .013$, $R^2_{\text{PA}} = .034$, $R^2_{\text{NA}} = .019$). More details about the model results (e.g., intraclass correlation coefficient, estimated variances) are reported in Supplemental Tables S5 and S6.

When differentiating between different types of apps used in Sample I, we can see that the effects on affect valence can be mostly attributed to using social media apps[7], $b = -0.005$, $\beta = -.04$, $t(214) = -3.86$, $p = <.001$, but not communication, $b = -0.003$, $\beta = -.01$, $t(7{,}351) = -1.45$, $p = .146$, or other app usage, $b = -0.001$, $\beta = -.00$, $t(7{,}612) = -0.91$, $p = .364$. In modeling loneliness, social media and other app usage were positively associated with loneliness[8], that is, social media: $b = 0.004$, $\beta = .06$, $t(124) = 5.32$, $p < .001$; other: $b = -0.005$, $\beta = -.04$, $t(182) = 2.90$, $p = .004$, but not with communication app usage, $b = 0.004$, $\beta = .02$, $t(7{,}293) = 1.75$, $p = .080$.

We further report on the correlation between the random intercept and the random slope in our analyses in Sample I. Supplemental Table S21 summarizes these correlations. These analyses indicate that individuals who generally score high in loneliness (i.e., higher random intercept estimate) tend to show a higher within-person association between momentary loneliness and prior social media use (i.e., random slope estimate) than individuals who generally score lower in loneliness, $r(223) = .60$, $p < .001$. These correlations were not significant in models examining the predictors of communication app use, $r(223) = -.10$, $p = .500$, or other app use, $r(223) = .23$, $p = .112$.

When differentiating between different types of apps used in Samples II and III, all within- or between-person associations were not significant (for details, see Supplemental Tables S7 and S8).

Media Selection Effects of Momentary Well-Being on Smartphone Usage (Hypothesis 2)

Figure 2 shows the estimated within-person associations between momentary well-being variables and subsequent smartphone usage. Detailed results of the multilevel models that were used to generate Figure 2 are reported in detail in Supplemental Tables S9 and S10. Figure 2 shows that there was a positive within-person association between loneliness and subsequent smartphone usage, $b = 0.47$, $t(183) = 2.79$, $p = .006$. There was no significant within-person association between affect valence, $b = 0.08$, $t(183) = 0.34$, $p = .731$; positive affect, $b = -0.12$, $t(29) = -0.551$, $p = .586$; negative affect, $b = -0.07$, $t(24) = -0.285$, $p = .778$; and subsequent smartphone usage. The standardized within-person effect size of loneliness on subsequent smartphone usage is small ($\beta = .04$); individuals who report one unit higher in loneliness than usual are estimated to subsequently spend $b = 0.47$ min (or 28 s) more on their smartphone within the next hour. Moreover, this effect is not robust when controlling for pre-ESM smartphone use (see the Robustness Analyses section for details).

In between-person comparisons, person-mean loneliness was associated with higher subsequent smartphone usage, $b = 1.67$,

[7] In a model, containing a random slope term for social media use.

[8] In models containing a random slope term of the respective within-person effects (i.e., social media and other app use).

Table 1
Means (Standard Deviation) of Smartphone Usage in Minutes and Momentary Well-Being Variables by Sample

