Insights – Future Implications of Passive Smartphone Sensing in the Therapeutic Context

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Keywords

Drive · Mood · Smartphone-tracking · Psychotherapy · Stress

Abstract

Background: Due to the ubiquitous use of smartphones in daily life, they offer unique opportunities to study human behavior. This study sheds light on associations between self-reported stress, drive, and mood levels and smartphone usage behavior. **Methods:** A total of 157 students installed the *Insights* app on their personal smartphone and tracked smartphone usage behavior. Furthermore, students assessed self-reported levels of stress, drive, and mood for 8 weeks. **Results:** Three multilevel models were used to associate smartphone usage behavior and self-reported mood, drive, and stress levels. Results indicate a negative association of self-reported stress and number of SMS (-3.539 , $SE = 0.937$) as well as a positive relation of stress and call duration (0.018 , $SE = 0.937$). Mood was linked negatively with total usage time (-0.019 , $SE = 0.004$) and call duration (-0.016 , $SE = 0.007$). Moreover, drive was negatively associated with Facebook usage time (-0.127 , $SE = 0.041$). **Discussion:** Overall smartphone usage behavior is negatively associated with measurements of well-being. **Conclusion:** Passive smartphone tracking could assist in the standardized assessment

of behavioral data in real life in the future. Due to the risk of data misuse, ethical, legal, and clinical guidelines have to be developed.

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Insights: Anwendungsmöglichkeiten von passivem Smartphone-Tracking im therapeutischen Kontext

Schlüsselwörter

Antrieb · Passives Smartphone-Tracking · Psychotherapie · Stimmung · Stress

Zusammenfassung

Hintergrund: Die Einbindung von Smartphones in den Alltag ermöglicht es, longitudinale Echtzeit-Daten aufzuzeichnen, die keine aktive Eingabe der Nutzer benötigen. Mithilfe der vorliegenden Studie soll gezeigt werden, dass das aktuelle Befinden (Stimmung, Antrieb, Stress) mit Smartphone-Nutzungsvariablen assoziiert ist. **Methoden:** An der Studie nahmen 157 Studierende teil, welche für 8 Wochen die App Insights auf ihrem Smartphone installierten. Insights zeichnete das Smartphone-Nutzungsverhalten (z.B. Gesamtnutzungsdauer, Anruf-

dauer, Anzahl der SMS, Facebook-Nutzung) auf und erfasste täglich mittels Selbstbericht Stimmung, Antrieb und Stress. **Ergebnisse:** In 3 Mehrebenenmodellen wurde das aktuelle Befinden über Smartphone-Nutzungsverhalten vorhergesagt. Die Ergebnisse demonstrieren, dass Stress negativ mit der Anzahl der SMS ($-3,539$, $SE = 0,937$) und positiv mit der Anrufdauer ($0,018$, $SE = 0,937$) assoziiert ist. Stimmung ist negativ mit der Gesamtnutzungsdauer ($-0,019$, $SE = 0,004$) und der Anrufdauer ($-0,016$, $SE = 0,007$) verbunden. Ebenso ist der Antrieb negativ mit der Facebook-Nutzung ($-0,127$, $SE = 0,041$) korreliert. **Diskussion:** In zukünftigen Studien sollte der Kausalität des negativen Zusammenhanges zwischen Befindlichkeitsparametern und der Smartphone-Nutzung nachgegangen werden. **Schlussfolgerung:** In Zukunft könnte passives Smartphone-Tracking eingesetzt werden, um standardisiert Verhaltensdaten von Personen mit psychischen Problemen zu sammeln. Aufgrund der immanenten Gefahr des Datenmissbrauchs sind ethische, rechtliche und berufspolitische Leitlinien zu entwickeln.

