



AKADÉMIAI KIADÓ

Associations between symptoms of problematic smartphone, Facebook, WhatsApp, and Instagram use: An item-level exploratory graph analysis perspective

Journal of Behavioral Addictions

9 (2020) 3, 686–697

DOI:
10.1556/2006.2020.00036
© 2020 The Author(s)

DMITRI ROZGONJUK^{1,2*} , CORNELIA SINDERMANN¹,
JON D. ELHAI^{3,4}, ALEXANDER P. CHRISTENSEN⁵ and
CHRISTIAN MONTAG¹

¹ Department of Molecular Psychology, Institute of Psychology and Education, Ulm University, Ulm, Germany

² Institute of Mathematics and Statistics, University of Tartu, Tartu, Estonia

³ Department of Psychology, University of Toledo, Toledo, OH, USA

⁴ Department of Psychiatry, University of Toledo, Toledo, OH, USA

⁵ Department of Psychology, University of North Carolina at Greensboro, Greensboro, NC, USA

Received: January 22, 2020 • Revised manuscript received: April 01, 2020; May 11, 2020 • Accepted: May 15, 2020
Published online: August 13, 2020

FULL-LENGTH REPORT



ABSTRACT

Background and aims: Studies have demonstrated associations between both problematic smartphone and social networks use with everyday life adversities. However, examination of associations between problematic smartphone use (PSU) and problematic use of specific social networking platforms, especially on item-level data, has received relatively little attention. Therefore, the aim of the current study was to explore how items of problematic smartphone, Facebook, WhatsApp, and Instagram use are associated. *Methods:* 949 German-speaking adults participated in a web survey study. The participants were queried about their socio-demographics as well as levels of problematic smartphone, Facebook, WhatsApp, and Instagram use. In addition to bivariate correlation analysis, exploratory graph analysis (EGA), a type of network analysis, was conducted. *Results:* The results showed that while problematic Facebook and Instagram use seem to be distinct phenomena, problematic smartphone and WhatsApp use were heavily intertwined. Furthermore, the only cross-platform symptom observed was the extent of reported pain in wrists and neck due to digital technology use. The EGA network models showed very good stability in bootstrap analyses. *Discussion and conclusions:* In general, the results of this study suggest that while Instagram and Facebook use may potentially constitute distinct problematic behaviors, problematic smartphone/WhatsApp use scales may be measuring highly similar or even the same construct.

KEYWORDS

problematic smartphone use, smartphone addiction, smartphone use disorder, Facebook, Instagram, WhatsApp

INTRODUCTION

As of October 2019, approximately 5.16 billion people use a mobile device (such as smartphone), 3.73 billion people actively use social networking sites (SNS), and around 3.66 billion people use SNS on their mobile device (We Are Social Ltd, 2019). Among the most popular SNS globally are Facebook, YouTube, WhatsApp, and Instagram (We Are Social Ltd, 2019), at least from a Western perspective (Montag, Becker, & Gan, 2018). Of these platforms,

*Corresponding author.
E-mail: dmroz@ut.ee

Facebook, WhatsApp, and Instagram are owned by a single company: Facebook, Inc. (Facebook, 2020).

While smartphone and social media use could enhance one's daily-life by providing access to information (e.g., news and study materials), facilitating social connectedness, and providing additional means for entertainment, there has been a growing concern over potentially adverse effects of excessive smartphone and social media use. This has led several researchers to start investigating the potential addictive use of these technologies (Bian & Leung, 2014; Kwon, Kim, Cho, & Yang, 2013). Although these earlier works adopted addiction-terminology (e.g., smartphone addiction, social media addiction), scholars have moved away from this approach, aiming to avoid over-pathologizing behaviors that may be the new normality (Billieux, Schimmenti, Khazaal, Maurage, & Heeren, 2015b; Billieux, Leaman, Trampusch, Osborne, & Liss, 2017; Kardefelt-Winther et al., 2017). Importantly, it has also been argued that not all people who are heavy digital technology users end up having problems in their life because of that behavior (Billieux, 2012; Brand, Young, Laier, Wölfling, & Potenza, 2016; Davis, 2001; Kardefelt-Winther et al., 2017). Nevertheless, research on this topic – as well as discussion on conceptualization of these phenomena – continues. This has resulted in different research groups working on “excessive smartphone use” (Karsay, Schmuck, Matthes, & Stevic, 2019), “smartphone overuse” (Inal, Demirci, Cetintürk, Akgonül, & Savas, 2015; Lee et al., 2017), “problematic smartphone/SNS use” (Banyai et al., 2017; Kim, 2018), and “smartphone/social networks use disorder” (Montag, Wegmann, Sariyska, Demetrovics, & Brand, 2019; Peterka-Bonetta, Sindermann, Elhai, & Montag, 2019), to name a few¹. In essence, likely the vast majority of works have operationalized this phenomenon – in whichever way they call it – as adversities and disruptions in everyday life due to excessive smartphone/social media use (Billieux, 2012). Therefore, while time-consuming use of digital technology is one part of the picture, the other one is the levels of disruption it causes in people's lives (Rozgonjuk, Sindermann, Elhai, & Montag, 2020).

In order to decrease the fragmentation in this research field, and to aim towards better clarity, researchers have proposed explicitly to either use the problematic digital technology (e.g., smartphone) use (Panova & Carbonell, 2018) or digital technology (e.g., smartphone) use disorder (Montag et al., 2019) terminology. However, both terms have their own limitations. For instance, in the “problematic use” approach, it is unclear whether it describes a person moving from “healthy” state towards experiencing full-blown psychopathology or if it is the end condition in itself (Rozgonjuk, Elhai, & Hall, 2019a). On the other hand, the

“use disorder” approach may be problematic as well, as smartphone nor problematic social networks use are recognized as disorders in common diagnostic manuals. It is important to note that, at the time of writing these lines, the debate regarding terminology (as well as these constructs) is ongoing. We acknowledge that researchers may prefer one term over another. For the current paper, we will use the “problematic smartphone/social networks use”, as proposed in Panova & Carbonell (2018). We do want to emphasize once again that problematic smartphone use (PSU) and problematic social networks use are currently not diagnosable conditions. To make clear that the majority of the individuals in our sample face no/low adversities due to their social network site use, we speak of individual tendencies towards PSU and/or social networks use.

This said, studies with mainly non-clinical samples have repeatedly demonstrated that PSU and problematic social networks use are associated with symptoms of depression and anxiety (Elhai, Dvorak, Levine, & Hall, 2017; Elhai, Levine, & Hall, 2019; Primack et al., 2017), as well as other important factors, such as poorer academic achievement (Kates, Wu, & Coryn, 2018; Rozgonjuk, Saal, & Täht, 2018), decreased productivity (Duke & Montag, 2017), and riskier driving (Oviedo-Trespalacios, Haque, King, & Demmel, 2018a; Oviedo-Trespalacios, Haque, King, & Washington, 2018b). In addition, PSU has been associated with transdiagnostic constructs relevant to development and maintenance of anxiety and mood disorders, such as emotion dysregulation (Hoffner & Lee, 2015; Pancani, Preti, & Riva, 2019; Rozgonjuk & Elhai, 2019), intolerance of uncertainty (Rozgonjuk et al., 2019b), excessive reassurance seeking (Billieux, Maurage, Lopez-Fernandez, Kuss, & Griffiths, 2015a; Elhai et al., 2020), personality traits, such as neuroticism (Balta, Emirtekin, Kircaburun, & Griffiths, 2018; Cho, Kim, & Park, 2017; Lachmann, Duke, Sariyska, & Montag, 2019) and impulsivity (Billieux, Van der Linden, d'Acremont, Ceschi, & Zermatten, 2007; Kim et al., 2016; Peterka-Bonetta et al., 2019), and fear of missing out (Gezgin, 2018; Servidio, 2019; Wolniewicz, Rozgonjuk, & Elhai, 2019). Similarly to PSU, studies have found problematic social networks use to be associated both with psychopathology (Shensa et al., 2017), transdiagnostic factors, such as fear of missing out and neuroticism (Blackwell et al., 2017), and decreased work productivity (Zivnuska, Carlson, Carlson, Harris, & Harris, 2019; Rozgonjuk, Sindermann, Elhai & Montag 2020).