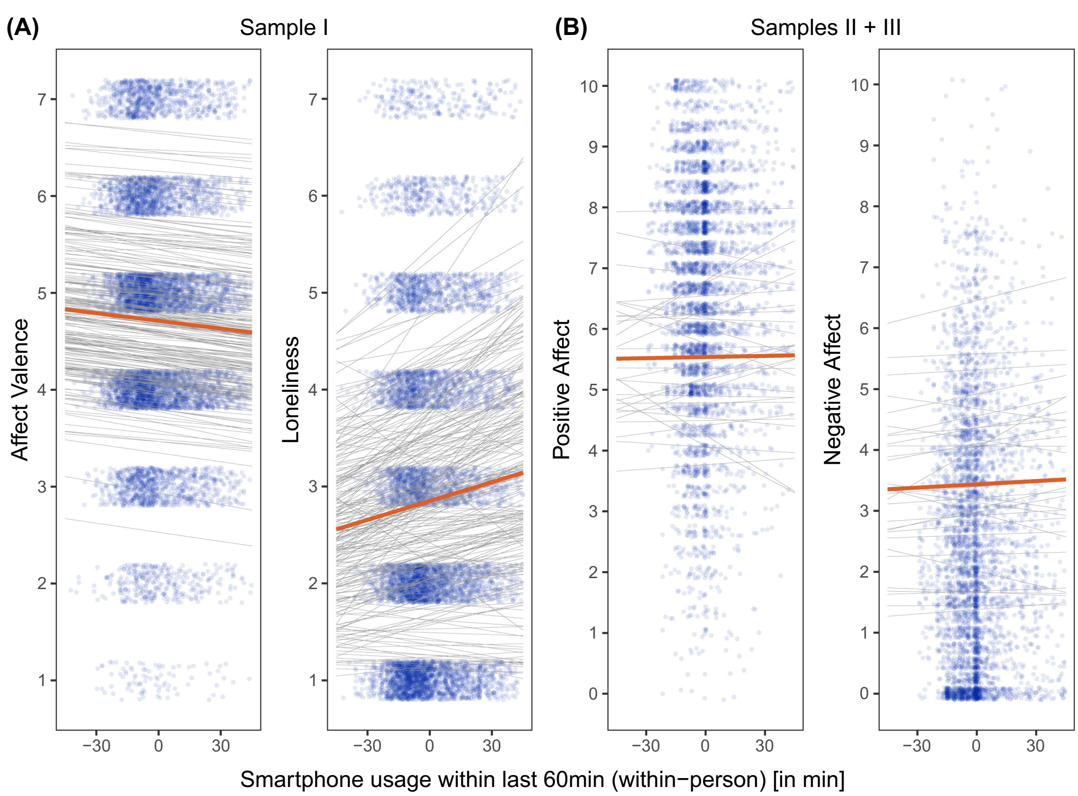
Variable	Sample I	Sample II	Sample III	F	p
Smartphone usage pre-ESM (in minutes)	19.16 (18.13)	11.53 (14.93)	13.43 (15.73)	313.09	<.001
Communication app use pre-ESM (in minutes)	3.89 (6.75)	3.51 (7.23)	3.53 (6.52)	6.46	<.011
Social media app use pre-ESM (in minutes)	6.14 (10.76)	3.39 (6.68)	3.73 (8.00)	154.56	<.001
Other app use pre-ESM (in minutes)	9.13 (13.84)	4.64 (9.26)	6.17 (10.52)	176.31	<.001
Smartphone usage post-ESM (in minutes)	18.19 (18.41)	14.98 (16.54)	18.57 (16.50)	6.73	.009
Communication app use post-ESM (in minutes)	3.82 (7.17)	3.35 (6.40)	4.04 (6.65)	0.06	.814
Social media app use post-ESM (in minutes)	5.74 (10.68)	4.31 (7.77)	4.56 (8.42)	37.62	<.001
Other app use post-ESM (in minutes)	8.63 (13.83)	5.23 (11.69)	9.97 (12.16)	40.50	.230
Affect valence	4.69 (1.32)				
Loneliness	2.87 (1.66)				
Positive affect		6.64 (2.02)	6.36 (1.87)	18.96	<.001
Negative affect		2.30 (1.93)	2.69 (2.19)	35.45	<.001

Note. $N_1 = 225$, $N_2 = 17$, $N_3 = 13$ participants, $T_1 = 7{,}874$, $T_2 = 2{,}566$, and $T_3 = 1{,}533$ time points. ESM = experience sampling methods.

β = .09, $t(219) = 2.89$, $p = .004$. There were no significant between-person associations between affect valence, $b = 0.37$, β = .01, $t(225) = 0.50$, $p = .619$; positive affect, $b = 4.02$, β = .44, $t(25) = 1.86$, $p = .075$; and negative affect, $b = 1.98$, β = .28, $t(25) = 1.17$, $p = .255$, and subsequent smartphone usage.

