

Discrepancies between Self-Reports and Behavior: Fear of Missing Out (FoMO), Self-Reported Problematic Smartphone Use Severity, and Objectively Measured Smartphone Use

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Abstract

Fear of Missing Out (FoMO) is associated with self-reported problematic smartphone use (PSU) severity, but there is little investigation that includes objectively measured smartphone use. The aim of the current study was to provide insights into this domain. We combined the partially published data from two previous U.S.-based studies with college student samples that tracked smartphone use data with a different focus from the current study. Both data sets included socio-demographic measures, FoMO and PSU scale scores, and data for objectively measured screentime and frequency of screen unlocks over a week, amounting up to more than a thousand observations. FoMO had a strong correlation with self-reported PSU severity; however, FoMO was not associated with objectively measured smartphone use variables. FoMO did not predict behavioral smartphone use over a week in multilevel modeling for repeated measures. Even though FoMO is a strong predictor of self-reported PSU severity, it does not predict objectively measured smartphone use.

Keywords: Fear of Missing Out, FoMO, problematic smartphone use, screentime, phone-checking, smartphone tracking

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1 Introduction

In recent years, a vast amount of research has focused on associations between digital technology use and daily life outcomes. In this light, laypersons as well as academics have been interested in how smartphone use correlates with psychological variables and behavior. One line of research has focused on adverse mental health associations with smartphone use; while this phenomenon has been labeled with several terms (including smartphone “addiction”), scholars have been increasingly using “problematic smartphone use” (PSU) over the past few years (Panova & Carbonell, 2018; but see also Elhai, Yang, & Levine, 2020). Yet, few studies have contrasted objectively measured smartphone use (OMSU) variables with PSU and psychological characteristics.

One of the most robust predictors of self-reported (problematic) smartphone use is fear of missing out (FoMO). FoMO is the fear regarding missing out on rewarding social experiences (Przybylski et al., 2013). FoMO has been treated as a potential causal factor for PSU not only in scientific literature, but also in

mass media (e.g., Kelly, 2015). Yet, there are currently no studies that have investigated it in comparison to behavioral smartphone use data. This is important, because recent studies have demonstrated that self-reported smartphone use assessments may not be (strongly) associated with objectively measured, actual smartphone use (Parry et al., 2020).

Of relevance, PSU severity has been associated with various psychopathology symptoms, e.g., depression and anxiety (Elhai, Levine, et al., 2019) and social anxiety (Bian & Leung, 2014). PSU severity is also associated with transdiagnostic factors, or characteristics that tend to overlap between different mental disorders, such as dysfunctional emotion regulation (Fu et al., 2020), procrastination (Wang et al., 2019), and trait neuroticism (Marengo et al., 2020). While correlations between PSU severity and other variables tend to be small-to-medium (e.g., $r = .20-.30$) in magnitude (Elhai et al., 2017), FoMO has been shown to consistently correlate with PSU, yielding medium-to-large correlations of r around .30 to .50 (Elhai, Yang, & Montag, 2020).

In addition to correlating FoMO with PSU severity in several works (Elhai, Yang, Rozgonjuk, et al., 2020; Wang et al., 2019), FoMO also correlates with other variables that are associated with PSU, e.g., procrastination (Müller et al., 2020), negative affectivity (Elhai, Rozgonjuk, Liu, et al., 2020), and trait neuroticism (Balta et al., 2018; Elhai, Yang, & Montag, 2020; Rozgonjuk et al., 2021). Of note, FoMO and PSU also correlate with nomophobia (Gezgin et al., 2018), or the fear of feeling disconnected to the digital world (Rodríguez-García et al., 2020). Yet, nomophobia is distinct from both of these constructs, since PSU reflects the extent of adversities due to excessive smartphone use (Billieux et al., 2015; Panova & Carbonell, 2018), while FoMO in the context of this work is not necessarily bound to digital settings, it could be treated as a trait-like characteristic, and it can also occur outside of the virtual world (Elhai, Yang, & Montag, 2020; Przybylski et al., 2013). Importantly, FoMO may drive more smartphone use, because the apprehension of missing out on experiences, news, etc., keeps people checking their smartphones and engaging in browsing the web and social media feeds (see Elhai, Yang, & Montag, 2020 for a review).

