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The relationship between smartphone use and smartphone addiction: An examination of logged and self-reported behavior in a pre-registered, two-wave sample

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ABSTRACT

There has been a growing literature that has utilized logged behavior from smartphones to study the impacts of technology use on individuals. One of these proposed impacts has been that people become addicted to their smartphones. Measurements of smartphone addiction do not appear to strongly correlate with actual behavior logged from smartphones. Instead, smartphone addiction may be better explained by distress rather than disordered behavior, but this has not been adequately tested. This study examined the relative contributions of self-reported and actual smartphone behavior alongside key mental health and individual differences in a pre-registered, two-wave study with a two-week re-test. 511 smartphone users (391 at Time 2) completed measures of smartphone usage, attitudes towards smartphone usage, smartphone addiction, other behavioral addictions, mental health, and individual differences. The results suggest smartphone addiction is principally driven by perceived rather than actual usage, especially where these are discordant. Self-reported smartphone usage, other behavioral addictions, and the impulsivity facet of negative urgency are more predictive of smartphone addiction than logged behavior. These results suggest that volume of smartphone usage is insufficient in and of itself to explain problematic smartphone behavior and questions the criterion validity of smartphone addiction measurements.

1. Introduction

Smartphones have become ubiquitous in society, but their prevalence and indispensability have led to concerns about the consequences of their proliferation (Panova & Carbonell, 2018). Principal among these concerns has been the perceived effects on health. The amount of 'screen time' spent on devices has been associated with a range of negative outcomes. One explanation for this has been the idea that people can become addicted to their smartphones, or the content on them, and lose control over the interactions they have with their devices (Olson et al., 2022). These concerns have been mirrored in public discourse (Yang et al., 2021), prompting inquiries into how negative effects can be managed and regulated (House of Commons Science and Technology Committee, 2019), including whether a public health approach should be taken to managing problematic smartphone behaviors similar to alcohol and gambling (Sohn et al., 2019; Van Velthoven et al., 2018). However, a critical examination of these concerns is warranted. The evidence used to justify this concern is predominantly based on self-report data (James et al., 2022). While such data is often valuable, there is mounting evidence that estimates of smartphone usage are systematically biased. Studies utilising data logged from users' smartphones have demonstrated that associations between actual smartphone use and negative outcomes, including addiction, are weaker than for self-reported use (Parry et al., 2021). The mechanisms behind this discrepancy are poorly understood. For example, it is possible there is a common psychological mechanism driving estimates of self-reported smartphone usage and smartphone addiction, such as distress (e.g. depression, anxiety) or impulsivity. These factors may precede the development of smartphone-related problems. The purpose of this study is to understand inconsistencies in the relationship between logged and perceived smartphone usage and smartphone addiction, whilst controlling for key individual differences associated with addictive

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behavior. The study adopts a pre-registered design, and a short-term retest to examine whether these associations replicate in the same sample of respondents.

1.1. Smartphone addiction

Smartphone addiction has been defined by researchers as comprising of behaviors such as overuse of one's smartphone (Kwon et al., 2013), requiring increasing levels of engagement to get the same perceived benefits (tolerance), and feelings of psychological dependence, withdrawal and relapse (Lin et al., 2014). It follows an increasing focus to consider activities like gaming (Petry & O'Brien, 2013), the internet (Sim et al., 2012), and social media (Van den Eijnden et al., 2016) as addictive behaviors. A cluster of behaviors, perceptions, and motivations are referenced to justify this conceptualization of addiction, including: i) instant gratification (Wilmer et al., 2017) ii) overlapping variable schedules of reinforcement (Veissière & Stendel, 2018), iii) physical separation anxiety (Twenge, 2017), and iv) the use of smartphones as a coping or compensatory mechanism (Kardefelt-Winther, 2014), but smartphone addiction has been associated with numerous physical detriments. These include disruptions to sleep (Demirci et al., 2015) and posture (Lee & Seo, 2014), repetitive strain injuries (Baabdullah et al., 2020), obesity (Kim et al., 2015), and hypertension (Zou et al., 2019). Excessive smartphone use has also been linked with social detriments such as reduced confidence and self-esteem (Yang et al., 2010), 'phubbing' companions (Chotpitayasunondh & Douglas, 2016), increased divorce rates (Roberts & David, 2016), and lower productivity (Duke & Montag, 2017). Most prominent has been the effect of smartphone addiction on mental health. Smartphone addiction has been linked with greater psychiatric morbidity, particularly depression, anxiety, stress, poor impulse control, and lower well-being levels (Hussain et al., 2017; Twenge et al., 2018). Smartphone addiction has also been identified as comorbid with other proposed addictions to technology such as gaming, social media and the internet (Wacks & Weinstein, 2021).