Together, loneliness and affect valence explained 1.0% of the variance (marginal R^2) in subsequent smartphone usage in Sample I. In Samples II and III, positive and negative affect explained 5.9% of the variance (marginal R^2) in subsequent smartphone usage.

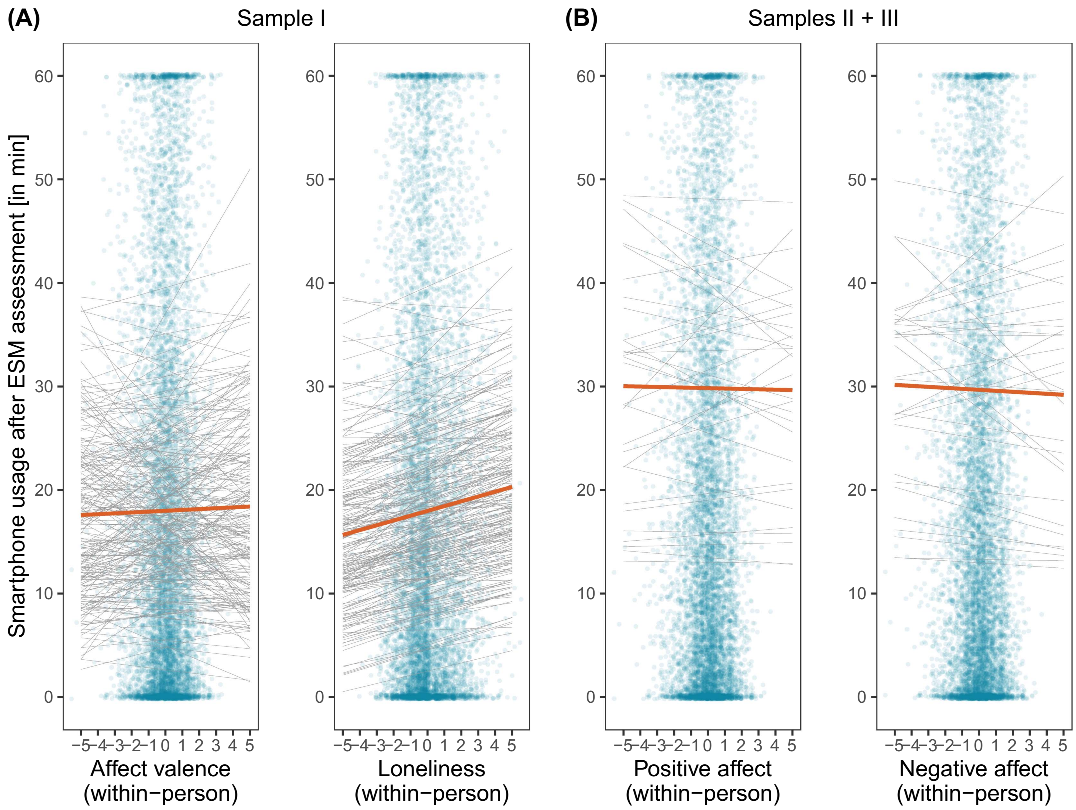
Figure 1
Within-Person Associations Between Smartphone Usage in 60 Min Prior to Experience Sampling Method Assessment and Momentary Well-Being Variables



Note. $N_1 = 225$, $N_2 = 17$, $N_3 = 13$ participants, $T_1 = 7{,}874$, $T_2 = 2{,}566$, and $T_3 = 1{,}533$ time points. The x-axis represents the person-mean-centered values of smartphone usage prior to experience sampling method assessment, with a value of zero representing the person's overall average smartphone use. A positive value, for example, indicates that this person used the smartphone in the previous hour for longer than this person usually does. See the online article for the color version of this figure.

Figure 2

Within-Person Associations Between ESM Momentary Well-Being Variables and Smartphone Usage in Subsequent 60 Min



Note. $N_1 = 225$, $N_2 = 17$, $N_3 = 13$ participants, $T_1 = 7{,}874$, $T_2 = 2{,}566$, and $T_3 = 1{,}533$ time points. The *x*-axis represents the person-mean-centered values of momentary well-being, with a value of zero representing the person's overall average value. ESM = experience sampling methods. See the online article for the color version of this figure.

