Fuzzy constructs in technology usage scales

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Abstract

The mass adoption of digital technologies raises questions about how they impact people and society. Associations between technology use and negative correlates (e.g., depression and anxiety) remain common. However, pre-registered studies have failed to replicate these findings. Regardless of direction, many designs rely on psychometric scales that claim to define and quantify a construct associated with technology engagement. These often suggest clinical manifestations present as disorders or addictions. Given their importance for research integrity, we consider what these scales might be measuring. Across three studies, we observe that many psychometric scales align with a single, identical construct despite claims they capture something unique. We conclude that many technology measures appear to measure a similar, poorly defined construct that sometimes overlaps with pre-existing measures of well-being. Social scientists should critically consider how they proceed methodologically and conceptually when developing psychometric scales in this domain to ensure research findings sit on solid foundations.

Keywords: Measurement, Screen time, Self-report, Social media, Smartphones, Technology use, Validity, Video games

1 Introduction

1.1 Measurement in the social sciences

The development of surveys or standardized assessments (often referred to as psychometrics) remain a cornerstone of many social science disciplines. However, exactly how we measure some ‘quantitative’ attributes often appears ambiguous. In contrast, within the natural sciences, systematic methods to develop measurements relate to a number of units within a given magnitude (Michell, 2000; Titchener, 1905). Such measures are additive. In the social sciences, however, measures of interest (e.g., intelligence or attitudes) cannot be quantified in a similar fashion (Titchener, 1905). Subsequent discussions have considered what empirical measurement means for psychology, specifically within psychometrics, where Stevens stated, ‘measurement, in the broadest sense, is defined as the assignment of numerals to objects or events according to rules. The fact that numerals can be assigned under different rules leads to different kinds of measurement,’ (Stevens, 1946, p. 677). As a result, one might conclude that many psychometric assessments are dynamic, fluid, and naturally inconsistent. This already creates an element of uncertainty: ‘The hazard of educational or psychological measurement is that almost anyone can devise his or her own set of rules to assign some numbers to some subjects,’ (Suen, 1990, p. 5). However, the impact of this ‘hazard’ depends on how a field has systematically developed and refined psychometric instruments over time, which varies across psychological science.

Such a discussion leads naturally to questions concerning psychometric validity. For example, predictive validity relates to whether scales are predictive of an outcome criterion and concurrent validity considers whether a psychometric scale can substitute another (Cronbach & Meehl, 1955). These two types of validity are seemingly easier to test and examine reliability. However, content and construct are less well defined. Content validity concerns how well each item measures the same construct, whilst also being sufficiently different from other items (Hardesty & Bearden, 2004; Rubio, Berg-Weger, Tebb, Lee, & Rauch, 2003). Construct validity is the extent to which a given measure can capture the criterion of interest (Rubio et al., 2003). Recent developments have extended traditional forms of validity to include discriminant validity, whereby a measure should diverge from unrelated constructs as expected (Campbell, 1960). Collectively, content, construct, and discriminant validity require slow, thoughtful work with strong qualitative foundations. However, while removing computational barriers has increased the pace of psychometric development, this has potentially reduced the space for slow and considered theorizing to ensure any new measure is fit for purpose (Ellis, 2020).

1.2 Measuring and understanding the impacts of technology

As the world becomes increasingly digitized, this raises questions and concerns about how various technologies impact people and society. For example, recent debates have focused on the negative impacts of ‘screen time’ on children and young adults (UK Parliament, 2018). However, many studies rely on self-reported scales or ask participants to estimate how long they spend using devices or services (known as screen time estimates), which do not align with objective logs of technology use (Ellis, Davidson, Shaw, & Geyer, 2019; Parry et al., 2021; Sewall, Bear, Merranko, & Rosen, 2020; Shaw et al., 2020). While subjective (psychometric) measures suggest that technology is inherently ‘bad’ for society (Ellis, 2019), pre-registered designs observe near-zero associations between well-being and objective technology use or screen time estimates (e.g., Orben & Przybylski, 2019; Shaw et al., 2020).

Perhaps contrasting findings like these should not come as a surprise. Increasing numbers of new technology usage scales appear annually (Ellis, 2019; Howard & Jayne, 2015). These often conceptualize use as ‘problematic’ or ‘addictive’, sometimes in direct conflict with evidence. For instance, the Problematic Series Watching Scale (PSWS) does not include the word addiction: ‘because we have no solid evidence regarding health-related negative consequences of this behavior’ (Orosz, Bóthe, & Tóth-Király, 2016, p. 145), yet the term ‘problematic’ remains. Many scales are adapted whereby only a single word relating to the technology changes with no consideration given to differences in affordances between technologies (Ellis, 2019, 2020; Thomée, 2018). For example, the Smartphone Addiction Scale (SAS) (Kwon et al., 2013b), while well cited, is based on the ‘internet addiction proneness scale’, also known as the ‘K scale’ (Dong-il, Yeo-ju, Eun-ah, Dong-min, & Young-mi, 2008). The SAS, among many others, including the Problematic Series Watching Scale and the Internet Gaming Disorder Scale, are rooted in a components model of addiction (Griffiths, 2005). Hence, measures based on this model may conceptually overlap. However, technology addiction scales can have different ontological groundings (e.g., pathological gambling vs components model of addiction), which likely contributes to variances in prevalence rates (Karhulahti, Martončík, & Adamkovič, 2021). Despite the lack of clarity regarding definitions, evidence, and measurement, gaming disorder remains a part of the ICD-11 (Karhulahti, Martončík, & Adamkovič, 2021). Even at the level of face validity, these inconsistencies serve to undermine how scales could diagnose any condition (Karhulahti, Vahlo, Munukka, Koskimaa, & von Bonsdorff, 2021).

Irrespective of whether technology use is considered an addiction or disorder, this should manifest as extreme behaviors in small sub-sections of the population, which may benefit from treatment (Addiction Centre, 2021; Goodman, 1990; White, 2007). However, research appears to suggest that large swathes (sometimes up to 34%) of the general population suffer from an addiction to technologies (Andreassen,

2015; Satchell et al., 2021). These results appear to be pathologizing everyday life (Cheng, Burke, & Davis, 2019; Ellis, 2019, 2020; Shaw et al., 2020), and suggest that the origins of such conclusions require further investigation.

Thus, we quantitatively consider how prevalent measurement issues are in scales used to study associations between technology use and well-being. Previous research by Adelhardt, Markus, and Eberle (2019) found that scores from the Smartphone Addiction Scale (short version) (SAS-SV) and the Compulsive Internet Use Scale (CIUS) were highly correlated ($r = 0.98$). Hence, we build on this recent work to better understand how far these measurement issues spread in smartphones before extending our investigation further. Specifically, we address two related research questions:

1. Do technology usage scales measure distinct constructs?
2. What do technology usage scales measure?

First, we determined whether there are overlaps in various smartphone usage scales specifically (Study one). We then analyzed other secondary data to investigate whether there is construct overlap between technology usage scales and mental health scales (Study two). Beyond smartphones, a final pre-registered study [<https://osf.io/gkyhz>] examined how widespread these measurement issues are by testing multiple scales relating to smartphone use, social media, series watching, and gaming (Study three). Data and code are available on the Open Science Framework (OSF) for all studies [<https://osf.io/84j6h>].

2 Study one: Are smartphone usage scales capturing distinct constructs?

2.1 Data

We first sought to understand how smartphone usage scales diverge as they appear, at face value, to define and quantify unique psychological constructs. The data obtained for this study previously appeared in Ellis et al. (2019). However, the secondary analysis reported here is distinct from the original article (see Ellis et al., 2019). Specifically, our analysis aimed to understand the overlap in constructs between ten distinct smartphone usage scales.

2.2 Analysis plan

We conducted a principal components analysis (PCA) as it reduces complex datasets into fewer components, revealing hidden and simplified structures (Shlens, 2014). Such an analysis can also highlight important information within a dataset and reduce its size via component reduction (Abdi & Williams, 2010). Further, parallel analysis (PA) can help determine the number of components to keep by simulating additional datasets. The average eigenvalue of each simulated component can then be compared to the eigenvalues from the original dataset.