However, there are multiple issues that challenge this conceptualization. Although several symptoms of smartphone addiction have been proposed, these have rarely been supported by markers of behavioral engagement, and instead rely on self-reports of these indicators (James et al., 2022) that have been shown to be biased. Despite extensive investigation, neither the American Psychiatric Association, nor the World Health Organization (Lin et al., 2016) currently recognize smartphone addiction as a clinical disorder. The literature does not distinguish the source of the addictive behavior, vacillating between the smartphone as a device, and as a medium for facilitating behavior (James et al., 2022). Instead, smartphone addiction might be best conceptualised as a spectrum, capturing a constellation of disordered behavior on smartphones (Starcevic et al., 2021). Indeed, recent proposals have included the creation of a taxonomy to first capture specific disordered behaviors, and then the means of access i.e. internet vs smartphone (Montag et al., 2021). Nonetheless, most research in the field has persisted with a unitary model focusing on the smartphone as the locus of addictive behavior (Yu & Sussman, 2020) and there is increasing evidence these measure a single, 'fuzzy' construct (Davidson et al., 2022).

1.2. Screen time

There is a similar societal debate around 'screen time' and its proposed toxic effects on mental health, particularly in children and adolescents. Despite considerable scope for conceptual manoeuvre in defining screen time (Kaye et al., 2020), it is claimed that there has been a worsening of mental health in young people in the last 15–20 years that has created a cohort effect, and most controversially, this is attributable to digital devices such as smartphones, computers, and TV (Twenge et al., 2018, 2022). As the main technological development over the intervening period, it is fair to conclude that much of this effect can be attributed to the proliferation of smartphones. Indeed, some have explicitly made this claim (Twenge et al., 2022). However, this work has faced significant challenge on a number of fronts, including choice of variable specification (Orben & Przybylski, 2019), negative meta-analytic findings (Ferguson et al., 2021), and heterogeneity in the selection of outcomes and effect sizes (Tang et al., 2021). Screen time is often treated as a distinct area of inquiry from smartphone addiction, but there is reason to consider the two in tandem. Studies of smartphone addiction often use global measures of smartphone usage similar to screen time (James et al., 2022). As a pathological form of smartphone use (Thomée, 2018), measures of screen time and smartphone addiction are correlated although not synonymous (Olson et al., 2022). Nonetheless, smartphone addiction scales have often been employed in the empirical literature to measure smartphone use (Shaw et al., 2020; Thomée, 2018). However, this practice is problematic because the use of smartphone addiction or problematic smartphone use scales is associated with stronger associations with mental health outcomes than behavioral markers. The primary difference is in the direction of inference, with mental health variables treated as an outcome in screen time research and often as predictors in smartphone addiction research.

1.3. Self-report vs logged behavior

The aim of this study is to examine the effect of self-report versus actual smartphone use on smartphone addiction and other psychosocial risk factors, and whether this is consistent in a short re-test. Self-reported behavior is the norm in smartphone addiction research (James et al., 2022). Increasingly, however, objective measurements have been utilized by taking logs from applications that track smartphone activity (Hodes & Thomas, 2021; Ryding & Kuss, 2020). A recent meta-analysis demonstrated that estimations of screen use are only moderately linked with logged behavior, and that logged behavior weakly correlates with smartphone addiction (Parry et al., 2021). These findings highlight that estimates of smartphone use are subject to bias in both directions. For example, some studies have shown that people underestimate (Felisoni & Godoi, 2018; Junco, 2013; Lin et al., 2015) and overestimate (Kobayashi & Boase, 2012) time spent on their smartphones.

Subjective and objective measures of smartphone behavior may capture different underlying constructs. Davidson et al. (2022) demonstrated that scores on the Smartphone Addiction Scale (Kwon et al., 2013) overlapped with depression, anxiety and stress more than logged smartphone usage. This could be due to the self-report nature of these measures capturing common variance in individual traits such as impulsivity, negative affect, or extraversion (Ellis et al., 2019), rather than specific smartphone 'addiction' (Shaw et al., 2020). Therefore, studies that have found associations between smartphone use and negative consequences such as depression and anxiety (Elhai et al., 2017) may be capturing a link between perceptions of usage and distress and these outcomes, rather than the outcomes of actual usage or problematic behavior. There are some caveats with logged time as a measure; Griffiths (2018) argues that volumetric measures of smartphone use are not useful in isolation as they miss important contextual factors i.e. work vs recreational use, or the type of behavior engaged in. Nonetheless, self-reported time spent is often one of the few measures of smartphone engagement reliably collected in smartphone addiction research and is often used to establish criterion validity (Yam et al., 2019). Understanding the relationship between these factors is therefore of considerable importance.

1.4. The present study

This study, therefore, aims to address two key gaps in the literature. The first is to understand and explain the relatively weak association between logged smartphone use and self-reported smartphone addiction. We report the findings of a study that measures these, alongside prominent psychosocial covariates of distress and impulsivity. We hypothesize these will be associated with greater levels of smartphone addiction (H1a and H1b). In doing so, we aim to replicate existing studies that have identified that subjective smartphone use is more strongly correlated with smartphone addiction than logged behavior (H2), and that objective and subjective smartphone use are weakly correlated (H3). We also examine whether these are consistent after a short retest period. While there is a plethora ofliterature looking at the relationship between smartphone use, individual differences and smartphone addiction, the degree to which these associations are consistent in the same sample has not been studied in detail. Then, in a set of exploratory analyses, we explore the mechanisms behind this, principally focusing on the gap between self-reported and logged smartphone usage. Our pre-registered hypotheses were.