Contemporary application design, especially for smartphones and social media, is fostering addictive behaviors (Eyal, 2014). Since there seems to be a significant overlap between problematic social networks use and PSU, high scores on PSU measures may reflect the extent of problematic use of specific communication-based applications

¹It should be noted that several works of some of the authors of this manuscript have also used the “use disorder” terminology, in line with suggestions in recent works (Brand et al., 2016, 2019; Montag et al., 2019). Nevertheless, as also discussed in the main text, there are reasons why “use disorders” terminology may not be currently acceptable for some researchers. Despite that, we believe that both terms can be used, since consensus regarding terminology has still not been reached. In general, we think that it is of importance to aim at a unification of terminology in the literature in the future, but we also see that much more work and evidence needs to come up to finally judge if other areas of problematic Internet use beyond gaming and gambling disorder can be seen as acknowledged use disorders.

(Montag et al., 2019). If that is the case, one may ask: are there specific platforms that are associated with higher levels of PSU? This question has been partially answered by Sha, Sariyska, Riedl, Lachmann, and Montag (2019) finding that PSU positively correlates strongly with problematic WhatsApp use (PWU) and problematic Facebook use (PFU). However, these authors only examined the link of PSU, PWU, and PFU on the bivariate correlation level. The current work aims to explore these associations, as well as the links with problematic Instagram use (PIU), on item-level data in a network analytic framework.

The aim of this study is to investigate if PSU and Facebook-owned SNS (Facebook, WhatsApp, and Instagram) use are associated with each other. This is important, as the SNS in this study have slightly different functionalities, allowing to better specify the potential PSU-driving mechanisms. Facebook, Inc. owns all of these mentioned platforms, being a parent company (Facebook, 2020). Facebook itself has more and varied functionalities, such as possibilities to join groups, follow pages and subscribe to news outlets, selling and buying goods, share and read posts (e.g., videos, pictures, text, or combinations of these), as well as post status updates (Facebook, 2020). WhatsApp is a messenger platform where users can send and receive text and voice messages as well as other multimedia, and one can make audio and video calls (WhatsApp Inc., 2020). Instagram is more of a picture- and video-based platform where users can edit their content (before uploading) and share it with others for viewing, commenting, and reacting (Instagram Inc., 2020).

We have posed the following research questions:

- R1: Is there an overlap between PSU items with specific SNS-based problematic use items?
- R2: Which problematic SNS use items associate with PSU items the strongest?
- R3: Do these problematic use scales constitute distinct conditions or is there a more general problematic technology use?

We aim to answer these questions by implementing exploratory graph analysis (EGA), a data-driven network analysis that aims to identify the dimensions of item-level data (Golino et al., 2020). With regards to the first research question (R1): if PSU items cluster together with any of the problematic social networks use items, one could assume that PSU is not strongly indistinguishable from problematic social networks uses. However, if PSU items do not strongly correlate with items of other scales, one may infer that PSU could constitute a distinct condition. In addition, there may also be a potential overlap between the symptoms of different problematic uses, e.g., some aspects of PSU may overlap with problematic social networks use but not completely (similarly to comorbidity in psychopathology). To our knowledge, this type of analysis that includes smartphone and different problematic social networks use scales has not been done before, and it could provide more detailed insights into the associations between these digital technology uses.

The second research question (R2) could be inferred from the results of both bivariate correlation analysis as well as

EGA results. The number of associations as well as effect sizes could indicate if PSU is driven by specific platform use. While previously Sha et al. (2019) found that PSU, PWU, and PFU were intercorrelated, and that PWU had a higher correlation with PSU than PFU, it is of interest to carve out what lies underneath these correlations. When the strongest-correlating SNS is determined, a network analytic approach could further indicate to which items and how exactly the problematic uses of different media are associated with each other.

The answer to the third research question (R3) allows to see whether these four measured conditions have significant overlap across symptoms, indicating to a more generalized problematic digital technology use, or if the items across platforms cluster together due to medium/media as the common denominator (as opposed to specific symptoms). The latter research question has not been studied in the domain of PSU and specific SNS, but Baggio et al. (2018) found that PSU, gaming disorder, and cybersex addiction are relatively independent conditions, while problematic Internet use was associated with all these conditions. The results could show if seemingly different platform-based problematic use symptoms are actually overlapping with PSU or not.

METHODS

Participants and procedure

Participants were recruited to take part in a smartphone and SNS usage study in an online environment called Survey-Coder (<https://www.surveycoder.com/>) developed by Christopher Kannen (<https://ckannen.com/>). The questionnaire was in German language. Participants were recruited via various media types, such as television, print media, and online environments. People were encouraged to take part in the study by allowing them to receive feedback for their survey results.

The initial dataset included 2,975 respondents. However, upon closer inspection there were some implausible values, e.g., in age. Respondents who were at least 12 years old were included (effective sample $n = 2,917$). Including participants who were 12+ years old was justified by some evidence suggesting that younger children may not comprehend the questions originally developed in adult samples well (Bell, 2007), as well as common requirements of the local Institutional Review Board. Because we were interested in study participants who reported using a smartphone, as well as WhatsApp, Facebook, and Instagram, our remaining effective sample was $n = 949$ (age $M = 31.82$, $SD = 11.38$; age range: 13 to 76; 64.70% women). 476 (50.16%) participants did not have a university degree, while 473 (49.84%) graduated from a university. 888 (94%) participants reported being from Germany, followed by 51 (5%) from Austria, 9 (1%) from Switzerland, and 1 from Liechtenstein.

Measures

We firstly asked participants about their general socio-demographics (e.g., age, gender, education level, and country



of residence). In addition, we also asked whether they used different social networking platforms (e.g., WhatsApp, Facebook, and Instagram). Finally, participants responded to problematic smartphone (PSU), WhatsApp (PWU), Facebook (PFU), and Instagram use (PIU) scales.

In order to assess PSU, we used the German short version of the Smartphone Addiction Scale (d-KV-SSS; Montag, 2018). It is a 10-item scale (1 = “strongly disagree” to 6 = “strongly agree”). The d-KV-SSS reflects the extent of PSU, with higher scores indicating more severe problems associated with smartphone use. It has good internal reliability, and has been validated against other Internet and smartphone use related measures (Kwon et al., 2013; Montag, 2018). The internal consistency for the d-KV-SSS for the effective sample was McDonald’s omega = 0.84 and Cronbach’s alpha = 0.83.

In addition, we also included questionnaires gauging the extent of PWU, PFU, and PIU. For that, the word “smartphone” in d-KV-SSS was substituted with WhatsApp, Facebook, and Instagram, respectively. While these scales were not validated in a traditional way, statistics across some recent studies (Sha et al., 2019; Sindermann, Duke, & Montag, 2020a; Sindermann, Elhai, & Montag, 2020b) seem to indicate these measures have adequate reliability as well as validity. For the former, Cronbach’s alphas were consistently higher than 0.87 for all scales; furthermore, correlations between the scales are moderate to high, indicating to acceptable construct validity. Finally, PWU and PFU also showed acceptable fit in confirmatory factor analysis (Sha et al., 2019). McDonald’s omegas/Cronbach’s alphas for the effective sample of the current study were 0.91/0.91 (PWU), 0.95/0.95 (PFU), and 0.95/0.95 (PIU), respectively. Additionally, we conducted confirmatory factor analysis for each scale, reported in Supplementary Materials A. As can be seen from there, all scales demonstrated acceptable fit. The generic content of items as well as their order number are in Table 1.

