Child Psychiatry & Human Development
https://doi.org/10.1007/s10578-022-01313-y

ORIGINAL ARTICLE

Piloting Smartphone Digital Phenotyping to Understand Problematic Internet Use in an Adolescent and Young Adult Sample

Meredith Gansner[1] · Melanie Nisenson[1] · Vanessa Lin[1] · Nicholas Carson[1] · John Torous[2]

Accepted: 4 January 2022

Abstract
Problematic Internet use (PIU) preferentially affects youth development, particularly youth with psychiatric conditions. Studies attempting to understand PIU and its impact on adolescent mental health have been limited by cross-sectional design and self-report data. Even with a small sample size, digital phenotyping (DP) methodology can address these limitations through repeated sampling and collection of survey and sensor data through personal smartphones. This study pilots a 6-week DP protocol in 28 youth in mental health treatment in order to assess relationships between PIU, mood symptoms, and daily behaviors like smartphone engagement and daily travel in this high-risk population. Our results found shared associations between depression and PIU, where symptom severity of both worsened in the setting of decreased smartphone engagement. These clinically relevant findings indicate that, rather than uniformly worsening mental health, increased digital engagement may actually provide short-term relief from negative affect in youth with psychiatric comorbidities.

Keywords Problematic internet use · Digital phenotyping · Adolescent psychiatry · Digital media · Smartphone data

Introduction

Problematic Internet Use, or PIU, has been defined as maladaptive preoccupation with Internet use that may be experienced as either an irresistible urge to use the Internet or excessive Internet use [1]. While PIU prevalence rates in adolescents and young adults vary widely, ranging between 0 and 26.3% [2–4], this population is often considered to be at greater risk of PIU development by virtue of their amount of daily screen media exposure, estimated at greater than 7 h [5], and increased neurobiological vulnerability towards engagement in high-risk behavior [6]. Digital media use itself is now considered a normative and important part of adolescent development and has a less evident connection to adverse mental health outcomes while the development of PIU appears tied to higher rates of negative mental health outcomes like aggression, self-injurious behavior or suicidal ideation [7, 8]. Youth with existing psychiatric diagnoses appear particularly vulnerable to developing PIU [9–12], and PIU is associated with increased adolescent-parent conflict [13] and a poorer rated quality of life [14].

Despite concerns about PIU's potential impact on this vulnerable population, the existing research has many limitations. Studies are often criticized for their cross-sectional design and reliance on self-report data [15]. Similar to more established behavioral addictions, an individual's excessive Internet use may change on a daily or weekly basis both in content and amount used; therefore, it is challenging to accurately capture an individual's PIU through a cross-sectional survey. Moreover, youth in particular may struggle to reflect accurately on their continuous patterns of Internet use [16]; one 2015 study found a false negative rate of 44% when using adolescent self-report for the similar diagnosis of Internet Gaming Disorder. Because of these research

✉ Meredith Gansner
meegansner@challiance.org

Melanie Nisenson
mnisenson@ucla.edu

Vanessa Lin
vlin7@bu.edu

Nicholas Carson
ncarson@challiance.org

John Torous
jtorous@gmail.com

[1] Department of Psychiatry, Cambridge Health Alliance, 1493 Cambridge Street, Cambridge, MA 02139, USA

[2] Department of Digital Psychiatry, Beth Israel Deaconess Medical Center, 330 Brookline Drive, Boston, MA 02215, USA

limitations, many questions regarding PIU in youth with psychiatric illness remain unanswered. In particular, there is debate over whether PIU represents a separate pathological construct that can be experienced independently from psychiatric comorbidities like anxiety or depression or a symptom that manifests in response to decompensated primary psychiatric disorder (e.g. a maladaptive coping mechanism to manage worsened generalized anxiety).