H1a. Impulsivity, specifically negative urgency and premeditation, will be associated with smartphone addiction.

H1b. Depression and anxiety will be associated with smartphone addiction.

H2. Subjective measures of smartphone use will be more strongly associated with smartphone addiction than objective measures.

H3. Objective and subjective smartphone use will be weakly correlated.

2. Methods

2.1. Participants

542 smartphone-owning respondents participated in the study. 31 responses were incomplete – leaving 511 responses (269 women, 232 men, 9 non-binary, 1 prefer not to say, mean age = 27.23, SD = 8.97). Participants were sampled from Prolific Academic (n = 380) who received an inconvenience allowance of £3.75 (approximately $5 USD at the time of the study), or volunteers (n = 131). Participants used either iOS (n = 223) or Android (n = 288). Participants resided in 30 countries with 120 (31.57%) in full-time employment, 69 (18.15%) part-time employed, 69 (18.15%) unemployed, 81 (21.13%) otherwise employed, and 185 (48.68%) students of those who provided up to date information to Prolific. 391 of the 511 participants provided data at the second time point (T2) two weeks later (206 women, 178 men, 7 non-binary), made up of 167 iOS users and 224 Android users.

Statistical power was estimated prior to data collection using G × Power (Faul et al., 2007). For the proposed effect size of 0.18 with a power of .90 when $\alpha = 0.05$, the study was adequately powered at n = 511. The hypotheses and analyses were preregistered on the Open Science Framework (https://osf.io/2bw4q/). The OSF page includes data, code, and materials.

2.2. Measures

Both surveys included measures of smartphone addiction, smartphone use and attitudes, and individual difference.

2.2.1. Contextual measures

The first survey gathered sociodemographic information about participant's age, gender identity, living circumstances (e.g. number of people living with, where they spend the majority of their week), their technology use including the make of their smartphone, what other technological devices they use, and their use of social media platforms.

The second survey also collected information about participants' attitudes towards smartphone use by asking questions about if they considered too much screen time harmful, whether they took breaks from social media, if children under 10 should have a smartphone, whether their usage was what they expected and if they would act differently following the study.

2.2.2. Smartphone usage

Subjective screen time was measured by asking participants: 'how much time do you estimate that you spend on your phone each day?' in hours and minutes.

Objective screen time information was subsequently collected by asking participants to report their recorded activity from device settings. iPhone users reported their daily average screen time, notifications, and pickups if they had 'Screen Time' recordings activated. Android users provided their recorded screen time and notifications for each day from the last 7 days due to differences in operating systems. Participants that did not have these activated were invited to enter estimates on a separate page and recorded as a separate variable.

2.3. Instruments

A series of psychometric inventories were used to measure individual differences related to smartphone and technological addiction, mental health, and risk-taking. The psychometric properties of each scale were assessed using the *reliability* function in the *psych* package (Revelle, 2023) to measure alpha and omega, and a confirmatory factor analysis was estimated using robust diagonally weighted least squared (DWLS) using the *lavaan* package (Rosseel, 2012), which is suited for ordinal data. Adequacy of fit was assessed using combinatorial rules previously developed by Hu and Bentler (1999).

2.3.1. Patient health questionnaire (PHQ-9) (Kroenke et al., 2001)

Depression severity was measured using the PHQ-9. The measure asks participants 'over the last two weeks, how often have you been bothered by the following problems?' followed by 9 items. Responses are given on a 4-point Likert scale ranging from 'not at all' (0) to 'several days' (3) with scores ranging from 0 to 27 indicating higher depression severity. The PHQ-9 has high sensitivity (88%) and specificity (88%) for a diagnosis of major depression (Kroenke et al., 2007; Levis et al., 2019). A single factor CFA generally fit the data well (CFI = 0.973, TLI = 0.965, RMSEA = 0.091, *90% C·I* = 0.076 - 0.106, SRMR = 0.059), and the scale showed strong internal consistency (a = 0.87, $\Omega = 0.89$, $\beta = 0.81$, $\lambda 4 = 0.9$).

2.3.2. Generalized anxiety disorder assessment (GAD-7) (Spitzer et al., 2006)

The GAD-7 was used to measure anxiety symptoms by asking participants 'how often in the last weeks have you been bothered by any of the following problems?' followed by 7 items of behavior. Each item is scored using a 4-point Likert scale from 'not at all' (0) to 'several days' (3) with scores ranging from 0 to 21. A single factor CFA fit the data well (CFI = 0.990, TLI = 0.984, RMSEA = 0.102, *90% C·I* = 0.082 - 0.123, SRMR = 0.042), and the scale showed excellent internal consistency ($\alpha = 0.9$, $\Omega = 0.92$, $\beta = 0.86$, $\lambda 4 = 0.91$).

2.3.3. Smartphone application-based addiction scale (SABAS) (Csibi et al., 2018)

The SABAS measures smartphone addiction using 6 items covering Griffiths (2005) components of addiction, scored on a 6-point Likert scale from 'strongly disagree' (1) to 'strongly agree' (6). Respondent's scores can range from 6 to 36 with higher scores indicating a higher level of addiction severity. A single factor CFA fit the data well (CFI = 0.980, TLI = 0.967, RMSEA = 0.88, *90% C·I* = 0.063 - 0.115, SRMR = 0.044), and the scale showed acceptable consistency ($\alpha = 0.78$, $\Omega = 0.81$, $\beta = 0.72$, $\lambda 4 = 0.82$).