Table 1. Items of scales

Item number	Item content
1	I miss planned work due to my XYZ use.
2	I am having a hard time concentrating in class, while doing assignments, or while working due to my XYZ use.
3	I feel pain in the wrists or at the back of the neck while using XYZ.
4	I won't be able to stand not having XYZ.
5	I feel impatient and fretful when I am not having XYZ.
6	I have XYZ in my mind even when I am not using it.
7	I will never give up using XYZ even when my daily life is already greatly affected by it.
8	I am constantly checking XYZ so as not to miss conversations.
9	I am using XYZ longer than I had intended.
10	The people around me tell me that I use XYZ too much.

Notes. XYZ = depending on the scale, either “smartphone”, “Facebook”, “WhatsApp”, or “Instagram”.

Analysis

The data and analysis script are available in the Open Science Framework. Data analysis was conducted in R version 3.6.3 (R Core Team, 2020). There were no missing data among the PSU and SNS use scales. We also checked the data for careless responses (Curran, 2016), using the *careless* package (v 1.1.3; Yentes & Wilhelm, 2018). There were only two respondents who had consequently given the same response value to all PSU as well as SNS use scales. Because, theoretically, these values could be possible, we decided to keep these rows of data in subsequent analyses. We computed both McDonald’s omegas (Revelle & Zinbarg, 2009) and Cronbach’s alphas using the *scaleDiagnosis()* function in the *userfriendlyscience* package (v. 0.7.2; Peters, 2019), treating the items of the scales as ordinal. We used summed scores for PSU and SNS use scales when describing centrality statistics. Because the skewness and kurtosis of summed scores were in the range of normality (Kim, 2013), we computed Pearson correlations to evaluate the strength and direction of associations between the summed scale scores. A correlation coefficient’s absolute value could be roughly interpreted as having a small (0.10–0.30), medium (0.30–0.50), or large (0.50–1.00) effect size (Cohen, 1992).

Because we were interested in how the items of the four scales (PSU, PWU, PFU, and PIU) were possibly intertwined, we used exploratory graph analysis (EGA) (Golino et al., 2020; Golino & Epskamp, 2017), a type of network analytic model. We bootstrapped results over 1,000 samples using the *bootEGA* function in *EGAnet* package in R (v. 0.9.5; Golino & Christensen, 2020). EGA is a method for identifying empirical dimensions in multidimensional data, and its advantages over more traditional exploratory methods (e.g., exploratory factor analysis, cluster analysis, and parallel analysis) is that the relations between single items and their clusters/dimensions are visualized with a network graph, improving the interpretation of results (Bringmann & Eronen, 2018). Furthermore, the dimensional structure is identified without the researcher’s direction, making this approach fully data-driven (Christensen & Golino, 2019). We also conducted item-level redundancy analysis (see Supplementary Materials B for detailed description) and report the results of EGA with redundant items merged as our main results (Christensen, Golino, & Silvia, 2020).

Structure and stability of the EGA network. EGA is based on the estimation of a network model which is followed by implementation of a community detection algorithm (Yang, Algesheimer, & Tessone, 2016). Two main graphical elements of a network are typically *nodes* and *edges*; the former represent variables, and the latter associations (e.g., correlations) between those variables. For network analysis, we estimated a Gaussian Graphical Model (GGM; Epskamp, Waldorp, Möttus, & Borsboom, 2018b), using the Graphical Least Absolute Shrinkage and Selection Operator in combination with Extended Bayesian Information Criterion (EBIC) model selection (GELASSO; Epskamp, Borsboom, &

Fried, 2018a). In GGM, edges are partial correlations between two nodes, controlled for other nodes in a given network. GELASSO is a graphical estimation method where unreasonably large coefficients are penalized and shrunk, and small coefficients are shrunk to zero, essentially conducting variable subset selection and resulting in a parsimonious model controlled for overfitting; furthermore, applying EBIC in this estimation helps to select the best-fitting model (Christensen & Golino, 2019; Epskamp & Fried, 2018). Of note, EGA implements absolute edge values.

After fitting the model, EGA implements a community detection algorithm in order to specify the number of dimensions. Recently, it has been shown that one of the best-performing algorithms, in terms of higher accuracy and less bias, in polytomous (e.g., ordinal) and multidimensional data is the Louvain algorithm (Christensen, 2020). It tends to perform better than, e.g., Spinglass algorithm, especially in this type of data (Christensen, 2020). The Louvain algorithm uses the modularity statistic to optimize its partitions (Blondel, Guillaume, Lambiotte, & Lefebvre, 2008). Firstly, as it aims to identify hierarchical structures in large networks, it exchanges nodes between communities/dimensions iteratively and evaluates the change in modularity (Christensen, 2020). Then, by creating latent nodes representing a collection of nodes, and identifying edge weights with other observed and latent nodes, the Louvain algorithm creates smaller networks (Christensen, 2020; Gates, Henry, Steinley, & Fair, 2016). The community to which a node belongs to is formed deterministically (e.g., without the researcher's direction) by the proportion of connected edges between nodes: densely connected edges form a community (Christensen & Golino, 2019). Finally, dimensions of the network are color-coded on the graph.

To estimate stability of the network's dimensions as well as the robustness of which community an item belongs to, we used non-parametric bootstrapping of EGA over 1,000 samples (Christensen & Golino, 2019). In other words, resampling with replacement from the original dataset was used, whereas with each new generated simulated dataset a network was estimated and the Louvain algorithm was implemented. This results in a large number of replica-networks, providing information on how stable is the estimated EGA network. Bootstrapping EGA, therefore, allows comparison of the original EGA network as well as a typical (e.g., median) EGA network from bootstrapped samples. In addition, the package bootEGA (Christensen & Golino, 2019) displays stability statistics of both dimensions as well as items. Dimension stability could be demonstrated by (a) comparing the EGA and median bootstrapped EGA figure, (b) observing the median number of dimensions (and 95% CI) retrieved from bootstrap analysis, and (c) comparing the likelihood of different dimensions observed in bootstrapped networks. Item stability could be used so that the dimensions are specified from bootstrapped EGAs and compared if an item is present in its corresponding dimension (for more details, see Christensen & Golino 2019). bootEGA provides (a) replicability of an item in the dimension, and (b) item likelihood across different dimensions. The results of these dimension and item stability

statistics are reported in Supplementary Materials C (for networks with redundant items merged).

Node strength statistics across dimensions. Finally, node strength for each item in each dimension or *network loadings* can be computed (these statistics could also be interpreted as factor loadings in exploratory factor analysis, see Hallquist, Wright, & Molenaar, 2019, for further details) (Christensen & Golino, 2020). Node strength (the sum of connections to a node) is calculated for each item's connections within its specified dimension and between every other dimension. Average node strength is retrieved across all replica networks. Items that have higher average node strength within their dimension could be interpreted as relatively stable and are associated with their dimension most strongly. If an item has a greater proportion of strength across other dimensions, it could indicate that the item might be multidimensional (e.g., belong to other dimensions).

Ethics

The study procedures were carried out in accordance with the Declaration of Helsinki. The Institutional Review Board of Ulm University approved the study. All subjects were informed about the study and all provided informed consent (including parental/legal guardian consent for underage participants).