But this line of research suffers from some major limitations. Namely, most studies relied on cross-sectional data and self-reported smartphone use measures. It is also noteworthy that a number of studies have not found a (strong) association between self-reported and objectively measured smartphone use (Ellis et al., 2019; Loid et al., 2020; Parry et al., 2020). One reason could be that OMSU reflects the extent of PSU in *some* participants, who may be vulnerable for developing this condition, but not in others. In other words, while high engagement in smartphone use may be productive for some (e.g., helping with their job or school), it could be problematic for other people (e.g., leading to procrastination, decreased socializing, etc). Another reason could be in operationalizing “smartphone use” – a given study may have focused on different aspects of logged smartphone use data, e.g., duration (screentime), active vs passive duration (e.g., actively browsing vs watching a video, respectively), and/or frequency of use (phone-checking behavior). Please also see that associations between smartphone use and productivity at school or at the job are not likely linear, but might be best depicted by an inverted U-curve (Montag & Walla, 2016). Hence, the “right kind” of smartphone use makes a person more productive, whereas constant interruptions might result in a loss of productivity (Duke & Montag, 2017). Research taking these ideas into account has been scattered thus far.

Because FoMO seems to be one of the more consistent and strongest correlates of PSU severity (e.g., reviewed in Elhai, Yang, & Montag, 2020), it would also be necessary to investigate if it predicts objectively measured smartphone use, namely, use duration (screentime) and frequency (screen unlocks, or phone-checking). For instance, a recent study showed that FoMO is associated with increased disruptions in daily activities from interruptive smartphone notifications, but not with the number of received notifications (Rozgonjuk et al., 2019). While that study used self-reports, it sets up the hypothesis that smartphone-

checking behavior (which could occur as a reaction to prompted notifications) could be associated with FoMO. This aspect is not yet explored in the literature. Similarly, knowledge on the association between FoMO and objectively measured smartphone use (screentime and phone-checking behavior) is limited (Elhai et al., 2021; Sela et al., 2020).

The aim of the current study is to investigate if FoMO predicts objectively measured smartphone use. For comparison, associations between FoMO and PSU severity are also examined. Because several studies have demonstrated the relatively strong link between FoMO and PSU severity (e.g., see Elhai, Yang, & Montag, 2020 for a review), we hypothesize that this is also the case in the current study.

H1: *FoMO and PSU are positively correlated.*

A recent study in a sample of adolescents found that FoMO is associated with objectively measured hours spent on the Internet, yielding a correlation of $r = .37$ (Sela et al., 2020). However, the study by Sela et al. (2020) focused only on adolescents and used the aggregated value of general Internet use in analyses and, therefore, did not implement a repeated-measures study design.

Additionally, FoMO is associated with disrupted activities due to push-notifications (Rozgonjuk et al., 2019). Based on this, our second hypothesis is:

H2: *FoMO is positively associated with objectively measured smartphone use duration and frequency.¹*

The current study can further clarify the role of FoMO in smartphone use and provide insights into the relationships between self-reported and objectively measured smartphone use.

2 Materials and methods

2.1 Data and samples

We used the combined data of two independent projects that included (but was not used in the published works) the same FoMO measure, coupled with PSU questionnaires, as well as similar retrieval methods of OMSU data (Elhai et al., 2018; Rozgonjuk et al., 2018). Both studies investigated associations between OMSU and other psychological variables. The data sets included socio-demographic variables, the FoMO scale (Przybylski et al., 2013), 10-item Smartphone Addiction Scale (SAS-SV; Kwon, Kim, et al., 2013), and objectively measured smartphone use data.

Specific procedures as well as details about samples could be found in the respective publications; both studies comprised American college student samples who were active iPhone us-

¹ In the light of the previous work, there are grounds to hypothesize that FoMO could be especially associated with smartphone checking *after receiving push-notifications*. However, we cannot test that hypothesis in the current study.

ers, since the application Moment used in those studies was only available for iOS smartphones.

In brief, the procedure was as follows: after completing the questionnaires in an online survey, eligible participants were invited to participate in a smartphone tracking part of the study. Participants who were interested were asked to install the Moment application on their phones. The participants were tracked for a total of nine days. However, the data from the first (Moment installation) and last (Moment deinstallation and data retrieval) days of tracking were excluded from the analyses. Of note, the Moment app only tracked general smartphone usage (duration and/or frequency) and did not provide information on specific application uses.

The effective sample comprised $n = 169$ (age $M = 19.62$, $SD = 3.57$; 120 women, 49 men) people who all provided insights into several variables (socio-demographics, FoMO, SAS-SV, and minutes of screentime for seven days). In total, this data set included $169 \times 7 = 1183$ observations for smartphone pickups and $101 \times 7 = 707$ observations for smartphone screentime, granting sufficient statistical power for analyses.

