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Digital generation: the association between daily smartphone app use and well-being

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ABSTRACT
Smartphones are omnipresent and serve as a tool for various purposes. In Switzerland, more than 90% of the population owns a smartphone and uses it on average around 2.0 to 5 h daily. Smartphone app use is linked with both higher and lower levels of well-being. However, it remains unclear whether smartphone app use is the antecedent or the consequence of well-being. Based on the stimulation (online communication increases well-being) and the displacement (online communication decreases well-being) hypotheses, this study explores how daily smartphone app use and well-being are associated over time. A total of $N = 130$ employees ($M = 35.61$; $SD = 10.62$) participated in a three-week intensive longitudinal study. Daily minutes of different types of smartphone app use (e.g. email apps and chat apps) were tracked by a mobile application. Furthermore, daily self-reports of positive and negative affect were assessed in a morning and end-of day diary. Positive morning affect was negatively associated with the use of email apps. Furthermore, a negative between-person relationship of chat app use with end-of day positive affect was observed. The results are in favour of the displacement hypothesis. Future studies should investigate causal relationships between specific forms of smartphone usage and the user's well-being.

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1. Introduction

In 2022, 54% of the global population (4.3 billion people) was smartphone users (Shanahan and Bahia 2023). In Switzerland, more than 90% of the entire population owns a smartphone, and among young adults, even 99% uses a smartphone (Gramp and Brandes 2018; Külling et al. 2022). In Switzerland, the average smartphone use is between 2 to 5 h a day (Külling et al. 2022). Most people use their smartphone for text messages within their social network, email communication, reading news, browsing the internet, taking photos, checking their social media accounts, and performing a variety of other activities.

Since 85% of the smartphone use is spent for utilising apps and apps differ vastly from each other, mobile apps should be classified into different types of use for investigating their antecedents and consequences (Perez 2015; Pew Research Centre 2019). According to Sust and colleagues (2023), smartphone apps should ideally be categorised into psychologically meaningful categories, that is, apps with similar functions for their users should be merged into the same category (e.g. communication). Previous studies often categorised mobile apps based on commercial platforms like Google play store (Gordon et al. 2019; Schoedel et al. 2022). Currently, 40 categories were counted in the Swiss version of the Google play store (Google Play 2022). Nevertheless, this categorisation lacks a theoretical or empirical justification. It must be emphasised that app categories on commercial platforms are based on marketing considerations (Stachl et al. 2017; Sust, Talaifar, and Stachl 2023). First attempts of a scientific classification roughly classified smartphone app use into two different types: social use and process use (Song et al. 2004; van Deursen et al. 2015). Social use covers all social interaction activities, including social networking,

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messaging and phone calls (Elhai et al. 2017b). Content-based consumption of media is covered by process use, e.g. reading the daily news (Elhai et al. 2017b; Elhai et al. 2018a). For instance, Schoedel and colleagues (2022) suggested classifying mobile apps into 26 psychologically meaningful categories, such as communication, gaming, news or social media.

Today, the most popular apps are instant messenger services, followed by social networks plus video and music streaming services. Social networks are more popular among younger people and women whereas instant messaging seems to be equally popular across generations and gender, while men spend more time with gaming apps (Andone et al. 2016; Anshari et al. 2016; Auxier and Anderson 2021).

Besides the content of use, daily smartphone app use can also be classified with respect to time: (i) non-use (less than 30 min), (ii) light use (30 min till two hours), (iii) moderate use (two to three hours) and (iv) and excessive use (more than three hours; Cheever et al. 2014; Przybylski and Weinstein 2017; Twenge 2019). According to Andone and colleagues (2016), women spend more time on their phones (on average 167 min per day) than men (on average 154 min per day). The amount of time spent on the phone decreases with increasing age. Young users spend most time with video and media apps, whereas users over 30 years spend less than 10 min a day on these apps.

An increasing number of recent studies investigated associations between smartphone app use and well-being (Elhai, et al., 2017a, 2017b; Horwood and Anglim 2019; Stevic et al. 2021). Well-being is defined as an individual conviction that life is enjoyable, happy and desirable and that one is emotionally satisfied (Sirgy 2002). According to this definition, well-being comprises positive and negative affect (Krohne et al. 1996). Positive affect is an aspect of positive and pleasant experiences describing the extent to which a person experiences positive mood such as pleasure, interest and alertness. Negative affect involves negative experiences like feeling negative emotions (e.g. anger, fear or anxiety) and more negative attitudes in relationships and environments. Negative affect is not the counterpart of positive affect (Russell and Carroll 1999); instead, these two constructs are independent of each other (Miller 2011).

For the association of well-being and smartphone app use, previous studies found mixed evidence and showed that the frequency and time spent with smartphone usage are both positively as well as negatively correlated with well-being outcomes (Deters and Schoedel 2023; Marciano et al. 2022).

On the one hand, smartphone app use was found to be negatively correlated with well-being (Jung et al. 2016). Non-users and excessive users generally report lower well-being than light users (Billieux et al. 2015; Horwood and Anglim 2019). Additionally, the consumption of news was found to be negatively correlated with the development of well-being over time (Boukes and Vliegenthart 2017). On the other hand, however, smartphone app use has also been found to be associated with an increase in well-being, less loneliness and shyness (Chan 2015; Chan 2018; Marciano et al. 2022; Wei and Lo 2006). In addition, smartphone app use was shown to be related to reduced negative emotions (Hoffner and Lee 2015), a higher satisfaction with interpersonal needs (such as social belonging) and improved self-realisation (Jin and Park 2010). A reason for these results might be the possibility to communicate and connect with family and friends (Chen and Li 2017).

In addition to the impact of smartphone app use on well-being, smartphone app use itself may depend on well-being. According to Horwood and Anglim (2019), positive affect is negatively related and negative affect is positively related to excessive smartphone app use. The latter can be explained either by excessive smartphone app use having a detrimental impact on affect or by the fact that when individuals are experiencing certain negative emotions, they tend to find distractions by using their smartphone e.g. as a way of coping (Aldao, Nolen-Hoeksema, and Schweizer 2010; Sun et al. 2015). A further assumption is that a strong positive or negative affect might motivate someone to share this experience via apps (Sarsenbayeva et al. 2020).

In general, these mixed results on smartphone app use and well-being are likely due to the different functionalities. For example, social media use is mostly related with higher well-being as well as lower depression and anxiety, which is probably due to being connected with others (Chan 2018). At the same time, reading text messages has been shown to be related to lower well-being (Allcott et al. 2020). Several studies found associations between depression and frequent gaming (via smartphone; Cheung et al. 2018; Mentzoni et al. 2011), but multiplayer games might combat feelings of loneliness (Visser, Antheunis, and Schouten 2013), which results in an overall pattern of mixed evidence and the need for more nuanced analyses on these associations.

The different findings regarding interrelations between smartphone app use and well-being may be explained by two opposing hypotheses: the stimulation hypothesis and the displacement hypothesis (Kraut et al. 1998). The stimulation hypothesis states that online contact and communication increase well-being by its positive effect on the time spent with friends and the quality of these friendships. Furthermore, it is assumed that digital technologies are used to maintain existing friendship and to encourage the communication between friends (Bryant, Sanders-Jackson, and Smallwood 2006; Valkenburg and Peter 2007).

In contrast, the displacement hypothesis asserts that online contacts and communication decreases well-being because a physical communication is replaced by an online communication. This results in reducing the quality of these friendships. Additionally, according to the displacement hypothesis, it is assumed that the internet motivates users to socialise online with strangers instead of maintaining their friendships with offline friends. As these online contacts are seen as superficial relationships with little emotional attachment and commitment, it is believed that the internet reduces the quality of someone's existing friendships and thus impairs their well-being. (Kraut et al. 1998; Valkenburg and Peter 2007). Since it displaces the physical valuable time spent with friends, it can lead to a lack of feeling affection and attachment (Kraut et al. 1998; Nie 2001; Nie, Hillygus, and Erbring 2002). Both hypotheses have been investigated by several studies and indicated mixed results (e.g. Huang 2010; Valkenburg and Peter 2007).