RESULTS

Descriptive statistics

Descriptive statistics for single scale items of PSU, PWU, PFU, and PIU are presented in Table 2, and descriptive statistics as well as bivariate correlations for summed scores of these scales and age are in Table 3. We have also included item-level frequency of responses to PSU/SNS use scales in Supplementary Materials D.

PSU scale scores were associated with problematic use of different SNS, with effects ranging from medium (Facebook) to strong (WhatsApp and Instagram). Similarly, PWU was positively associated with both PFU and PIU, with strong to medium effects, respectively. PIU and PFU had a medium positive correlation. Age was negatively associated with PSU (small effect size), as well as PWU (small effect) and PIU (medium effect). Age was positively (but with a small effect) associated with PFU.

Structure and stability of the EGA network

Redundancy analysis (see Supplementary Materials B) suggested that it would be justified to merge some of the items. Interestingly, every PWU item was suggested to be redundant with at least one other PSU item (usually corresponding to its identically worded counterpart). In addition to statistical reasons, merging the redundant items of PSU-PWU would also be theoretically justified, since PWU is a smartphone-based application. Similarly, merging other



Table 2. Descriptive statistics for the scale items

Item	M	SD	Item	M	SD
PSU1	2.58	1.44	PWU1	1.98	1.15
PSU2	2.75	1.44	PWU2	2.29	1.33
PSU3	2.13	1.34	PWU3	1.86	1.24
PSU4	3.72	1.45	PWU4	3.18	1.57
PSU5	3.52	1.43	PWU5	2.54	1.38
PSU6	2.48	1.30	PWU6	2.08	1.28
PSU7	2.49	1.26	PWU7	2.20	1.31
PSU8	3.22	1.40	PWU8	2.85	1.50
PSU9	4.38	1.25	PWU9	2.91	1.54
PSU10	2.75	1.46	PWU10	1.87	1.24
PFU1	1.63	1.00	PIU1	2.32	1.52
PFU2	1.57	0.98	PIU2	2.23	1.45
PFU3	1.47	0.96	PIU3	1.78	1.27
PFU4	1.76	1.12	PIU4	2.16	1.37
PFU5	1.38	0.77	PIU5	1.78	1.15
PFU6	1.40	0.81	PIU6	2.02	1.34
PFU7	1.43	0.86	PIU7	1.74	1.17
PFU8	1.64	1.08	PIU8	2.34	1.54
PFU9	2.40	1.57	PIU9	3.41	1.84
PFU10	1.43	0.91	PIU10	1.94	1.39

Notes. N = 949. PSU = problematic smartphone use; PWU = problematic WhatsApp use; PFU = problematic Facebook use; PIU = problematic Instagram use. Observed Min for all items = 1; Max for all items = 6.

Table 3. Descriptive statistics and Pearson correlations for the key variables

	M	SD	Min	Max	1	2	3	4
1. PSU	30.03	8.37	10	57	–			
2. PWU	23.75	9.55	10	57	0.755***	–		
3. PFU	16.12	7.54	10	53	0.484***	0.448***	–	
4. PIU	21.72	10.90	10	59	0.572***	0.545***	0.284***	–
5. Age	31.82	11.38	13	76	–0.159***	–0.222***	0.130***	–0.393***

Notes. N = 949. PSU = problematic smartphone use; PWU = problematic WhatsApp use; PFU = problematic Facebook use; PIU = problematic Instagram use scores, respectively. *** $P < 0.001$.

redundant items would be justified by either being redundant within the scale (e.g., some PFU, and some PIU items) or across a specific symptom (e.g., item 3). After merging the items, EGA and bootstrapped EGA networks were computed. The graphical depiction of these networks is presented in Fig. 1, and statistics for the stability of this network structure are presented in Supplementary Materials C. We have also included the results of EGA analysis for networks where redundant items were not merged (see Supplementary Materials E). In general, the EGA network was highly similar to the median network from bootstrap analysis, with having a very similar structure as well as node strengths.

There were relatively lower-likelihood-cases when the bootstrapped samples computed four dimensions (e.g., see Supplementary Materials C); mostly, the networks suggested forming three dimensions. Firstly, one may see from Fig. 1 that both EGA and median bootstrapped EGA networks are highly similar. Three clusters could be observed: the PFU, PIU, and a joint cluster for PSU-PWU. Interestingly, the only symptom that seemed to form its own entity (as also demonstrated in redundancy analysis), item 3 (“I feel pain in

the wrists or at the back of the neck while using smartphone/WhatsApp/Facebook/Instagram.”), was assigned to the PFU dimension – yet the loadings show that this was the case by just a small margin, suggesting that this item/symptom could be a dimension on its own.

Node strength statistics across dimensions. How strongly are items associated within and between different dimensions? Table 4 provides some insights.

As mentioned earlier in the Methods section, average node strength statistics are also interpretable as factor loadings in exploratory factor analysis (Christensen & Golino, 2020). From Table 4, therefore, one may notice that although the “item 3” loaded onto the dimension of some of the PSU-PWU items, the average node strength statistics had only slight differences with loadings to other dimensions. However, as also in other analyses, PFU and PIU tended to form their own clusters with respective scale items, while PSU-PWU items loaded onto dimensions where the respective medium and media SNS were present. Therefore, there is evidence for PSU-PWU items being more intertwined with each other than with other platforms.

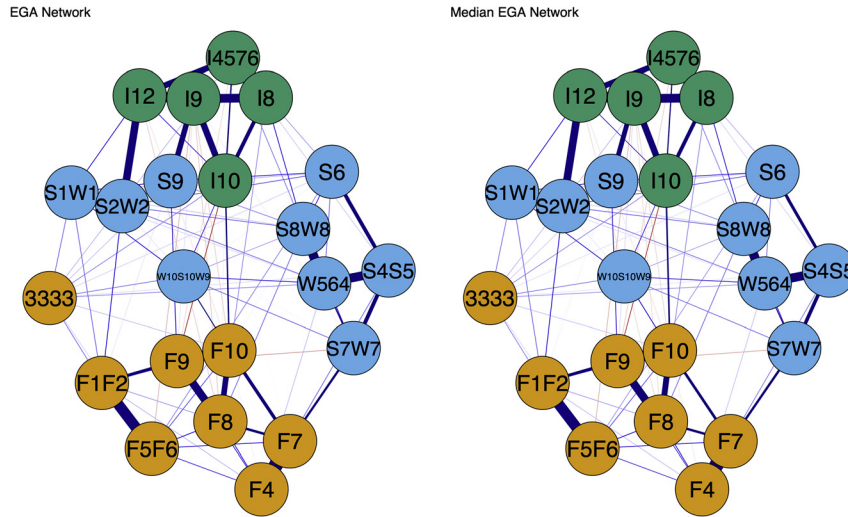


Fig. 1. EGA (left) and bootstrapped EGA median network (left) with redundant items merged. Notes. S = problematic smartphone use; W = problematic WhatsApp use; F = problematic Facebook use; I = problematic Instagram use. Numbers in item name correspond to items in the respective scales. Combination of different letters and numbers indicates to merged redundant variables. Please note that each network/factor is depicted by a unique color. Items forming dimensions are: (1) Smartphone-WhatsApp items, (2) Instagram items, and (3) Facebook items and item 3. The thickness of lines (edges) depicts the strength of the relationship between two nodes

DISCUSSION

The aim of this study was to explore how problematic smartphone, Facebook, WhatsApp, and Instagram use (PSU,

PFU, PWU, PIU, respectively) were potentially associated. Furthermore, we aimed to investigate which platforms use associated more with PSU, and if PSU constitutes a distinct phenomenon. We conducted both bivariate analyses with

Table 4. Average network loading for each variable in each dimension over 1,000 bootstrapped samples for EGA network with redundant items merged

