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Objectively-measured and self-reported smartphone use in relation to surface learning, procrastination, academic productivity, and psychopathology symptoms in college students

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Abstract

Numerous psychological variables are associated with self-reported/estimated smartphone use in college students. However, less is known about how additional psychological variables involving academic study and productivity relate to objectively-measured smartphone usage, such as procrastination, surface learning, and academic productivity. We administered psychological surveys to 103 college students from an American university and collected their objective smartphone use data using the iPhone's Screentime feature. Levels of depression, anxiety, and stress symptoms, as well as greater procrastination and surface learning, mildly-to-moderately inversely correlated with the number of objectively-measured phone pickups/screen-unlocks. Academic productivity moderately inversely correlated with objectively-measured smartphone use minutes. Unemployed students had more pickups and received more notifications. Results are discussed in the context of theory on pathways to excessive internet use, and the threaded cognition model of cognitive task interference.

KEYWORDS
anxiety, depression, procrastination, productivity, smartphone use

1 | INTRODUCTION

A substantial body of work has studied individual psychological differences associated with greater levels of self-reported/estimated and objectively-measured smartphone use in college students, such as depression, anxiety and stress levels. However, less is known about additional psychological variables associated with increased smartphone use—especially variables involving academic-related study and productivity. We present objective and estimated smartphone use data in association with such traditionally and lesser studied psychological constructs in this article.

The benefits of smartphone use likely follow an inverse U-shaped curve, where milder levels offer more benefits over non-use, but excessive levels have adverse effects (Montag & Walla, 2016). "Problematic smartphone use" (PSU) involves excessive levels of use in addition to functionally impairing symptoms observed in substance use disorders (e.g., withdrawal when unable to use one's phone, reckless use when driving), accompanied by impairments in work, school or social functioning (Billieux, Maurage, Lopez-Fernandez, Kuss, & Griffiths, 2015; De-Sola Gutierrez, Rodriguez de Fonseca, & Rubio, 2016). PSU severity has been found higher in women and younger individuals (Busch & McCarthy, 2020).

One line of research has investigated psychological variables associated with self-reported/estimated smartphone use frequency and PSU severity. Depression severity demonstrates moderate positive associations (Elhai, Dvorak, Levine, & Hall, 2017), while anxiety and stress severity show small-to-moderate positive relationships with PSU severity (Elhai, Levine et al., 2019; Vahedi & Saiphoo, 2018). Also note that milder associations are found between self-reported/estimated smartphone use frequency with depression/anxiety/stress symptoms (Elhai et al., 2017; Vahedi & Saiphoo, 2018).

Another line of research has investigated psychological variables associated with objectively-measured smartphone use frequency, reviewed by Ryding and Kuss (2020). Objective use in this work has been measured mostly with third party smartphone apps, and also built-in OS features. Smartphone use minutes and pickups moderately *inversely* correlate with depression and anxiety severity (Elhai, Tiamiyu, et al., 2018; Rozgonjuk, Levine, et al., 2018). Beyond this, Prasad et al. (2018) revealed that use frequency correlates with higher perceived stress, external locus of control, and lower conscientiousness, with small-to-medium effects.

Thus, when estimated by self-report, smartphone use and PSU severity *positively* relate to depression, anxiety and stress symptoms in several studies (Elhai et al., 2017; Elhai, Levine, et al., 2019; Vahedi & Saiphoo, 2018). And, when measured objectively, smartphone use *inversely* relates to depression and anxiety severity in other studies (Elhai, Tiamiyu, et al., 2018; Rozgonjuk, Levine, et al., 2018), though positively relates to stress (Prasad et al., 2018).

1.1 | Aims

Our aim was to assess objective and self-reported/estimated smartphone use in conjunction with psychological variables and demographics previously examined, extending findings to additional, understudied psychological variables involving academic-related study and productivity. We measured objective use with the iPhone's Screentime feature, assessing use minutes, number of pickups and notifications.