Correlations were first calculated between measures to assess overlap (see Supplementary Materials 1). Next, we ran PCA and PA analyses to ensure our findings were robust. We expected to reveal several (ideally ten) components based on the ten scales assuming they measured unique constructs. All analysis was conducted in R, using the ‘factoextra’ package (Kassambara & Mundt, 2017). We report PA findings from the ‘psych’ package (Revelle, 2018) and used ‘oblimin’ rotations in all studies.

2.3 Results

2.3.1 PCA and PA

The ten scales (see Table 1) correlated with each other (all r 's $>.35$) apart from two comparisons (see Supplementary Materials 1). For example, the Mobile Phone Problematic Use Scale (MPPUS) and Smartphone Addiction Scale (SAS) were remarkably similar ($r = 0.82$), as were the MPPUS and the Smartphone Application-Based Addiction Scale (SABAS) ($r = 0.77$). Typically, before conducting a PCA, one would drop highly correlated measures. However, to check if scales captured unique constructs, all were included in the following analysis. Prior to our PCA analysis, we checked sampling adequacy (MSA) using the Kaiser-Meyer-Olkin (KMO) test. The average MSA for our sample was 0.9,

more than sufficient to proceed. We ran a PCA with PA, which simulated random datasets ($N = 100$). If the eigenvalues from our dataset exceed the simulated average eigenvalues, we retain them as a component. The PA revealed one component (see Fig. 1). Our simulated eigenvalue was 1.33 in comparison to 5.75 (our dataset). See Supplementary Materials 2 for all eigenvalues from the original data and simulated values.

Table 1. Descriptive Statistics (means (M), standard deviations (SD), and Cronbach's Alpha (α)) for measures reported in Ellis et al. (2019). 238 participants (124 Female) had a mean age of 31.88 ($SD = 11.19$) and were all iPhone users (iPhone 5 or above running the latest iOS at the time of data collection in November 2018).

Self-report measures	Items	M	SD	α
Mobile phone Problem Use Scale (MPPUS) (Bianchi & Phillips, 2005)	27	111.90	43.12	.94
Nomophobia Scale (NS) (Yildirim & Correia, 2015)	11	82.57	25.76	.96
Possession Incorporation in the Extended Self (ES) (Sivadas & Venkatesh, 1995)	6	21.53	8.99	.93
Smartphone Attachment Scale (SA _t) (Sivadas & Venkatesh, 1995)	4	17.02	6.05	.87
Smartphone Addiction Scale (SAS) (Kwon, et al., 2013b)	33	94.20	30.17	.95
Smartphone Application-Based Addiction Scale (SABAS) (Csibi, Griffiths, Cook, Demetrovics, & Szabo, 2018)	6	15.83	5.89	.81
Problematic Mobile Phone Use Questionnaire (PMPUQ-SV) (Lopez-Fernandez et al., 2018)	15	27.54	5.85	.72
Media and Technology Usage and Attitudes Scale (MTUAS) (Rosen, Whaling, Carrier, Cheever, & Rokkum, 2013)	9	6.24	1.33	.84
Smartphone Use Questionnaire (General) (SUQ-G) (Marty-Dugas & Ralph, 2018)	10	48.45	8.89	.78
Smartphone Use Questionnaire (Absent Minded) (SUQ-A) (Marty-Dugas & Ralph, 2018)	10	45.60	14.37	.95

Fig. 1. Scree plot from the PA. The blue line represents actual data and the red dotted line simulated data. Both suggest the existence of only one component.

2.3.2 Quality of representation

Alongside the PA, we visualized and assessed the quality of representation (cosine2) across all scales by plotting the amount of variance explained across two components (Fig. 2). Most scales aligned with component one (57.5% variance explained) (x-axis) with few aligning with component two (y-axis) (11.5% variance explained). This provides further evidence for the existence of a single component. Based on cosine2, which reveals what scale(s) contribute the most to each component, the SAS (Kwon et al., 2013a) is the most representative scale across the whole sample. These scales, therefore, fall into one cluster (Gabriel, 1971) (Fig. 2) and hence, appear to measure a very similar, if not identical, construct.

Fig. 2. Plot showing the first two components of the PCA. The x-axis is component one, the y-axis is component two. Arrows represent a single scale. All arrows point towards the left-hand quadrants indicating alignment with component one. Arrow color denotes the quality of representation, whereby red denotes higher quality and blue denotes lower quality. Small angles between arrows represent stronger correlations between scales (see Supplementary Materials 1).

2.4 Discussion

These results suggest that one component (a unidimensional construct) is sufficient when explaining variation between measures. Despite a single component only capturing 57.5% of the variance, diminishing returns are evident. Adding multiple components to reach 70 or 80% of the variance explained is unnecessary due to the high correlations between measures reported in Supplementary Materials 1 and Fig. 2 (denoted by small angles between the arrows).

These measures were developed on the premise that they capture a variety of different smartphone ‘usage’ behaviors, attitudes, or feelings. However, they appear to be measuring one construct, and lack construct and discriminant validity. Thus, we should be highly critical of the continued development of related scales that claim novelty. However, while these results confirm the existence of a unidimensional construct, in a second study, we now turn to what these scales are measuring based on the most representative scale, the SAS.

3 Study two: What is the SAS measuring?

Here, we aim to understand what construct the SAS is measuring. We consider this scale in more detail for two reasons: first, it is highly cited across numerous research fields and remains influential. Second, it was the most representative scale based on the ten scales used in Study one. Specifically, the SAS had the highest cosine² value across a single dimension, meaning it captured the majority of variance from the construct shared across all measures.

As stated previously, these scales demonstrate links between smartphone use and negative outcomes including depression, anxiety (e.g., Elhai, Levine, Dvorak, & Hall, 2017; Rozgonjuk, Levine, Hall, & Elhai, 2018), and impaired sleep (Rosen, Carrier, Miller, Rokkum, & Ruiz, 2016). However, there are already well-documented comorbidities between genuine addictions and several mental health symptomologies (Potenza, 2006). Previous results may be driven by how a scale overlaps with sub facets of depression or anxiety.

3.1 Data

The data used for Study two has appeared in Shaw et al. (2020). Akin to the previous study, none of the analyses reported here appears elsewhere. We extracted the following variables: median smartphone use and the average number of daily pickups (via Apple Screen Time), an estimate of use along with SAS (Kwon et al., 2013a), anxiety (GAD7), depression (PHQ9), and perceived stress (PSS) scores (Cohen, Kamarck, & Mermelstein, 1983). Descriptive statistics appear in Table 2.

Table 2. Descriptive Statistics (means (M), standard deviations (SD), and Cronbach's Alpha (α)) for measures in Study two. 199 participants (137 Female), had a mean age of 30.18 (SD = 9.46) There were no missing data nor were any participants removed from analyses.

Measures	Items	M	SD	α
Objective smartphone use (median hours)		4.62	2.30	
Objective smartphone use (pickups)		85.76	39.94	
Time estimate of use (hours)		4.38	2.15	

Smartphone Addiction Scale (SAS)	33	105.80	24.36	.92
Anxiety (GAD7)	7	7.35	5.85	.94
Depression (PHQ9)	9	8.01	6.30	.90
Stress (PSS)	14	26.57	8.23	.85

3.2 Analysis plan

We use exploratory factor analyses (EFA) in this study as we are interested in the relationships between constructs (mental health, SAS, and smartphone use) rather than reducing the dimensionality of a dataset (PCA) (Budaev, 2010; Norris & Lecavalier, 2010). Hence, EFA allows researchers to determine unobservable relationships between constructs (Budaev, 2010; Norris & Lecavalier, 2010), which is ideal for examining whether there is a relationship between constructs captured by mental health scales and the SAS. These analyses are exploratory; hence we pose no predictions or hypotheses.