Item	Dimension	Dimension				
		1	2	3	4	5
ITEM 3	1	0.239	0.048	0.023	0.132	0.156
F1F2	1	0.278		0.004	0.016	
F10	1	0.043		0.045	0.085	0.114
F9	1	0.271		0.002	0.008	0.041
F5F6	1	0.328			0.081	
F8	1	0.307		-0.002	0.015	
F7	1	0.361		-0.027	0.001	
F4	1	0.312		-0.035	0.063	
S9	2	0.036	0.137	0.092	0.238	
S2W2	2	0.055	0.145	0.125	0.157	
S1W1	2		0.262	0.009	0.047	
W10S10W9	2	0.026	0.199	0.044	0.126	0.021
S6	2		0.129		0.117	
W564	2		0.214		0.056	
S8W8	2		0.249		0.115	
S7W7	2		0.108		0.122	
S4S5	2		0.355		0.138	
I10	3	-0.010		0.316	0.179	0.076
I12	3			0.306	0.027	
I9	3			0.362	0.014	
I8	3			0.345	0.097	
I4576	3			0.291	0.072	

Notes. S = problematic smartphone use; W = problematic WhatsApp use; F = problematic Facebook use; I = problematic Instagram use. Numbers in item name correspond to items in the respective scales. Combination of different letters and numbers indicates to merged redundant variables. An item's highest average node strength across dimensions is highlighted in bold font.



summed scale scores of the measures of those constructs, as well as bootstrapped EGA to identify how single scale items form dimensions of problematic digital technology use.

Our results showed major overlap between PSU and PWU. This was indicated by both bivariate correlation analysis, where summed scores of these scales had a very strong association of $r = 0.756$, as well as in EGA. Regarding the latter, it seems that while PFU and PIU constitute distinct conditions, PSU and PWU are intertwined, forming a cluster of their own. These findings may indicate that, as has been discussed elsewhere (Brand et al., 2016; Rozgonjuk, 2019), PSU could not be necessarily indistinguishable from problematic Internet-based communication uses, as the main functions of WhatsApp are smartphone-based text messaging and phone calls. It is interesting, however, that both PFU and PIU do not seem to be highly associated with PSU on item-level data in EGA. Perhaps it could be due to Facebook having more features that can be accessible from one's computer in addition to smartphone, and because Instagram is more of an image-based platform. To illustrate this further: Facebook originally developed as a platform accessed via desktop and then swapped over to the smartphone (when this was introduced to the market). In so far this is coherent with the results that the Facebook application is not a genuine smartphone application. The Instagram findings are somewhat more surprising, because Instagram is more of a smartphone-based application and because some features are only accessible via smartphone (e.g., instant messaging), one might assume that most Instagram users access their accounts via the smartphone. It has also been recently demonstrated that higher Instagram use frequency is associated with higher levels of PSU (Rozgonjuk, Pruunsild, Jürimäe, Schwarz, & Aru, 2020). Therefore, future research should also focus more on these findings.

Back to WhatsApp: Another important feature of this messenger (and why it may be more associated with PSU) is that it is an *instant* messenger. Hence, people are confronted with messages in the moment they receive the messages (note: one can also turn off the push notifications of WhatsApp). This is not necessarily true for Facebook and Instagram, although it may depend on account settings.

Curiously, the only items that seemed to cluster together (indicating to redundancy) regarded wrist and neck pain resulting from both excessive smartphone as well as SNS platforms use. Perhaps this is an occasion where smartphone use could explain the results, because it is the physical object that could be held accountable for these adversities. SNS platforms are more abstract entities that could drive one's engagement, but, ultimately, it is the smartphone use (or, e.g., typing in messages via the smartphone) that could cause physical pain and discomfort (Xie, Szeto, Dai, & Madeleine, 2016; Yang et al., 2019).

The results of this study suggest that PSU could be, in fact, a reflection of active communication based platform use, instead of being a problematic phenomenon in itself. While there is some evidence that PSU could differ from other behavioral addictions, such as online gambling and cybersex disorder (e.g., see Baggio et al. 2018), our study was the first to

include several SNS platforms and PSU into a comprehensive EGA. The results are novel, since they demonstrate on item-level data that while PFU and PIU are likely problematic phenomena in themselves, the overlap between PSU and PWU suggests that perhaps engagement in text-messaging app use could drive higher smartphone use. Of practical implication is the notion that perhaps people who feel they are experiencing smartphone or problematic social networks use symptoms should look into which platform they are using the most. If it is the concern over smartphone use, it could be likely that the actual driving force is WhatsApp use. The results also provide further evidence for PSU research where it has been found that social media use is one of the drivers of developing PSU (Lopez-Fernandez, Honrubia-Serrano, Freixa-Blanxart, & Gibson, 2014); our results show that social networks may not be equal in the contribution of developing a PSU-like condition.

The limitations of this study include using self-reports, cross-sectional study design, and convenience sampling. Recent findings have demonstrated that self-reported PSU may not be strongly associated with objectively measured smartphone use. It should be noted, however, that the scales used in this study measure the extent of adverse effects associated with specific medium (e.g., smartphone) or platform (e.g., WhatsApp, Facebook, or Instagram) use; therefore, the self-reports in this case are more dependent on subjective perception of the effects of digital technology use on one's everyday life. Nevertheless, in order to be able to detect and provide a remedy for potential illness, it would be useful to also understand the objectively measured behavioral patterns, which make the self-report not obsolete, but add a new important data layer to the psychodiagnostics process (Baumeister & Montag, 2019; Montag & Elhai, 2019). The second limitation, cross-sectional study design, hinders from interpreting the correlational results as a potential causal mechanism. The third limitation was the use of convenience sampling in the form of self-selected German-speaking individuals. While there was more variation in socio-demographics, such as age, than in several other studies in this domain (e.g., that have only included undergraduate students), it could be that some subgroups of smartphone and social media users are less likely to take part in studies like this, posing further restrictions on generalization. Future studies could aim to overcome this limitation, and address whether SNS platforms drive problematic use of other platforms, and whether features of WhatsApp cause more engagement in one's smartphone.

CONCLUSION

In conclusion, our study was the first to implement EGA to assess how problematic smartphone (PSU), Facebook (PFU), WhatsApp (PWU), and Instagram use (PIU) are potentially intertwined. The results show that while PFU and PIU seem to form their own respective dimensions of problematic SNS use, PSU and PWU are largely intertwined. However, it seems that pain in wrists and neck due to technology use is

the single generic symptom that seems to be present across smartphone and SNS platforms use.

Funding sources: DR, CS, APC, JDE, and CM declare no funding for this work.

Authors' contribution: DR designed the study, wrote the manuscript, performed the data analysis, and revised the manuscript. CS designed the study, collected the data, wrote and revised the manuscript. JDE revised the manuscript. APC reviewed and revised the manuscript and contributed to analysis. CM designed the study, collected the data, and wrote and revised the manuscript. All authors had full access to all data in the study and take responsibility for the integrity of the data and the accuracy of the data analysis.

Conflict of interest: The authors report no financial or other relationship relevant to the subject of this article. Despite this CM mentions that he has received (to Ulm University and earlier University of Bonn) grants from the German Research Foundation (DFG). CM has performed grant reviews for several agencies; has edited journal sections and articles; has given academic lectures in clinical or scientific venues or companies; and has generated books or book chapters for publishers of mental health texts. For some of these activities he received royalties, but never from the gaming or social media industry. CM mentions that he is part of a discussion circle (Digitalität und Verantwortung; <https://about.fb.com/de/news/h/gesprachskreis-digitalitaet-und-verantwortung/>) debating ethical questions linked to social media, digitalization and society/democracy at Facebook. In this context, he receives no salary for his activities.