Research methodologies such as ecological momentary assessment, or EMA, can address these limitations through the use of repeated sampling to survey participants in a naturalistic environment, decreasing recall bias while increasing ecological validity [17]. More recently, the ubiquitous ownership of personal smartphones has made them a convenient tool for the collection of survey data (also known as "active" data because the data can only be obtained through active participant engagement). In addition, smartphones also allow for the collection of "passive" data: objective behavioral measurements that can be obtained through use of phone sensors without requiring a person to actively provide the information e.g. accelerometer or geolocation data. The use of a personal smart device to obtain passive and active data to identify common patterns of behavior at the level of the individual has been referred to as "digital phenotyping" [18]. In this manner, a person can provide daily feedback about psychiatric symptoms in the context of behaviors like going to school or work, exercising, or engaging in screen time. For youth in particular, who spend approximately 9 h a day on their phones, digital phenotyping might prove especially useful as researchers attempt to understand etiologic underpinnings of PIU. Our prior research using app-based EMA to explore youth PIU was found to be a favorable experience for the majority of participants, with 83.3% reporting an increased awareness to the relationship between their mood symptoms and digital media use and 70.8% stating that they would use this app again in the clinical setting [19].

Our previous EMA study also showed that for youth with existing psychiatric illness, higher anxiety and depressive symptoms correlated with endorsement of higher PIU scores, and that anxiety appeared to improve temporally after episodes of PIU [19]. However, despite providing more granularity on the relationship between PIU and mood symptoms, this study was reliant upon repeated subjective measurements. Passive data collection can help to provide objective feedback surrounding an individual's daily mobility and routine, as well as clarify the way that an individual may be engaging with technology. To our knowledge, no study has previously examined youth PIU through the collection of passive data variables from smartphone sensors. This study is the first of its kind to explore the relationships between youth PIU and behavioral metrics of screen use and physical activity and to examine how they compare to behavioral metrics associated with anxiety and depression, which are both often comorbid with PIU. As with prior PIU studies, we hypothesized that we would find a positive correlation between screen time metrics (e.g. screen time) and severity of PIU. Additionally, if PIU results from an underlying depressive or anxiety disorder, we expected to see PIU severity (measured via the PIU-SF-6 scale) significantly associated with the same passive data-derived behavioral metrics as elevated anxiety or depression (as measured by GAD-7 or PHQ-8 scores). A more granular understanding of PIU and PIU-associated behavioral changes in youth may help to distinguish pathological digital media use from digital media use that exists as a part of normative adolescent development.

Methods

The study recruited 28 adolescents and young adults between the ages of 12 and 23 who were in active outpatient mental health treatment within an academic community health system in the greater Boston area. Examples of power or sample size analysis for DP in psychiatric research are limited. However, in the field to-date, multiple proof-of-concept studies have found evidence that using sample sizes under 50, DP studies are still adequately powered to detect clinically meaningful changes in disease state given collection of repeated, longitudinal measurements [20, 21]. In addition to criteria related to age and engagement in mental health care, participants were also required to have their own smartphone and be proficient in 6th grade English. If a participant was under age 18, parental consent was also a requirement. Participants were compensated for their time with a $25 Amazon gift card at the beginning and end of the study. No incentives were tied to app use; subjects could never use the study smartphone app and still receive full compensation, in order to avoid coercion to engage with the app.

Study Design

Study participants completed daily surveys through the mindLAMP app (Learn, Assess, Manage, Prevent) for 6 weeks. MindLAMP is a free-rein research platform that includes an online portal system and smartphone app [22]. Participants received a daily survey reminder via push notification once every evening. For collection of passive data (i.e. sensor-based data collected in the background that requires no active input from the participant), the research app Beiwe was used [23]. Beiwe is a native smartphone application that collects raw sensor data from digital devices and processes data into a readable JSON (JavaScript Object Notation) formatted file. The Beiwe research platform also includes the Beiwe back end and the Beiwe data analysis pipeline.

The back end uses the Amazon Web Services (AWS) cloud computing infrastructure to manage study creation and data collection. The analysis pipeline uses AWS Elastic Beanstalk to process data, check data quality, and computes summary statistics of interest (e.g., total distance traveled daily). For our study, the Beiwe app collected several streams of raw, passive smartphone data in the background: accelerometer, GPS and phone power state data. Each time a participant's phone connected to WiFi, survey data was uploaded to a secure, HIPAA-compliant server.