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Theoretical Background

Digital interventions lead to behavior changes in individuals as well as societal adjustments [Montag and Diefenbach, 2018]. For the first time in history, it is economically possible to collect and analyze longitudinal data on a big scale [Montag et al., 2016, 2019]. The rise of technology is increasingly affecting mental health care through technology-assisted diagnostic, prevention, treatment, and big data-based guidance in treatment decisions [Ebert et al., 2017, 2018; Rathner and Probst, 2018].

The majority of the collected data is sensitive in nature (e.g., biographical data, GPS location, social contacts, activity patterns, etc.) and requires a high standard of data protection and further ethical consideration regarding patient safety [Harari et al., 2016; Rubeis and Steger, 2019]. If these requirements are met, the collection and analysis of big data on specific mental conditions could enhance diagnostic possibilities in the future [Onnela and Rauch, 2016; Ben-Zeev et al., 2015]. This form of direct unobtrusive behavior observation (e.g., movement patterns, number of social interactions, etc.) could provide deeper insight into the development and preservation of mental disease. Moreover, data-driven knowledge could in turn enhance established psychotherapeutic processes (e.g., passive monitoring of therapeutic processes) and lead to the development of novel internet- and mobile-based interventions [Baumeister et al., 2018; Domhardt et al., 2018]. The distribution of tailored interventions could furthermore reduce health care costs through shortened referral and decreased treatment duration [Insel, 2017; Markowitz et al., 2014;

Mohr et al., 2017; Onnela and Rauch, 2016; Raballo, 2018; Rathner et al., 2018a, 2018b; Torous et al., 2017].

The smartphone is one possibility to collect behavioral data in everyday life [Alvarez-Lozano et al., 2014; Canzian and Musolesi, 2015; LiKamWa et al., 2013; Mehrotra et al., 2014; Saeb et al., 2015; Suhara et al., 2017]. Currently, around 36% of individuals all over the world and 81% of Germans own at least one smartphone, which is used by youths and young adults for an average of 162 min a day [Montag et al., 2015].

The analysis of smartphone usage like daily usage time, size of the social network, number of daily short messages and texts, number and duration of calls, or application use is not only providing insights into an individual's online life but also into their routine behavior [Harari et al., 2016, 2017; Servia-Rodríguez et al., 2017a].

In addition to the smartphone usage, smartphone sensors can be used to observe everyday behavior [Miller, 2012]. By using smartphone sensors (e.g., GPS, microphone, accelerometer, camera, light sensors, Bluetooth, etc.) the assessment and analysis of position, movement patterns, voice, environmental sounds, and distance to other smartphones is attainable [Cummins et al., 2013, 2017; Mehrotra et al., 2014; Mehrotra and Musolesi, 2017; Stasak et al., 2016]. This allows inferring to environmental conditions (such as noise, surrounding, etc.), characteristics of the person itself (e.g., well-being, mood, etc.), or an individual's behavior (e.g., movement, social interaction, etc.) [Harari et al., 2017; Saeb et al., 2015; Servia-Rodríguez et al., 2017a].

To date, mainly self-reports (e.g., questionnaires) have been used to assess such characteristics. Passive sensing of behavior offers unique advantages when compared to self-report. First, individuals have a limited capability of insight and are rather poor at objectively assessing their own mood [Sariyska et al., 2018]. Secondly, humans are prone to recall biases [Montag et al., 2015; Stone and Shiffman, 2002]. Thirdly, a tendency to socially desired answer behavior is present [Paulhus, 2017]. Fourthly, adherence to repetitive data input is low and diminishing with progressing time [Donkin and Glozier, 2012; Markowitz et al., 2014].

One app that combines the advantages of mobile assessment and passive sensing is the *Insights* app [Montag et al., 2019; Sariyska et al., 2018]. Prior studies using the *Insights* app showed a correlation of the size of the social network with genetic polymorphisms that are related to attachment [Sariyska et al., 2018] and the usefulness of the *Insights* app to assess personality traits [Montag et al., 2019]. A detailed description of possible applications of the *Insights* app can be found in the article by Montag and colleagues [2019].