Here, we report four EFAs alongside correlations as follows: (1) an EFA of overall scores of depression, anxiety, stress, SAS, the screen time estimate, objective smartphone use, and pickups; (2) an EFA of individual items from scales that assess depression, anxiety, stress, SAS. This includes a time estimate, hours of use, and pickups; (3) an EFA of individual items from scales that assess depression, anxiety, stress, and SAS; and (4) an EFA of individual items of the SAS, a time estimate, hours of use, and pickups. Finally, we compute correlations to understand the relationship between three sub-components of the SAS (tolerance, withdrawal, and overuse) and objective measures.

3.3 Results and discussion

3.3.1 EFA: overall scores

Before analysis, we conducted KMO tests to show that MSA, which equalled 0.76, was sufficient to proceed. We first analyzed overall scores: anxiety, depression, stress, SAS, and the behavioral measures. A PA with N = 100 random, simulated datasets revealed two factors split between depression, anxiety, stress, SAS, a time estimate, and objective use and pickups (Table 3). The eigenvalues from our original dataset were 2.64 and 0.85, and the corresponding simulated eigenvalues were 0.62 and

0.18. An exploratory factor analysis that included two factors generated loadings for each scale (Table 3). Factor one relates to mental health and factor two relates to behaviors, with the SAS loading across both. This suggests that the SAS may be somewhat associated with behavior and well-being, but measures both poorly. Here, researchers would typically drop the SAS and rely on the mental health scales or objective behavioral measures like use or pickups to retain heterogeneity. Further, it is interesting to note that pickup behaviors load with usage behaviors but are somewhat separate from objective smartphone use and the time estimate.

Table 3. Factor loadings, with the cut-off set at 0.3, shows two factors. The SAS loads onto both factors (in bold). See Table 2 for abbreviations. Due to the cross-loading nature of the SAS, we decided to run an additional EFA of all scales but using individual items rather than overall scores. We aimed to understand why the SAS may be cross-loading with mental health by revealing which items are related to both mental health scales and behavioral measures.

	Factor 1	Factor 2
GAD7	0.91	
PHQ9	0.90	
PSS	0.82	
SAS	0.33	0.44
Time Estimate of Use (hours)		0.76
Objective smartphone use (median hours)		0.74
Objective smartphone use (pickups)		0.35

3.3.2 EFA: all individual items

The KMO analysis generated an MSA of 0.88 (more than sufficient to proceed). Using individual items from the scales (depression, anxiety, stress, SAS, time estimate, objective use, and objective pickups), the PA revealed seven factors (using 100 simulated datasets). The original eigenvalues were: 16.13, 6.05, 2.71, 1.92, 1.31, 1.11, and 0.97; and the simulated average eigenvalues were: 1.43, 1.27, 1.16, 1.09, 1.02, 0.95, and 0.89. When running an EFA with these seven factors and examining factor loadings, we observe some overlap between the mental health scales and the SAS (see Supplementary Materials 3). Three factors showed overlap between the SAS and mental health (factors 5, 6, and 7). No overlap was present between objective behavioral measures (time estimate, objective use, and pickups) with any self-reported measure (SAS and mental health). The overlap between mental health and the SAS typically revealed participants who were ‘feeling calm or cozy while using a smartphone,’ or ‘liberal,’ and ‘most confident,’ with their smartphones, which related to stress and depression items that focus on a lack of control in their lives or thoughts of self-harm. Collectively, these items tap into general mental health issues and the emotive areas of the SAS.

3.3.3 EFA: individual items – SAS and mental health

KMO analysis revealed the MSA was 0.88. Due to the observed overlap between mental health scales and the SAS at the individual item level, we explored this further in another EFA entering only the mental health (anxiety, depression, and stress) and the SAS. We tested if the overlap increased when behavioral measures were removed, which previously loaded separately to the SAS. The PA revealed seven factors, where the original eigenvalues were: 15.91, 5.88, 2.69, 1.91, 1.25, 1.09, and 0.97; and the simulated average eigenvalues were: 1.39, 1.21, 1.13, 1.05, 0.98, 0.91, and 0.86. The factor loadings replicated the overlap between the SAS and mental health scales (see Supplementary Materials 4). Depression items concerning self-harm and others noticing changes in behavior (e.g., being fidgety), for example, overlapped with SAS items relating to being tired or feeling aches when using a device. As before, this appears to tap into general symptoms of mental health rather than revealing anything specific about smartphones.

3.3.4 EFA: individual items - SAS and smartphone use

The KMO analysis revealed the MSA was 0.86. We then explored if the overlap between SAS and behavioral measures would hold after removing mental health items (as seen in Table 3). Therefore, our

final EFA included only SAS and behavioral items: time estimate, objective smartphone use, and objective smartphone pickups. The PA again, revealed seven factors, where the original eigenvalues were: 9.41, 2.19, 1.60, 1.02, 0.76, 0.58, and 0.56; and the simulated average eigenvalues were: 0.98, 0.82, 0.72, 0.65, 0.59, 0.53, and 0.48. We observe no overlap between the SAS and behavior (see Supplementary Materials 5).

3.3.5 Correlations between sub-components of the SAS and objective smartphone use

We were also interested in understanding the lack of overlap in some components of the SAS, objective smartphone use, and pickups. The SAS is rooted in the components model of addiction, which should conceptually overlap with objective behaviors, for instance, tolerance. Griffiths (2005, p. 194) describes tolerance as ‘the process whereby increasing amounts of the particular activity are required to achieve the former effects. The classic example of tolerance is a heroin addict's need to increase the size of their ‘fix’ to get the type of feeling (e.g., an intense ‘rush’)’. Therefore, one would expect that those with higher scores on items of the SAS that measure tolerance symptomology should also have higher levels of smartphone use and pickups. The latter is more likely to reflect impulsive behavior. We also computed related correlations between use and withdrawal and overuse components. Throughout, we follow recommendations that ‘small’, ‘typical’, and ‘relatively large’ effect sizes correspond to $r = \sim 0.10$, ~ 0.20 , and ~ 0.30 (Gignac & Szodorai, 2016).

Correlations between tolerance (3 items), use (hours), $r(197) = 0.16$, $p = .02$; $r_s(197) = 0.21$, $p = .003$; and pickups, $r(197) = 0.14$, $p = .05$; $r_s(197) = 0.15$, $p = .03$, demonstrate small-typical relationships. The relationship between withdrawal (6 items), use (hours), $r(197) = 0.27$, $p < .001$; $r_s(197) = 0.28$, $p < .001$; and pickups, $r(197) = 0.17$, $p = .01$; $r_s(197) = 0.16$, $p = .02$ were typical in magnitude. While overuse is not explicitly part of the components model of addiction, it overlaps conceptually as a classic set of addictive behaviors (e.g., relapse). We therefore computed correlations between overuse (4 items), use (hours) $r(197) = 0.27$, $p < .001$; $r_s(197) = 0.25$, $p < .001$; and pickups, $r(197) = 0.10$, $p = .15$; $r_s(197) = 0.11$, $p = .12$, with small to typical effect sizes being common.

In summary, smartphone usage scales load onto a single construct, which overlaps with mental health. In addition, portions of the SAS have some consistent small-typical relationships with objective smartphone use.

4 Study three: What are technology usage scales measuring?

In a final study, and broadening our scope, we collected new data to test if the measurement issues identified previously appear in other scales that aim to capture problematic and addictive behaviors when using technology. Here, measures included the Smartphone Addiction Scale (Kwon et al., 2013b), the Internet Gaming Disorder Scale (Pontes & Griffiths, 2015), the Bergen Social Media Addiction Scale (Andreassen, Torsheim, Brunborg, & Pallesen, 2012; Andreassen et al., 2016), and the Problematic Series Watching Scale (Orosz et al., 2016). We also considered how mental health scores overlap with these measures.

4.1 Method

4.1.1 Participants

This study was ethically approved by The University of Bath. Participants were recruited via Prolific. They were paid £7.50/ hr for their time and provided informed consent. 745 participants took part and responses were checked for obvious errors. 33 participants were removed for entering >24 hr as their estimated or objective smartphone use. Several participants' data was also removed due to other data entry errors, leaving 701. Finally, one participant requested for their data to be withdrawn, leaving a final sample of $N = 700$, (352/342/6; male/female/other), with a mean age of 25.23 ($SD = 7.64$). We additionally asked participants to disclose whether they had a formal mental health diagnosis (e.g., via a primary care provider) if they felt comfortable. Out of the 700 participants, 143 self-reported a diagnosis of depression or anxiety. 105 of these participants had been on medication and 107 had received therapy. Descriptive statistics for these measures appear in Table 4.