Daily surveys included measures of problematic Internet use, anxiety and depression. Degree of depression and anxiety was assessed using the Patient Health Questionnaire-8 (PHQ-8) and Generalized Anxiety Disorder-7 (GAD-7), respectively. The PHQ-8 is a modified version of the PHQ-9 that omits the final question assessing suicidality due to the fact that positive responses could not be actively monitored remotely. PIU was assessed for using the Problematic Internet Use Short Form-6 (PIU-SF-6), a validated self-report scale for assessing PIU in youth (α = 0.77) [24]. The PIU-SF-6 includes questions related to an individual's inability to separate from the Internet, and withdrawal symptoms when not able to use the Internet, such as "How often do you spend time online when you'd rather sleep?", "How often do you feel tense, irritated, or stressed if you cannot use the Internet for as long as you want to?", and "How often does it happen to you that you wish to decrease the amount of time spent online but you do not succeed?". Because these three self-report scales were not designed to be administered on a daily basis, screening questions were reworded to ask participants to answer questions based on symptoms in the prior 24 h. More frequent administration has not been determined to impact scale validity [25]. Figure 1 shows the data collected on a daily basis.

Study procedures were approved by the hospital's institutional review board and complied with the latest revision of the Declaration of Helsinki. Study investigators explained the study procedures in detail to participants and parents or guardians (when participant was a minor). Informed consent was obtained from each participant over 18 years of age and guardians of all minor children, and informed assent collected from youth under the age of 18.

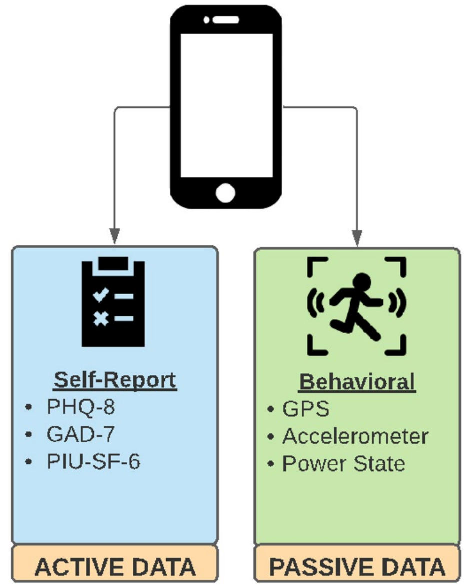

Fig. 1 Active and passive data collected

Data Processing and Analyses

Mobility measures were inferred using GPS sensors and screen metrics derived from phone power state data and calculated daily within a 24 h timeframe based on prior feature extraction in the literature [26]:

- *Time Spent at Home* was the daily amount of time spent at home, measured in minutes, and Home was considered to be the location where the largest amount of time was spent between 2100 and 0600.
- *Average Flight Length* was the average duration in meters of a participant's daily flights, with a flight defined as a burst of continuous travel traveled per day.
- *Average Flight Duration* was considered the average duration (in seconds) of all flights that occurred on a given day.
- *Number of Significant Locations* refers to the number of significant locations visited daily. Significant locations are locations where subjects paused for greater than 10 min. K means clustering was performed and any pauses that occurred within a 200-m radius of a cluster center was considered part of that center (i.e. the same location). Larger values indicate that an individual is spending their time across many locations evenly throughout the day. A small value means there is less time spent at significant locations.
- *Circadian Routine* approximates daily routine, comparing fractions of time individuals spend at the same locations compared to prior days. When values are high, an individual has spent a greater fraction of time in the same location, maintaining their daily routine. Lower values indicate that an individual deviated from their daily routine.
- *Screen Time* was estimated as total seconds per day that the phone was registered as "unlocked" with screen on.
- *Daily Phone Sessions* per day was calculated as the number of discreet phone sessions (a "phone on" event followed by "phone" off event).
- *Phone Session Time* was the average daily session length in seconds.

- *Daily Phone Checks* referred to the number of daily phone sessions lasting less than 15 s, which has previously been found to be indicative of habitual smart phone use [27].

Statistical analyses were run in Stata Version 1.2.5033. Demographic characteristics were calculated as percentages. Mixed effects linear regression models were performed to account for longitudinal data with multiple measurements from each participant over the course of the study. Participants were excluded from analyses if no passive data was obtained from the participant during the 6-week study period.

Results

At the end of the 6-week period, 64% of participants (n = 18) had adequate passive data collected at the end of the study to perform proposed analyses on passive data. Either due to personal choice or smartphone privacy controls, the remaining 10 individuals did not have any passive data collected during the study period. Descriptive statistics regarding participant demographics are summarized in Table 1. The average age of participants was 15.6 years, with equal numbers of both genders. The majority of participants identified as white, non-Hispanic/Latinx.