The use of passive sensing in the health care sector could lead to reduced burden in health care providers and

Table 1. Characteristics of the sample

Variable	Parameter		
Age	m = 22.53	SD = 6.12	range = 18–63
Education	A levels	n = 136	85.53%
	university degree	n = 23	14.47%
Gender	male	n = 44	27.67%
	female	n = 115	72.33%

m, mean; SD, standard deviation; n, number of participants.

patients. Passive sensing software could assist in (a) early detection of disease, (b) diagnostics, (c) evaluation of treatment course, (d) evaluation of treatment outcome, (e) giving feedback on a patient's behavior, (f) delivering tailored interventions, and finally, developing new internet-, mobile-, or face-to-face-based therapeutic interventions.

As a first step to achieve these far-reaching visions, proof-of-concept studies are needed which test whether mental well-being or disease is linked to variables that can be tracked via smartphone. This feasibility study provides first insights into the use of smartphone usage behavior to predict mental states such as self-reported mood, drive, and stress. These variables mirror core symptoms of affective disorders [Kessler et al., 2003].

Currently between 9.3 and 23% of the population worldwide are affected by depression [Moussavi et al., 2007]. Thereby, depression is the most common mental disease [Kessler et al., 2003; Richards, 2011; Richards and Salamanca-Sanabria, 2014]. Major depression is characterized by diminished affect and drive over a period exceeding 2 weeks. Furthermore, changes in appetite, sleep, concentration, psychomotor speed, and exhaustion are symptoms associated with depression [ICD-10; WHO, 2001]. Besides depression, a variety of mental diseases are defined by the trans-diagnostic variables mood, drive, and stress.

Moreover, there is an association of self-reported stress and the development of physical and mental disease [de Boer et al., 2017; Cohen et al., 2007; Mund and Mitte, 2012; Slavich, 2016; van Praag, 2004; Wang, 2005]. Thus, the assessment of self-reported stress as a general risk factor for the development of disease is expedient, especially when self-reported stress is elevated over an extended period of time [de Boer et al., 2017]. Vice versa, individuals affected by mental disease report higher levels of stress when compared to healthy individuals, pointing towards a bidirectional association [Kamplung et al., 2014; Milczarek et al., 2009].

Previous studies differ in their findings [Alvarez-Lozano et al., 2014; Canzian and Musolesi, 2015; Elhai et al.,

Table 2. Characteristics of the variables

Variable	Values		
	m	SD	range
Call duration ^a	2.11	2.14	0.07–16.27
Number of messages ^b	0.64	1.04	0–8.81
Daily usage time ^c	168.77	98.52	0.25–692.83
Facebook usage time ^d	8.73	12.98	0–63.47
Mood	63.83	11.78	28–92
Drive	50.94	10.31	24–81
Stress	38.70	14.18	28–81

m, mean; SD, standard deviation. ^a Total time of incoming and outgoing calls per day. ^b Total number of received and sent text messages per day. ^c Total daily usage time. ^d Total daily usage time of the Facebook app in minutes.

2017; Ferdous et al., 2015; Rozgonjuk et al., 2018; Saeb et al., 2015; Seabrook et al., 2016; Servia-Rodríguez et al., 2017; Suhara et al., 2017]. According to Saeb and colleagues [2015], an association between depression severity and smartphone usage behavior was found. Other research groups could not find any associations between daily usage time and depression [Elhai et al., 2017; Rozgonjuk et al., 2018].

The largest study using smartphone tracking to predict mood in daily life was conducted by Servia-Rodríguez and colleagues [2017]. They used smartphone sensors (such as accelerometer, microphone, and location) as well as smartphone usage data (number of text messages and calls) and collected self-reported mood twice a day between 8 a.m. and 10 p.m. To assess self-reported mood, the core affect model by Russell [1999; 2003], which quantifies mood on the subscales valence and arousal, was used. The self-reported valence and arousal scores could be predicted through the models with an accuracy of 64 and 60%. In a rather limited subset of the original data (1,600 participants), it was shown that the percentage of significant correlation was higher when using smartphone sensor variables compared to smartphone usage variables. A major limitation is the high amount of missing values in this study and the so far insufficient prediction models.