2.3.4. Short internet addiction test (s-IAT) (Pawlikowski et al., 2013)

The short version of the IAT (Young, 1998) was used to assess internet addiction severity. The short version asked, 'how often do you … ' followed by 12 statements about ways excessive internet usage may impact daily life which were rated on a 5-point Likert scale from 'never' (1) to 'always' (5). Higher scores suggest higher levels of internet addiction. The scale has good internal consistency (α = 0.86, Ω = 0.88, β = 0.71, λ4 = 0.91), but both a single factor (CFI = 0.862, TLI = 0.832, RMSEA = 0.145, 90% CI = 0.135- - 0.156, SRMR = 0.11), and the two factor models proposed by Pawlikowski et al. (2013) (CFI = 0.873, TLI = 0.842, RMSEA = 0.141, 90% CI = 0.131 - 0.152, SRMR = 0.106) were poor fits of the data. Modification indices indicated this was due to residual covariance (items 1 and 2, 10 and 11), and cross loading of items onto both factors (items 9, 1, 4, 2, and 8).

2.3.5. Bergen Facebook addiction scale (BFAS) (Andreassen et al., 2012)

The BFAS consists of 6 items scored on a 5-point Likert scale from 'very rarely' (1) to 'very often' (5)'. The statements aim to detect the presence and severity of Facebook addiction within the past year by looking at the core components of addiction (Griffiths, 2005), with higher scores indicating a higher level of Facebook addiction. A single factor CFA fit the data well (CFI = 0.990, TLI = 0.984, RMSEA = 0.091, *90% C·I* = 0.066 - 0.118, SRMR = 0.032), and the scale showed strong internal consistency (α = 0.89, Ω = 0.91, β = 0.85, λ4 = 0.91).

2.3.6. Short UPPS-P impulsive behavior scale short version (Cyders et al., 2014)

The 20-item short version of the UPPS-P (Lynam et al., 2006) was used to assess five impulsivity facets: negative urgency, positive urgency, sensation seeking, lack of premeditation, and lack of perseverance (Whiteside & Lynam, 2001). The 20 statements ask about the ways participants think and act in relation to risky behavior and are scored on a 4-point Likert scale from 'disagree strongly' (1) to 'strongly agree' (4). Each facet is represented by 4 items. A CFA modelling the five factors showed a good fit (CFI = 0.914, TLI = 0.897, RMSEA = 0.067, 90% CI = 0.060 - 0.073, SRMR = 0.070). The subscales had acceptable internal consistency, although the Premeditation subscale performed less well than other subscales (Negative Urgency α = 0.72, Ω = 0.75, β = 0.66, λ4 = 0.75; Positive Urgency α = 0.79, Ω = 0.81, β = 0.77, λ4 = 0.81; Sensation Seeking α = 0.68, Ω = 0.75, β = 0.59, λ4 = 0.74; Premeditation α = .64, Ω = 0.66, β = 0.61, λ4 = 0.66; Perseverance α .73, Ω = 0.76, β = 0.72, λ4 = 0.75).

2.4. Procedure

Participants were directed to complete the first Qualtrics survey (2021, http://www.qualtrics.com). Participants gave informed consent to participation and data sharing. Participants then answered questions on sociodemographic factors, their technology use, and their estimated daily screen time. Data was collected on objective screen time by asking about the operating system of the participant's phone, iOS or Android. iOS users were asked if they had 'Screen Time' turned on with instructions directing them to the information. iOS users that had 'Screen Time' recordings provided their daily average for screen time, notifications and pickups; those without 'Screen Time' recordings activated were instructed to provide estimates for these measures and asked to turn it on for the follow-up survey. Mental health and individual differences measures were administered as follows: PHQ-9, GAD-7, SABAS, *s*-IAT, BFA scale, and UPPS. Participants were asked to provide their Prolific ID or their email address to enable them to be re-contacted for the second part of the study. Two weeks later, all participants received an invitation to complete the second survey either through Prolific or via the email provided in the first survey. Participants provided their Prolific ID or email address again to match results across the two time points. Screen Time was recorded using the same procedure for iOS and Android users. The scales were presented in the following order: PHQ-9, GAD-7, SABAS, UPPS, *s*-IAT, and BFAS. In addition, measures of personality (TIPI), reinforcement sensitivity (BIS/BAS) and smartphone addiction pathways (PMPUQ) were incorporated at time point 2. The methods for these are reported on the OSF. Additionally, questions on attitudes towards smartphone use were dispersed in between the scales. Participants were provided with full debrief information.

2.5. Statistical analyses

2.5.1. Pre-registered analyses

Correlation matrices were calculated for the measures at Time 1 (Table 1) and Time 2 (Tables S1–S2) to test H1a, H1b and H3 initially. To test H2, ordinal least squares linear regression models were estimated with screen time and smartphone addiction as the dependent variables, predicted by age, gender, impulsivity, and depression in the first stage, and then incorporating smartphone addiction (for screen time analyses), and phone usage (for smartphone addiction analyses). Phone usage included self-report and actual phone usage, as well as notifications.