Table 4. Descriptive Statistics (means (M), standard deviations (SD), and Cronbach's Alpha (α)) for measures in Study three. $N = 700$ unless otherwise stated.

Measures	Items	M	SD	α
Objective screen time (mins)	-	354.27	186.16	-
Objective pickups ^a	-	136.64	174.46	-
Screen Time Estimate (mins)	-	379.73	206.86	-

Pickups Estimate	-	52.05	54.71	-
Smartphone Addiction Scale (SAS)	33	109.55	25.84	.92
Internet Gaming Disorder Scale (IGDS) ^b	9	18.49	7.00	.87
Bergen Social Media Addiction Scale (BSMAS)	6	15.08	5.33	.86
Problematic Series Watching Scale (PSWS) ^c	6	12.86	4.46	.81
Anxiety (GAD7)	7	8.66	5.54	.90
Depression (PHQ9)	9	10.36	6.52	.88
Stress (PSS) ^d	14	28.49	5.93	.52

^a Objective pickups were based on n=699 as one participant did not provide this information.

^b IGDS score is based on n=491 participants who reported being a gamer.

^c Due to a technical error we only have 5 out of the 6 items of this scale. However, the Cronbach's alpha was sufficiently high to proceed.

^d The Cronbach's alpha is lower than expected, but we proceeded with all analyses in line with our original pre-registration.

4.1.2. Self-report measures

Smartphone Addiction Scale (SAS) (Kwon et al., 2013b). 33-item scale measuring smartphone addiction via a 6-point Likert Scale from strongly disagree to strongly agree. It consists of six factors: daily life disturbance, positive anticipation, withdrawal, cyberspace-orientated relationship, overuse, and tolerance. These can be combined into a single score, with higher scores corresponding to higher addiction.

Internet Gaming Disorder Scale (IGDS) (Pontes & Griffiths, 2015). 9-item scale measuring gaming disorder via a 5-point Likert scale from never to very often. Responses are combined to generate a single score, with higher scores corresponding to higher levels of disorder.

Bergen Social Media Addiction Scale (BSMAS) (Andreassen et al., 2012; Andreassen et al., 2016). 6-item scale measuring social networking addiction via a 5-point Likert scale from never (the original scale used 'very rarely') to very often. Responses are combined to generate a single score, with higher scores corresponding to greater levels of addiction.

Problematic Series Watching Scale (PSWS) (Orosz et al., 2016). 6-item scale measuring problematic series watching behavior via a 5- point Likert scale from never to always. Responses are combined to generate a single score, with higher scores corresponding to higher levels of problematic behavior.

Anxiety (GAD7) (Spitzer, Kroenke, Williams, & Löwe, 2006). 7-item scale to measure symptoms of anxiety via a 4-point Likert scale from not at all to nearly every day. Higher total scores correspond to increased levels of anxiety. It is often used in clinical settings and has high sensitivity with a diagnosis of generalized anxiety disorder.

Depression (PHQ9) (Kroenke, Spitzer, & Williams, 2001). 9-item scale to measure symptoms of depression via a 4-point Likert scale from not at all to nearly every day. Higher total scores correspond to increased levels of depression. It is often used in clinical settings and has high sensitivity with a diagnosis of major depression.

Perceived Stress (PSS) (Cohen et al., 1983). 14-item scale that measures the degree of stress perceived by participants via a 5-point Likert scale from never to very often. Higher total scores indicate higher levels of perceived stress.

4.1.3. Procedure

Participants completed an online survey hosted by Qualtrics. They were first required to provide consent. Participants then estimated their daily smartphone screen time (hours/minutes) and the number of pick-ups. They also reported their objective smartphone use from Apple Screen Time (we asked participants to check they were only reporting smartphone use and not shared screen time across multiple devices). Next, participants completed several technology usage scales and mental health assessments (Table 4). Participants were also asked whether they identified as a gamer (inc. mobile gaming), where only those who reported yes completed the IGDS. Finally, participants self-reported whether they had received a diagnosis of depression or anxiety from a primary healthcare provider and whether they were currently receiving any treatment.

4.2 Analysis plan

Our analysis plan was preregistered [<https://osf.io/gkyhz>] and included: (1) a correlational analysis between all variables, (2) a PCA across all technology usage scales to examine divergence of constructs measured, (3) EFAs to understand conceptual overlaps between the technology usage and mental health

scales, and (4) a replication of the correlational analysis reported in Study two), which explores relationships between sub-components of the SAS and related behaviors. An additional preregistered analysis examining the relationship between technology usage scales and mental health can be found in Supplementary Materials 6.

4.3 Results

4.3.1 Correlations

We first report correlations between objective and estimated smartphone behaviors, mental health scales, and technology usage scales (Table 5). There are relatively large relationships between various technology usage scales. Similar effects are also present between mental health and technology usage scales.

Table 5. Spearman and Pearson's correlations between technology use (objective and estimated), technology usage scales, and mental health measures. See Table 4 for abbreviations.

	Screen time estimate (mins)	Pickups estimate	Objective screen time (mins)	Objective pickups	SAS	IGDS	BSMAS	PSWS	GAD7	PHQ9	PSS
Screen time estimate (mins)		0.02	0.45***	0.07	0.46***	0.15**	0.35***	0.25***	0.18***	0.21***	0.23***
Pickups estimate	0.04		-0.02	0.02	0.01	-0.01	0.05	0.01	0.04	0.03	0.03
Objective screen time (mins)	0.59***	-0.01		0.11**	0.34***	0.05	0.27***	0.13***	0.15***	0.18***	0.13***
Objective pickups	0.12**	0.18***	0.17***		0.06	-0.05	0.06	0.03	0.05	0.05	0.08
SAS	0.47***	0.01	0.39***	0.10**		0.39***	0.73***	0.48***	0.41***	0.43***	0.29***
IGDS	0.14**	0.00	0.04	0.07	0.39***		0.38***	0.35***	0.33***	0.38***	0.23***
BSMAS	0.36***	0.09*	0.30***	0.14***	0.73***	0.38***		0.49***	0.39***	0.41***	0.25***
PSWS	0.23***	-0.02	0.14***	0.05	0.45***	0.36***	0.50***		0.40***	0.43***	0.26***
GAD7	0.20***	0.04	0.18***	0.05	0.41***	0.34***	0.39***	0.40**		0.80***	0.47***
PHQ9	0.22***	0.03	0.22***	0.03	0.43***	0.39***	0.42***	0.45***	0.79***		0.43***
PSS	0.28***	0.05	0.19***	0.07	0.26***	0.16***	0.23***	0.24***	0.44***	0.40***	

Bottom Left-Hand Side = Spearman;
Top Right-Hand Side = Pearson;
*p<.05, **p<.01, ***p<.001

4.3.2 PCA and PA

We computed a PCA using the four technology usage scales (see Table 4) and included 491 participants as not everyone played games (e.g., online, mobile). The technology usage scales correlated with each other (all r 's > 0.4) (see Table 5). Noting it is typical to drop highly correlated measures, as in Study one, in the interest of understanding whether these scales were capturing different constructs, all were kept for the following analysis. Before our PCA analysis, we checked sampling adequacy (MSA) using the Kaiser-Meyer-Olkin (KMO) test, which was 0.73. We ran a PCA with PA, which simulated random datasets ($N = 100$). The PA again revealed one component (see Fig. 3 and 4). Our simulated eigenvalue was 1.10 in comparison to 2.44 (our dataset).

In addition, we ran an exploratory PCA analysis on all 700 participants that included the SAS, BSMAS, and PSWS only. The KMO value was 0.66 and adequate to continue. This PCA also had $N = 100$ simulated datasets. The PA revealed one component (see Fig. 3). Our simulated eigenvalue was 1.06 in comparison to 2.15 (our dataset). See Supplementary Materials 7 for all eigenvalues from the original data and simulated values.