Table 1 Demographics of participants

Demographics	Participants with passive data
Age (mean)	15.6
Gender	
Female	9
Male	9
Ethnicity	
White (Latinx/Hispanic)	5
White (non-Latinx/Hispanic)	13

GPS/Accelerometer Sensor Data

On average, youth in the study spent 12.1 h at home per day. They visited an average 1.6 significant locations daily, with the average daily "flight" duration being 2.87 min long. As seen in Table 2, higher PIU-SF-6 scores were significantly associated with less departure from daily routine, as evidenced by higher values for circadian routine (p = 0.007). Trending towards significance, higher GAD-7 scores were positively correlated with an increased daily number of significant locations visited (p = 0.06). Average flight length and duration, as well as time spent at home, were not found to be significantly associated with an increase or decrease in any of the scale scores.

Power State Data

Youth in our study spent an estimated average of 5.57 h on their smartphones daily. They had an average 68.7 phone sessions during that time, and each phone session averaged 7.79 min. The average daily number of phone checks was 29.7. While total screen time and session duration were unrelated to scale score severity, both PIU-SF-6 and PHQ-8 scores were less severe with an increasing number of daily phone checks (p = 0.03, p = 0.01 respectively) and phone sessions (p = 0.046, p = 0.02 respectively).

Discussion

This novel study provides increased granularity about the phenomenon of PIU by capturing the relationship between PIU and objective behavioral metrics like screen time, phone checks, and daily activity. Consistent with prior studies in the overall population of youth and adolescents[9, 28–31], our findings indicated a connection between PIU and depression; however, these shared behavioral associations, number of daily checks and phone sessions, were not in the direction that has been hypothesized by those prior studies.

Instead of increased digital media use acutely worsening depressive symptoms, our study showed that depressive

Table 2 Relationships between behavioral metrics obtained from GPS/accelerometer data and severity of PHQ-8, GAD-7 and PIU-SF-6 self-report scale scores using mixed effects linear regression models

	PHQ-8 score			GAD-7 score			PIU-SF-6 score		
	β	*z*	*p*	β	*z*	*p*	β	*z*	*p*
Amount of time spent home per Day (in seconds)	− 4.69	− 0.64	0.52	− 10.21	− 1.42	0.16	8.54	1.04	0.30
Number of significant locations visited per day	.003	0.26	0.80	.026	1.90	0.06	− .0009	− 0.06	0.95
Average distance (in meters) of daily flights	− 7.17	− 1.14	0.26	− 7.50	− 1.17	0.24	− 0.96	− 0.13	0.90
Average duration (in seconds) of daily fligHTS	− 0.76	− 0.08	0.97	10.25	0.98	0.33	− 12.80	− 1.01	0.31
Circadian routine	.003	0.76	0.44	.003	0.85	0.40	.001	2.69	0.007*

symptoms were worse for youth on days with decreased engagement with their smartphones. The negative correlation between phone checks and sessions and PHQ-8 score could represent the well-established increase in withdrawal and isolation seen with elevated depressive symptoms [32]. Considering the multiple ways in which youth engage with digital media on a daily basis (e.g. for school, socialization, to support hobbies), decreased digital media use may also be a sign of anhedonia. However, because PIU symptoms are also more severe when phone engagement is decreased, we propose a different model (Fig. 2). For adolescents with psychiatric illness, the phone and social media may be an increasingly relied-upon tool to escape acutely worsening depressive symptoms, like feeling isolated or experiencing low self-esteem. On days when these youth are less able to access their smartphones, symptoms of PIU may be far more noticeable, similar to how symptoms of substance dependence might be more prominent in the absence of the substance. Our findings also indicate that these adolescents display significantly fewer departures from day-to-day routine (i.e. increased circadian routine values) when experiencing significant PIU symptoms. Especially following periods of decreased engagement with smartphones, youth may be less likely to deviate from standard daily routines that allow for predictable use of their smartphones. Prior research has supported an overall link between PIU and sedentary behavior, as well as decreased engagement in extracurricular activities [33]. Because our methodology indicates that these factors are linked on a daily basis, we hypothesize that these youth retreat to the digital world when PIU symptoms are elevated, rather than youth with non-divergent daily routines being more prone to PIU development. Perhaps most importantly, our findings suggest that adolescents with psychiatric comorbidities have a complicated relationship with the Internet, where symptoms appear to worsen with decreased digital media use, and ongoing media use may be at the expense of increased day-to-day variability in adolescent lives. To tease apart further these relationships and test these hypothesized models, it may be necessary for DP studies to be performed over a longer period of time and in a larger number of individuals in order to capture a sufficient number of episodes of worsening mood symptoms with accompanying passive data measurements (Table 3).