2.5.2. Exploratory analyses

Three different sets of analyses were conducted. First, mediation models were estimated using the *lavaan* package in *R* to assess whether the relationship between logged smartphone use and smartphone addiction was mediated by perceived smartphone usage. Second, a misestimation score was calculated by subtracting perceived smartphone use from actual smartphone use. This was then correlated with the individual difference variables, first using the raw misestimation score (to test directionality), and then using absolute misestimation (to test for inaccuracy). Evidence of incongruence was then tested with Response Surface Analysis (RSA) (Humberg et al., 2019), following Sewall and Parry (2021). RSA was conducted as it is a more powerful method of testing for congruence effects. RSA involves the use of polynomial regressions of two independent variables (logged and actual smartphone use) on a dependent variable (smartphone addiction), which are then checked visually to see whether there is incongruence.

3. Results

The descriptive statistics and correlations are reported in Table 1. At Time 1 (T1), 84.5% of respondents had logging information turned on, which increased to 95.2% at Time 2 (T2).

3.1. Pre-registered analyses

Correlation analyses (Table 1) revealed that logged and self-reported smartphone usage were associated with behavioral (pickups and self-reported use), and individual (smartphone, internet, and Facebook addictions, depression, anxiety, positive and negative urgency) factors. The relationships between individual variables were moderate to small in effect size, ranging from 0.35 to 0.14. Internet and smartphone addiction were associated with logged smartphone use to a similar degree. Smartphone addiction was associated with positive and negative urgency, but no other facets of impulsiveness, providing partial support for H1a. Smartphone addiction showed stronger associations with depression, anxiety, and urgency than logged phone usage, these significant associations supporting H1b. All three behavioral addictions were associated with these constructs, internet addiction slightly more so than smartphone addiction, and Facebook addiction slightly less. Depression and anxiety were heavily associated with negative urgency.

Regression analyses indicated there were few consistent predictors of logged smartphone usage; younger age, female (vs male) gender identity, and greater depressive traits were associated with longer logged phone use at T1 (Table 2), but only the gender effect was significant at T2 (Table 2). The smartphone addiction analyses were more consistent; both female (vs male) gender and greater negative urgency predicted higher smartphone addiction scores at both time points, whereas younger age and higher depression were associated at time points 1 or 2 respectively (Table 2). The models predicting smartphone addiction using individual differences and smartphone use behaviors were similarly consistent (Table 3). Self-reported and logged smartphone use predicted smartphone addiction at both time points, as did negative urgency. Gender identity (female) and lack of premeditation predicted higher smartphone addiction at T1 but not T2, and depression at T2 but

Table 1
Descriptive statistics of behavioral and individual difference variables at time 1, including correlation coefficients.

	M	SD	1	2	3	4	5	6	7	8	9	10	11	12	13	14
1 Logged daily phone use	281.59	149.09	–													
2 Daily notifications	199.68	643.91	.07	–												
3 Daily pickups (iOS only)	82.12	49.16	.25**	.56**	–											
4 Self-report daily phone use	273.3	165.03	.62**	.02	.14	–										
5 Smartphone addiction	15.87	5.69	.35**	.01	.06	.38**	–									
6 Internet addiction	27.23	8.58	.30**	.05	.02	.32**	.64**	–								
7 Facebook addiction	14.43	3.98	.14**	.04	−.20*	.15**	.41**	.43**	–							
8 Depression	8.31	6.07	.24**	.03	.05	.23**	.31**	.46**	.21**	–						
9 Anxiety	6.88	5.50	.18**	.04	.08	.19**	.30**	.38**	.21**	.79**	–					
10 Negative Urgency	9.10	2.85	.20**	.07	.15	.20**	.35**	.45**	.24**	.46**	.49**	–				
11 Positive Urgency	7.47	2.74	.14**	.03	−.05	.16**	.20**	.36**	.25**	.29**	.28**	.53**	–			
12 Sensation Seeking	9.67	2.91	.03	−.03	.05	−.01	.02	.11*	−.01	.03	.00	.06	.29**	–		
13 Lack of premeditation	7.53	2.17	.06	−.01	−.17*	.10*	.04	.17**	.12*	.12*	.06	.22**	.36**	.07	–	
14 Lack of perseverance	7.73	2.10	.01	.01	−.14	.03	.01	.13**	.06	.04	.07	.04	.11*	.00	.47**	–

Note: * = $p < .05$, ** = $p < .01$.