The effective sample included 94 (56%) freshmen, 48 (28%) sophomores, 14 (8%) juniors, ten seniors (6%), and three (2%) people who responded with “other”. Among the effective sample, 85 (50%) college students reported being part-time employed, 12 (7%) study participants were full-time employed, and 72 (43%) people reported being unemployed. 79 (47%) respondents reported being in a relationship, whereas 89 (53%) people were not in a relationship.

2.2 Measures

Socio-demographic variables

While there were different socio-demographic variables queried in the two studies, the overlapping variables were age, gender, employment status, student status, and relationship status.

Fear of Missing Out scale

In both studies, the FoMO scale by Przybylski et al. (2013) was used. It is a 10-item Likert-type scale, with responses anchored to 1 = “not at all true of me” to 5 = “extremely true of me”. We used the summed score of FoMO. Cronbach’s alpha for the merged data set was $\alpha = .89$; internal consistency ranged from $\alpha = .88$ to $.89$, when analyzed separately for each data set.

Smartphone Addiction Scale short version

Although one of the studies (Rozgonjuk et al., 2018) administered the 33-item Smartphone Addiction Scale (Kwon, Lee, et al., 2013), we extracted the ten-item subset that represents the Smartphone Addiction Scale-Short-Version (SAS-SV; Kwon, Kim, et al., 2013) that was used in the other study. Therefore, in the merged data set, the outcome measure was the summed score of the SAS-SV, where each item’s response ranged from 1 = “strongly disagree” to 6 = “strongly agree”. This scale measures

the extent of experiencing PSU. Cronbach’s alpha for the scale was $\alpha = .86$ in the combined data set and ranged from $\alpha = .82$ to $.89$, when analyzed separately for each data set.

Objectively measured smartphone use

Both studies by Elhai, Tiamiyu, et al. (2018) and Rozgonjuk, Levine, et al. (2018) included daily objectively measured smartphone use duration (screentime) measures for seven days. Additionally, the Rozgonjuk, Levine, et al. (2018) data encompassed daily objectively measured smartphone use frequency (phone-checking behavior that we operationalize here as the number of screen unlocks) data for seven days. The two studies used an iOS app (Moment) to obtain iPhone screentime estimates. Daily averages across one week were computed for the merged data set.

2.3 Analysis

The data were analyzed in R software version 4.0.3 (R Core Team, 2021). Data analysis was carried out using the combined data where possible. We computed internal consistency statistics using the *psych* package v 2.1.3 (Revelle, 2021). We used Spearman correlation analysis (p-values adjusted with Holm’s method) to investigate relationships between PSU, FoMO, and objectively measured smartphone use variables, using the *RcmdrMisc* package v 2.7-1 (Fox, 2020).

Additionally, we computed latent growth curve models with the *lavaan* package v 0.6-8 (Rosseel, 2012). FoMO was treated as a predictor variable, while the intercept (baseline) and slope (growth over the week) of smartphone use screentime and number of phone-checks (screen unlocks) were estimated with the robust maximum likelihood estimator. The intercept and slope were set to co-vary.

3 Results

3.1 Descriptive statistics and correlation analysis

Descriptive statistics and Spearman correlation coefficients are presented in Table 1; statistics per each data set are presented in Supplementary Table S1.

Bivariate correlation analysis showed that even though the positive correlation between FoMO and PSU measures yielded a large effect size, FoMO was not correlated with OMSU. Phone-checking behavior yielded a medium-sized positive correlation with screentime, and PSU had a small positive correlation with screentime. Age was not associated with these measures. While FoMO had a strong correlation with PSU, associations between FoMO and OMSU variables were very weak.

Table 1. Descriptive statistics and Spearman correlation analysis results (p-values in parentheses)

Variable	Descriptive statistics			Correlations			
	N	M	SD	1	2	3	4
1. PSU	168	26.71	9.41	–			
2. FoMO	169	22.23	8.32	.563*** ($< .001$)	–		
3. Screen-time	169	241.99	101.21	.224* (.028)	.067 (1.000)	–	
4. Phone-checking	101	88.20	46.67	.063 (1.000)	-.092 (1.000)	.317* (.110)	–
5. Age	169	19.62	3.57	-.103 (.733)	-.146 (.348)	-.139 (.358)	-.224 (.171)

Notes. PSU = self-reported problematic smartphone use; FoMO = fear of missing out.

Screen-time minutes and number of phone-checking (screen unlocks) are the week’s average values. Summed scores for FoMO and SAS-SV (as a measure of PSU) were used. In bivariate correlations, the sample size was the lower number for a given pair’s Ns. P-values (exact values in parentheses) were adjusted with the Holm’s method. *** $p < .001$, * $p < .05$.