1.1. Current research gap and this study's aim

Previous research in this field often lacks an objectively measured outcome of time spent with the smartphone, differentiated by various types of apps (e.g. social media use), as well as longitudinal research designs to assess change over time. For examining the relationship between smartphone use and well-being, previous studies rather assessed smartphone app use by self-reports (Andone et al. 2016; Orben, Dienlin, and Przybylski 2019; Twenge 2019). Retrospective self-reports have the disadvantage that individuals often over- or underestimate their own behaviours (Stone and Shiffman 2002), which might limit our understanding of interrelations between smartphone app use and well-being over time (Otten, Littenberg, and Harvey-Berino 2010). Since objective assessment of smartphone app use is more accurate (Ryding and Kuss 2020) and different app categories might have different associations with well-being (Boukes and Vliegenthart 2017; Chan 2018), the present study focusses on objectively measured smartphone app use.

Additionally, a limitation of previous studies is that commonly, total smartphone app use was investigated, i.e. no differentiation was made between the types of the individual app categories. Hence, a further aim of this study is to examine the link between different objectively measured daily smartphone app categories and daily self-reported affect within the framework of the stimulation hypothesis and the displacement hypothesis (Kraut et al. 1998). Moreover, most studies rely on a cross-sectional design and therefore do not satisfactorily consider that smartphone app use not only varies between individuals (henceforth: between-person app use) but also on a day-by-day basis for each individual (henceforth: within-person app use; Andone et al. 2016; Orben, Dienlin, and Przybylski 2019; Twenge 2019). By analysing intensive, longitudinal data, i.e. multiple days of smartphone app use for each individual, we are able to evaluate both within-person and between-person effects in a multilevel framework (Bolger and Laurenceau 2013). With this study, we aim to investigate (1) direct temporal effects, e.g. the influence of within- and between-person morning affect on evening affect and (2) mediated temporal effects, e.g. if morning affect relates to within- and between-person app use, which, in turn, relates to affect in the evening.

Specifically, we hypothesise that for both the within- and between-person level, positive and negative morning affect are directly linked to end-of day positive and negative affect. We further hypothesise that persons' (within- and between-person) app use mediates the relationships between morning and end-of day affect.

2. Methods

2.1. Participants

Participants were employees recruited in the German speaking part of Switzerland. A total of $N = 1073$ individuals were interested in study participation. Of these, $n = 151$ participants met the inclusion criteria (see below) and were randomised into an intervention or control group. Three participants did not continue after the baseline assessment and two participants dropped out before the start of the intervention. Overall, $n = 146$ completed the study. However, eight participants did not install the app to track objective smartphone data, and another eight participants had technical problems or implausible values with the assessment of the smartphone app use and were therefore excluded from the analyses. In total, $n = 130$ participants (60 women, 46%) completed all study procedures and were included in the analyses (see supplemental A). The age range of the sample was between 16 and 62 years ($M = 35.61$; $SD = 10.62$), which reflects an approximation of the age spectrum of employees in Switzerland (Federal Statistical Office 2024).

Participants were recruited via advertisements on webpages, mailing lists, newspapers and flyers. Inclusion criteria were the availability of only one android smartphone for both daily work and leisure activities. Participants needed to speak German fluently and be at least

16 years old. Other inclusion criteria were an employment for at least 80% of the regular working time in Switzerland. Shift workers, on-call duty and employees being on vacation during the study period were uneligible.

As an incentive, all participants received a Fitbit Flex® fitness tracker after completing the study. All individuals attended voluntarily, signed an informed consent, which was obtained for experimentation with human participants, and were treated in accordance with the ethical standards of the American Psychological Association (APA [APA 2016]) and the Declaration of Helsinki (World Medical Organization 1996). The study was approved by the Ethics Committee of the first author's institution (16 April, 2014).

2.2. Study design

This study is part of the 'My Time – My daily timeout from the smartphone' project, which is a single-blinded two-arm cluster-randomised controlled trial. The study comprised a longitudinal design with a baseline and follow-up assessment three weeks apart, as well as a daily diary period over 21 days. During the daily diary period, participants received a questionnaire in the morning (at 5am) and a second one in the evening (at 8pm) each taking about five to ten minutes to complete. Additionally, the smartphone activities of the participants were tracked by the Offtime study app (Curtaz, Hoppe, and Nachtwei 2015). After the first seven diary days of participation, participants were randomised to an intervention group ($N = 68$) that implemented two daily timeouts (one hour each) from their smartphone or a waiting-list control group ($N = 62$). For details of the study design, see Figure 1. The data collection took place between June 2015 and February 2016. Since the intervention is not the focus of the present research questions, the analyses for this paper focus on the full sample and controlled for the experimental conditions.

2.3. Measurements

The outcome variable *smartphone app use* was objectively assessed by the Offtime study app. For the analysis, the individual time frame between the morning and the end-of day diary was considered for each participant. The Offtime study app assesses the name of the app used as well as the time (in seconds) spent using the app. With the support of two student assistants, the first author of the present study classified all apps into one of six categories: social networking site (SNS), chats, emails, games, news, and others based on similar classifications from Agarwal, Garg, and Chugh (2014), Anshari and colleagues (2016), Elhai and colleagues (2018a, 2018b), Gandhewar and Sheikh (2010), Google Play (2022), Gupta and colleagues (2018) and Islam and Mazumder (2010). The *SNS* category involves social media applications like Facebook or Instagram. Here, users create and share information or knowledge on communication platforms with a network community. Theses platforms allow a public and personal communication (Boyd and Ellison 2007; Meikle 2016). *Chats:* This category includes communication apps providing written or audio messages and keeps the option to forward pictures and videos (e.g. WhatsApp or Viber). Additionally, most applications in this category can be used to send group messages and to call someone (Montag et al. 2015). *Mails*: This category consists of apps allowing receiving and sending of emails in the form of an asynchronous communication (e.g. gmail.com or Microsoft Outlook; Frehner 2008). *Games*: This category provides interactive activity apps for entertainment purposes, which can be played in a single or multiplayer modus (e.g. chess; Jeong and Kim 2009). *News:* This includes apps presenting information about daily news (e.g. BBC News or reddit.news). The category *others* refer to apps, which could not be allocated to the other categories (e.g. e-book or language-learning apps).

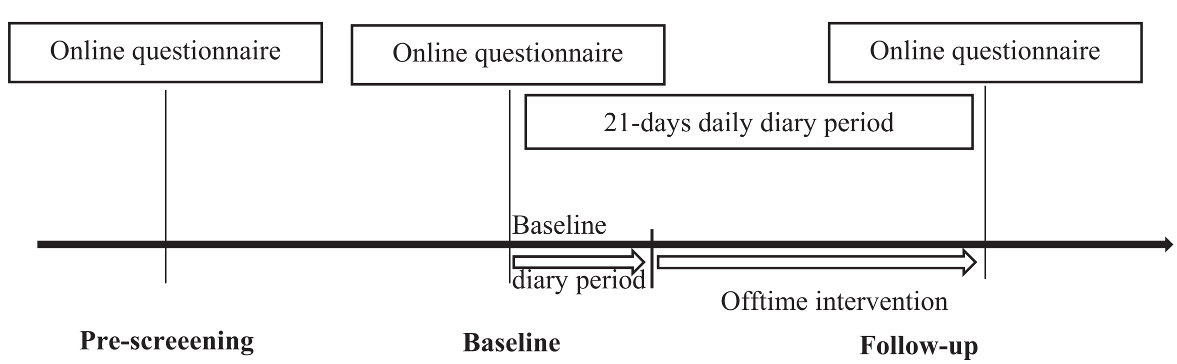

Figure 1. Study design.
Note. Current analyses refer to the baseline and offtime intervention period.

Two raters (student assistants of the first author) individually categorised all 1500 apps that were used by the participants during the study. Afterwards, apps that needed discussion were categorised with the advice of a third rater (first author). An inter-rater reliability analysis using the Kappa statistic across the two raters was performed and was $\varkappa = .97$ ($p <$ 0.001, indicating almost perfect agreement (Landis and Koch 1977).