Fig. 3. Scree plots from the Parallel Analyses. Plot A includes all four technology usage scales ($n = 491$). Plot B includes the SAS, BSMAS, and PSWS ($N = 700$). Both suggest the existence of one component.

Fig. 4. Plot showing the first two components of the PCA. The x-axis is component one, the y-axis is component two. Arrows represent a single scale. All arrows point towards the left-hand quadrants indicating alignment with component one. Arrow color denotes the quality of representation, whereby red denotes higher quality and blue denotes lower quality. Small angles between arrows represent stronger correlations between scales.

4.3.3 EFA

Based on our preregistration, we ran an EFA on overall scores of depression, anxiety, stress, the SAS, BSMAS, PSWS, and IGDS ($n = 491$). We first conducted a KMO analysis revealing the MSA value to be 0.80, which allowed us to proceed. The analysis revealed two factors, splitting mental health and technology usage scales with no cross-loading (Table 6).

We then ran an additional EFA with overall scores from technology use scales along with estimates and objective measures of screen time ($n = 490$). This revealed a three-factor solution, with one additional factor containing the screen time estimate and objective screen time (see Supplementary Materials 8). Here, the screen time estimate cross-loaded with the technology usage scales factor. Further, estimated

smartphone pickups and objective pickups do not load anywhere (cut-off set at 0.3). These behavioral measures are distinct from any self-report measure.

A final EFA included all the mental health scales (anxiety, depression, stress) and technology usage scales (SAS, IGDS, PSWS, BSMAS) at the individual item level as per our preregistration ($n = 491$). The KMO analysis revealed an MSA score of 0.93. The EFA revealed 11 factors. However, within these 11 factors (Supplementary Materials 9, there was no item overlap between the technology usage scales and the mental health scales. Hence, we failed to replicate the effects reported in Study two.

Table 6. Factor loadings, with the cut-off set at 0.3, shows two factors. See Table 4 for abbreviations.

	Factor 1	Factor 2
SAS		0.89
IGDS		0.36
BSMAS		0.82
PSWS		0.50
GAD7	0.92	
PHQ9	0.88	
PSS	0.44	

4.3.4 Replicating correlations between sub-components of the SAS and objective smartphone use (exploratory)

Finally, we replicated prior correlational analyses from Study two between specific sub-components of the SAS: tolerance, withdrawal, and overuse in our new sample with objective measures (minutes and pickups).

Correlations between tolerance (3 items), use (mins) $r(697) = 0.30$, $p < .001$; $r_s(697) = 0.34$, $p < .001$; and pickups, $r(697) = 0.07$, $p = .06$; $r_s(697) = 0.13$, $p < .001$, demonstrate relatively large and small relationships accordingly. Associations between withdrawal (6 items), use (mins) $r(697) = 0.22$, $p < .001$; $r_s(697) = 0.25$, $p < .001$, demonstrate relatively large and small relationships accordingly.

.001; $r_s(697) = 0.25$, $p < .001$; and pickups, $r(697) = 0.01$, $p = .073$; $r_s(697) = 0.06$, $p = .12$ were small or typical. Finally, correlations between overuse (4 items), use (mins) $r(697) = 0.29$, $p < .001$; $r_s(697) = 0.36$, $p < .001$; and pickups, $r(697) = 0.04$, $p = .22$; $r_s(697) = 0.07$, $p = .08$ were relatively large or small. Overall, effect sizes are similar to those observed in Study two. However, relationships between all three sub-components and pickups are consistently smaller.

5 General Discussion

We aimed to understand what technology usage scales are measuring. Taking a deep dive into smartphone usage scales, we first demonstrate that these capture a single construct despite claims that they each capture unique psychological phenomena (e.g., phobia, addiction, problematic use, absent-minded use). We then examined whether these issues cascade across other technology usage scales (e.g., gaming, social media, and series watching). These scales also capture a single component. So, what might these scales be measuring? In Study two, the SAS cross-loaded with mental health and technology behaviors. This finding held when running an EFA on individual SAS and mental health items but failed to replicate in a final study involving other technology usage scales. Given these inconsistencies, we continue to ask what these scales measure? The answer: they remain fuzzy.

Some limitations may have made it difficult to provide a definitive answer. For example, participants had to complete scales sequentially, which may increase similarities between measures. Of course, this may conversely result in reduced overlap as people think about specific technologies. Priming effects, for example, have been observed when participants complete social media measures before depression/mental health assessments (Mieczkowski, Lee, & Hanock, 2020). A future design might spread out the administration of psychometric measures over time to test this further. In support of our ecological approach, however, it is common for participants to complete mental health measures alongside technology usage scales. In addition, order effects do not explain why the conceptual overlap between SAS and mental health assessments was inconsistent between Studies two and three. These discrepancies are more likely due to the influence of other measures, differences between samples, or a lack of reliability.

5.1 Psychometric problems in the field

Our findings illustrate how problems with inappropriate scale development can distort the direction of multiple relationships. For instance, the SAS contains several items that suggest normative usage and

positive impacts (e.g., ‘feeling confident with my smartphone,’ or ‘getting rid of stress while using a smartphone,’). These get scored as ‘addictive’, whereby participants who agree that they feel calmer and less stressed with their phone will receive a higher score. Such outcomes create artificial relationships. For example, participants with higher levels of depressive symptoms, but at the same time report feeling better after using their smartphone (e.g., feeling confident), will generate positive associations between smartphone ‘addiction’ and low mood. Higher levels of problematic use may therefore be associated with positive impacts when technology has helped an individual feel more ‘confident’ or ‘pleasant’ in themselves (Hunter, Hooker, Rohleder, & Pressman, 2018).

Many other scales have equivalent problems yet continue to suggest a clinical manifestation. While gaming disorder appears in the ICD-11, rates of diagnoses are inconsistent and vary based on the ontological underpinning of different scales. For instance, the Gaming Addiction Scale comes from pathological gambling, which means it must fulfill four out of the seven criteria for a diagnosis. On the other hand, the Internet Gaming Disorder Scale relies on the DSM-5, whereby five of the nine criteria must be met (Karhulahti, Vahlo, et al., 2021).

Beyond the quantitative analyses reported here, there is little qualitative evidence to support the use of such measures in basic or applied contexts (Cheng et al., 2019; Karhulahti, Martončík, & Adamkovič, 2021; Karhulahti, Vahlo, et al., 2021). While there are several ways to develop new psychometric instruments, guidelines provided by Carpenter (2018) provide ten clear steps as part of a checklist. Using the technology usage scales assessed here, we considered whether the original articles that underpin each scale follow Carpenter's steps (Table 7). The field appears to have repeatedly failed to grasp the importance of measurement. Hence, rather than rapidly developing poorly validated measures that offer nothing new (Ellis, 2020), scholars should produce measurement tools that engage with suitable validity checks throughout the development process (Howard & Jayne, 2015). Technological innovation has allowed researchers to compute the statistics to support such development with relative ease, but scale development was historically (and should remain) a lengthy process. Measures developed slowly tend to sit on robust theoretical foundations (Clark & Watson, 1995).

Table 7. A checklist for scale development in sequential steps from Carpenter (2018). X denotes a process reported in the original paper documenting scale development. Almost every scale failed to follow basic principles associated with psychometric development. However, variability between scales is not systematic. Researchers are, therefore, not consistently following any specific set of protocols.

While authors may have completed various analyses, which went unreported, presenting all results is the tenth and final step identified by (Carpenter, 2018).