When differentiating between different categories of apps used in Sample I, only loneliness was associated with subsequent use of social media apps on a within-person level, $b = 0.24$, $\beta = .03$, $t(134) = 2.67$, $p = .008$. No other within-person associations between the momentary well-being measures and different categories of app usage were significant in all three samples. Detailed models in which we differentiate between different categories of app usage after ESM assessment are presented in Supplemental Tables S9 and S10. On a between-person level, loneliness was associated with longer use of social media apps, $b = 0.83$, $\beta = .20$, $t(219) = 2.66$, $p = .008$, indicating that individuals who generally score one unit higher in loneliness tend to spend 50 s more on social media apps than individuals who generally score lower on loneliness. There were no other significant between-person effects.

Robustness Analyses

To test the robustness of our findings, we conducted four additional analyses. First, we examined different time intervals of smartphone usage before and after ESM assessment (i.e., 30 min and 90 min). These results for Hypothesis 1 and 2 are summarized in Supplemental Table S11 (detailed model results can be found in the R Markdown file on the OSF at https://osf.io/5yt8h). The conclusions of the analyses are identical to the ones presented above.

Second, while our estimated models demonstrated satisfactory fit with the observed data (i.e., normality of residuals, homoscedasticity; see R Markdown file on the OSF at https://osf.io/5yt8h), we further applied γ distribution multilevel models for loneliness and negative affect and tweedie distribution multilevel models for subsequent smartphone usage measures. This strategic choice was driven by the distribution characteristics of these variables. Specifically, loneliness and negative affect exhibited right-skewed distributions, for which a γ distribution may be used. Subsequent smartphone usage exhibited bimodal distributions, for which a tweedie distribution may be applied (Gilchrist & Drinkwater, 2000). These models are reported in the Supplemental Tables S12 and S13. The conclusions drawn from these models are identical to the models presented above.

Third, for Hypothesis 1 in Sample I, we estimated models including autocorrelation controls of the outcome measures (e.g., controlling for previously measured affect when estimating the effects of smartphone use on current affect). By controlling for such autoregressive effects, we can examine, for example, if smartphone usage is associated with *changes* in momentary well-being (Castro-Schilo & Grimm, 2018). This was only possible for Sample I, as in

Samples II and III the time intervals between observations were not equidistant due to the mix of signal-contingent and event-contingent sampling procedures. Using nonequidistant measures for time-lagged modeling approaches would induce biases in the estimates (Elmer, van Duijn, et al., 2023; Voelkle et al., 2012). The results of these preregistered, time-lagged models were in line with the main results presented here (for details, see Supplemental Table S14–S16). Only the within-person effect of loneliness on subsequent social media use was not robust, $b = 0.35$, $t(225) = 1.46$, $p = .144$, when controlling for prior social media use, $b = 0.228$, $t(225) = 13.64$, $p < .001$. However, the time gap between pre- and post-ESM measures is so short that meaningful changes in smartphone use are not to be expected, which might explain the absence of a media selection effect in this particular model.

Fourth, we estimated parsimonious models where each type of app usage was included as the sole predictor of momentary well-being rather than all three types being entered simultaneously. The results of these analyses, provided in Supplemental Tables S17–S20, indicate that the conclusions remain consistent regardless of whether the app types are included together or separately.

Discussion

This study examined the bidirectional relationships between smartphone usage and momentary well-being in daily life with smartphone log data and ESM in three samples. In examining media effects with the within-person association between smartphone usage and subsequent momentary well-being (Hypothesis 1), our analyses indicate that smartphone usage within the hour prior to ESM assessment was associated with lower affect valence and higher loneliness in Sample I, but not with positive and negative affect in Samples II and III. These findings suggest that using the smartphone more than usual can be associated with feeling slightly worse and more lonely; however, we only found small effect sizes with little practical relevance. When differentiating between different categories of smartphone apps (i.e., communication, social media, and other), social media use was related to lower levels of subsequent affect valence and higher levels of subsequent loneliness. Moreover, the use of other apps (e.g., YouTube, Netflix, Chrome) was associated with higher levels of loneliness on a within-person level. On a between-person level, the data indicate that those individuals generally high in loneliness showed a higher association between momentary loneliness and social media use than individuals generally low in loneliness. There were no significant within-person associations between smartphone usage and subsequent positive and negative affect in Samples II and III.