Affect (morning- and end-of day diary) was measured with the German version of the Positive and Negative Affect Schedule (Krohne et al. 1996). Participants answered to three items each for positive (Cronbach's $\alpha_{\text{morning diary}} = .746$, Cronbach's $\alpha_{\text{end-of day diary}} = .641$) and negative affect (Cronbach's $\alpha_{\text{morning diary}} = .685$, Cronbach's $\alpha_{\text{end-of day diary}} = .746$). Answering the question 'How do you feel right now?', the items were 'determined', 'active', and 'at ease' for positive affect and 'upset', 'afraid', and 'irritable' for negative affect (1 = *not at all*; 5 = extremely).

The following between-person *control variables* were included in the models: (i) experimental condition with 0 = control group and 1 = intervention group, (ii) age, (iii) gender (0 = female; 1 = male), (iv) marital status (0 = without partner; 1 = with partner), and (v) number of family members living in the same household (0 = without children, 1 = with children). All control variables were used for sensitivity analyses.

3. Statistical modelling and analyses

Descriptive statistics and correlation analyses were conducted using SPSS 27. Hypothesis testing was done using Mplus 8 (Muthén and Muthén 1998-2017). Since the models incorporate latent variable interactions, we used Bayesian estimation based on the Gibbs sampler with the random walk algorithm. For the estimates, we used the (default) median point, estimates, i.e. estimates are median values of the posterior distribution (Asparouhov and Muthén 2021).

Analyses include measures from the baseline questionnaire and second diary period (from day 8 to day 21). The first diary period (days 1–7) and the follow-up measurements are not included in the analyses due to technical problems with the objective measurement. Furthermore, only workdays were analysed since possible weekend-specific aspects (e.g. recovery from work) may lead to different effects of app use between work days and weekends. To determine temporal effects between morning affect, app use, and end-of day diary affect, app use between the morning diary and end-of day diary was used for the analyses.

Due to the nested structure of the data (days nested within persons), we employed a multilevel modelling approach with within-person effects on level-1 and between-person effects on level-2, where both the mediator (app use) and the predictor (morning affect) are modelled at both levels, resulting in a 1-1-1 mediation model according to Preacher, Zyphur, and Zhang (2010). In a preliminary step, separate empty models were fitted to each app use and evening affect variable to analyse the intraclass-correlation-coefficient (ICC) values, i.e. the proportion of variance located at the between-person level.

To test our hypotheses regarding the direct and mediated relationships between morning affect, app use, and end-of day affect at both the within-person and between-person level, we conducted a total of 14 multilevel moderated mediation models: one for each individual app use and affect variable (6×2 [positive and negative affect] = 12 models) and two models with the total app use across categories for positive and negative affect, respectively.

Figure 2 depicts the conceptual model for a specific app category and affect. At the within-person level, the effect of morning affect on end-of day affect is (incompletely) mediated by app use. At the between-person level, the same relation is modelled; hence, the between-person level depicts the 'average' relation across days, whereas the within-person level depicts day-specific deviations from the 'average' relations. AW, BW, and CW, as well as AB, BB and CB name the specific effects of the mediation model (W = within-person level and B = between-person level). At the between-person level, we included the group variable as well as the other covariates (marital status, age, gender and number of family members).

MOR describes grand-mean centred values for the morning affect on the within-level (MOR_{ij}) or between-level (MOR_j), APPS describes grand-mean centred values for the use of any of the app categories (or the total use of apps) at the within-level ($APPS_{ij}$) or between-level ($APPS_j$), EOD_{ij} describes values for the end-of day affect, Groupj denotes the group control variable, and $Conk_j$ encompasses the remaining four control variables marital status, age, gender and household family members, where age has been grand-mean centred and divided by five to facilitate computation. The group variable and the covariates predict the average app use (mediator) and the average end-of day affect (outcome). The group variable additionally moderates the day-specific effect of the app use on the end-of day affect and the effect of morning affect on end-of day affect in a cross-level moderation (depicted by the arrows leading to BW and CW at the between-person

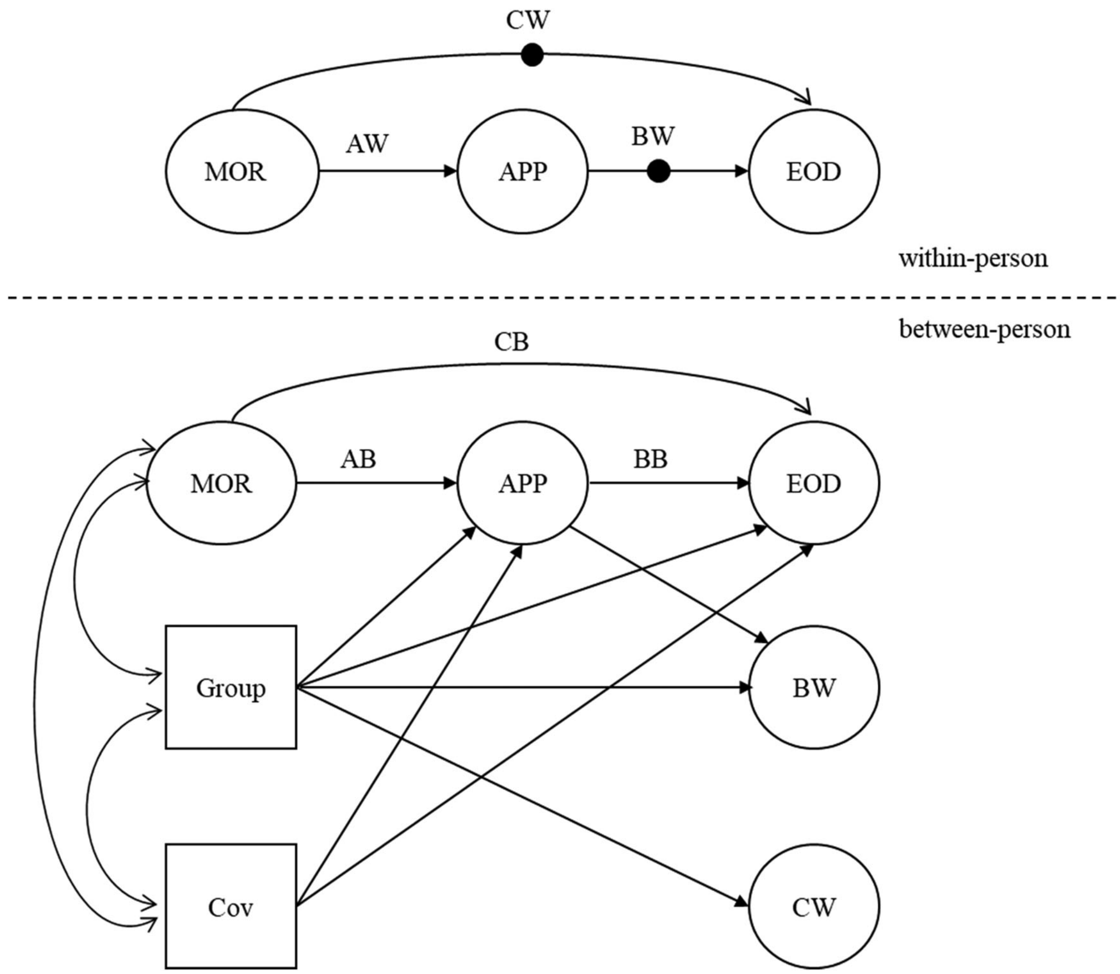

Figure 2. Conceptual model of analysed models.