Another comparably small study ($n = 18$) provides first insights into a relationship between daily usage time as well as the usage of social applications (e.g., Facebook, WhatsApp) and negative mood [Alvarez-Lozano et al., 2014].

In this study, the following three research questions are addressed: Is it possible to predict self-reported mood (model 1), self-reported drive (model 2), and self-reported stress (model 3) via smartphone usage variables?

Table 3. Correlation matrix at baseline

	Mood	Drive	Stress	Tele ^a	SMS ^b	TDU ^c	FBU ^d
Mood	1**						
Drive	0.653**	1**					
Stress	-0.427**	-0.157	1**				
Tele ^a	-0.266	-0.198	0.081	1**			
SMS ^b	-0.638*	-0.416	0.495	-0.072	1**		
TDU ^c	0.095	-0.116	-0.018	0.104	-0.036	1**	
FBU ^d	-0.063	-0.005	-0.06	0.009	0.049	0.454**	1**

* Significant correlation, $p < 0.05$; ** highly significant correlation, $p < 0.01$. ^a Daily incoming and outgoing calls. ^b Daily received and sent messages. ^c Total daily usage time. ^d Total daily usage time of the Facebook app in minutes.

Method

Participants

Participants were recruited via the online platform SONA of the Ulm University as well as via flyers and posters. Data were obtained in two waves from April to September 2017 and November 2017 to February 2018 at Ulm University. The local ethics committee approved the study. From a total of 253 participants, 157 (62.1%) were included in the study. People were excluded for the following reasons: technical failure ($n = 85$; 33.5%) or noncompliance with the study protocol ($n = 11$; 4.3%). Technical failures were for example a server breakdown, insufficient battery status of the smartphone, or compatibility problems of specific smartphones with the *Insights* app. The *Insights* app is continuously refined and the occurrence of malfunction was less prone in the second wave of data collection. Noncompliance with the study protocol was defined as missing data above 25% [Enders, 2003].

Inclusion criteria were age above 18, ownership of a private smartphone running on Android ≥ 4.1 Jelly Bean, and agreement with informed consent. The sample consisted mainly of young (mean = 22.4; SD = 6.1) females ($n = 115$; 72.3%) with higher education ($n = 113$; 85.5%). Details can be obtained from Table 1.

Study Design

At first, the *Insights* app was installed on the participants' private smartphone. A detailed description of the *Insights* app and its applicability can be found in the article by Montag and colleagues [2019]. Subsequently, demographic variables and personality characteristics were obtained. Results regarding these variables have been published elsewhere [Sariyska et al., 2018]. During the following 8 weeks, participants were asked to report their mood, drive, and stress three times a day. Due to the extensive study duration, a sample rate of three times a day was deemed sufficient. The largest comparable study in the field only obtained mood twice a day [Servia-Rodríguez et al., 2017a]. In addition to these self-reports, the *Insights* app collected smartphone usage data passively. After completion of the 8 weeks, participants were either reimbursed with EUR 10 or 5.5 credits in the SONA system. Finally, the *Insights* app was uninstalled.

Variables

Smartphone Usage Behavior

The *Insights* app recorded smartphone usage behavior as anonymized data tuples and automatically generated participant codes. The raw data was encrypted via an SHA-2 algorithm (version SHA-512) by the National Institute of Standards and Technology and transferred to an encrypted server of Ulm University.