By examining within-person media selection effects (Hypothesis 2), we found that within-person loneliness was associated with subsequent smartphone usage in Sample I, specifically social media use. These effects were also generally small. Affect valence (Sample I) and positive and negative affect (Samples II and III) were not associated with subsequent smartphone usage.

In line with previous studies (Große Deters & Schoedel, 2024; Krämer et al., 2024; Marciano et al., 2022; Vaid et al., 2024), our results indicate that the short-term effect of smartphone usage on momentary well-being may be relatively weak or nonexistent. Our findings suggest that only potentially the feeling of loneliness plays a role, as loneliness was bidirectionally associated with smartphone usage. These effects were most pronounced for social media use. However, even then, these effects were small, aligning with previous research demonstrating weak associations between social media usage and negative well-being outcomes (e.g., Colasante et al., 2024; Verbeij et al., 2023).

While the hypothesized within-person effects were small or nonexistent, we observed a particularly strong between-person effect that was not part of our original hypotheses: Individuals who generally report higher levels of loneliness are more likely to feel lonely after increased smartphone use compared with those who report lower levels of loneliness. This finding aligns with those by Vaid et al. (2024) who showed that individuals high in loneliness, depressive symptoms, and low in life satisfaction show a heightened sensitivity in well-being indicators to social media usage.

Our between-person finding also provides a potential explanation for the absence of the hypothesized within-person effects: In the general population, people are usually not immediately affected in their momentary well-being by smartphone usage, but vulnerable groups of people (e.g., those scoring high in loneliness) potentially are, as also Vaid et al. (2024) have suggested. Hence, identifying and examining individual vulnerability factors in the relationship between smartphone use and (momentary) well-being would be a necessary step forward. Such examinations would further help identify the underlying mechanisms of, for example, problematic social media use (Huang, 2022; Valkenburg, 2022).

Overall, this study makes several contributions to the understanding of the relationship between smartphone usage and momentary well-being. First, it addresses a critical methodological gap by employing a multimethod approach, which combines passive sensing data from smartphones with ESM reports to provide a more comprehensive and accurate understanding of how smartphone usage and well-being are *bidirectionally* associated. By doing so, it overcomes the limitations of previous research heavily reliant on self-reported data and unidirectional analyses, allowing for a more objective assessment of smartphone usage and well-being dynamics through jointly examining media effects and media selection effects.

Second, this study examined the often-overlooked within-person dynamics of the relationship between smartphone use and well-being, capturing fluctuations and immediate affective responses to smartphone usage. This level of analysis offers insights into the micromechanistic aspects of this relationship (Büchi, 2021; Radtke et al., 2021) and complements the more common between-person analyses in the existing literature.

Third, by categorizing smartphone app usage into communication, social media, and other, this study explores the role of specific activities within the smartphone usage context. It is key to understand what people are doing on their phones to understand how it affects them (Büchi, 2021). This granular examination allows for a better understanding of how different types of smartphone activities may be associated with momentary well-being. While our analyses indicated small effect sizes and accounted for a modest portion of the variance in the outcome measures, it is important to contextualize these effects. Everyday life is influenced by a multitude of factors beyond smartphone usage that can impact momentary well-being. Furthermore, smartphone usage is influenced not only by one's emotional state but also by contextual variables, such as whether an individual is in the company of others. At the same time, it is also worth noting that we used objective measures of smartphone usage, which minimize common method biases and may explain less variance when compared with relying purely on subjective self-report measures (Baumgartner et al., 2021).

Limitations and Future Directions

Several limitations must be acknowledged. First, while we utilized smartphone log data to objectively measure smartphone usage, these data are inherently limited, as it was sometimes ambiguous how to categorize certain apps. For example, should the app Snapchat be categorized as social media or communication? Although Schoedel et al. (2022) provided a proposal for categorizing more than 3,000 commonly used apps, we found that this categorization was miscategorizing certain important apps (e.g., the calling app was categorized as a system app instead of a communication app). For a detailed list of apps in each category and a comparison with Schoedel et al.'s (2022) categories, refer to the OSF at https://osf.io/5yt8h and Supplemental Table S1.