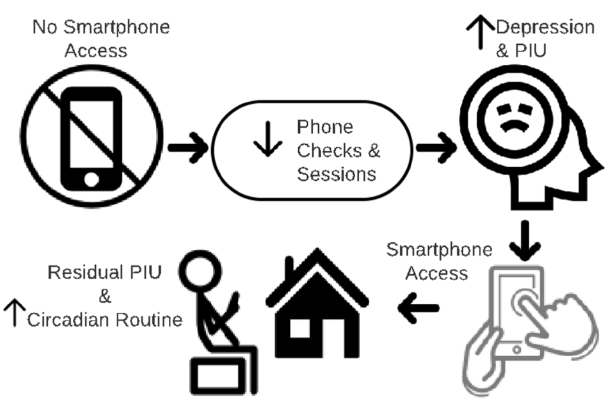

Fig. 2 Modeled Relationship between depression, PIU and identified behavioral metrics

Another surprising finding in our study was the lack of a significant relationship between screen time and PIU despite repeated connections found between these two variables in prior studies[34, 35]. This discrepancy could be similar to our findings that daily PIU scores were negatively associated with checking one's smartphone or number of daily sessions; PIU symptoms may be not be significantly noticeable when one is actively engaged in screen time. However, unlike number of daily checks and sessions, screen time was not negatively associated with elevated PIU scores. This finding could instead be related to the differing methodologies used in prior studies versus this current one. Previously, many PIU studies have asked youth to estimate the number of hours they spent daily on digital media; our study approximated daily smartphone screen time directly from smartphone devices. It is possible that the screen time unaccounted for by our methodology (e.g. daily time spent on desktop or laptop) may have contributed to a Type II error. However, we do not consider this likely given that youth in our study's age range spend the majority of their daily digital media time on smartphones specifically [5]. Thus, smartphone use is likely one of the best approximations of daily digital media use in this age group. Alternatively, we propose that methodology

Table 3 Relationships between smartphone use metrics obtained from smartphone power state data and severity of PHQ-8, GAD-7 and PIU-SF-6 self-report scale scores using mixed effects linear regression models

	PHQ-8 score			GAD-7 score			PIU-SF-6 score		
	β	*z*	*p*	β	*z*	*p*	β	*z*	*p*
Daily screen time (in seconds) on smartphone	− 393.05	− 1.40	0.16	− 524.6	− 1.84	0.07	195.52	0.59	0.56
Number of sessions on smartphone per day	− 2.10	− 2.59	0.01*	− 0.10	− 0.13	0.90	− 1.87	− 2.12	0.03*
Number of times smartphone is checked per day	− 1.32	− 2.31	0.02*	− 0.32	− 0.57	0.57	− 1.27	− 2.00	0.046*
Average duration per day (in seconds) of each smartphone session	9.42	0.77	0.44	− 5.02	− 0.38	0.70	3.72	0.26	0.79

reliant upon subjective reporting of daily digital media use may be unreliable; personal estimation of daily screen time may be increasingly challenging for an age group where nearly half report "continuous" smartphone use [36]. Prior research in adults confirms a tendency towards inaccuracy and over-reporting [37]. Youth who perceive that they have less control over navigating their personal smartphone use may also be more liable to overestimate the amount of time they spend online. Similar to substance use disorders, where the exact amount of substance use is not relevant in determining the severity of the disorder [38], youth PIU severity may be independently related to the actual amount of time spent on digital media, length of phone sessions, or amount of checking one's smartphone.

Future studies should attempt to achieve more granularity in type of media use, including active or passive engagement with technology. As researchers continue to clarify PIU as a pathological construct, they should consider focusing on perceived consequences of digital media use as they relate to PIU scores. The degree to which a youth believes that personal Internet use might be impacting academics, extracurricular activities or interpersonal relationships may be more closely tied to PIU severity than amount of time spent online.