Table 4. Model 1: multivariate multilevel model to predict self-reported mood

	Parameter	SE
Model fit		
Restricted -2LL ^a	26,744.1	
AIC ^b	26,766.1	
BIC ^c	26,799.2	
Fixed effects*		
Level 1 intercept	68.803*	1.490*
Call duration ^d *	-0.016*	0.007*
Number of SMS ^e	0.657	0.655
Daily usage time ^f *	-0.019*	0.004*
Daily Facebook usage ^g	-0.065	0.037
Random effects*		
Level 2 intercept	89.342*	19.005*
Call duration ^d *	0.001*	0.000*
Number of SMS ^e	1.707	1.939
Daily usage time ^f *	0.000	0.000
Daily Facebook usage ^g	0.005	0.006

* Significant result, $p < 0.05$. ^a Log likelihood. ^b Akaike criterion. ^c Bayesian criterion. ^d Total daily time of incoming and outgoing calls in minutes. ^e Number of received and sent text messages per day. ^f Total daily usage time. ^g Total daily Facebook usage time in minutes.

For the current study, the total daily smartphone usage time, the total time of incoming and outgoing calls per day in minutes, the daily total number of sent and received text messages (SMS), and the usage of the Facebook app were extracted from the database. A detailed description of the variable characteristics can be obtained from Table 2.

Mood, Drive, Stress

The self-reported mood was assessed via the question "How are you feeling right now?" on a visual analogue scale ranging from 0 to 100 with the endpoints "very bad" and "very good." The default mode of the cursor was set at 50. All three variables were collected three times a day (8 a.m., 12 a.m., 8 p.m.). Correspondingly, drive was captured via the question "How active do you feel

Table 5. Model 2: multivariate multilevel model to predict self-reported drive

	Parameter	SE
Model fit		
Restricted -2LL ^a	27,899.1	
AIC ^b	27,921.1	
BIC ^c	27,954.3	
Fixed effects*		
Level 1 intercept	54.412*	1.528*
Call duration ^{d*}	-0.007	0.006
Number of SMS ^e	0.284	0.729
Daily usage time ^{f*}	-0.009	0.005
Daily Facebook usage ^g	-0.127*	0.041*
Random effects*		
Level 2 intercept	83.875*	17.567*
Call duration ^{d*}	0.000	0.000
Number of SMS ^e	1.308	2.800
Daily usage time ^{f*}	0.000	0.000
Daily Facebook usage ^g	0.005	0.011

* Significant result, $p < 0.05$. ^a Log likelihood. ^b Akaike criterion. ^c Bayesian criterion. ^d Total daily time of incoming and outgoing calls in minutes. ^e Number of received and sent text messages per day. ^f Total daily usage time. ^g Total daily Facebook usage time in minutes.

right now?” with an endpoint caption of “very passive” to “very aroused.” Those two items were developed to assess the core affect according to Russel [2003] as well as Russell and Barrett [1999], which consists of the dimensions valence (mood) and arousal (drive). The item to assess self-reported stress was as follows: “How stressed do you feel right now?” with the endpoints “extremely relaxed” to “extremely stressed.” For the association of self-reported mood, stress, and drive, these values have been averaged on a daily basis. A correlation matrix of the variables at baseline is depicted in Table 3.

Statistical Analysis

To account for the nested structure of the data, we used multivariate multilevel models (MLM) [Goldstein, 2008; Laurenceau and Bolger, 2012; MacCallum et al., 1997; Nezlek, 2012]. MLM take into account that answers are nested within persons and the resulting dependence between variables [Nezlek, 2001; Nezlek et al., 2006]. In this study, the repeated measurements (level 1) are nested within a person (level 2).

To test the association between smartphone usage behavior and mood (model 1), drive (model 2), and stress (model 3), three MLM with a random intercept and a random slope were modelled. Therefore, the random intercept mirrors the variance between individuals. Mood, drive, and stress were predicted via smartphone usage variables (total usage time, total calls, total texts, and total Facebook app usage). For an easier interpretation the variables were z -standardized. The intercept represents the average mood, drive, or stress across the study and the slope pictures the association between mood, drive, or stress and smartphone usage behavior.