JDE notes that he receives royalties for several books published on posttraumatic stress disorder (PTSD); is a paid, full-time faculty member at University of Toledo; is a paid, visiting scientist at Tianjin Normal University; occasionally serves as a paid, expert witness on PTSD legal cases; and receives grant research funding from the U.S. National Institutes of Health and Department of Defense.

REFERENCES

- Baggio, S., Starcevic, V., Studer, J., Simon, O., Gainsbury, S. M., Gmel, G., et al. (2018). Technology-mediated addictive behaviors constitute a spectrum of related yet distinct conditions: A network perspective. *Psychology of Addictive Behaviors*, 32(5), 564–572. <https://doi.org/10.1037/adb0000379>.
- Balta, S., Emirtekin, E., Kircaburun, K., & Griffiths, M. D. (2018). Neuroticism, trait fear of missing out, and phubbing: The mediating role of state fear of missing out and problematic Instagram use. *International Journal of Mental Health and Addiction*, 18, 628–639. <https://doi.org/10.1007/s11469-018-9959-8>.
- Banyai, F., Zsila, A., Kiraly, O., Maraz, A., Elekes, Z., Griffiths, M. D., et al. (2017). Problematic social media use: Results from a large-scale nationally representative adolescent sample. *PLoS One*, 12(1), e0169839. <https://doi.org/10.1371/journal.pone.0169839>.
- Baumeister, H., & Montag, C. (Eds.). (2019). *Digital phenotyping and mobile sensing: New developments in psychoinformatics*. Springer International Publishing. <https://doi.org/10.1007/978-3-030-31620-4>.
- Bell, A. (2007). Designing and testing questionnaires for children. *Journal of Research in Nursing*, 12(5), 461–469. <https://doi.org/10.1177/1744987107079616>.
- Bian, M., & Leung, L. (2014). Linking loneliness, shyness, smartphone addiction symptoms, and patterns of smartphone use to social capital. *Social Science Computer Review*, 33(1), 61–79. <https://doi.org/10.1177/0894439314528779>.
- Billieux, J. (2012). Problematic use of the mobile phone: A literature review and a pathways model. *Current Psychiatry Reviews*, 8(4), 299–307. <https://doi.org/10.2174/157340012803520522>.
- Billieux, J., Maurage, P., Lopez-Fernandez, O., Kuss, D. J., & Griffiths, M. D. (2015a). Can disordered mobile phone use be considered a behavioral addiction? An update on current evidence and a comprehensive model for future research. *Current Addiction Reports*, 2(2), 156–162.
- Billieux, J., Schimmenti, A., Khazaal, Y., Maurage, P., & Heeren, A. (2015b). Are we overpathologizing everyday life? A tenable blueprint for behavioral addiction research. *The Journal of Behavioral Addictions*, 4(3), 119–123. <https://doi.org/10.1556/2006.4.2015.009>.
- Billieux, J., van Rooij, A. J., Heeren, A., Schimmenti, A., Maurage, P., Edman, J., et al. (2017). Behavioural addiction open definition 2.0-using the open science framework for collaborative and transparent theoretical development. *Addiction*, 112(10), 1723–1724. <https://doi.org/10.1111/add.13938>.
- Billieux, J., Van der Linden, M., d'Acremont, M., Ceschi, G., & Zermatten, A. (2007). Does impulsivity relate to perceived dependence on and actual use of the mobile phone? *Applied Cognitive Psychology*, 21(4), 527–537. <https://doi.org/10.1002/acp.1289>.
- Blackwell, D., Leaman, C., Trampusch, R., Osborne, C., & Liss, M. (2017). Extraversion, neuroticism, attachment style and fear of missing out as predictors of social media use and addiction. *Personality and Individual Differences*, 116, 69–72. <https://doi.org/10.1016/j.paid.2017.04.039>.
- Blondel, V. D., Guillaume, J.-L., Lambiotte, R., & Lefebvre, E. (2008). Fast unfolding of communities in large networks. *Journal of Statistical Mechanics: Theory and Experiment*, 2008(10), P10008. <https://doi.org/10.1088/1742-5468/2008/10/P10008>.
- Brand, M., Wegmann, E., Stark, R., Müller, A., Wolfing, K., Robbins, T. W., et al. (2019). The Interaction of Person-Affect-Cognition-Execution (I-PACE) model for addictive behaviors: Update, generalization to addictive behaviors beyond internet-use disorders, and specification of the process character of addictive behaviors. *Neuroscience & Biobehavioral Reviews*, 104, 1–10. <https://doi.org/10.1016/j.neubiorev.2019.06.032>.
- Brand, M., Young, K. S., Laier, C., Wölfling, K., & Potenza, M. N. (2016). Integrating psychological and neurobiological considerations regarding the development and maintenance of specific Internet-use disorders: An Interaction of Person-Affect-Cognition-Execution (I-PACE) model. *Neuroscience &*