1.2 | Theory

We present our study within context of the Interaction of Person-Affect-Cognition-Execution (I-PACE) model of pathways to problematic internet use (PIU) (Brand et al., 2019; Brand, Young, Laier, Wolfling, & Potenza, 2016). I-PACE is a theoretical model conceptualizing a major set of such pathways to specific forms of PIU (including PSU), involving background, predisposing influences such as biology, childhood stressors, personality, and mental health. I-PACE also theorizes a set of affective and cognitive response variables, influenced by predisposing variables, and driving PIU, including coping, self/emotional regulation styles, internet-related cognitive bias, and disinhibition. These pathways can lead to specific types of healthy, gratifying internet use, or—when the Internet used is as a maladaptive coping strategy to problems in everyday life—PIU. I-PACE addresses how a variety of specific types of PIU arise, such as PSU, and problematic gaming, social networking, and so on. (Brand et al., 2016). In fact, PSU has been conceptualized as a mobile form of PIU (Montag, Wegmann, Sariyska, Demetrovics, & Brand, 2020). Furthermore, I-PACE has been supported in numerous studies specifically on PSU (Elhai, Yang, Dempsey, et al., 2020; Elhai, Yang, Rozgonjuk, et al., 2020; Wolniewicz, Rozgonjuk, & Elhai, 2020).

We included depression, anxiety, and stress symptom severity as predisposing variables within I-PACE—that is, background variables influencing PSU. We also included affective/cognitive response variables, previously related to greater (albeit, self-reported) smartphone use. Specifically, fear of missing out (FOMO) on rewarding experiences is an internet-related cognitive bias (Elhai, Yang, et al., n.d.) associated with increased smartphone and social media use (Elhai, Yang, et al., 2019; Sha, Sariyska, Riedl, Lachmann, & Montag, 2019). And FOMO is positively related to negative affectivity such as depression and anxiety severity (Elhai, Yang, et al., n.d.), and the personality trait of neuroticism (Rozgonjuk, Sindermann, Elhai, & Montag, n.d.).

We additionally included variables related to academic study and productivity, though previously understudied in relation to objectively-measured smartphone use. Procrastination in task completion involves dysfunction in self-regulation (Steel, 2007), correlated with PSU severity (Rozgonjuk, Kattago, et al., 2018). Additionally, surface learning involves rote/superficial rather than comprehensive/deep learning, focusing primarily on what is (presumably) needed to pass one's exams rather than truly understanding the information. Surface learning is driven by increased cognitive demands and attention to other tasks (Dolmans, Loyens, Marcq, & Gijbels, 2016). Thus, deep (rather than surface) learning is found to positively correlate with improved academic outcomes (Asikainen & Gijbels, 2017). Surface learning is related to PSU severity (Rozgonjuk, Saal, et al., 2018). Finally, we included self-reported academic productivity, associated with increased smartphone use (Kushlev, Proulx, & Dunn, 2016).

These academic-related variables (surface learning, procrastination, and poor academic productivity) would be conceptualized as negative consequences in daily life from increased smartphone use within I-PACE (Brand et al., 2016). And these academic-related variables are associated with poor academic outcomes (Asikainen & Gijbels, 2017; Kim & Seo, 2015), a known consequence of PSU (Grant, Lust, & Chamberlain, 2019; Nayak, 2018) and PIU (Feng, Wong, Wong, & Hossain, 2019). Furthermore, poor academic outcomes are related to negative affect such as depression and anxiety (DeRoma, Leach, & Leverett, 2009; Hysenbegasi, Hass, & Rowland, 2005; Owens, Stevenson, Hadwin, & Norgate, 2012).