Future Directions and Limitations

Despite DP's ability to obtain repeated measurements and collect potentially more objective data [39], our study was limited by its sample size, both in participant number and in collection of passive data samples. Robust DP studies require simultaneous collection of both active and passive data [39], and this appears not without challenges when using smartphone technology. Changes in smartphone privacy policies at the level of the corporation frequently alter permission settings for apps that continuously collect passive data. In 2020, for example, Apple began requiring that all apps that collected background passive data obtain user permission [40]. DP apps are also not allowed to collect passive data while an iPhone is in power-saving mode. While important, these privacy changes increase the likelihood that users of a DP app might inadvertently cease passive data collection, eliminating the continuous data stream. It is for this reason that missing data is still a potential problem even with passive collection. Additionally, phone companies do not currently allow for the passive collection of data on qualitative smartphone use (e.g. number of minutes using X app daily). Clarifying the differing mental health effects of various types of smartphone use may be critical for our understanding of youth digital media use. To address these restrictions, future DP protocols should include reminders to check smartphone permissions and for participants with iPhones, ask them to share company-provided screen report data to approximate qualitative use. Finally, it is critical to note that due to both the aforementioned challenges in the collection of passive smartphone data and the methodology still being in its infancy, high-fidelity replication studies that assess research platform validity are lacking in number. Thus, while our results represent a novel next step in adolescent smartphone research, our findings are limited in generalizability until replication studies using the same protocol and capturing the same passive sensor data can be performed. Fortunately, the passive data collection app that this study uses, Beiwe, was designed to support high-fidelity study reproducibility, where investigators can replicate existing study protocols or data analyses through obtaining the study's JSON configuration file [41].

Summary

Despite the limitations of this evolving technology, this novel pilot study exemplifies the potential use of digital phenotyping in a population where reliable clinical data can be hard to obtain. Prior to this study, understanding PIU and its potential impact on adolescent growth and development has been limited by subjective methodology. Our results suggest that the utilization of more objective behavioral metrics may help to dispel and correct certain assumptions about the connections between youth development, screen time, and mental health based on retrospective, cross-sectional data. For example, our findings highlight the clinical importance of understanding how increased digital engagement might provide relief from negative affect in the short-term, particularly for those youth with psychiatric comorbidities. Additionally, the results suggest the ongoing need for mental health professionals to inquire about more than quantitative screen time use alone when assessing adolescent PIU. Research that subsequently tailors DP protocols to optimize adherence and passive data collection will be instrumental to harness this technology for both clinical and research purposes in this population.

Funding This study was supported by the DuPont Warren Fellowship and Livingston Award, awarded to Dr. M.G. by the Department of Psychiatry, Harvard Medical School.

Declarations

Conflict of interest Dr. John Torous receives research support from Otsuka Pharmaceuticals for work unrelated to this manuscript. Drs. Gansner and Carson and Ms. Nisenson and Ms. Lin have no competing financial interests or other conflicts of interest to disclose.

Consent to Participate and Publish Written informed consent was obtained for all participants over 18 years of age. For participants under 18 years of age, parental consent and adolescent assent was obtained.

Ethical Approval This study was conducted in compliance with the ethical standards as outlined in the latest version of the Declaration of Helsinki. This study was approved by the Cambridge Health Alliance Institutional Review Board on 12/24/2021 for continuing review.