Table 6. Model 3: multivariate multilevel model to predict self-reported stress

	Parameter	SE
Model fit		
Restricted -2LL ^a	28,071.3	
AIC ^b	28,093.3	
BIC ^c	28,126.4	
Fixed effects*		
Level 1 intercept	36.730*	2.324*
Call duration ^{d*}	0.018*	0.006*
Number of SMS ^e	-3.539*	0.937*
Daily usage time ^{f*}	0.015	0.009
Daily Facebook usage ^g	-0.016	0.052
Random effects*		
Level 2 intercept	36.730*	2.324*
Call duration ^{d*}	0.000	0.000
Number of SMS ^e	8.915	5.864
Daily usage time ^{f*}	0.002*	0.001*
Daily Facebook usage ^g	0.017	0.020

* Significant result, $p < 0.05$. ^a Log likelihood. ^b Akaike criterion. ^c Bayesian criterion. ^d Total daily time of incoming and outgoing calls in minutes. ^e Number of received and sent text messages per day. ^f Total daily usage time. ^g Total daily Facebook usage time in minutes.

For all computations, a two-sided alpha error likelihood of $p < 0.05$ was used. The software SPSS (version 24; IBM, 2016) and SAS (version 9.4 M4, www.sas.com) were used for statistical analysis. Due to the explorative nature of the research questions no a priori power analysis was conducted. Not alpha error adjusted significance indications are reported but should not be interpreted as in confirmatory studies [Bender and Lange, 2001].

Results

Table 3 presents a Spearman correlation matrix of the variables at baseline. There is a correlation ($p < 0.01$) between mood and drive ($r = 0.635$) as well as between total usage time and Facebook app usage time ($r = 0.427$). Furthermore, there is a negative correlation between mood and stress ($r = -0.427$) and a negative correlation ($p < 0.05$) between mood and number of SMS ($r = -0.638$). There are no gender differences between the variables.

Mood

In model 1, self-reported mood was predicted through smartphone usage variables. With every additional minute of calls, mood decreased 0.0166 (SE = 0.007). Furthermore, mood attenuated by 0.019 (SE = 0.003) with every minute of total usage time. The number of daily SMS and Facebook app usage were not associated with self-reported mood. Pa-

rameters can be seen in Table 4. The model shows the association between self-reported mood and call duration varies between individuals ($\text{var} = 0.001$, $\text{SE} = 0.000$).

Drive

Analogous to model 1, in model 2, the self-reported drive was predicted via smartphone usage behavior. Drive decreased by 0.127 points ($\text{SE} = 0.041$) with every additional minute spent using the Facebook app. The number of SMS, call duration, and total usage time were not associated with self-reported drive. There was no variance between individuals regarding the association between smartphone usage and drive. Detailed parameters of the MLM are depicted in Table 5.

Stress

In model 3, self-reported stress was predicted over smartphone usage variables. With every additional minute of call duration, the self-reported stress level was increased by 0.018 points ($\text{SE} = 0.006$). Every additional SMS was associated with a 3.539 ($\text{SE} = 0.937$) reduction in self-reported stress. Facebook app usage time and total usage time were not associated with self-reported stress. In regard to the association between smartphone usage and self-reported stress, differences between individuals ($\text{var} = 0.002$, $\text{SD} = 0.001$) were found. Parameters are shown in Table 6.

Discussion

This feasibility study shows that passively sensed smartphone usage is associated with self-reported mood, drive, and stress. In general, current mental states emerge in reaction to various internal and external demands. One of these external demands is smartphone usage. The magnitude of these associations is minor and can be rooted in the fact that not only usage duration but also content or intention of use contribute to well-being [Harari et al., 2016]. There are associations between smartphone usage variables and the dependent variables as well as variance between individuals. These interpersonal variances should be addressed in further studies. In regard to the dependent variable, different smartphone usage variables were useful predictors. Therefore, it is recommended to shed light on different smartphone usage patterns in relation to specific psychopathological states.