Note: MOR = grand-mean centred values for the morning affect on the within-level, APP = grand-mean centred values for the use of any of the app categories (chats, social networking site, emails, others, games and news) or the total use of apps and EOD = values of the end-of day diary. AW, AB, BW, BB, CW and CB = specific effects of the mediation model.

level). Following the notational strategy laid out in Hox, Moerbeek, and van de Schoot (2017), the modelling equations for our final models are as follows:

$$Level\ 1{:}APPS_{ij} = \beta_{0j} + \beta_{1j}{*}MOR_{ij} + e_{ij}$$

$$EOD_{ij} = \pi_{0j} + \pi_{1j}{*}APPS_{ij} + \pi_{2j}{*}MOR_{ij} + \epsilon_{ij}$$

$$Level\ 2{:}\beta_{0j} = \gamma_{00} + \gamma_{01}{*}MOR_j + \gamma_{02}{*}Group_j + \left(\sum_{3\leq k\leq 6} \gamma_{0k}{*}Con_{kj}\right) + u_{0j}$$

$$\beta_{1j} = \gamma_{10}$$

$$\pi_{0j} = \tau_{00} + \tau_{01}{*}MOR_j + \tau_{02}{*}Group_j + \left(\sum_{3\leq k\leq 6} \tau_{0k}{*}Con_{kj}\right) + \tau_{04}{*}APPS_j + v_{0j}$$

$$\pi_{1j} = \tau_{10} + \tau_{11}{*}APPS_j + \tau_{12}{*}Group_j + v_{1j}$$

$$\pi_{2j} = \tau_{20} + \tau_{21}{*}Group_j + v_{2j}$$

At level 1, βs describe regression weights for predictors to explain variance in app use, while πs describe regression weights to explain variance in end-of day affect. At level 2, the respective symbols are γ for app use and τ for end-of day affect. $e_{ij} \sim N(0, \sigma_e^2)$ and $\epsilon_{ij} \sim N(0, \sigma_\epsilon^2)$ are random variables containing the level-1 residual variances for app use (σ_e^2) and end-of day affect (σ_ϵ^2). $u_{0j} \sim N(0, \sigma_{u0}^2)$ and $v_{0j} \sim N(0, \sigma_{v0}^2)$ are random variables containing the respective random intercept variances σ_{u0}^2 and σ_{v0}^2, while random variables

$u_{0j} \sim N(0, \sigma^2_{u1})$ and $v_{0j} \sim N(0, \sigma^2_{v1})$ contain the random slope variances for the effect of app use (σ^2_{u1}) or morning affect (σ^2_{v1}) on end-of day affect.

Covariates, including the grouping variable, and morning affect were allowed to covary, while covariances between the endogenous variables and random effects covariances were not permitted to covary in order to ensure model convergence.

To obtain meaningful between-level predictor and mediator values, each participant's daily scores for morning affect and app use were grand-mean centred, i.e. averaged at the sample mean (Bolger and Laurenceau 2013). Hence at the between-level, positive values indicate above-average app use or affect relative to the sample.[1] For the mediation model, grand-mean centreing of the effects directly determines the meaning of the regression coefficients: They express effects that are solely found at the respective level, e.g. at the between-person level, coefficients express relationships that have been controlled for effects within individuals, referred to as contextual effects (Lüdtke et al. 2008). To obtain all relevant effects and to evaluate mediation effects at each level individually and both levels combined, we computed additional variables (see supplemental B).

In preparatory analyses, we also modelled slopes as outcomes (cross-level interactions) for AW, but models did not converge. Since this did not affect hypothesis testing, we proceeded with the simplified models. Covariance between random effects has been restricted to ensure convergence.

4. Results

4.1. Descriptives

Table 1 shows descriptive statistics for the study variables. On average, participants completed the morning diary at 6 am (M = 06:03:14; SD = 1:15:46) and the end-of day diary at 9 pm (M = 21:00:25; SD = 03:03:17). Positive morning affect was $M = 3.07$ (range 1–5), $SD = 0.87$ and positive end-of day diary affect was $M = 2.84$ (range 1–5), $SD = 0.87$. The participants had an average $M = 1.28$ (range 1–5), $SD = 0.49$ of negative morning affect and $M = 1.24$ (range 1–5), $SD = 0.50$ of end-of day diary affect. The average app use between the morning diary and end-of day diary was about 29.31 min (SD = 40.79) per day. Apps of the category '*chats*' were used most frequently (M = 10.70 min; SD = 17.81), followed by the category '*SNS*' (M = 7.17 min; SD = 27.09). On average, the category '*Mails*' was used for 3.12 min (SD = 5.29) per day. Apps from the category '*others*' (M = 2.89 min, SD = 8.81), '*gaming apps*' (M = 2.84, SD

Table 1. Descriptive statistics of the study variables.

		Total sample						Intervention group						Control group						
		All		Men		Women		All		Men		Women		All		Men		Women		
		$N = 130$		$N = 70$		$N = 60$		$N = 68$		$N = 38$		$N = 30$		$N = 62$		$N = 33$		$N = 29$		
Measures	ICC	*M*	*SD*	*M*	*SD*	*M*	*SD*	*M*	*SD*	*M*	*SD*	*M*	*SD*	*M*	*SD*	*M*	*SD*	*M*	*SD*	Range
Age		35.61	10.62	39.01	10.95	31.52	8.61	35.85	11.49	41.37	11.44	28.64	6.45	35.36	9.67	36.40	9.75	34.21	9.47	16–62
Morning affect																				
Positive		3.07	.87	3.30	.84	2.80	.83	3.14	.88	3.42	.811	2.76	.82	3.00	.87	3.17	.86	2.84	.83	1–5
Negative		1.28	.49	1.60	.44	1.31	.55	1.27	.48	1.25	.47	1.29	.47	1.30	.51	1.27	.40	1.33	.61	1–5
End-of day diary affect																				
Positive	.63	2.84	.87	3.07	.84	2.59	.83	2.89	.86	3.16	3.33	2.53	.82	2.80	.88	2.96	.88	2.64	.85	1–5
Negative	.57	1.24	.50	1.21	.43	1.27	.56	1.24	.45	1.21	.43	1.27	.48	1.24	.54	1.21	.44	1.27	.63	1–5
App category use*																				
Total app use	.44	29.31	40.79	25.91	30.49	33.10	50.70	33.38	46.58	24.58	27.86	44.47	62.04	25.14	33.31	27.38	33.15	22.39	33.82	0–809.07*
Chats	.60	10.70	17.81	7.85	14.80	14.08	20.56	12.69	18.10	8.54	14.39	18.13	21.04	8.66	17.31	7.10	15.22	10.29	19.40	0–196.57*
SNS	.15	7.17	27.09	4.61	10.27	10.07	38.70	9.00	36.58	3.83	9.49	15.63	54.28	5.29	10.38	5.47	11.03	4.87	9.65	0–796.87*
Mails	.38	3.12	5.29	3.37	5.77	2.69	4.63	3.26	4.80	3.25	4.99	3.05	4.59	2.98	5.76	3.50	6.62	2.40	4.65	0–53.73*
Others	.54	2.89	8.81	3.71	11.06	0.13	5.00	2.61	6.44	2.60	7.01	2.74	5.74	3.17	10.72	4.98	14.16	1.21	4.06	0–109.68*
Games	.59	2.84	10.41	2.80	10.38	2.84	10.53	3.48	11.99	3.70	12.84	3.02	10.86	2.18	8.45	1.81	6.58	2.66	10.23	0–128.25*
News	.48	2.60	6.60	4.61	10.27	4.73	4.73	2.34	5.98	2.70	6.56	1.90	5.39	2.87	7.18	4.53	8.87	.99	3.97	0 –62.18*

Note: ICC = intraclass-correlation coefficient; *in minutes per day; SNS = social networking site.

= 10.41) and '*news*' were used with the lowest frequency ($M = 2.60$ min; $SD = 6.60$). Looking at the results differentiated by group, the intervention group had a higher total app use ($M = 33.38$ min; $SD = 46.58$) in comparison to the control group ($M = 25.14$ min; $SD = 33.32$; $t(1076) = 3.33$; $d = 0.20$; $p = 0.001$) even though they were instructed to define a timeout from smartphone app use. In total, men had a lower smartphone app use ($M = 25.91$; SD 30.49) than women ($M = 33.10$; $SD = 50.70$; $t(1059) = -2.837$; $p = 0.005$).

Table 2 shows the inter-correlations between the variables. The total smartphone app use was negatively correlated with positive morning affect ($r = -.089$; $p < 0.01$) and positive end-of day diary affect ($r = -.112$, $p < 0.01$).

4.2. ICC values

Results show that for all variables, there is considerable between-person variance (see Table 1). Specifically, more than half of the variance in positive and negative affect, chat use, gaming, and use of apps categorised as 'other' is rather explained by between-person differences than within-person differences. The lowest ICC (.15) was found for SNS use, indicating that 15% of the variance in SNS use is due to differences between participants.