References

1. Shapira NA, Lessig MC, Goldsmith TD et al (2003) Problematic internet use: proposed classification and diagnostic criteria. Depress Anxiety 17:207–216. https://doi.org/10.1002/da.10094
2. Durkee T, Kaess M, Carli V et al (2012) Prevalence of pathological internet use among adolescents in Europe: demographic and social factors. Addiction 107:2210–2222. https://doi.org/10.1111/j.1360-0443.2012.03946.x
3. Moreno MA, Jelenchick L, Cox E et al (2011) Problematic internet use among US youth: a systematic review. Arch Pediatr Adolesc Med 165:797–805. https://doi.org/10.1001/archpediatrics.2011.58
4. Vigna-Taglianti F, Brambilla R, Priotto B et al (2017) Problematic internet use among high school students: prevalence, associated factors and gender differences. Psychiatry Res 257:163–171. https://doi.org/10.1016/j.psychres.2017.07.039
5. Rideout V, Robb M (2019) The common sense census: media use by tweens and teens. commonsense media, San Francisco
6. Hammond CJ, Mayes LC, Potenza MN (2015) Neurobiology of adolescent substance use and addictive behaviors: prevention and treatment implications. State of the Art Rev 25(1):15–21
7. Fuchs M, Riedl D, Bock A et al (2018) Pathological internet use: an important comorbidity in child and adolescent psychiatry: prevalence and correlation patterns in a naturalistic sample of adolescent inpatients. BioMed Res Int. https://doi.org/10.1155/2018/1629147
8. Gansner M, Belfort E, Cook B et al (2019) Problematic internet use and associated high-risk behavior in an adolescent clinical sample: results from a survey of psychiatrically hospitalized youth. Cyberpsychol Behav Soc Netw 22:349–354. https://doi.org/10.1089/cyber.2018.0329
9. Kim B-N, Park S, Park M-H (2017) The Relationship of sexual abuse with self-esteem, depression, and problematic internet use in Korean adolescents. Psychiatry Investig 14:372–375. https://doi.org/10.4306/pi.2017.14.3.372
10. Rideout V, Fox S (2018) Digital Health Practices, Social Media Use, and Mental Well-Being Among Teens and Young Adults in the U.S. Hopelab Well Trust 1–95
11. Wang C-Y, Wu Y-C, Su C-H et al (2017) Association between Internet gaming disorder and generalized anxiety disorder. J Behav Addict 6:564–571. https://doi.org/10.1556/2006.6.2017.088
12. Yen J-Y, Ko C-H, Yen C-F et al (2007) The comorbid psychiatric symptoms of internet addiction: attention deficit and hyperactivity disorder (ADHD), depression, social phobia, and hostility. J Adolesc Health 41:93–98. https://doi.org/10.1016/j.jadohealth.2007.02.002
13. Özaslan A, Yıldırım M, Güney E et al (2021) Association between problematic internet use, quality of parent-adolescents relationship, conflicts, and mental health problems. Int J Ment Health Addict. https://doi.org/10.1007/s11469-021-00529-8
14. Gao L, Gan Y, Whittal A, Lippke S (2020) Problematic internet use and perceived quality of life: findings from a cross-sectional study investigating work-time and leisure-time internet use. Int J Environ Res Public Health 17:4056. https://doi.org/10.3390/ijerph17114056
15. Kaye K, Orben A, Ellis D et al (2020) The conceptual and methodological mayhem of “Screen Time.” Int J Environ Res Public Health 17:3661. https://doi.org/10.3390/ijerph17103661
16. Jeong H, Yim HW, Lee S-Y et al (2018) Discordance between self-report and clinical diagnosis of Internet gaming disorder in adolescents. Sci Rep 8:10084. https://doi.org/10.1038/s41598-018-28478-8
17. Stone AA, Shiffman S (1994) Ecological momentary assessment (EMA) in behavorial medicine. Ann Behav Med 16:199–202. https://doi.org/10.1093/abm/16.3.199
18. Insel TR (2018) Digital phenotyping: a global tool for psychiatry. World Psychiatry 17:276–277. https://doi.org/10.1002/wps.20550
19. Gansner M, Nisenson M, Carson N, Torous J (2020) A pilot study using ecological momentary assessment via smartphone application to identify adolescent problematic internet use. Psychiatry Res 293:113428. https://doi.org/10.1016/j.psychres.2020.113428
20. Barnett I, Torous J, Reeder HT et al (2020) Determining sample size and length of follow-up for smartphone-based digital phenotyping studies. J Am Med Inform Assoc. https://doi.org/10.1093/jamia/ocaa201
21. Onnela JP Digital phenotyping power calculation. https://onnela-lab.shinyapps.io/digital_phenotyping_sample_size_calculator/. Accessed 23 Nov 2020
22. Torous J (2020) LAMP. In: Div. Digit. Psychiatry BIDMC. https://www.digitalpsych.org/lamp.html. Accessed 20 Apr 2020
23. Torous J, Kiang MV, Lorme J, Onnela J-P (2016) New tools for new research in psychiatry: a scalable and customizable platform to empower data driven smartphone research. JMIR Ment Health 3:e16. https://doi.org/10.2196/mental.5165
24. Demetrovics Z, Király O, Koronczai B et al (2016) Psychometric properties of the problematic internet use questionnaire short-form (PIUQ-SF-6) in a nationally representative sample of adolescents. PLoS ONE. https://doi.org/10.1371/journal.pone.0159409
25. Bauer AM, Baldwin SA, Anguera JA et al (2018) Comparing approaches to mobile depression assessment for measurement-based care: prospective study. J Med Internet Res 20:e10001. https://doi.org/10.2196/10001
26. Barnett I, Onnela J-P (2018) Inferring mobility measures from GPS traces with missing data. Biostat Oxf Engl 21:e98–e112. https://doi.org/10.1093/biostatistics/kxy059
27. Wilcockson TDW, Ellis DA, Shaw H (2018) Determining typical smartphone usage: what data do we need? Cyberpsychol Behav Soc Netw 21:395–398. https://doi.org/10.1089/cyber.2017.0652
28. Kaess M, Durkee T, Brunner R et al (2014) Pathological Internet use among European adolescents: psychopathology and self-destructive behaviours. Eur Child Adolesc Psychiatry 23:1093–1102. https://doi.org/10.1007/s00787-014-0562-7
29. Tan Y, Chen Y, Lu Y, Li L (2016) Exploring associations between problematic internet use, depressive symptoms and sleep disturbance among southern chinese adolescents. Int J Environ Res Public Health. https://doi.org/10.3390/ijerph13030313
30. Park M-H, Park S, Jung K-I et al (2018) Moderating effects of depressive symptoms on the relationship between problematic use of the Internet and sleep problems in Korean adolescents. BMC Psychiatry. https://doi.org/10.1186/s12888-018-1865-x
31. Park S, Hong K-EM, Park EJ et al (2013) The association between problematic internet use and depression, suicidal ideation and bipolar disorder symptoms in Korean adolescents. Aust N Z J Psychiatry 47:153–159. https://doi.org/10.1177/0004867412463613
32. Kupferberg A, Bicks L, Hasler G (2016) Social functioning in major depressive disorder. Neurosci Biobehav Rev 69:313–332. https://doi.org/10.1016/j.neubiorev.2016.07.002