- Biobehavioral Reviews*, 71, 252–266. <https://doi.org/10.1016/j.neubiorev.2016.08.033>.
- Bringmann, L. F., & Eronen, M. I. (2018). Don't blame the model: Reconsidering the network approach to psychopathology. *Psychological Review*, 125(4), 606–615. <https://doi.org/10.1037/rev0000108>.
- Cho, H. Y., Kim, D. J., & Park, J. W. (2017). Stress and adult smartphone addiction: Mediation by self-control, neuroticism, and extraversion. *Stress and Health*, 33(5), 624–630. <https://doi.org/10.1002/smi.2749>.
- Christensen, A. P. (2020). *Towards a network psychometrics approach to assessment: Simulations for redundancy, dimensionality, and loadings* [Unpublished doctoral dissertation]. University of North Carolina at Greensboro, Greensboro, NC, USA. <https://doi.org/10.31234/osf.io/84kgd>.
- Christensen, A. P., & Golino, H. (2019). Estimating the stability of the number of factors via bootstrap exploratory graph analysis: A tutorial [preprint]. *PsyArXiv*. <https://doi.org/10.31234/osf.io/9deay>.
- Christensen, A. P., & Golino, H. (2020). Statistical equivalency of factor and network loadings [Preprint]. *PsyArXiv*. <https://doi.org/10.31234/osf.io/xakez>.
- Christensen, A. P., Golino, H., & Silvia, P. J. (2020). A psychometric network perspective on the validity and validation of personality trait questionnaires. *European Journal of Personality*. <https://doi.org/10.1002/per.2265>.
- Cohen, J. (1992). A power primer. *Psychological Bulletin*, 112(1), 155–159. <https://doi.org/10.1037/0033-2909.112.1.155>.
- Curran, P. G. (2016). Methods for the detection of carelessly invalid responses in survey data. *Journal of Experimental Social Psychology*, 66, 4–19. <https://doi.org/10.1016/j.jesp.2015.07.006>.
- Davis, R. (2001). A cognitive-behavioral model of pathological internet use. *Computers in Human Behavior*, 17, 187–195.
- Duke, E., & Montag, C. (2017). Smartphone addiction, daily interruptions and self-reported productivity. *Addictive Behaviors Reports*, 6, 90–95. <https://doi.org/10.1016/j.abrep.2017.07.002>.
- Elhai, J. D., Dvorak, R. D., Levine, J. C., & Hall, B. J. (2017). Problematic smartphone use: A conceptual overview and systematic review of relations with anxiety and depression psychopathology. *Journal of Affective Disorders*, 207, 251–259. <https://doi.org/10.1016/j.jad.2016.08.030>.
- Elhai, J. D., Levine, J. C., & Hall, B. J. (2019). The relationship between anxiety symptom severity and problematic smartphone use: A review of the literature and conceptual frameworks. *Journal of Anxiety Disorders*, 62, 45–52. <https://doi.org/10.1016/j.janxdis.2018.11.005>.
- Elhai, J. D., Rozgonjuk, D., Alghraibeh, A. M., Levine, J. C., Alafnan, A. A., & Aldraiweesh, A. A., et al. (2020). Excessive reassurance seeking mediates relations between rumination and problematic smartphone use. *Bulletin of the Menninger Clinic*, 84, 137–155. https://doi.org/10.1521/bumc_2020_84_07.
- Epskamp, S., Borsboom, D., & Fried, E. I. (2018a). Estimating psychological networks and their accuracy: A tutorial paper. *Behavior Research Methods*, 50(1), 195–212. <https://doi.org/10.3758/s13428-017-0862-1>.
- Epskamp, S., & Fried, E. I. (2018). A tutorial on regularized partial correlation networks. *Psychological Methods*, 23(4), 617–634. <https://doi.org/10.1037/met0000167>.
- Epskamp, S., Waldorp, L. J., Mõttus, R., & Borsboom, D. (2018b). The Gaussian graphical model in cross-sectional and time-series data. *Multivariate Behavioral Research*, 53(4), 453–480. <https://doi.org/10.1080/00273171.2018.1454823>.
- Eyal, N. (2014). *Hooked: How to build habit-forming products*. Portfolio/Penguin.
- Facebook. (2020). *Company info | about Facebook*. Company info | about Facebook. <https://about.fb.com/company-info/>.
- Gates, K. M., Henry, T., Steinley, D., & Fair, D. A. (2016). A Monte Carlo evaluation of weighted community detection algorithms. *Frontiers in Neuroinformatics*, 10, 45. <https://doi.org/10.3389/fninf.2016.00045>.
- Gezgin, D. M. (2018). Understanding patterns for smartphone addiction: Age, sleep duration, social network use and fear of missing out. *Cypriot Journal of Educational Science*, 13(2), 166–177.
- Golino, H. F., & Christensen, A. P. (2020). *EGAnet: Exploratory Graph Analysis—A framework for estimating the number of dimensions in multivariate data using network psychometrics* (Version 0.9.5) [Computer software].
- Golino, H. F., & Epskamp, S. (2017). Exploratory graph analysis: A new approach for estimating the number of dimensions in psychological research. *PLoS One*, 12(6), e0174035. <https://doi.org/10.1371/journal.pone.0174035>.
- Golino, H. F., Shi, D., Christensen, A. P., Garrido, L. E., Nieto, M. D., & Sadana, R., et al. (2020). Investigating the performance of exploratory graph analysis and traditional techniques to identify the number of latent factors: A simulation and tutorial. *Psychological Methods*, 25(3), 292–320. <https://doi.org/10.1037/met0000255>.
- Hallquist, M. N., Wright, A. G. C., & Molenaar, P. C. M. (2019). Problems with centrality measures in psychopathology symptom networks: Why network psychometrics cannot escape psychometric theory. *Multivariate Behavioral Research*, 1–25. <https://doi.org/10.1080/00273171.2019.1640103>.
- Hoffner, C. A., & Lee, S. (2015). Mobile phone use, emotion regulation, and well-being. *Cyberpsychology, Behavior, and Social Networking*, 18(7), 411–416. <https://doi.org/10.1089/cyber.2014.0487>.
- Inal, E. E., Demirci, K., Cetintürk, A., Akgonül, M., & Savas, S. (2015). Effects of smartphone overuse on hand function, pinch strength, and the median nerve. *Muscle & Nerve*, 52(2), 183–188. <https://doi.org/10.1002/mus.24695>.
- Instagram Inc. (2020). *Terms of use*. <https://help.instagram.com/581066165581870>.
- Kardefelt-Winther, D., Heeren, A., Schimmenti, A., van Rooij, A., Maurage, P., Carras, M., et al. (2017). How can we conceptualize behavioural addiction without pathologizing common behaviours? *Addiction*, 112(10), 1709–1715.
- Karsay, K., Schmuck, D., Matthes, J., & Stevic, A. (2019). Longitudinal effects of excessive smartphone use on stress and loneliness: The moderating role of self-disclosure. *Cyberpsychology, Behavior, and Social Networking*, 22(11), 706–713. <https://doi.org/10.1089/cyber.2019.0255>.
- Kates, A. W., Wu, H., & Coryn, C. L. S. (2018). The effects of mobile phone use on academic performance: A meta-analysis. *Computers & Education*, 127, 107–112. <https://doi.org/10.1016/j.compedu.2018.08.012>.