4.3. Hypothesis testing

Tables 3 and 4 show results for the multilevel models for positive affect (Table 3) and negative affect (Table 4). To keep results concise, we chose not to tabulate effects that do not relate to our hypotheses, i.e. coefficients regarding control variables (e.g. age), covariances, or means and variances of the exogeneous variables. Full results can be found in supplemental C.

Regarding hypothesis 1, we found in all models a significant positive direct relationship between morning affect and evening affect at the between-person level, suggesting that participants with higher positive or negative morning affect also report higher positive or negative end-of day affect across all days (positive: range from $\beta = 0.86$, posterior $SD = 0.05$ for the chat and news apps models to $\beta = 0.89$ with posterior $SD = 0.05$ in the SNS apps model and posterior $SD = 0.06$ in the email apps model; negative: from $\beta = 0.60$, posterior $SD = 0.05$ in the SNS apps model to $\beta = 0.89$, posterior $SD = 0.05$ in the news apps model). These associations extend to a significant total effect (direct and indirect effect) in all models (positive: range from $\beta = 0.91$, posterior $SD = 0.07$ in the chat apps model to $\beta = 0.95$ with posterior $SD = 0.07$ in the SNS apps model and posterior $SD = 0.08$ in the email apps model; negative: from $\beta = 0.67$, posterior $SD = 0.09$ in the total apps model to $\beta = 0.93$, posterior $SD = 0.08$ in the news and email apps models). At the within-person level, however, these associations are not statistically significant. That is, the relationship between morning and end-of day use is supported at the between-person but not within-person level, reflecting stable, general associations.

Regarding hypotheses 2, there were no significant relationships between morning affect and app use, or app use and end-of day affect at the within-person level. At the between-person level, there is a significant negative relationship between positive morning affect and use of email apps, indicating that participants with overall higher positive morning affect use email apps less frequently ($\beta = -1.24$, posterior $SD = 0.50$). This relationship between the total effect of morning affect on email app use is significant ($\beta = -1.14$, posterior $SD = 0.55$). Furthermore, there is a significant negative relationship of between-person chat app use with end-of day positive affect ($\beta = -0.00$, posterior $SD = 0.00$). However, we did not find any significant indirect effect between morning positive affect via between-person chat app use and end-of day positive affect.

Table 2. Inter-correlations of the main variables.

Variables	1	2	3	4	5	6	7	8	9	10	11	12
Positive morning affect	1											
Positive end-of day diary affect	**.618****	1										
Negative morning affect	**−.222****	**−.138****	1									
Negative end-of day diary affect	**−.103****	**−.191****	**.565****	1								
Total app use	**−.089****	**−.112****	**−.064***	−.033	1							
Social networking site	**−.068***	−.052	−0.033	−.006	**.768****	1						
Chats	**−.091****	**−.143****	−0.003	−.009	**.552****	**.110****	1					
Mails	**−.097****	**−.065***	**−.067***	**−.060***	**.283****	**.083****	**.111****	1				
Games	−.020	−.034	**−.073***	.006	**.381****	.050	**.125****	.016	1			
News	−.009	−.031	−.044	−.052	**.304****	**.082****	−.015	**.190****	**.179****	1		
Others	**.073***	.034	−.034	−.048	**.304****	**.085****	−.007	**.066***	.031	**.111****	1	
Age	**.279****	**.291****	**−.124****	**−.146****	**−.189****	**−.127****	**−.241****	.058	−.049	**.102****	−.048	1

Note: † $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.00$.

Table 3. Unstandardised results of the models of the associations between smartphone app use and positive affect (without covariates).

	Total app use			Chat			Games			Mails			News			SNS			Other		
Mediation effects	ν (SE)*	*p*	95%-CI lwr; upr	ν (SE)*	*p*	95%-CI lwr; upr	ν (SE)*	*p*	95%-CI lwr; upr	ν (SE)*	*p*	95%-CI lwr; upr	ν (SE)*	*p*	95%-CI lwr; upr	ν (SE)*	*p*	95%-CI lwr; upr	ν (SE)*	*p*	95%-CI lwr; upr
Within-person																					
MOR → APP	0.35 (2.04)	.43	−3.64; 4.24	−0.07 (0.84)	.46	−1.69; 1.60	0.05 (0.48)	.45	−0.89; 1.04	0.09 (0.27)	.37	−0.44; 0.61	0.10 (0.33)	.39	−0.58; 0.71	−0.102 (1.62)	.47	−3.35; 2.96	0.16 (0.39)	.32	−0.61; 0.96
APP → EOD	>−0.01 (<0.01)	.42	−0.01; 0.01	<0.01 (<0.01)	.49	−0.01; 0.01	−0.01 (0.01)	.32	−0.03; 0.02	−0.01 (0.01)	.17	−0.03; 0.01	<0.01 (0.01)	.50	−0.03; 0.02	>−0.01 (0.01)	.45	−0.02; 0.01	−0.01 (0.01)	.20	−0.03; 0.01
MOR → EOD	0.06 (0.05)	.11	−0.04; 0.15	0.05 (0.05)	.15	−0.06; 0.15	0.05 (0.05)	.16	−0.05; 0.16	0.06 (0.06)	.15	−0.06; 0.16	0.07 (0.05)	.11	−0.04; 0.17	0.06 (0.05)	.09	−0.03; 0.17	0.05 (0.05)	.14	−0.05; 0.16
Indirect	<0.01 (0.01)	.49	−0.02; 0.02	<0.01 (0.01)	.49	−0.01; 0.01	<0.01 (0.01)	.49	−0.01; 0.01	<0.01 (0.01)	.42	−0.01; 0.01	<0.01 (<0.01)	.49	−0.01; 0.01	< 0.01 (0.01)	.49	−0.02; 0.03	>−0.01 (0.01)	.39	−0.01; 0.01
Between-person																					
MOR → APP	−2.11 (4.13)	.30	−10.16; 5.94	0.61 (2.14)	.39	−3.72; 4.76	−0.05 (1.27)	.48	−2.46; 2.36	−1.24 (0.50)*	.006	−2.24; −0.28	−0.81 (0.70)	.13	−2.20; 0.55	−0.36 (1.88)	.42	−4.00; 3.36	1.08 (0.93)	.13	−0.71; 2.94
APP → EOD	>−0.01 (<0.01)	.25	−0.00; 0.00	−0.01 (<0.01)*	.02	−0.01; −0.00	>−0.01 (0.01)	.42	−0.01; 0.01	0.02 (0.01)	.09	−0.01; 0.04	>−0.01 (0.01)	.29	−0.02; 0.01	<0.01 (<0.01)	.46	−0.01; 0.01	>−0.01 (0.01)	.36	−0.01; 0.01
MOR → EOD	0.88 (0.05)*	<.001	0.78; 0.97	0.86 (0.05)*	<.001	0.76; 0.96	0.87 (0.05)*	<.001	0.77; 0.97	0.89 (0.06)*	<.001	0.78; 1.00	0.86 (0.05)*	<.001	0.76; 0.96	0.89 (0.05)*	<.001	0.79; 0.98	0.87 (0.05)*	<.001	0.77; 0.96
Indirect	<0.01 (0.01)	.44	−0.01; 0.02	>−0.01 (0.02)	.38	−0.04; 0.02	<0.01 (0.01)	.43	−0.02; 0.01	−0.02 (0.02)	.10	−0.06; 0.01	<0.01 (0.01)	.36	−0.01; 0.02	<0.01 (0.01)	.46	−0.02; 0.01	>−0.01; 0.01	.36	−0.02; 0.01
Total effects																					
MOR → APP	−1.81 (4.48)	.35	−10.45; 7.06	0.50 (2.23)	.41	−3.99; 4.95	−0.04 (1.29)	.49	−2.58; 2.49	−1.14 (0.55)*	.02	−2.25; −0.08	−0.72 (0.76)	.17	−2.19; 0.77	−0.52 (2.42)	.42	−5.28; 4.26	1.26 (0.99)	.11	−0.72; 3.20
APP → EOD	>−0.01 (<0.01)	.34	−0.01; 0.01	−0.01 (0.01)	.15	−0.02; 0.01	−0.02 (0.01)	.30	−0.03; 0.02	<0.01 (0.02)	.39	−0.03; 0.04	>−0.01 (0.01)	.39	−0.03; 0.02	>−0.01 (0.01)	.45	−0.02; 0.01	−0.01 (0.01)	.18	−0.03; 0.01
MOR → EOD	0.94 (0.07)*	<.001	0.80; 1.08	0.91 (0.07)*	<.001	0.77; 1.05	0.92 (0.07)*	<.001	0.78; 1.06	0.95 (0.08)*	<.001	0.80; 1.09	0.93 (0.07)*	<.001	0.79; 1.06	0.95 (0.07)*	<.001	0.81; 1.09	0.92 (0.07)*	<.001	0.78; 1.06
Indirect	< 0.01 (0.02)	.46	−0.04; 0.05	>−0.01 (0.02)	.42	−0.05; 0.04	<0.01 (0.02)	.49	−0.04; 0.04	>−0.01 (0.02)	.39	−0.05; 0.03	<0.01 (0.02)	.42	−0.03; 0.04	<0.01 (0.02)	.50	−0.04; 0.05	−0.01 (0.02)	.24	−0.07; 0.02
Random Effects	Variance	*p*	R^2	Variance	*p*	R^2	Variance	*p*	R^2	Variance	*p*	R^2	Variance	*p*	R^2	Variance	*p*	R^2	Variance	*p*	R^2
Within-person																					
EOD	0.27	<.001	0.38	0.27	<.001	0.23	0.28	<.001	0.15	0.27	<.001	0.10	0.28	<.001	0.09	0.28	<.001	0.44	0.28	<.001	0.12
APP	962.07	<.001	< 0.01	156.38	<.001	< 0.01	48.99	<.001	<0.01	17.56	<.001	<0.01	23.10	<.001	<0.01	629.64	<.001	<0.01	35.17	<.001	< 0.01
Between-person																					
EOD	0.03	<.001	0.93	0.06	<.001	0.89	0.06	<.001	0.88	0.07	<.001	0.87	0.07	<.001	0.87	0.03	<.001	0.94	0.07	<.001	0.88
APP	701.20	<.001	0.16	201.80	<.001	0.21	71.91	<.001	0.08	9.64	<.001	0.19	20.90	<.001	0.12	98.08	<.001	0.25	41.47	<.001	0.10
Total model Deviance		15070.68			13214.53			11981.57			10816.54			11177.35			14600.32			11627.87	