Second, sensing methods present additional challenges, such as potential technical issues during the study resulting in missing data and the lack of clear guidelines for data cleaning and analysis, which leads to a large number of researcher degrees of freedom (e.g., Huckvale et al., 2019). To address these challenges, we preregistered our study and conducted various preregistered robustness checks relating to different data processing choices. Recently, a preregistration template specifically designed for digital phenotyping data has become available, which can be used for future studies (Langener, Siepe, et al., 2024). It is also important to acknowledge the absence of systematic studies validating the reliability of the app usage data. While we performed manual comparisons using our own collected data and visually compared the app usage recorded by Behapp with the time that participants filled out the ESM questionnaire, future research should prioritize conducting systematic validation studies.

Third, the study predominantly involved young adults living in European countries who were willing to provide their smartphone log data, potentially limiting the generalizability of the findings across diverse age groups and cultural contexts. Particularly noteworthy is the high average smartphone usage in our samples (see Table 1). Such elevated usage rates may not be representative of older adults (Andone et al., 2016). Moreover, acknowledging the potential presence of selection effects is crucial, as participants who chose to participate in the study may differ from those who opted out due to privacy concerns or other factors related to smartphone usage patterns (e.g., all samples include only Android users). These selection biases potentially affected our sample, which further limits the generalizability of our results.

Fourth, the small sample size at Level 2 in Samples II and III raises concerns about the robustness of estimates. Results, particularly for Samples II and III, should be interpreted cautiously, as small variations in participant inclusion may influence estimates. Future research should replicate these findings with larger samples.

Finally, the study focused on the quantity of smartphone usage, but the qualitative aspects of this interaction, such as the content viewed or the emotional tone of communications, were not explored. Future investigations could benefit from a more detailed examination of specific smartphone activities. Understanding the influence of various app functions, such as social interaction or passive consumption of content, can provide more granular insights into how smartphone usage affects momentary well-being (Büchi, 2021; Hall, 2018). For example, Colasante et al. (2024) found that browsing on social media was weakly associated with higher levels of negative emotions hours later, while posting on social media was not. In addition, more qualitative and quantitative work on the individual and contextual factors that moderate how smartphone usage affects well-being negatively would help to make progress in this area (Vaid et al., 2024).

Given that our findings were of correlational nature, future intervention studies could be conducted to further understand the bidirectional relationships between smartphone usage and well-being. Interventions specifically aimed at vulnerable individuals (e.g., high trait loneliness) reducing smartphone usage in daily life (especially social media use) could help assess the impact of reduced usage on momentary well-being and, particularly, feelings of loneliness. So far, existing experimental studies on the effects of reducing social media use showed mixed findings regarding global levels of loneliness in general population samples (Agadullina et al., 2020; Hunt et al., 2018), potentially because vulnerability factors were disregarded.

We further see the need for a theoretical framework that unifies the multiplex bidirectional mechanisms between smartphone use and well-being (e.g., under which conditions can a feedback loop be expected). While such theoretical frameworks exist for the reinforcing mechanisms between for media consumption and the formation of social identities and attitudes (Slater, 2007, 2015) and for the unidirectional association between smartphone use and well-being (Kushlev & Leitao, 2020), a bidirectional framework is missing for smartphone use and momentary well-being (see also Taylor et al., 2022). Such a theoretical framework would help to align research efforts through a focused theoretical basis and a potential research agenda.

Conclusion

This study examined the bidirectional relationships between smartphone usage and momentary well-being in daily life. The findings suggest that the relationship is weak—only loneliness may play a considerable role. Additionally, social media use may be bidirectionally associated with negative momentary well-being outcomes. The study makes several contributions to the field; it addresses several methodological gaps, theorizes about bidirectional mechanisms, examines within-person dynamics, and explores the role of specific app categories. Future research could investigate the influence of various app functions on momentary well-being, examine contextual and individual vulnerability factors, and conduct intervention studies to further understand the bidirectional relationships.

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