Table 2
Regression models of the predictors of logged phone use at times 1 (a) and 2 (b), and smartphone addiction at times 1 (c) and 2 (d).

a (R^2 = .118)	b	se	t	p	*b* (R^2 = .033)	b	se	t	p
Intercept	275.885	14.595	18.903	<.001***	Intercept	15.280	0.527	28.988	<.001 ***
Age	−2.582	0.768	−3.362	<.001***	Age	−0.058	0.028	−2.092	.037 *
Sex (REF: Female)					Sex (REF: Female)				
Male	−41.428	13.740	−3.015	.003**	Male	−1.678	0.502	−3.341	<.001 ***
Non-binary	−0.353	48.546	−0.007	.994	Non-binary	0.508	1.789	0.284	.777
Anxiety (GAD-7)	−1.942	2.013	−0.964	.335	Anxiety (GAD-7)	0.050	0.073	0.682	.496
Depression (PHQ-9)	4.759	1.785	2.667	.008 **	Depression (PHQ-9)	0.115	0.065	1.762	.079
Negative Urgency	4.153	3.000	1.384	.167	Negative Urgency	0.465	0.109	4.254	<.001 ***
Positive Urgency	2.438	3.020	0.808	.420	Positive Urgency	0.107	0.113	0.943	.346
Sensation Seeking	0.502	2.441	0.206	.837	Sensation Seeking	0.020	0.088	0.228	.820
Lack of Premeditation	0.315	3.589	0.088	.930	Lack of Premeditation	−0.189	0.133	−1.424	.155
Lack of Perseverance	−0.252	3.631	−0.070	.945	Lack of Perseverance	0.110	0.131	0.838	.402
c (R^2 = .181)					*d* (R^2 = .185)				
Intercept	302.509	18.036	16.773	<.001 ***	Intercept	15.385	0.618	24.897	<.001 ***
Age	−0.703	0.965	−0.728	.467	Age	−0.039	0.033	−1.162	.246
Sex (REF: Female)					Sex (REF: Female)				
Male	−37.322	17.546	−2.127	.034 *	Male	−1.578	0.600	−2.632	.009 **
Non-binary	89.370	60.177	1.485	.138	Non-binary	1.132	2.100	0.539	.590
Anxiety (GAD-7)	0.404	2.466	0.164	.870	Anxiety (GAD-7)	−0.056	0.084	−0.661	.509
Depression (PHQ-9)	0.883	2.226	0.397	.692	Depression (PHQ-9)	0.218	0.074	2.946	.003 **
Negative Urgency	−0.971	3.752	−0.259	.796	Negative Urgency	0.482	0.128	3.757	<.001 ***
Positive Urgency	3.514	4.063	0.865	.388	Positive Urgency	0.137	0.139	0.989	.328
Sensation Seeking	−0.904	3.006	−0.301	.764	Sensation Seeking	−0.012	0.103	−0.117	.907
Lack of Premeditation	2.023	4.829	0.419	.676	Lack of Premeditation	0.004	0.163	0.026	.980
Lack of Perseverance	−1.758	4.818	−0.365	.715	Lack of Perseverance	−0.094	0.165	−0.571	.569

not T1.

A violin plot of the different (logged and self-perceived) estimates of smartphone use is displayed in Fig. 1, which reports measures of central tendency and the range of responses to the measures. The data shows that participants' self-reported and logged estimates of smartphone use across the sample were relatively well calibrated, falling at around 4 and a half hours per day. These were substantially correlated (r = 0.62), meaning that H3 was rejected.

3.2. Exploratory analyses

The pre-registered analyses indicated that self-reported smartphone usage might mediate the relationship between logged smartphone use and smartphone addiction. As such, mediation models were estimated to test whether this was the case. There was consistent evidence that perceived smartphone use partially mediated this association (Fig. 2), with just over half of the total effect (52.0% at T1, 56.4% at T2) attributed to the mediating effect of self-reported smartphone use (Table 4). In both cases the direct and indirect effects were significant, suggesting support for partial mediation. This indicates that although there was still an association between logged smartphone use and smartphone addiction, most of the effect can be attributed to perceived smartphone use.

Although the average estimates of smartphone use and logged behavior were relatively similar (r = 0.62), the observed correlation indicates there was some errors in estimation. As such, a misestimation score was calculated by subtracting self-reported smartphone usage from logged behavior; with positive numbers indicating people underestimated their actual smartphone use, and negative numbers indicating overestimation. This misestimation score negatively correlated with SABAS scores at T1 ($r = -0.104$, $p = .031$), and T2 ($r = -0.144$, $p = .005$). This indicated that people with higher levels of self-reported smartphone addiction tend to overestimate their self-reported smartphone usage. Further, this effect does not seem to simply be due to people with higher levels of smartphone addiction being less able to estimate their smartphone usage. Further analyses reporting the absolute deviation were not significant (T1 $r = 0.080$, $p = .098$, T2 $r = 0.101$ $p = .061$).

The correlation analyses appeared to suggest that there was incongruence, or at least an asymmetric congruence effect, in the relationship between self-reported and logged smartphone use, and smartphone addiction. To test between these possible accounts more thoroughly, we

Table 3
Regression model predicting smartphone addiction, adjusting for logged and self-reported phone usage at Time point 1 (a) and Time point 2 (b).