Step		MPPUS	NS	ES	SAt	SAS	SABAS	PMPUQ	MTUAS	SUQ-G&A	IGDS	BSMAS	PSWS
Research the intended meaning and breadth of the theoretical concept	Select appropriate conceptual labels						N/A ^b			N/A ^g	X	N/A ⁱ	
	Select conceptual definitions		X	X	X								X
	Identify potential dimensions and items		X										
	Conduct qualitative research to generate dimensions and items		X						X ^d				
	Use feedback to refine scale		X										
	Expert feedback, pre-tests, cognitive interviews, or pilot tests can be employed to evaluate item wording, item validity, questionnaire design, and model structure		X										
Determine sampling procedure (5:1)		X	X	X	X	X		X	X				
Examine data quality						X		X	X				X
Verify the factorability of the data	Bartlett's Test of Sphericity ($\leq .05$)		X						X		X		
	Kaiser-Meyer-Olkin test of sampling adequacy ($\geq .60$)		X								X		
	Inspect correlation matrix ($\geq .30$)												
Conduct Common Factor Analysis			X	X ^a	X ^a	X		X	X ^e		X ^h		X ^a
Select factor extraction method	Principal Factors Analysis		X			X							
	Maximum Likelihood					X		X					X
Determine number of factors	Theoretical convergence and parsimony		X										
	Scree test		X								X		

	Parallel Analysis (PA)							X		
	Minimum Average Partial (MAP)									
Rotate factors	Oblique rotation (Direct Oblimin, Promax)		X			X	X	X ^f		
Evaluate items based on a priori criteria	Theoretical convergence		X				X			
	Parsimony									
	Weak loadings ($\geq .32$)		X			X	X ^c	X	X	X
	Cross loadings									
	Inter-item correlations		X							
	At least three-item factors		X			X	X			
	Communalities of items ($\geq .40$)		X			X				

Table 7 footnotes:

A Confirmatory Factor Analysis (CFA) was reported.

^B Article is only available in Hungarian.

^c Sums of the square loadings checked.

^d Reported in another article.

^e Type of factor analysis not specified.

^f Varimax rotation used.

g No details are provided in the reference.

^h Exploratory Factor Analysis was reported followed by a CFA to confirm factor structure.

ⁱ Authors replaced the technology type for every item and deployed the scale with no further development or validation.

5.2 Psychometric problems in the social sciences

The issues reported here pertain to the development of technology usage scales. However, psychometric scales in other areas of psychology likely have related problems. Specifically, construct validity ensures that a measure can capture a criterion of interest (Rubio et al., 2003), but many scales are weak in this regard. For instance, a new wave of scales aim to measure the psychological impacts of COVID-19 (e.g., Obsession with COVID-19 scale, COVID-19 Phobia Scale, Fear of COVID-19 Scale, COVID-19 Anxiety Scale (Chandu, Marella, Panga, Pachava, & Vadapalli, 2020)). Whether these quantify anything specific about COVID-19 or provide another proxy for general anxiety remains unclear.

Construct validity often aligns with content validity, which concerns how well items measure the same construct. We did not consider this due to a lack of well-defined constructs in the first instance. However, even well-defined constructs such as major depressive disorder (MDD) severity/symptomology suffer from related weaknesses. For instance, Fried (2017) observed that only 12% of MDD symptoms were present across multiple instruments. Discriminate validity requires that a measure or test does not overlap with other constructs as expected (Campbell, 1960). Again, the array of scales mentioned throughout suffer from a lack of discriminate validity due to conceptual overlaps and similar wording of items.

Psychometric scales are often the building blocks of collective knowledge and individual research empires. Unfortunately, many are grounded in face validity and based around arbitrary ‘rules’ (Cronbach & Meehl, 1955; Michell, 2000; Rubio et al., 2003; Suen, 1990). For example, typical methods to examine items can often struggle to identify deliberately flawed wordings (Pargent, Hilbert, Eichhorn, & Bühner, 2018). Developing new constructs remains challenging (Clifton, 2020), despite computational innovations. Researchers, however, can engage with other fields where appropriate and embrace open science practices. Without clear, transparent reporting of how measures are developed and used, ‘we can still be left wondering if we were ever measuring <insert construct of interest> at all,’ (Flake & Fried, 2019, p. 22).

6 Conclusion

This article sought to illuminate issues associated with psychometric tools that have driven research agendas, informed policy, and even attempted to define new clinical disorders (Andrews, Ellis, Shaw, & Piwek, 2015; Karhulahti, Vahlo, et al., 2021). Many of these scales are poorly developed, with measures unable to capture unique constructs as intended. Perhaps more importantly, it does not matter

which technology usage scale one uses, nor the conceptualization because all scales measure the same construct. While we also sought to understand what these scales were measuring, answering this question definitively will require more research. Developing validated scales should be a priority in the first instance.

Many psychometric scales have driven the notion that mass adopted technologies lead to predetermined outcomes and fueled moral panics that dilute genuine online harms (Davidson et al., 2019; Orben, 2020; Twenge, 2017). For example, a lack of access to technologies for children and adolescents can provide a comparable risk to mental health (Metherell, Ghai, McCormick, Ford, & Orben, 2021). Hence, those developing new psychometric scales and constructs that fall into the ‘unobservable’ might consider whether they are simply capturing their own beliefs or experiences. None of this suggests that psychometric tests are measuring ‘nothing’. We merely highlight that many measures are grounded in the subjectivity of individuals rather than following the scientific method (Table 7) (Michell, 2000; Suen, 1990). One wonders if many who develop such instruments have become complacent in what good measurement looks like.

Author contribution

B.I. Davidson drafted the manuscript, designed studies one and two, wrote the R code, and analyzed the results. B.I. Davidson, H. Shaw, and D.A. Ellis contributed to the design of Study three. B.I. Davidson and H. Shaw coded Table 7. All authors edited the manuscript.

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Open science statement

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Supplementary data

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Supplementary Materials

S1: Pearson's Correlations between all smartphone scales (Study one)

	MPPUS	NS	ES	SAt	SAS	SABAS	PMPUQ	MTUAS	SUQ-G
MPPUS									
NS	.74								
ES	.53	.56							
SAt	.46	.54	.69						
SAS	.82	.75	.62	.59					
SABAS	.77	.68	.55	.52	.76				
PMPUQ	.55	.46	.38	.37	.56	.48			
MTUAS	.36	.38	.23	.32	.34	.25	.37		
SUQ-G	.56	.54	.39	.41	.57	.43	.42	.60	
SUQ-A	.66	.58	.35	.40	.62	.53	.47	.45	.69

MPPUS = Mobile Phone Problematic Use Scale, NS = Nomophobia Scale, ES = Possession Incorporation in the Extended Self, SAt = Smartphone Attachment, SAS = Smartphone Addiction Scale, SABAS = Smartphone Application-based Addiction Scale, PMPUQ = Problematic Mobile Phone Use Questionnaire, MTUAS =Media and Technology Usage and Attitudes Scale, SUQ-G = Smartphone Use Questionnaire (general), SUQ-A = Smartphone Use Questionnaire (absent minded).

S2: Eigenvalues (Study two)

	Eigenvalue	Simulated Eigenvalue
Component 1	5.75	1.33
Component 2	1.15	1.23
Component 3	0.81	1.15
Component 4	0.61	1.08
Component 5	0.44	1.02
Component 6	0.32	0.96
Component 7	0.30	0.90
Component 8	0.25	0.84
Component 9	0.21	0.78
Component 10	0.16	0.70

One component to retain is highlighted in bold where the actual eigenvalue > simulated eigenvalue.