1.3 | Hypotheses

We anticipated increased smartphone use and PSU severity to relate to worse academic study and productivity variables (PSU's daily life consequences in I-PACE), given prior associations for PSU severity with poor academic outcomes (Grant et al., 2019; Nayak, 2018). We expected depression and anxiety symptoms (I-PACE predisposing variables) to positively correlate with self-reported PSU severity based on prior theory (Brand et al., 2019), and empirical work (Elhai et al., 2017; Elhai, Levine, et al., 2019; Vahedi & Saiphoo, 2018). Yet based on prior research findings, we expected depression and anxiety symptoms to *inversely* correlate with objectively-measured smartphone use (Elhai, Tiamiyu, et al., 2018; Rozgonjuk, Levine, et al., 2018). We anticipated stress severity (an I-PACE predisposing variable) to positively relate to objective smartphone use (Prasad et al., 2018). We expected younger age and female sex to correlate with increased smartphone use (Busch & McCarthy, 2020); we did not have a priori hypotheses about racial or employment associations with smartphone use because of limited prior relevant work.

2 | METHOD

2.1 | Participants

In Fall 2019, we recruited undergraduates from a large Midwestern U.S. university psychology department's online research pool. After presenting an online consent statement, those consenting were presented web-based survey measures below. We followed Declaration of Helsinki research principles, with university institutional review board approval.

Of 181 consenting participants, we excluded six for answering few survey items, another 6 for participating twice, and another five for carelessly, consecutively inputting the same response across dozens of items, resulting in 164 participants. Among these participants, 148 participants reported owning an iPhone as their primary phone (required for objective phone data), of which 103 (the effective sample) agreed to and successfully provided phone data screenshots.

Among the effective sample, age averaged 19.28 years (SD = 2.46). A slight majority were women (n = 69, 66.99%). Most identified as Caucasian (n = 82, 79.61%), with (non-mutually exclusive) minority representation from African Americans (n = 17, 16.50%), Latinx (n = 9, 8.74%), and Asians (n = 3, 2.91%). Participants were mostly freshman (n = 56, 54.37%) or sophomores (n = 34, 33.01%). They primarily worked part-time (n = 50, 48.54%) or were unemployed (n = 44, 42.72%).

2.2 | Procedure

First, we created identification numbers for participants by asking for their last four cellphone number digits and birth-month (e.g., 1500–10). Next, we presented web survey measures described below. Finally, we instructed iPhone users to obtain past-week objective smartphone use data by locating these data in the Screentime feature. We provided details for capturing screenshots of these data, sent to us via email or text, along with identification numbers to match Screentime and survey data. On average, participants sent their screenshots 0.18 days (SD = 1.91) after web survey completion.

2.3 | Measures

We first queried demographic variables such as sex, age, and race. Next, we presented our self-report measures. Sample internal consistency estimates are in Table 1.

2.3.1 | Depression Anxiety Stress Scale-21 (DASS-21)

We administered this 21-item scale (Lovibond & Lovibond, 1995), including depression, anxiety, and stress subscales. Likert-type

TABLE 1 Internal consistency, means, and standard deviations for the psychological scales and screentime variables, and differences across sexes

Variable	Alpha	Sample M	Sample SD	Men (n = 34) M	Men SD	Women (n = 69) M	Women SD	$F_{(1,101)}$	p	η^2_p
1. Depression	.93	4.75	5.17	4.03	4.22	5.10	5.58	.97	.325	.010
2. Anxiety	.86	4.59	4.44	3.35	3.62	5.20	4.70	4.06	.046	.039
3. Stress	.89	6.53	5.15	5.15	4.47	7.22	5.36	3.775	.055	.036
4. FOMO	.92	23.81	9.14	22.79	9.14	24.30	9.16	.62	.433	.006
5. Procrastination	.82	25.89	5.78	25.12	5.70	26.28	5.82	.91	.342	.009
6. Surface	.84	27.19	7.22	27.82	8.21	26.88	6.72	.38	.537	.004
7. Productivity	.89	12.95	3.65	12.24	3.61	13.30	3.65	1.97	.163	.019
8. SUF	.74	50.08	6.59	47.56	6.83	51.32	6.14	7.93	.006	.073
9. PSU	.89	27.62	10.21	24.94	8.80	28.94	10.65	3.59	.061	.034
10. Minutes	—	325.79	130.82	335.15	145.47	321.17	123.84	.26	.612	<.001
11. Pickups	—	122.37	57.63	119.32	60.38	123.87	56.61	.14	.709	.001
12. Notifications	—	172.53	118.11	166.71	123.81	175.41	116.01	.12	.727	.001

Note: The last three columns to the right indicate ANOVA F statistics (with degrees of freedom in parentheses), p values, and partial eta-squared values for comparing men and women on each variable.