Notes: *v* = unstandardisedunstandardised coefficients, MOR = grand-mean centred values for the morning affect on the within-level, APP = grand-mean centred values for the use of any of the app categories (or the total use of apps) and EOD = values of the end-of day. Random intercepts are not presented here due to lack of space. However, they were modelled for the analyses.

Table 4. UnstandardisedUnstandardised results of the models of the associations between smartphone app use and negative affect (without covariates).

	Total app use			Chat			Games			Mails			News			SNS			Other		
Mediation effects	*v* (SE)*	*p*	95%-CI lwr; upr	*v* (SE)*	*p*	95%-CI lwr; upr	*v* (SE)*	*p*	95%-CI lwr; upr	*v* (SE)*	*p*	95%-CI lwr; upr	*v* (SE)*	*p*	95%-CI lwr; upr	*v* (SE)*	*p*	95%-CI lwr; upr	*v* (SE)*	*p*	95%-CI lwr; upr
Within-person																					
MOR → APP	−2.56 (3.32)	.21	−8.97; 3.88	1.90 (1.36)	.08	−0.76; 4.43	−0.84 (0.80)	.14	−2.38; 0.75	0.09 (0.44)	.42	−0.81;0.94	−0.45 (0.54)	.19	−1.50; 0.57	−2.81 (2.60)	.13	−8.02; 2.17	−0.43 (0.65)	.25	−1.72; 0.89
APP → EOD	<0.01 (<0.01)	.48	−0.01; 0.01	<0.01 (<0.01)	.33	−0.01; 0.01	−0.01 (0.01)	.20	−0.03; 0.01	−0.01 (0.01)	.29	−0.02; 0.01	−0.01 (0.01)	.19	−0.03; 0.01	<0.01 (0.01)	.35	−0.01; 0.01	<0.01 (0.01)	.48	−0.02; 0.02
MOR → EOD	0.05 (0.07)	.23	−0.08; 0.19	0.07 (0.07)	.16	−0.07; 0.22	0.04 (0.06)	.19	−0.06; 0.16	0.05 (0.07)	.23	−0.08; 0.18	0.04 (0.07)	.25	−0.08; 0.18	0.09 (0.07)	.08	−0.04; 0.23	0.03 (0.07)	.36	−0.10; 0.16
Indirect	<0.01 (0.01)	.47	−0.03; 0.03	<0.01 (0.01)	.36	−0.03; 0.02	0.01 (0.02)	.27	−0.02; 0.05	<0.01 (0.01)	.46	−0.01;0.01	<0.01 (0.01)	.33	−0.01; 0.03	>−0.01 (0.02)	.40	−0.05; 0.03	<0.01 (0.01)	.49	−0.02; 0.02
Between-person																					
MOR → APP	−10.91 (6.60)	.05	−23.61;2.30	−2.81 (3.78)	.23	−9.84; 4.73	−1.36 (2.17)	.26	−5.49; 2.97	−1.03 (0.85)	.12	−2.73;0.67	−0.36 (1.19)	.38	−2.61; 2.08	−2.34 (2.87)	.22	−7.59; 3.47	−0.57 (1.62)	.37	−3.69; 2.72
APP → EOD	<0.01 (<0.01)	.26	−0.00; 0.00	<0.01 (<0.01)	.29	−0.00; 0.00	<0.01 (<0.01)	.26	−0.00; 0.01	<0.01 (0.01)	.48	−0.01; 0.01	<0.01 (<0.01)	.23	−0.01; 0.01	<0.01 (<0.01)	.15	−0.00; 0.01	<0.01 (<0.01)	.43	−0.00; 0.01
MOR → EOD	0.61 (0.05)*	<.001	0.53; 0.72	0.73 (0.06)*	<.001	0.63; 0.86	0.77 (0.07)*	<.001	0.66; 0.90	0.88 (0.05)*	<.001	0.79; 0.97	0.89 (0.05)*	<.001	0.80; 0.98	0.60 (0.05)*	<.001	0.53; 0.74	0.88 (0.05)*	<.001	0.78; 0.97
Indirect	<0.01 (0.01)	.27	−0.03; 0.01	<0.01 (<0.01)	.37	−0.02; 0.01	>−0.01 (0.01)	.34	−0.02; 0.01	<0.01 (0.01)	.46	−0.02;0.01	<0.01 (0.01)	.47	−0.01; 0.01	>−0.01 (0.01)	.26	−0.02; 0.01	<0.01 (<0.01)	.44	−0.01; 0.01
Total effects																					
MOR → APP	−13.52 (7.21)	.03	−27.27;0.63	−1.02 (3.92)	.40	−8.22; 7.03	−2.20 (2.21)	.16	−6.50; 2.10	−0.92 (0.93)	.16	−2.75; 0.90	−0.84 (1.26)	.26	−3.25; 1.74	−5.14 (3.75)	.08	−12.36; 2.29	−0.97 (1.70)	.29	−4.36; 2.33
APP → EOD	<0.01 (<0.01)	.46	−0.01; 0.01	<0.01 (0.01)	.41	−0.01; 0.01	−0.01 (0.01)	.23	−0.03; 0.01	<0.01 (0.01)	.33	−0.02; 0.01	−0.01 (0.01)	.13	−0.04; 0.01	<0.01 (0.01)	.25	−0.01; 0.01	<0.01 (0.01)	.49	−0.02; 0.02
MOR → EOD	0.67 (0.09)*	<.001	0.50; 0.85	0.80 (0.09)	<.001	0.64; 0.99	0.82 (0.08)*	<.001	0.69; 0.99	0.93 (0.08)*	<.001	0.78; 1.08	0.93 (0.08)*	<.001	0.78; 1.10	0.70 (0.09)*	<.001	0.55; 0.88	0.90 (0.08)*	<.001	0.75; 1.06
Indirect	>−0.01 (0.04)	.46	−0.10; 0.08	<0.01 (0.02)	.50	−0.04; 0.04	0.01 (0.04)	.32	−0.05; 0.11	<0.01 (0.01)	.40	−0.02; 0.03	0.01 (0.02)	.33	−0.04; 0.07	−0.01 (0.04)	.29	−0.10; 0.04	<0.01 (0.02)	.48	−0.05; 0.04
Random Effects	Variance	*p*	R^2	Variance	*p*	R^2	Variance	*p*	R^2	Variance	*p*	R_2	Variance	*p*	R^2	Variance	*p*	R^2	Variance	*p*	R^2
Within-person																					
EOD	0.10	<.001	.40	0.11	<.001	.30	0.10	<.001	.29	0.11	<.001	.15	0.11	<.001	.17	0.10	<.001	.53	0.10	<.001	.21
APP	956.81	<.001	<.01	157.97	<.001	<.01	49.52	<.001	<.01	17.56	<.001	<.01	23.18	<.001	<.01	622.26	<.001	<.01	35.39	<.001	<.01
Between-person																					
EOD	<0.01	<.001	.99	<0.01	<.001	.98	<0.01	<.001	.98	0.01	<.001	.92	0.01	<.001	.95	<.01	<.001	.99	0.01	<.001	.96
APP	728.25	<.001	.18	208.92	<.001	.18	71.23	<.001	.09	10.24	<.001	.15	21.11	<.001	.12	99.12	<.001	.24	42.39	<.001	.09
Total model Deviance		12691.80			11005.50			9602.87			8828.72			9090.81			12057.22			9477.92	