S3: Factor Loadings from all individual items (Study two)

	Factor 1	Factor 2	Factor 3	Factor 4	Factor 5	Factor 6	Factor 7
PSS_1	0.63						
PSS_2	0.57					0.30	
PSS_3	0.83						
PSS_4	0.33		0.37				
PSS_5			0.62				
PSS_6			0.81				
PSS_7			0.71				
PSS_8	0.54						
PSS_9			0.56				
PSS_10			0.69				
PSS_11	0.55						
PSS_12	0.38						
PSS_13			0.36				
PSS_14	0.60						
GAD7_1	0.84						
GAD7_2	0.83						
GAD7_3	0.81						
GAD7_4	0.86						
GAD7_5	0.67						
GAD7_6	0.71

SAS_13	0.70		
SAS_14	0.41		
SAS_15	0.33	0.43	
SAS_16		0.48	
SAS_17		0.32	-0.31
SAS_18		0.31	
SAS_19		0.31	
SAS_20			0.63
SAS_21			0.80
SAS_22	0.30		0.53
SAS_23			0.88
SAS_24		0.36	0.48
SAS_25		0.41	
SAS_26			0.79
SAS_27			
SAS_28		0.34	
SAS_29		0.66	
SAS_30		0.66	
SAS_31		0.76	
SAS_32		0.65	
SAS_33		0.49	

Time_Est

Objective_use

Objective_pickups

PSS = Stress, GAD7 = Anxiety, PHQ9 = Depression, SAS = Smartphone Addiction Scale, Time_Est = Time estimate of use (hours), Objective_use = Objective smartphone use (median hours), Objective_pickups = Objective smartphone use (pickups)

S4: Factor loadings from individual items: mental health and SAS (Study two)

	Factor 1	Factor 2	Factor 3	Factor 4	Factor 5	Factor 6	Factor 7
PSS_1	0.63						
PSS_2	0.57					0.30	
PSS_3	0.83						
PSS_4	0.33		0.37				
PSS_5			0.62				
PSS_6			0.81				
PSS_7			0.71				
PSS_8	0.54						
PSS_9			0.55				
PSS_10			0.69				
PSS_11	0.55						
PSS_12	0.38						
PSS_13			0.36				
PSS_14	0.61						
GAD7_1	0.84						
GAD7_2	0.83						
GAD7_3	0.81						
GAD7_4	0.85						
GAD7_5	0.67						
GAD7_6	0.71

SAS_13	0.71		
SAS_14	0.41		
SAS_15	0.35	0.42	
SAS_16		0.48	
SAS_17		0.31	-0.31
SAS_18		0.32	
SAS_19		0.30	
SAS_20			0.63
SAS_21			0.81
SAS_22	0.31		0.53
SAS_23			0.89
SAS_24		0.35	0.48
SAS_25		0.41	
SAS_26			0.79
SAS_27			
SAS_28		0.33	
SAS_29		0.66	
SAS_30		0.66	
SAS_31		0.77	
SAS_32		0.66	
SAS_33		0.49	

PSS = Stress, GAD7 = Anxiety, PHQ9 = Depression, SAS = Smartphone Addiction Scale

S5: Factor loadings from individual items: SAS and smartphone use (Study two)

	Factor 1	Factor 2	Factor 3	Factor 4	Factor 5	Factor 6	Factor 7
SAS_1						0.62	
SAS_2						0.48	
SAS_3						0.52	
SAS_4						0.49	
SAS_5						0.56	
SAS_6			0.68				
SAS_7			0.73				
SAS_8			0.52				
SAS_9			0.68				
SAS_10	0.76						
SAS_11	0.59						
SAS_12	0.50						
SAS_13	0.69						
SAS_14	0.53						
SAS_15	0.39						
SAS_16	0.43						0.42
SAS_17	0.41						0.41
SAS_18							
SAS_19							0.32
SAS_20				0.60			

SAS_21		0.80	
SAS_22	0.38	0.47	
SAS_23		0.91	
SAS_24		0.40	0.39
SAS_25			0.52
SAS_26		0.81	
SAS_27			0.40
SAS_28			
SAS_29	0.52		0.32
SAS_30	0.44		0.35
SAS_31	0.87		
SAS_32	0.79		
SAS_33	0.46		
<hr/>			
Time_Est		0.54	
Objective_use		0.93	
Objective_pickups		0.36	

SAS = Smartphone Addiction Scale, Time_Est = Time estimate of use (hours), Objective_use = Objective smartphone use (median hours), Objective_pickups = Objective smartphone use (pickups)

Due to issues of multicollinearity, the GAD7 and SAS were removed. Only the PHQ9 is predictive of a mental health diagnosis (Table S6a). However, the GAD7 can act as a significant predictor when replacing the PHQ9 in an otherwise identical model.

Table S6a. Binary logistic regression model predicting the diagnostic status

Predictor	95% Confidence Interval			SE	Z	p	Odds ratio
	Estimate	Interval					
		Lower	Upper				
Intercept	2.903	1.604	4.203	0.663	4.380	< .001	18.237
Screen time estimate (mins)	0.000	-0.001	0.002	0.000	0.426	0.670	1.000
Pickups estimate	-0.000	-0.005	0.003	0.002	-0.659	0.510	0.999
Objective screen time (mins)	-0.000	-0.002	0.001	0.000	-0.558	0.577	1.000
Objective pickups	-0.001	-0.002	0.000	0.000	-0.786	0.432	1.000
IGD	0.006	-0.030	0.041	0.019	0.311	0.756	1.006
BSMAS	0.037	-0.014	0.088	0.026	1.409	0.159	1.037
PSWS	0.015	-0.044	0.074	0.030	0.495	0.621	1.015

Predictor	Estimate	95% Confidence Interval		SE	Z	p	Odds ratio
		Interval					
		Lower	Upper				
PHQ9	-0.111	-0.153	0.068	0.022	-5.072	<0.001	0.895
PSS	-0.035	-0.078	0.079	0.022	-1.598	0.110	0.966

Estimates represent the log odds of "MH_diagnosis = 1 [No Diagnosis]" vs. "MH_diagnosis = 0 [Diagnosis]"

IGD = Internet Gaming Disorder Scale, BSMAS = Bergen Social Media Addiction Scale, PSWS = Problematic Series Watching Scale, PHQ9 = Depression, PSS = Stress

Next, we report three linear regression models using screen time estimates, objective screen time, and technology usage scales to predict anxiety (GAD7), depression (PHQ9), and stress (PSS). Due to issues of multicollinearity, the SAS was removed from all models.

First, when predicting anxiety (GAD7), the IGD, BSMAS, PSWS, and Objective screen time were significant predictors (Table S6b).

Table S6b. Linear model predicting anxiety (GAD7).

Predictor	Estimate	SE	t	p	Stand. Estimate	95% Confidence Interval	
						Lower	Upper
Intercept	-1.553	0.886	-1.752	0.080			
Screen time estimate (mins)	-0.000	0.001	-0.603	0.547	-0.029	-0.122	0.065
Pickups estimate	0.005	0.004	1.324	0.186	0.053	-0.026	0.131
Objective screen time (mins)	0.003	0.001	2.176	0.030	0.101	-0.010	0.192
Objective pickups	0.000	0.001	0.366	0.714	0.015	-0.064	0.094
IGD	0.141	0.035	4.032	< .001	0.178	0.091	0.265
BSMAS	0.226	0.051	4.461	< .001	0.219	0.123	0.316
PSWS	0.223	0.059	4.313	< .001	0.201	0.109	0.292

IGD = Internet Gaming Disorder Scale, BSMAS = Bergen Social Media Addiction Scale, PSWS = Problematic Series Watching Scale

Second, when predicting depression (PHQ9), the IGD, BSAS, PSWS, and Objective screen time were significant predictors (Table S6c).

Table S6c. Linear model predicting depression (PHQ9)

Predictor	Estimate	SE	t	p	Stand. Estimate	95% Confidence Interval	
						Lower	Upper
Intercept	-2.812	1.013	-2.783	0.006			
Screen time estimate (mins)	-0.000	0.002	-0.681	0.496	-0.031	-0.122	0.059
Pickups estimate	0.005	0.004	1.056	0.292	0.041	-0.035	0.117
Objective screen time (mins)	0.004	0.002	2.621	0.009	0.117	0.029	0.205
Objective pickups	0.000	0.001	0.404	0.686	0.016	-0.061	0.092
IGD	0.201	0.040	5.039	< .001	0.215	0.131	0.299
BSMAS	0.250	0.058	4.317	< .001	0.206	0.112	0.299
PSWS	0.352	0.067	5.257	< .001	0.237	0.148	0.325

IGD = Internet Gaming Disorder Scale, BSMAS = Bergen Social Media Addiction Scale, PSWS = Problematic Series Watching Scale, PHQ9 = Depression, PSS = Stress

Third, when predicting stress (PSS), the IGD, BSMAS, PSWS, and the Screen time estimate were significant predictors (Table S6d).