- Kim, H.-Y. (2013). Statistical notes for clinical researchers: Assessing normal distribution (2) using skewness and kurtosis. *Restorative Dentistry & Endodontics*, 38(1), 52. <https://doi.org/10.5395/rde.2013.38.1.52>.
- Kim, J.-H. (2018). Psychological issues and problematic use of smartphone: ADHD's moderating role in the associations among loneliness, need for social assurance, need for immediate connection, and problematic use of smartphone. *Computers in Human Behavior*, 80, 390–398. <https://doi.org/10.1016/j.chb.2017.11.025>.
- Kim, Y., Jeong, J. E., Cho, H., Jung, D. J., Kwak, M., Rho, M. J., et al. (2016). Personality factors predicting smartphone addiction predisposition: Behavioral inhibition and activation systems, impulsivity, and self-control. *PLoS One*, 11(8), e0159788. <https://doi.org/10.1371/journal.pone.0159788>.
- Kwon, M., Kim, D. J., Cho, H., & Yang, S. (2013). The smartphone addiction scale: Development and validation of a short version for adolescents. *PLoS One*, 8(12), e83558. <https://doi.org/10.1371/journal.pone.0083558>.
- Lachmann, B., Duke, E., Sariyska, R., & Montag, C. (2019). Who's addicted to the smartphone and/or the Internet? *Psychology of Popular Media Culture*, 8(3), 182–189. <https://doi.org/10.1037/ppm0000172>.
- Lee, H. K., Kim, J. H., Fava, M., Mischoulon, D., Park, J. H., Shim, E. J., et al. (2017). Development and validation study of the smartphone overuse screening questionnaire. *Psychiatry Research*, 257, 352–357. <https://doi.org/10.1016/j.psychres.2017.07.074>.
- Lopez-Fernandez, O., Honrubia-Serrano, L., Freixa-Blanxart, M., & Gibson, W. (2014). Prevalence of problematic mobile phone use in British adolescents. *Cyberpsychology, Behavior, and Social Networking*, 17(2), 91–98. <https://doi.org/10.1089/cyber.2012.0260>.
- Montag, C. (2018). *Homo Digitalis: Smartphones, soziale Netzwerke und das Gehirn*. Springer Fachmedien Wiesbaden GmbH.
- Montag, C., Becker, B., & Gan, C. (2018). The multipurpose application WeChat: A review on recent research. *Frontiers in Psychology*, 9, 2247. <https://doi.org/10.3389/fpsyg.2018.02247>.
- Montag, C., & Elhai, J. D. (2019). A new agenda for personality psychology in the digital age? *Personality and Individual Differences*, 147, 128–134. <https://doi.org/10.1016/j.paid.2019.03.045>.
- Montag, C., Wegmann, E., Sariyska, R., Demetrovics, Z., & Brand, M. (2019). How to overcome taxonomical problems in the study of Internet use disorders and what to do with “smartphone addiction”? *Journal of Behavioral Addictions*, 1–7. <https://doi.org/10.1556/2006.8.2019.59>.
- Oviedo-Trespalacios, O., Haque, M. M., King, M., & Demmel, S. (2018a). Driving behaviour while self-regulating mobile phone interactions: A human-machine system approach. *Accident Analysis & Prevention*, 118, 253–262. <https://doi.org/10.1016/j.aap.2018.03.020>.
- Oviedo-Trespalacios, O., Haque, Md, M., King, M., & Washington, S. (2018b). Should I text or call here? A situation-based analysis of drivers' perceived likelihood of engaging in mobile phone multitasking: Mobile phone multitasking engagement. *Risk Analysis*, 38(10), 2144–2160. <https://doi.org/10.1111/risa.13119>.
- Pancani, L., Preti, E., & Riva, P. (2019). The psychology of smartphone: The development of the smartphone impact scale (SIS). *Assessment*, 1073191119831788. <https://doi.org/10.1177/1073191119831788>.
- Panova, T., & Carbonell, X. (2018). Is smartphone addiction really an addiction?. *The Journal of Behavioral Addictions*, 7(2), 252–259. <https://doi.org/10.1556/2006.7.2018.49>.
- Peterka-Bonetta, J., Sindermann, C., Elhai, J. D., & Montag, C. (2019). Personality associations with smartphone and internet use disorder: A comparison study including links to impulsivity and social anxiety. *Front Public Health*, 7, 127. <https://doi.org/10.3389/fpubh.2019.00127>.
- Peters, G.-J. (2019). *Userfriendlyscience (UFS)*. <https://doi.org/10.17605/OSF.IO/TXEQU>.
- Primack, B. A., Shensa, A., Escobar-Viera, C. G., Barrett, E. L., Sidani, J. E., Colditz, J. B., et al. (2017). Use of multiple social media platforms and symptoms of depression and anxiety: A nationally-representative study among U.S. Young adults. *Computers in Human Behavior*, 69, 1–9. <https://doi.org/10.1016/j.chb.2016.11.013>.
- R Core Team. (2020). *R: A language and environment for statistical computing (Version 3.6.3) [Computer software]*. R Core Team.
- Revelle, W., & Zinbarg, R. E. (2009). Coefficients alpha, beta, omega, and the glb: Comments on sijtsma. *Psychometrika*, 74(1), 145–154. <https://doi.org/10.1007/s11336-008-9102-z>.
- Rozgonjuk, D. (2019). *Problematic smartphone use: Behavioral, psychopathological, dispositional, and educational correlates*. University of Tartu Press.
- Rozgonjuk, D., & Elhai, J. D. (2019). Emotion regulation in relation to smartphone use: Process smartphone use mediates the association between expressive suppression and problematic smartphone use. *Current Psychology*, 1–10. <https://doi.org/10.1007/s12144-019-00271-4>.
- Rozgonjuk, D., Elhai, J. D., & Hall, B. J. (2019a). Studying psychopathology in relation to smartphone use. In H. Baumeister & C. Montag (Eds.), *Digital phenotyping and mobile sensing* (pp. 185–199). Springer International Publishing. https://doi.org/10.1007/978-3-030-31620-4_11.
- Rozgonjuk, D., Elhai, J. D., Täht, K., Vassil, K., Levine, J. C., & Asmundson, G. J. G. (2019b). Non-social smartphone use mediates the relationship between intolerance of uncertainty and problematic smartphone use: Evidence from a repeated-measures study. *Computers in Human Behavior*, 96, 56–62. <https://doi.org/10.1016/j.chb.2019.02.013>.
- Rozgonjuk, D., Pruunsild, P., Jürimäe, K., Schwarz, R.-J., & Aru, J. (2020). Instagram use frequency is associated with problematic smartphone use, but not with depression and anxiety symptom severity. *Mobile Media & Communication*, 2050157920910190. <https://doi.org/10.1177/2050157920910190>.
- Rozgonjuk, D., Saal, K., & Täht, K. (2018). Problematic smartphone use, deep and surface approaches to learning, and social media use in lectures. *International Journal of Environmental Research and Public Health*, 15(1), 92. <https://doi.org/10.3390/ijerph15010092>.
- Rozgonjuk, D., Sindermann, C., Elhai, J. D., & Montag, C. (2020). Fear of missing out (FoMO) and social media's impact on daily-life and productivity at work: Do WhatsApp, Facebook, Instagram and Snapchat use disorders mediate that association?.



- Addictive Behaviors*, 110, 106487. <https://doi.org/10.1016/j.addbeh.2020.106487>.
- Servidio, R. (2019). Self-control and problematic smartphone use among Italian University students: The mediating role of the fear of missing out and of smartphone use patterns. *Current Psychology*. <https://doi.org/10.1007/s12144-019-00373-z>.
- Sha, P., Sariyska, R., Riedl, R., Lachmann, B., & Montag, C. (2019). Linking internet communication and smartphone use disorder by taking a closer look at the Facebook and WhatsApp applications. *Addictive Behaviors Reports*, 9, 100148. <https://doi.org/10.1016/j.abrep.2018.100148>.
- Shensa, A., Escobar-Viera, C. G., Sidani, J. E., Bowman, N. D., Marshal, M. P., & Primack, B. A. (2017). Problematic social media use and depressive symptoms among U.S. Young adults: A nationally-representative study. *Social Science & Medicine*, 182, 150–157. <https://doi.org/10.1016/j.socscimed.2017.03.061>.
- Sindermann, C., Duke, E., & Montag, C. (2020a). Personality associations with Facebook use and tendencies towards Facebook use disorder. *Addictive Behaviors Reports*, 11, 100264. <https://doi.org/10.1016/j.abrep.2020.100264>.
- Sindermann, C., Elhai, J. D., & Montag, C. (2020b). Predicting tendencies towards the disordered use of Facebook's social media platforms: On the role of personality, impulsivity, and social anxiety. *Psychiatry Research*, 285, 112793. <https://doi.org/10.1016/j.psychres.2020.112793>.
- We Are Social Ltd. (2019). *Digital 2019 Q4 global digital statshot*. https://www.slideshare.net/slideshow/embed_code/key/NSBCWzcfbsGXTg.
- WhatsApp Inc. (2020). *About WhatsApp*. <https://www.whatsapp.com/about/>.
- Wolniewicz, C. A., Rozgonjuk, D., & Elhai, J. D. (2019). Boredom proneness and fear of missing out mediate relations between depression and anxiety with problematic smartphone use. *Human Behavior and Emerging Technologies*, 2, 61–70. <https://doi.org/10.1002/hbe2.159>.
- Xie, Y., Szeto, G. P., Dai, J., & Madeleine, P. (2016). A comparison of muscle activity in using touchscreen smartphone among young people with and without chronic neck-shoulder pain. *Ergonomics*, 59(1), 61–72. <https://doi.org/10.1080/00140139.2015.1056237>.
- Yang, Z., Algesheimer, R., & Tessone, C. J. (2016). A comparative analysis of community detection algorithms on artificial networks. *Scientific Reports*, 6(1), 30750. <https://doi.org/10.1038/srep30750>.
- Yang, G., Cao, J., Li, Y., Cheng, P., Liu, B., Hao, Z., et al. (2019). Association between internet addiction and the risk of musculoskeletal pain in Chinese college Freshmen – a cross-sectional study. *Frontiers in Psychology*, 10, 1959. <https://doi.org/10.3389/fpsyg.2019.01959>.
- Yentes, R. D., & Wilhelm, F. (2018). *Careless: Procedures for computing indices of careless responding*. (Version 1.1.3) [Computer software].
- Zivnuska, S., Carlson, J. R., Carlson, D. S., Harris, R. B., & Harris, K. J. (2019). Social media addiction and social media reactions: The implications for job performance. *The Journal of Social Psychology*, 159(6), 746–760. <https://doi.org/10.1080/00224545.2019.1578725>.

SUPPLEMENTARY MATERIAL

The online version of this article offers supplementary material (<https://doi.org/10.1556/2006.2020.00036>).