Abbreviations: FOMO, fear of missing out; Minutes, averaged daily minutes of smartphone use (objectively reported); Notifications, averaged daily number of notifications (objectively measured); Pickups, averaged daily number of pickups (objectively measured); PSU, problematic smartphone use severity (self-reported); SUF, smartphone use frequency (self-reported); Surface, surface learning.

response options range from "0 = Did not apply to me at all" to "3 = Applied to me very much, or most of the time." Higher scores indicate greater symptom severity levels. The subscales have been widely validated (Zanon et al., n.d.).

2.3.2 | FOMO scale

The 10-item FOMO Scale (Przybylski, Murayama, DeHaan, & Gladwell, 2013) measures FOMO on rewarding social experiences. The scale has Likert-type responses from "1 = Not at all true of me" to "5 = Extremely true of me." Higher scores indicate greater FOMO levels. The scale has adequate psychometrics (recently reviewed in Elhai, Yang, et al., n.d.).

2.3.3 | Irrational Procrastination Scale (IPS)

We used this 9-item survey of procrastination with three reverse-coded items (Steel, 2010). The IPS uses Likert-type responses from "1 = Very seldom or not true of me" to "5 = Very often true, or true of me." Higher scores indicate greater procrastination levels. The IPS has been previously validated (Svartdal et al., 2016).

2.3.4 | Study process questionnaire-revised

This 20-item scale (Biggs, Kember, & Leung, 2001) measures deep and surface learning approaches. The measure uses Likert-type responses from "1 = Never or rarely true of me" to "5 = Always or almost always true of me." We administered only the 10-item surface learning subscale, with adequate validity (Martinelli & Raykov, 2017). Higher scores indicate greater surface learning tendencies.

2.3.5 | Productivity

We used a three-item scale measuring school and work productivity (Kushlev & Dunn, 2015), adapted for university students querying only school-related items (Kushlev et al., 2016). The instrument uses Likert-type options from "0 = Not at all" to "6 = Very much." Higher scores indicate greater academic productivity. Validity has been established (Kushlev & Dunn, 2015).

2.3.6 | Smartphone Use Frequency Scale (SUF)

We used an 11-item self-report scale querying estimated frequency of using common smartphone features, including voice/video calls, text/instant messaging, email, social media use, website use, listening entertainment, video watching, games, reading, and navigation (Elhai, Levine, Dvorak, & Hall, 2016). The measure uses Likert-type responses from "1 = Never" to "6 = Very often." Higher scores indicate more frequent (self-reported) smartphone use. The scale has shown relations with other similar scales (Elhai, Levine, et al., 2018; Elhai, Yang, Fang, et al., 2020).

2.3.7 | Smartphone addiction scale-short version (SAS)

This 10-item self-report scale (Kwon, Kim, Cho, & Yang, 2013) measures smartphone-related daily life dysfunction (PSU). It uses Likert-type responses from "1 = Strongly disagree" to "6 = Strongly agree." Higher scores indicate greater PSU severity. The SAS has been validated (Harris, McCredie, & Fields, 2020). We used an adapted version voiced in the first-person (Duke & Montag, 2017).