	b	*se*	*t*	*p*
a ($R^2 = .286$)				
Intercept	15.234	0.560	27.225	<.001 ***
Age	−0.010	0.030	−0.336	737
Sex (REF: Female)				
Male	−1.081	0.531	−2.037	.042 *
Non-binary	−0.035	1.798	−0.020	.984
Logged phone use	0.005	0.002	2.181	.030 *
Self-report phone use	0.009	0.002	4.240	<.001 ***
Logged notifications	−0.0002	0.0003	−0.695	.488
Anxiety (GAD-7)	0.047	0.076	0.623	.534
Depression (PHQ-9)	0.097	0.068	1.433	.153
Negative Urgency	0.406	0.113	3.586	<.001 ***
Positive Urgency	0.088	0.115	0.767	.444
Sensation Seeking	0.027	0.093	0.285	.776
Lack of Premeditation	−0.323	0.137	−2.356	.019 *
Lack of Perseverance	0.176	0.138	1.269	.205
b ($R^2 = .293$)				
Intercept	15.070	0.584	25.804	<.001 ***
Age	−0.007	0.032	−0.221	.826
Sex (REF: Female)				
Male	−0.425	0.576	−0.738	.461
Non-binary	0.348	1.935	0.180	.857
Logged phone use	0.005	0.002	2.729	.007 **
Self-report phone use	0.010	0.002	5.422	<.001 ***
Logged notifications	−0.001	0.001	−1.552	.122
Anxiety (GAD-7)	−0.057	0.079	−0.717	.474
Depression (PHQ-9)	0.168	0.072	2.343	.020 *
Negative Urgency	0.508	0.121	4.187	<.001 ***
Positive Urgency	0.024	0.131	0.185	.853
Sensation Seeking	−0.050	0.097	−0.516	.606
Lack of Premeditation	0.017	0.156	0.109	.913
Lack of Perseverance	−0.095	0.155	−0.613	.540

Note: * = $p < .05$, ** = $p < .01$, *** = $p < .001$.

conducted Response Surface Analyses (RSA), specifying smartphone addiction as the dependent variable and self-reported and logged behavior as the independent variables. The data met the necessary assumptions of RSA (i.e. low multicolinearity) (Humberg et al., 2019). The cubic model was the best fit of the data (Table S3 reports full model parameters including measures of goodness of fit). The results indicated there was evidence for a broad congruence effect. Fig. 3 reports the graphical representation of the cubic RSA model. The lines in blue represent the lines of congruence and incongruence. In support of the assertion there is a broad congruence effect, the principal axis of the surface does not deviate from the line of congruence (Fig. 3), nor does

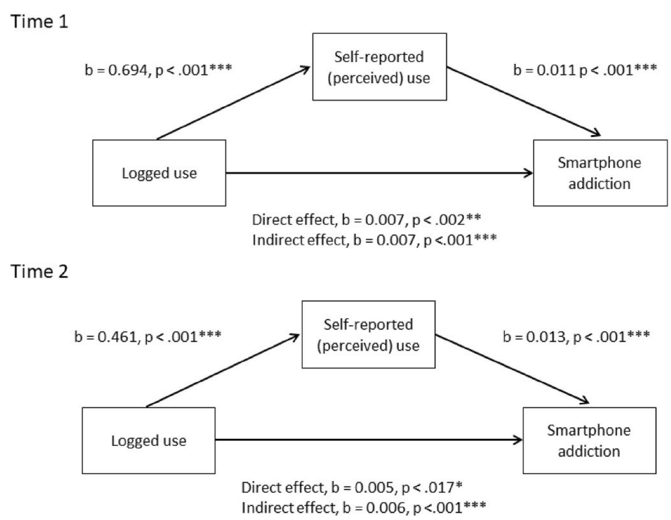

Fig. 2. Mediation models of the relationship between logged smartphone use, perceived smartphone use (as mediator), and smartphone addiction.