In regard to mood, there was a negative association between call duration and total usage time. This negative correlation between total usage time and mood was already reported in a smaller sample [Alvarez-Lozano et al., 2014]. The elevated smartphone usage when experiencing negative mood could be explained via the mood management theory by Zillmann [1988a; 1988b]. The central assumption is that media consumption is used to enhance one's

own mood. In line with that, individuals suffering from foul mood would try to improve their mood by using their smartphone. Correspondingly, the increased call duration could be interpreted as a form of mood manipulation through social contacts. On the other hand, there are findings which show a direct influence of media consumption on mood [David et al., 2018]. Due to the correlative study design, there is no way to make causal assumptions about the association between smartphone usage and negative mood. Furthermore, some studies could not show a correlation between mood and smartphone usage or found a positive association between mood and total usage time [Elhai et al., 2017; Rozgonjuk et al., 2018; Saeb et al., 2015]. This could be a hint that associations between smartphone usage and mood are nonlinear [Scherr, 2018]. Moreover, mood and drive represent two core symptoms of depression. Their different expression in diverse clinically relevant subtypes could play a moderating role [Baumeister and Parker, 2012; Saeb et al., 2015]. Moreover, variance in measurement methods could account for the inconsistent findings [Stone und Shiffman, 2002].

Drive was best predicted via Facebook app usage time. This finding was confirmed by Alvarez-Lozano and colleagues [2014], who also found a negative correlation between mood and the usage of social networks. Again, the usage of social networks could be seen as an attempt to manipulate one's own mood through social contacts. Or on the other hand, smartphone usage could be the cause of negative emotions [Lachmann et al., 2018]. In line with this, Rotondi and colleagues [2017] could show that technological interruptions reduce the quality of face-to-face interactions. Distinct smartphone usage patterns (e.g., active versus passive usage) are associated with diverse outcomes [Burke et al., 2010; McCord et al., 2014; Primack et al., 2017; Verduyn et al., 2017]. Tando and colleagues [2015] could show that the correlation between depression and Facebook app usage was moderated by envy.

In the current study, stress was associated negatively with number of SMS and positively with call duration. Likewise, Sano and Picard [2013] could show that with elevated self-reported stress levels, the number of SMS diminished. Overall, the literature regarding the association between stress and smartphone usage is contradicting [Vildjiounaite et al., 2018]. One reason could be that the used variables are not suitable to capture the difference between relaxed and stressed behavior. The use of smartphone sensors (e.g., accelerometer) could in future improve the stress prediction models. Furthermore, the content of SMS or calls could contribute more to changes in mental states than the frequency of the latter [David et al., 2018; Przybylski and Weinstein, 2017]. Due to the significance of the association between mental states and smartphone usage, further studies could test the clinical relevance of manipulating smartphone usage.

Due to the complexity of the original data set, further explorative analysis using deep machine learning approaches could be fruitful. Deep machine learning is a method which can handle big data very well and results in data-driven theories and hypotheses, which can be subsequently tested in confirmatory studies [Oquendo et al., 2012]. In deep machine learning approaches, the computer iteratively tries to find patterns in big data in a bi-directional manner, so that additional data input leads to better models [Bengio et al., 2013; Långkvist et al., 2014; Miotto et al., 2018; Mohr et al., 2017].

The results of the current study should be interpreted with caution because 85 (33.5%) participants have been excluded due to technical failure. In future, the *Insights* app should be expanded to the iOS operating system to broaden its application. Due to the closed functionality of iOS products, this is hardly realizable. According to Götz and colleagues [2017], there are no differences in personality characteristics like well-being, self-efficacy, or big five personal dimensions between iOS and android users.

Due to the high homogeneity of the sample in regard to age, gender, and educational status, the generalizability is questionable. Therefore, a replication study including participants of diverse gender, educational status, and age is needed [Thomee, 2018]. With regard to psychotherapy research, this requires the use of passive sensing in patients who are validly diagnosed.