2.3.8 | Screentime data

After survey administration, we collected objective use data from the Screentime feature, first released in iOS 12. We included detailed instructions for obtaining data regarding one's own iPhone rather than other Apple devices on one's account, and only past-week (rather than past-day) data. Instead of asking participants to obtain their data and self-report them to us (which could involve error), we instructed participants to objectively capture/send screenshots of these Screentime data: (1) total use minutes, (2) minutes per use category (e.g., social networking, information and reading), (3) number of pickups, and (4) number of notifications received. For a given participant who did not provide screenshots on the day of participation, we sent a reasonable number of reminders on subsequent days until receiving them. However, the second screenshot (minutes per use category) sent by many participants indicated use minutes per app or website (Screentime's default) rather than modifying the display (as instructed) for use categories, so we do not present data from this variable. Prior to iOS 13, some data were reported by Apple in the Screentime feature as weekly totals (categories of use, and notifications), while the remaining data were reported as daily averages; for consistency, we converted week data into daily averages (by dividing week totals by 7 days). iOS Screentime data have been used in recent studies (David, Roberts, & Christenson, 2018; Ellis, Davidson, Shaw, & Geyer, 2019; Gower & Moreno, 2018).

2.4 | Analysis

We used R software version 3.6.2 (R Core Team, 2020) for data preprocessing and analysis. We used several R packages, including *careless* (for careless responding), *mice* (missing data treatment), *fmsb* (coefficient alphas), *pastecs* (descriptives), *corrplot* (correlations), and *sjstats* (ANOVA effects). We imputed missing item-level data using maximum likelihood procedures (first reverse-coding IPS items) before summing scale scores. No substantial skewness (>2) or kurtosis (>7) were observed for continuous variables. We conducted bivariate

Pearson correlations among psychological scale scores, age, and Screentime variables. We statistically compared relevant pairs of correlations using *t*-tests for dependent correlations. We used between-group ANOVAs (with Type III sums of squares, robust to unequal cell sizes) to assess relations for categorical demographic variables with psychological scales and Screentime variables.

3 | RESULTS

Table 1 presents internal consistency and descriptive statistics for the psychological scales, and associations with sex (discussed below). Figure 1 displays Pearson correlations between scales and Screentime, and associations with age. From Figure 1, self-reported/estimated smartphone use frequency and PSU severity did not significantly correlate with objective Screentime variables. Interestingly, among Screentime variables, use minutes did not correlate with pickups or notifications. However, pickups and notifications substantially correlated.

Depression, anxiety and stress symptoms significantly *positively* related to self-reported/estimated smartphone use and PSU severity (Figure 1). Yet, these psychopathology variables *inversely* related to objectively-measured smartphone pickups. Additionally, a similar pattern emerged for procrastination and surface learning. Depression, anxiety and stress did not differentially correlate with pickups, using *t*-tests for dependent correlations: depression versus anxiety $t(100) = .30$, $p = .77$; depression versus stress $t(100) = .17$, $p = .87$; anxiety versus stress $t(100) = .50$, $p = .62$. Additionally, procrastination and surface learning did not differentially correlate with pickups, $t(100) = .18$, $p = .86$.

Productivity was the only variable correlated (inversely) with objective use minutes (Figure 1). No psychological scales significantly correlated with notifications. While FOMO positively correlated with self-reported PSU severity, it did not correlate with objective Screentime variables.

We assessed sex differences (Table 1), finding that women reported significantly greater smartphone use frequency (and anxiety) than men. We also assessed other demographic variables for relations with Screentime (Table 2), finding that racial minorities had more minutes used, while unemployed participants had more pickups and notifications.