Table S6d. Linear model predicting stress (PSS)

Predictor	Estimate	SE	t	p	Stand. Estimate	95% Confidence Interval	
						Lower	Upper
Intercept	20.118	1.005	20.018	< .001			
Screen time estimate (mins)	0.003	0.002	2.138	0.033	0.107	-0.009	0.206
Pickups estimate	-0.000	0.004	-0.204	0.839	-0.008	-0.091	0.074
Objective screen time (mins)	0.000	0.002	0.247	0.805	0.012	-0.084	0.108
Objective pickups	0.000	0.001	0.732	0.465	0.031	-0.052	0.115
IGD	0.079	0.040	2.005	0.045	0.093	-0.002	0.185
BSMAS	0.190	0.057	3.301	< .001	0.171	0.069	0.273
PSWS	0.218	0.067	3.282	< .001	0.161	0.065	0.258

IGD = Internet Gaming Disorder Scale, BSMAS = Bergan Social Media Addiction Scale, PSWS = Problematic Series Watching Scale, PHQ9 = Depression, PSS = Stress

Finally, a series of t-tests compared participants with (N=143; 64/76/3 male/female/other; aged 25.06±7.41) and without (N=557; 288/266/3 male/female/other; aged 25.29±7.70) a mental health

diagnosis of anxiety or depression (Table S6e). As expected, there are significant differences between groups in depression, anxiety, and stress scores, which confirms the accuracy of self-reported diagnoses. However, no significant differences were observed between groups in any other measure.

Table S6e. T-tests comparing those with and without a mental health diagnosis and group means

	t-test Type	Statistic	df	p	Effect Size (Cohen's d)	95% Confidence Interval		Mean	
						Lower	Upper	No Diagnosis	Diagnosis
Screen time estimate (mins)	Student's t	0.20	698	0.84	0.02	-0.17	0.20	379	383
	Welch's t	0.21	240	0.83	0.02				
Pickups estimate	Student's t	0.79	698	0.43	0.07	-0.11	0.26	51.2	55.3
	Welch's t	0.78	215	0.44	0.07				
Objective screen time (mins)	Student's t	1.10	698	0.27	0.10	-0.08	0.29	350	370
	Welch's t	1.10	220	0.27	0.10				
Objective pickups	Student's t	0.86	697	0.39	0.08	-0.10	0.27	134	148
	Welch's t	0.76	190	0.45	0.08				
SAS	Student's t	1.81	698	0.07	0.17	-0.02	0.35	109	113

	Welch's t	1.78	217	0.08	0.17				
IGD	Student's t	1.66	489	0.10	0.18	-0.03	0.40	18.2	19.5
	Welch's t	1.57	159	0.12	0.18				
BSMAS	Student's t	0.85	698	0.40	0.08	-0.10	0.26	15.0	15.4
	Welch's t	0.86	224	0.39	0.08				
PSWS	Student's t	1.90	698	0.06	0.18	-0.01	0.36	12.7	13.5
	Welch's t	1.90	219	0.06	0.18				
GAD7	Student's t	7.94	698	< .001	0.74	0.54	0.95	7.85	11.8
	Welch's t	7.75	214	< .001	0.74				
PHQ9	Student's t	7.59	698	< .001	0.71	0.51	0.91	9.44	13.9
	Welch's t	7.10	204	< .001	0.69				
PSS	Student's t	5.03	698	< .001	0.47	0.28	0.66	27.9	30.7
	Welch's t	4.44	192	< .001	0.44				

SAS = Smartphone Addiction Scale, IGD = Internet Gaming Disorder Scale, BSMAS = Bergen Social Media Addiction Scale, PSWS = Problematic Series Watching Scale,

GAD7 = Anxiety, PHQ9 = Depression, PSS = Stress

S7: Eigenvalues (Study three)

Top table reports n=491 participants (IGD, SAS, BSMAS, and PSWS). Bottom table reports n=700 participants (SAS, BSMAS, and PSWS).

N=491	Eigenvalue	Simulated Eigenvalue
Component 1	2.44	1.10
Component 2	0.71	1.03
Component 3	0.57	0.97
Component 4	0.27	0.90
N = 700	Eigenvalue	Simulated Eigenvalue
Component 1	2.15	1.05
Component 2	0.58	1.00
Component 3	0.27	0.94

One component to retain is highlighted in bold where the actual eigenvalue > simulated eigenvalue.

S8: Factor Loadings (Study 3)

	Factor 1	Factor 2	Factor 3
Screen time estimate		0.47	0.33
Pickups estimate			
Objective screen time (mins)		0.81	
Objective pickups			
SAS			0.89
IGD			0.45
BSMAS			0.78
PSWS			0.55
GAD7	0.93		
PHQ9	0.86		
PSS	0.43		

SAS = Smartphone Addiction Scale, IGD = Internet Gaming Disorder Scale, BSMAS = Bergen Social Media Addiction Scale, PSWS = Problematic Series Watching Scale, GAD7 = Anxiety, PHQ9 = Depression, PSS = Stress

S9: Factor Loadings (Study three)

	Factor 1	Factor 2	Factor 3	Factor 4	Factor 5	Factor 6	Factor 7	Factor 8	Factor 9	Factor 10	Factor 11
SAS_1	0.24									0.34	
SAS_2	0.30								0.22	0.21	
SAS_3										0.64	
SAS_4										0.62	
SAS_5	0.23									0.42	
SAS_6					0.75						
SAS_7					0.71						
SAS_8					0.63						
SAS_9					0.60						
SAS_10				0.49	0.27					0.30	
SAS_11				0.27				0.45			
SAS_12				0.30	0.41			0.23			

SAS_13		0.52			0.22
SAS_14				0.45	
SAS_15	0.25			0.30	0.30
SAS_16	0.28	0.32			0.21
SAS_17		0.25		0.37	
SAS_18	0.26	0.26			
SAS_19	0.34			0.20	
SAS_20		0.36	0.25		
SAS_21		0.70			
SAS_22		0.40		0.31	
SAS_23		0.71			
SAS_24	0.20			0.27	0.21
SAS_25	0.30			0.25	0.29
SAS_26		0.72			

SAS_27	0.24			0.25
SAS_28	0.24			
SAS_29	0.60			
SAS_30	0.60			
SAS_31	0.63			
SAS_32	0.62			
SAS_33	0.30		0.28	
IGD_1		0.73		
IGD_2		0.77		
IGD_3		0.76		
IGD_4		0.72		
IGD_5		0.69		
IGD_6		0.65		
IGD_7		0.56		

IGD_8	0.25	0.34	-0.23			
IGD_9		0.46	0.21			0.22
BSMAS_1						0.72
BSMAS_2						0.64
BSMAS_3						0.56
BSMAS_4	0.30				-0.22	0.41
BSMAS_5			0.25			0.43
BSMAS_6						0.50
PSWS_1				0.61		
PSWS_2				0.72		
PSWS_3				0.69		
PSWS_4				0.56		
PSWS_5				0.53		
GAD7_1r	0.78					

GAD7_2r	0.81			
GAD7_3r	0.82			
GAD7_4r	0.67			
GAD7_5r	0.63			
GAD7_6r	0.55			
GAD7_7r	0.67			
PSS_1r	0.46		0.20	
PSS_2r	0.57			
PSS_3r	0.75			
PSS_4r				0.48
PSS_5r				0.40
PSS_6r			0.69	
PSS_7r				0.46
PSS_8r				0.32

PSS_9r			0.62	
PSS_10r			0.76	
PSS_11r		0.55		
PSS_12r		0.41	0.23	
PSS_13r			0.47	
PSS_14r		0.54		
PHQ9_1r		0.38		
PHQ9_2r		0.70		
PHQ9_3r		0.47		
PHQ9_4r		0.53		
PHQ9_5r		0.48		-0.21
PHQ9_6r		0.57	-0.22	
PHQ9_7r	0.22	0.52		
PHQ9_8r		0.41		-0.27

PHQ9_9r

0.45

0.23

SAS = Smartphone Addiction Scale, IGD = Internet Gaming Disorder Scale, BSMAS = Bergen Social Media Addiction Scale, PSWS = Problematic Series Watching Scale,
GAD7 = Anxiety, PPS = Stress, PHQ9 = Depression