33. Oberle E, Ji XR, Kerai S et al (2020) Screen time and extracurricular activities as risk and protective factors for mental health in adolescence: a population-level study. Prev Med 141:106291. https://doi.org/10.1016/j.ypmed.2020.106291
34. Aşut Ö, Abuduxike G, Acar-Vaizoğlu S, Cali S (2019) Relationships between screen time, internet addiction and other lifestyle behaviors with obesity among secondary school students in the turkish republic of northern cyprus. Turk J Pediatr 61:568. https://doi.org/10.24953/turkjped.2019.04.014
35. Guo N, Luk TT, Wang MP et al (2021) Self-reported screen time on social networking sites associated with problematic smartphone use in Chinese adults: a population-based study. Front Psychiatry 11:614061. https://doi.org/10.3389/fpsyt.2020.614061
36. Jiang J (2018) How Teens and Parents Navigate Screen Time and Device Distractions. Pew Research Center
37. Araujo T, Wonneberger A, Neijens P, de Vreese C (2017) How much time do you spend online? Understanding and improving the accuracy of self-reported measures of internet use. Commun Methods Meas 11:173–190. https://doi.org/10.1080/19312458.2017.1317337
38. American Psychiatric Association (2013) Diagn. Stat. Man. Ment. Disord.
39. Onnela J-P, Rauch SL (2016) Harnessing smartphone-based digital phenotyping to enhance behavioral and mental health. Neuropsychopharmacology 41:1691–1696. https://doi.org/10.1038/npp.2016.7
40. O'Flaherty K (2021) Apple's stunning iOS 14 privacy move: a game-changer for all iPhone users. In: Forbes. https://www.forbes.com/sites/kateoflahertyuk/2021/01/31/apples-stunning-ios-14-privacy-move-a-game-changer-for-all-iphone-users/. Accessed 19 March 2021
41. Onnela JP Beiwe-Frequently Asked Questions. https://www.beiwe.org/about/.