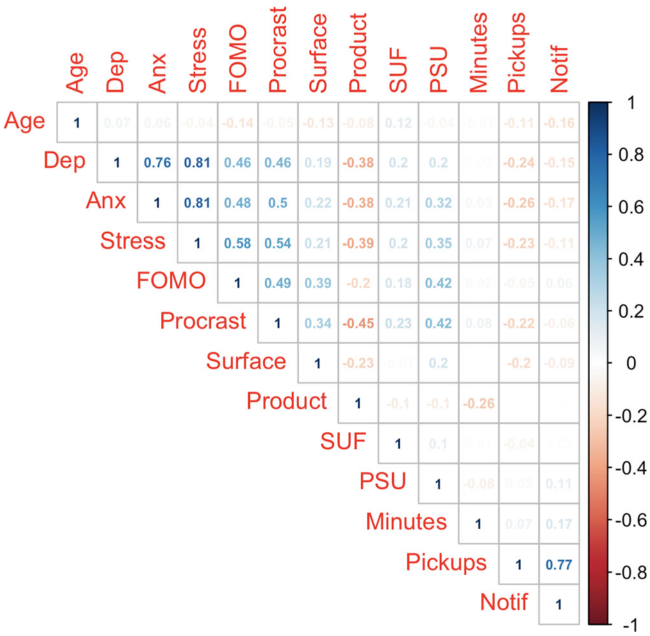

FIGURE 1 Bivariate Pearson correlations among age, psychological scale scores, and screentime variables ($N = 103$).
Note: Correlation heatmap displays stronger absolute correlations in a darker shade (blue for positive correlations, red for negative correlations). For correlations between .20 and .25 in absolute size, p <.05; for absolute correlations higher than .25, p <.01. Anx, anxiety; Dep, depression; FOMO, fear of missing out; Minutes, averaged daily minutes of smartphone use (objectively reported); Notif, averaged daily number of notifications (objectively measured); Pickups, averaged daily number of pickups (objectively measured); Procrast, procrastination; Product, productivity; PSU, problematic smartphone use severity (self-reported); SUF, smartphone use frequency (self-reported); Surface, surface learning

4 | DISCUSSION

We measured smartphone use with self-reported/estimated and objective methods, correlating such use measurements with psychological and sociodemographic variables. We found novel relationships between smartphone use and understudied psychological constructs involving academic study and productivity.

One of our primary findings was that increased surface learning and procrastination related to fewer smartphone pickups. This is a novel finding not reported previously in the literature. Pickups can be behavioral measures of organizational skills, attention to detail, and task management productivity (Walter, Dunsmuir, & Westbrook, 2015). It is possible that students with poor academic organizational skills, such as more surface learning and procrastination, also experience difficulty in keeping up with their notifications (including university-related communication) as a result. Such findings can be explained by the threaded cognition model, clarifying cognitive resource limitations resulting from competing task activity and multitasking (Salvucci & Taatgen, 2008), such as interacting with notifications while studying (Elhai, Rozgonjuk, et al., 2021; Rozgonjuk, Elhai, Ryan, & Scott, 2019). In this model, receiving and interacting with interruptive smartphone notifications may interfere with some students' reading and schoolwork completion, making it impossible to engage in greater levels of both pickups and comprehensive studying. In fact, Ward, Duke, Gneezy, and Bos (2017) reported that the mere presence of one's smartphone next to them reduced IQ and working memory test performance. Yet relations between prolonged use (e.g., more minutes/hours used) especially if intruding into work or school time, and decreased productivity, may more likely suggest poor time management and neglect of important daily activities from prolonged use (Duke & Montag, 2017).

TABLE 2 Significant associations between demographics and screentime variables

Dependent variable	Group 1 *M*	Group 1 *SD*	Group 2 *M*	Group 2 *SD*	$F_{(1,101)}$	*p*	η^2_p
	Racial minorities (*n* = 29)		*Caucasians* (*n* = 74)				
Minutes	377.31	166.54	305.59	108.66	6.61	.011	.061
Pickups	*Unemployed* (*n* = 59)		*Employed* (*n* = 44)				
	140.05	53.36	109.18	57.58	7.70	.007	.071
Notifications	*Unemployed* (*n* = 59)		*Employed* (*n* = 44)				
	210.41	124.18	144.29	105.83	8.48	.004	.077

Note: The last three columns to the right indicate ANOVA *F* statistics (with degrees of freedom in parentheses), *p* values, and partial eta-squared values for comparing group means on each dependent variable.
Abbreviations: Minutes, averaged daily minutes of smartphone use (objectively reported); Notifications, averaged daily number of notifications (objectively measured); Pickups, averaged daily number of pickups (objectively measured).