Overall, the knowledge about being observed could have led to an alteration of smartphone usage behavior in participants. With the concept of habituation in mind, an explorative analysis between the first and the other weeks of smartphone usage was conducted. No differences were found. These first results point in the direction that an alteration of smartphone usage through the observation itself is unlikely, given the assumption that individuals would not show altered usage behavior over the span of 8 weeks.

On the other hand, there is evidence that repetitive assessment of mental states is itself a minimal intervention [Runyan et al., 2013]. According to this, the iterated focus on one's own mental state leads to an altered perception of the same [Shiffman, 2009]. In future, an automated detection of mental states could avoid those natural processes of attention control.

Future studies should also take human rhythmicity into account (e.g., differences between weekdays and weekends or variance within a day). A study by Servia-Rodriguez and colleagues [2017] showed differences in prediction accuracy between weekends and weekdays.

Moreover, there are first hints that the association between mental states and smartphone usage are nonlinear [Scherr, 2018; Przybylski and Weinstein, 2017]. Future studies should test whether cubic or quadratic models have a better fit.

Due to the fact that the observed associations between smartphone usage and mental states were of small nature, the analysis of content could be promising [Harari et al., 2016]. In future, the content of apps (e.g., data mining of messages or on social networks) could be used to develop better mental state prediction models. Despite this, potential ethical considerations have to be taken into account [Schwartz et al., 2014].

Moreover, the combination of smartphone usage variables with smartphone sensor variables could lead to more precise results, due to the fact that smartphone usage provides more insight into the online life of a person, whereas sensor variables provide deeper insight into everyday life [Servia-Rodríguez et al., 2017a].

Future Developments

If these preliminary results can be replicated in a confirmatory study, the future implications could be as following: self-report tools like questionnaires could be complemented through automatized smartphone usage and sensor analysis. Therapists and patients could therefore have more time to work on interpersonal or disease-specific topics, and errors in questionnaire analysis or other diagnostic methods (such as structured interviews) could be avoided. By using passive sensing, the issue of poor long-term adherence could be circumvented because there will be no need for active user input. Moreover, clinical judgements could be augmented through comparably objective automated analyses. The extension of diagnostic possibilities through technology-based assistance (e.g., voice or video analyses) could, in the long term, result in more accurate international standards in diagnostics.

Given the assumption that enough primary data is available, therapy courses could be captured in an automatized way and therapists could get feedback if the therapy course deviates from the predicted one.

Overall, automatized behavior observations of any kind are highly prone to misuse for individuals or vulnerable person groups. Up to date, there are no international standards on how privacy and sensitive data can be protected sufficiently [Mohr et al., 2017; Shilton and Sayles, 2016]. In respect of the novel general data protection regulation (GDPR) of the European Union, the current solution is to give the rights to use data to the individual who produced it. Individuals can therefore maximize their control over who is collecting, using, and sharing their data. To increase the acceptance, comprehensible informed consent and data safety-friendly default modes are inevitable [Shilton, 2009]. There is hope that data handling will be improved through the GDPR because it improved an individual's right on his data by allowing him to obtain all collected data from a given data collection, a right that all collected data will be erased, a right to know which data is collected, where this data is stored, and with

whom it is shared (see <https://dsgvo-gesetz.de/>). All organizations which collect or process data can be fined by the European Union with 4% of their revenue or 20 million. Furthermore, software which is used for the administration, maintenance, or improvement of health of individuals is affected by the IEC82304 of the Medical Devices Act since May 2017. Tracking apps which are used in the medical or psychotherapeutic context are affected by the IEC82304 and are tested for their functionality and data safety.

Taking into account the previous arguments, it becomes obvious that digitalization in health care carries enormous social, legal, and ethical challenges. Psychotherapists should contribute to the developments with their expert knowledge.

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Statement of Ethics

The local ethics committee approved the study.

Disclosure Statement

The authors declare no conflict of interest.

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