3.2 Does FoMO predict screentime and phone-checking over a week?

We also investigated, if FoMO scores predicted OMSU duration and phone-checking behavior over a week. We conducted latent growth curve analyses with screentime measures for a seven-day period for the combined data. The results of this model are presented in Table 2; analyses for these two data sets separately are presented in Supplementary Table S2.

While screentime data were available for both data sets, phone-checking behavior for seven days was available only in Rozgonjuk, Levine, et al. (2018), with $n = 101$ study partici-

pants. Table 2 shows that FoMO was not a significant predictor of OMSU screentime baseline nor growth over one week. In addition, FoMO did not predict the baseline nor growth of smartphone use frequency (smartphone screen unlocks).

4 Discussion

The aim of this study was to investigate if FoMO correlates with self-reported PSU severity as well as objectively measured smartphone use (OMSU) duration and frequency.

Our first hypothesis (H1) was confirmatory – we expected that FoMO and self-reported PSU severity are positively correlated. This hypothesis found support from the data – FoMO and PSU severity had a relatively strong correlation in the merged data set. Therefore, results are consistent with previous findings from other studies outlining FoMO as a significant correlate of self-reported PSU severity (Elhai, Yang, Rozgonjuk, et al., 2020).

We expected FoMO to correlate with objectively measured smartphone use as well (H2). This hypothesis, however, did not find support from the data. In both bi- and multivariate analyses, FoMO did not predict OMSU duration nor frequency. This is surprising, given the strong association between FoMO and self-reported PSU severity, as well as previous findings outlining associations of FoMO and self-reported frequency of disrupted activities due to push-notifications (Rozgonjuk et al., 2019).

It could be that objectively measured smartphone use may reflect *both* problematic and non-problematic smartphone use. In other words, while people may be engaged in using their digital technology to excessive levels (e.g., for a longer time), in some cases, this excessive use may lead to adversities in everyday life. For instance, some people with higher FoMO could use their technology in a more productive way, such as learning new things, socializing, or working, while other people could use the technology in ways that distracts them from their work or school duties. There is some evidence suggesting that specific social media platform uses may mediate the negative effects of

Table 2. Results of latent growth curve analysis with FoMO predicting objectively measured smartphone use variable

Variable	Outcome: minutes of screentime ^a							
	Intercept				Slope			
	B (SE)	β	z	p	B (SE)	β	z	p
FoMO	1.308 (.984)	.108	1.330	.184	-.176 (.161)	-.176	-1.090	.276

Variable	Outcome: number of smartphone pick-ups ^b							
	Intercept				Slope			
	B (SE)	β	z	p	B (SE)	β	z	p
FoMO	-.602 (.618)	-.116	-0.973	.330	.023 (.074)	.116	.311	.756

Notes. ^a = for 169 people across 7 days = 1183 observations; ^b = for 101 people across 7 days = 707 observations.

social media use on daily life and productivity (Rozgonjuk, Sindermann, Elhai, & Montag, 2020).

Another theoretical explanation is that higher levels in both FoMO and PSU could be explained by underlying causal factors. One such factor could be trait neuroticism. FoMO and PSU are associated with greater neuroticism (Marengo et al., 2020; Rozgonjuk et al., 2021). People with high neuroticism trait tend to worry more – including about their health (Costa & McCrae, 1985), and this may reflect in elevated PSU levels in the context of the current study. Importantly, worry is also associated with higher levels of PSU (Elhai, Rozgonjuk, et al., 2019), and FoMO, by definition, is aligning with worrying tendencies. Finally, the link between neuroticism and OMSU screentime has been found to be small (Montag et al., 2015). All these results suggest that perhaps PSU reflects levels of *worrying about smartphone use*, not *actual smartphone use*. This hypothesis, however, needs to be tested in subsequent research.

The present study has both theoretical as well as practical implications. To our knowledge, this is the first study aiming to predict OMSU variables from FoMO by investigating correlations as well as studying the potential changes of smartphone use over a period of one week. The results showed that while FoMO was associated with PSU, it did not predict OMSU screentime, nor phone-checking behavior. Therefore, these findings suggest that FoMO may not play a major role in the duration and frequency of smartphone use. While reducing FoMO could be the target for reducing the urge or craving to use one's smartphone (as reflected in PSU scores), it may not lead to actual smartphone use reduction. These results also have implications for further research. Specifically, as FoMO does not seem to be (strongly) correlated with OMSU, the results regarding FoMO's associations with self-reported smartphone use should be interpreted with caution. The findings also demonstrate that a person's FoMO levels cannot be directly inferred from how much time or how frequently a person uses their smartphone. At least this phenomenon seems to be true for the present dataset, where the FoMO measure only contained few items related to the online world. Newer measures such as by Wegmann et al. (2017) also include a FoMO-facet called "state FoMO" which deals exclusively with FoMO in an online context and here the results might be different. Additionally, results of the current study direct future research towards focusing on the objective recording of specific application use in relation with FoMO (e.g., see overlap between FoMO and problematic WhatsApp or Facebook use tendencies; Sha et al., 2019), which might explain the consistent and relatively strong relationship between FoMO and PSU found in previous literature. Focusing on specific application usage could differentiate smartphone applications with regards to their interplay with FoMO.