Notes: MOR = grand-mean centred values for the morning affect on the within-level, APP = grand-mean centred values for the use of any of the app categories (or the total use of apps) and EOD = values of the end-of day. Random intercepts are not presented here due to lack of space. However, they were modelled for the analyses.

5. Discussion

To the best of our knowledge, this is the first study investigating the association between affect and smartphone app use with objective data and across the whole day over a period of two weeks. This study confirmed the hypotheses partially. The results indicated that on the between-person level morning affects are positively associated with end-of day affects. Additionally, in the framework of the stimulation and displacement hypotheses, positive morning affect was negatively related with the use of email apps on the between-person level. Furthermore, there was a negative significant relationship between between-person use of chat apps and end-of day positive affect.

We will first discuss the results with respect to the stimulation and displacement hypotheses. Afterwards, we will focus on the specific hypotheses of the current study. Especially, the link between the use of the category '*chatting*' and a lower positive affect in the end-of day diary rejects the stimulation hypothesis and rather speaks in favour of the displacement hypothesis (Kraut et al. 1998). The displacement hypothesis assumes that online communication reduces well-being since it displaces the physical time spent with friends resulting in a reduced friendship quality and low well-being (Kraut et al. 1998). In the current analyses, the participants mostly chatted during working hours. They were short on time to exchange information in detail with their chat partners. This might be associated with lower well-being and could be an indication for the displacement theory. Additionally, time spent on chatting is linked with the feeling of not having done anything meaningful (Sagioglou and Greitemeyer 2014). This might also explain the effect why individuals with higher chat use report lower positive affect. Chatting is often used by chat partners with close social ties, where personal information can be exchanged (Liu et al. 2019). Depending on how the chat partner reacts about the exchange of personal information, this might have a negative or positive association with the well-being of the sender (Blabst and Diefenbach 2017). For example, an interactive, private and immediate response can create social pressure and lead to a lower well-being (Pielot et al. 2014).

Another reason for the negative association between chatting and positive affect can be derived from the media richness theory (Daft and Lengel 1986). According to this theory, media differ with respect to their richness. The more ambiguous, unreliably transmissible and multi-layered the facts to be communicated are, the richer the chosen medium must be. The richness of a medium indicates its potential to reduce ambiguity in communication. For instance, a video call is a highly rich medium because it transmits information, social cues like facial expressions and gestures but also allows a direct interaction. In contrast, chatting might be classified as a low rich medium since it only transmits content information and (almost) no social cues (Daft and Lengel 1986; Dennis and Valacich 1999). This framework describes that the reproduction of the information of the conversation depends on the communication medium. Rich media are generally more effective in contrast to less rich media due to more personal communication. Ambiguous messages are more likely to be understood correctly in rich media. A better understanding in turn is positively associated with well-being (Goodman-Deane et al. 2016). Furthermore, the features and functions of chatting apps might be related with well-being, too. Many chatting apps have the functions 'Last Seen' (the presentation when a chat partner was the last time online) and 'Read Receipts' (the information whether the chat partner has read the message) plus single chats and group chats (Ahad and Lim 2014). These functions might foster addictive-like checking behaviour and are highly correlated with perceived stress, waste of time and could be negatively associated with well-being (Ahad and Lim 2014; Church and Oliveira 2013).

Furthermore, since chat partners have often strong relationships, the reaction of the chat partner might have a strong association with the well-being of the sender (Blabst and Diefenbach 2017). This might also be the case for the participants in the current study if their chatting partner did not response as hoped.

The analyses further showed that positive morning affect was negatively linked with email use. This means that those in a good mood use the email apps for a shorter period of time. This is only partly in line with previous studies. A study by Morahan-Martin and Schumacher (2003) for example also showed that individuals with higher positive affect use less email. However, the same study also indicated that individuals with high negative affect, a high depressive level or a bad mood use more emails than people with a lower depressive level. A finding that is supported in other studies, too (e.g. Raudsepp and Kais 2019). However, previous studies examined that especially less email use is correlated with positive affect (Mano and Mesch 2010). One reason for the link between less email use and a higher positive affect might be that the participants anticipate having a quiet day at work or there is little to organise privately (Kushlev and Dunn 2015). In the current study, the category '*Mails*' was applied for private and work-related use. As shown in Table 1, the app category '*Mails*' was averagely used for 3.12 min a day (SD = 5.29), indicating that the participants had not so many incoming emails on their smartphone and were therefore less worried about them. This might explain the positive relation of email app use with the positive end-of day diary affect. However, these analyses are based on a correlation, which is why it is not possible to assess the causal direction of these links. Future studies should examine this more closely on the basis of experiments in order to allow causal inferences.

For the first time, this study examined objective data over one day lasting two weeks and allowing to establish an association between smartphone app use and well-being being free of common method bias. The effects are small, but considering that the models control for experimental conditions and morning affect, still different correlations were found between the type of smartphone app use and affect. Moreover, analyses focusing on media usage time often find no or only very weak correlations between electronic media usage time and well-being (e.g. Best, Manktelow, and Taylor 2014; Dienlin and Johannes 2020; Huang 2017; Meier 2022; Orben, Dienlin, and Przybylski 2019; Przybylski and Weinstein 2019 Tromholt 2016;).

A reason that the hypotheses were only partially confirmed in the current study might be due to the assessment of the smartphone app use. This type of measurement has the advantage that usage is not over- or underestimated and is therefore more reliable than, for example, self-reports (Orben 2020). Many previous studies on the association between smartphone app use and well-being used either the assessments ‘technology addiction’ or ‘screen time’. However, these strategies have faced significant conceptual and methodological limitations although the measurement of smartphone app usage was developed further in this paper by categorising the type of usage and the objective assessment of the number of clicks on a screen or on a specific app (Meier 2022). However, it was not possible to distinguish active (e.g. chatting with a chat partner) or passive use (e.g. scrolling through text messages). This is important to know because active and passive use might have different effects on well-being (Dienlin and Johannes 2020). In addition, one could not track the direct content of the app use. It was measured which app was opened (e.g. WhatsApp). Due to privacy settings, it was not tracked which content was viewed or how many people were in contact (i.e. group chat vs. individual chat).

Perhaps, the assessment of usage time as a predictor is not sufficient. An alternative measurement assumes that technology use is not inherently problematic for well-being. Instead, smartphone app use – particularly mobile checking behaviours – is conceptualised and measured based on the Technology Habits Approach (e.g. Bayer et al. 2016; Bayer and LaRose 2018; LaRose 2010). This approach assumes that checking habits can influence the balance between connectivity and disconnection (Vanden Abeele 2021), potentially explaining problem outcomes and well-being much better compared to usage time only.