We also discovered sociodemographic associations with estimated and objectively measured smartphone use. Women had greater self-reported/estimated smartphone use than men, corroborating prior work (Andone et al., 2016, September; Busch & McCarthy, 2020). We discovered that racial minorities had more minutes of use, and unemployed participants had more notifications and pickups. We could not find race or employment status related to objective smartphone use in prior work, and thus these findings would require replication in order to draw firm conclusions.

We should address the discrepancy in our findings between our variables' relations with self-reported/estimated vs. objective smartphone use. Psychopathology symptom relations with decreased objective smartphone use (despite greater self-reported use) can be explained in several ways. First, people experiencing greater negative affectivity (e.g., depression/anxiety) self-report more adverse experiences, and greater negativity across the board (Auerbach, Stanton, Proudfit, & Pizzagalli, 2015; Morgado, Smith, Lecrubier, & Widlöcher, 1991; Shestyuk & Deldin, 2010), including greater self-reported phone use (Elhai et al., 2017; Elhai, Levine, et al., 2019; Vahedi & Saiphoo, 2018). Yet, objective smartphone measurement does not lie, and therefore can demonstrate opposite/inverse, probably more accurate findings. Second, people with greater negative affectivity engage in less actual behavioral activity/socializing (Dimidjian, Barrera Jr., Martell, Munoz, & Lewinsohn, 2011; Santini, Koyanagi, Tyrovolas, Mason, & Haro, 2015), perhaps including social smartphone interactions; though at times a smartphone is used to alleviate negative affect (Kardefelt-Winther, 2014). Depressed persons tend to socially withdraw from their social contacts, and this even has been made visible with meaningful GPS correlations such as more often staying at home (Saeb et al., 2015).

We did not have structured diagnostic interviews to assess mental disorders, instead using standardized self-report instruments, a possible limitation. We also note that levels of depression and anxiety were quite low, in the healthy range. We also only included iPhone users. Furthermore, objective phone use measurement may have limitations as well, including counting minutes of use for features passively used, such as navigation or music listening.

Nonetheless, our focus on objective smartphone use measurement is an advantage over the literature on self-reported/estimated use, as objective measures are more reliable yet less frequently used. Additionally, our analysis of lesser examined academic-related study and productivity variables in relation to increased smartphone use is an innovation over prior work. Specifically, primary findings suggest that increased surface learning and procrastination relate to fewer smartphone pickups, and lower productivity relate to increased minutes of use. Future research could examine psychological variables in relation to additional objective smartphone use variables, such as GPS/phone location data (Saeb et al., 2015), calling behavior (Montag et al., 2019), and text messaging (Messner et al., n.d.).

CONFLICT OF INTEREST

The authors report no conflicts of interest with this article's study. Outside the scope of the present article, Dr. Elhai 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. Dr. Montag mentions that he has received (to Ulm University and earlier University of Bonn) grants from agencies such as the German Research Foundation (DFG). Dr. Montag 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. Dr. Montag mentions that he is part of a discussion circle (Digitalität und Verantwortung: https://about.fb.com/de/news/h/gespraechskreis-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. Finally, he mentions that he currently functions as independent scientist on the scientific advisory board of the Nymphenburg group. This activity is financially compensated.

DATA AVAILABILITY STATEMENT

The data presented in this article are available upon reasonable request from the first author.

ETHICS STATEMENT

This study's project was first approved by the University of Toledo's Social Behavioral Institutional Review Board.

PARTICIPANT CONSENT STATEMENT

All participants were provided a detailed informed consent statement to acknowledge prior to deciding to participate in the study.

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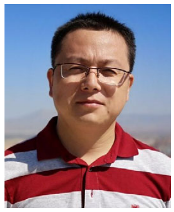

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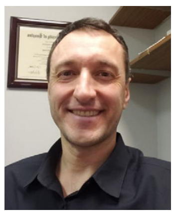

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