The limitations are primarily related to sample size and composition. Collecting tracked smartphone use data may be challenging, as also indicated by other studies with similar- or smaller-sized samples (e.g., reviewed in Parry et al., 2020). Therefore, although the sample size of this study was in line with previ-

ous studies, there may still be a risk of bivariate analyses being underpowered with very small effects. However, that does not change the implications of the main finding: while self-reported (problematic) smartphone use is associated with FoMO, objectively measured smartphone use is not (or at least not with comparable strength). In addition, the sample was biased towards female iOS users – but recent studies have shown that at least gender should not have strong effects on the associations investigated in the present study (Horwood et al., 2021; Rozgonjuk et al., 2021). Another major limitation is the nature of OMSU data: the data do not include a more fine-grained view on what exactly people were doing on their smartphones. Recent work has shown that communication, social media, and instant messaging-based applications may primarily drive engagement in smartphone use (Lowe-Calverley & Pontes, 2020; Rozgonjuk, Sindermann, Elhai, Christensen, et al., 2020), and altering the settings of one's smartphone (e.g., grayscaling the screen, hiding notifications, etc) may reduce one's smartphone usage (Holte & Ferraro, 2020; Olson et al., 2021). Based on these results, one may hypothesize that FoMO, too, may be associated with specific applications use – for instance, reducing the functionality of image and video content-based applications (e.g., Instagram, YouTube, etc) may lead to decreases in the use of those applications, and perhaps also in the long run in FoMO. However, the more general smartphone use duration and frequency data used in the current study do not provide insights into these nuances. Furthermore, there was no differentiation with regards to the type of smartphone use – in addition to specific applications use mentioned above, it should be further investigated how private vs work-related smartphone use is associated with FoMO.

In conclusion, while we replicated the previous findings of FoMO's association with self-reported PSU, the results showed that the FoMO and OMSU duration and frequency do not have as strong links.

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Supplementary Material

Table S1. Descriptive statistics and Spearman correlation analysis results for each data set (p-values in parentheses)

Variable	Elhai et al (2018)							
	Descriptives			Correlations				
	N	M	SD	1.	2.	3.		
1. PSU	68	25.82	10.57					
2. FoMO	68	19.77	7.27	.440** (.001)				
3. Screentime	68	240.48	98.43	.204 (.473)	.067 (1.000)			
4. Age	68	19.75	2.03	.064 (1.000)	-.027 (1.000)	-.165 (.710)		
Variable	Rozgonjuk et al (2018)							
	Descriptives				Correlations			
	N	M	SD	1.	2.	3.	4.	
1. PSU	100	27.31	8.54					
2. FoMO	101	23.88	8.60	.606*** ($<.001$)				
3. Screentime	101	243.01	103.52	.213 (.236)	.054 (1.000)			
4. Phone-checking	101	88.20	46.67	.063 (1.000)	-.092 (1.000)	.317* (.110)		
5. Age	101	19.54	4.31	-.141 (.964)	-.127 (1.00)	-.104 (1.000)	-.224 (.195)	

Notes. PSU = self-reported problematic smartphone use; FoMO = fear of missing out. Screentime minutes and number of phone-checking are the week's average values. In bivariate correlations, the sample size was the lower number for a given pair's Ns. P-values (exact values in parentheses) were adjusted with the Holm's method. * $p < .05$, ** $p < .01$, *** $p < .001$.

Table S2. Results of latent growth curve analysis with FoMO predicting objectively measured screentime in two separate data sets

Variable	Outcome: minutes of screentime (Elhai et al., 2018)							
	Intercept				Slope			
	B (SE)	β	z	p	B (SE)	β	z	p
FoMO	1.030 (1.601)	.082	0.644	.520	.078 (.214)	.093	.365	.715
Variable	Outcome: minutes of screentime (Rozgonjuk et al., 2018)							
	Intercept				Slope			
	B (SE)	β	z	p	B (SE)	β	z	p
FoMO	1.281 (1.280)	.105	1.001	.317	-.228 (.210)	-.199	-1.087	.277