An additional explanation for the partially missing effect might be the low explained variance of well-being through electronic media use (Appel, Marker, and Gnambs 2020; Liu et al. 2019). Overall, our modelling approach explains 9% (news app use as mediator) to 44% (SNS app use as mediator) of variance for positive end-of day affect at the within-person level, and 87% (news and email app use as mediators) to 94% (SNS app use as mediator) of variance at the between-person level (see Tables 3 and 4). Explained variance of negative end-of day affect ranges from 15% (email app use as mediator) to 53% (SNS app use as mediator) at the within-person level, and from 92% (email app use as mediator) to 99% (total app use and SNS app use as mediators) at the between-person level (see Tables 3 and 4). Across models, variance in end-of day affect is mostly explained by morning affect. While the app use for all categories varies both on a day-by-day basis and between participants in general, it does not meaningfully contribute to explaining differences in end-of day affect. Moreover, the overall small random slope variance of the relationship between within-person app use and end-of day affect ($Var(BW) \leq .001$ in all models) – in combination with the absence of a moderating effect of the between-level app use – indicate that the association between day-by-day app use and end-of day affect does not vary substantially across participants in general.

Without consideration of the content, a further reason for the partial effects might be the short usage time. Overall, the participants used their smartphones much less than the Swiss average. The average daily total app use in this study was below 30 min ($M = 29.\ 31$; SD = 40.79). Since smartphone app use was primarily tracked during working hours and since 87% of employed people in Switzerland use a computer or other electronic equipment at work (Federal Statistical Office 2019), it could be possible that other electronic devices were also used to access apps or the internet for private purposes. Furthermore, it should also be considered that it is not always possible and permitted to use a smartphone for private purposes during working hours. Future studies should track all available electronic devices in the working and leisure time. When interpreting the results, it should also be borne in mind that the data collection took place in 2015 and 2016. In recent years, there has been a change in smartphone app use due to the further developments of the technology but also due to the Covid-19 pandemic (e.g. Jonnatan et al. 2022; Sidoti et al. 2024). Nowadays, smartphones are being used longer, more often and increasingly for other areas (e.g. online shopping). In general, there is an increasing mix of professional and private use on smartphones (Neştian, Silviu, and Turnea 2019).

An additional reason for the partial effect that needs to be mentioned is the power of the statistical analysis. A post hoc simulation for all 14 models was conducted to estimate the power for the effects of interest (see details in Supplemental D). The power analyses indicated that the c-path of the mediation has a consistently high power; all other effects of the mediation do not. Due to the low levels of smartphone app use and the small actual sample size, not all paths of interest were sufficiently powered. However, smartphone-based studies with an intensive longitudinal design are often confronted with low power (de Vries, Baselmans, and Bartels 2021). Thus, issues of low statistical power should be considered, when interpreting present results from mediation models.

Another reason for partially missing associations might be the sample. The sample was non-representative to the general public and included average middle-aged and highly educated Swiss city residents showing under-average levels of smartphone app use. It might, hence, be that in a more diverse sample, we might have found different associations.

5.1. Strengths and limitations

In contrast to previous studies (Cui 2016; Liu et al. 2019; Twenge 2019), this study used an intensive longitudinal design, an objective assessment of smartphone app use and a categorisation of the smartphone apps.

Yet, some limitations also need to be kept in mind when interpreting the results. First, due to the non-experimental nature of the study, causal inferences are not possible. Second, the smartphone app use was aggregated between the completion times of the morning and the end-of day diary during working days and therefore mostly during working hours. Thus, the smartphone app uses (1) before the participants completed the morning diary, (2) after the end-of day diary, and (3) on days off are missing. This is problematic because most smartphone app use takes place during leisure time as shown in a previous study (Külling et al. 2022). However, because well-being was also to be investigated, it was not considered appropriate to send the diaries too late. Furthermore, in the current study, only the app use was assessed. Texting via short message services (SMS) or phone calls were not included. However, phone calls in particular might have an effect on well-being (Liu et al. 2019). This might also explain the rather low average amount of times of smartphone app use. Future studies should therefore measure the effects of total smartphone app use during leisure time on well-being as well as the influence of well-being during leisure time on smartphone app use. Third, some participants uninstalled the Offtime application, assessing the objective measure for smartphone app use, during the study period resulting in missing values. Also due to privacy reasons, the direct content and the chat partner/partners were not assessed during the study period. This might be important since the content of the conversations might provide more information on the association with people's well-being (Dienlin and Johannes 2020). Fourth, the multifunctionality of apps (especially social media apps) should be considered when interpreting present findings. Narrowly defined app categories can make it difficult to clearly assign apps with multiple functionalities. For example, some apps can be used for social media, news reading and chatting (Alshakhsi et al. 2022; Ma, Muthukrishnan, and Simpson 2016). Future research could suggest a multi-label approach to categorise apps based on persons' usage patterns (e.g. Xu et al. 2014). A last limitation to be mentioned is the missing analyses of the within-person level, and this was not possible despite the use of an intensive longitudinal design. This was due to the very low explained variance within persons of daily smartphone app use. In future studies, the assessment of further app use times (e.g. during leisure time, at the weekend) is needed.

5.2. Implications

Our study provides further insights into the possible effects from different types of smartphone app use on well-being and vice versa. However, future research should expand our findings: So far, no study provided insights on the causal direction of smartphone app use and well-being. Experimental research is needed for addressing this question. As previous and current studies have shown, the effect sizes between smartphone app use and well-being are mostly small. Furthermore, other covariates possibly influencing well-being should be investigated, for example, personality traits and states (Emmons and Diener 1985). Since especially the content and the social network might have both positive or negative influences on well-being, their analysis should be included in future studies. However, privacy issues need to be considered.

Furthermore, procrastination and passive use (e.g. scrolling through websites or apps) are related to more negative effects (Dienlin and Johannes 2020), future studies should distinguish between active and passive smartphone app use and which features of the apps were used (e.g. group chat, or 'Last Seen'). Next to procrastination, personality traits like neuroticism might be related to smartphone app use (Alam et al. 2023), which could be followed up by future research.

6. Conclusion

This study investigated the associations between well-being and the objectively measured use of different types of smartphone apps in people's everyday lives within days across two weeks. Especially apps used for social exchange were negatively related to well-being and vice versa, speaking in favour of the displacement hypothesis. In contrast, the stimulation hypothesis could not be confirmed in this study.

Note

1. The age variable was grand-mean centred to obtain meaningful interpretation of its effect.

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Submission declaration and verification

Hereby, we confirm that all authors have read and followed the instructions for authors, that the submitted manuscript is the intellectual property of the authors, that all authors have contributed substantially, seen and approved the current version of the manuscript, that there are no competing interests to declare, that it has not been published before, that it does not contain data that is currently submitted or published elsewhere, that we have full control of all primary data and that we agree to allow the journal to review our data if requested. We confirm that if the manuscript will be accepted, it will not be published elsewhere in the same form, in English or in any other language, including electronically without the written consent of the copyright holder. The study was registered on 09/06/2023 at OSF: osf.io/2wz94

Author statement

Konstantin Schenkel prepared the first draft of the manuscript. Theda Radtke and Urte Scholz contributed in generating the idea for the study, administered and also implemented the study. Konstantin Schenkel, Fridtjof Nussbeck, Denny Kerkhoff, Jan Keller and Theda Radtke significantly contributed to the idea of the analysis, the analysis itself, and the interpretation of the data. All authors contributed in reviewing, revising and finalising the manuscript. All authors critically revised the first draft for content and contributed to the final draft. All authors read and approved the final manuscript. Further, all authors agreed to be accountable for all aspects of the work. No one received any financial reward for contributing to the paper.

Trial registration & data availability

The study was registered on 09/06/2023 at OSF: (https://osf.io/qf57a/?view_only=1da15a0949344fb58ba415dad2d01430), where all study materials, data, and analysis scripts can be accessed.

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