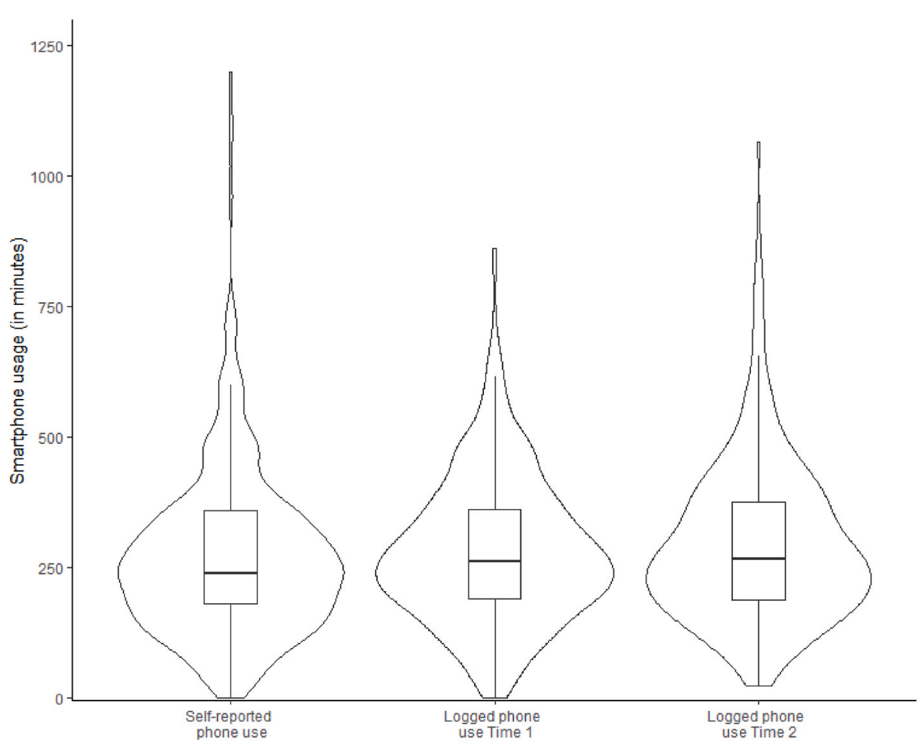

Fig. 1. Violin and box plot of the distribution of self-reported (at Time 1) and logged (at Times 1 and 2) smartphone usage indicators. The violin plot represents the kernel density of each of the indicators, capturing the range and frequency of the different responses. The box plot captures the mean (as the line in the box plot) and the inter quartile ranges (as the edges of the box).

Table 4
The mediating effect of self-reported smartphone use on the relationship between logged phone use and smartphone addiction.

		Time 1			Time 2	
	b	*se*	*p*	*b*	*se*	*p*
c (Smartphone addiction ~ logged use) – direct effect	0.007	0.002	.002 **	0.005	0.002	.017 *
a (Self reported use ~ logged use)	0.694	0.042	<.001 ***	0.461	0.049	<.001 ***
b (Smartphone addiction ~ self reported use)	0.011	0.002	<.001 ***	0.013	0.002	<.001 ***
Total indirect	0.007	0.001	<.001 ***	0.006	0.001	<.001 ***
Total effect	0.014	0.002	<.001 ***	0.011	0.002	<.001 ***
Indirect/total effect ratio	0.520			0.564		

Note: * = $p < .05$, ** = $p < .01$, *** = $p < .001$.

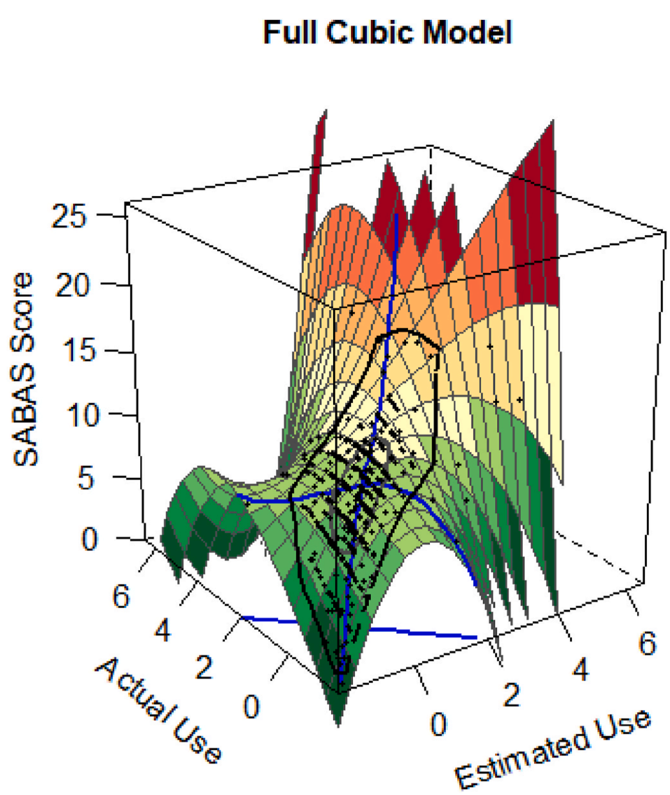

Fig. 3. Response Surface Analysis plot of the congruency between estimates and actual smartphone use on smartphone addiction. Estimated and actual smartphone use are plotted as the *x* and *y* axis, and smartphone addiction scores as the *z* axis. The blue lines represent the lines of congruence (LOC) and incongruence (LOIC).

the line of incongruence deviate from an inverted U shape. However, an examination of the coefficients for the RSA (Table 5) suggests there were additive and curvilinear effects that support broad rather than strict congruence. These effects demonstrate additional effects of perceived smartphone use. Specifically, people who perceived higher levels of overall use report greater smartphone addiction. An examination of the regression coefficients indicates that only perceived smartphone use and perceived use^2 were associated with smartphone addiction. The surface plot confirms this further. Levels of smartphone addiction were greater in people that self-reported high smartphone use but lower logged use,

Table 5
Response surface analyses regressions of self-reported and logged smartphone usage on smartphone addiction.

	b	se	p
Intercept	10.716	0.318	<.001 ***
Self reported use	1.539	0.461	<.001 ***
Logged use	0.743	0.533	.163
Self reported use^2	−0.879	0.403	.029 *
Self reported x logged use	0.142	0.533	.790
Logged use^2	−0.284	0.423	.504
Self reported use^3	−0.041	0.134	.761
Self reported use^2 x logged use	0.715	0.372	.055
Self reported use x logged use^2	0.000	0.158	.999
Logged use^3	−0.067	0.126	.596

Note: * = p < .05, ** = p < .01, *** = p < .001.

but not in reverse.

4. Discussion

There has been growing concerns about the potential negative impacts of smartphone use on society. One of these concerns has been that smartphone use might become disordered, problematic or addictive. Our results highlight the potential consequences of this, specifically how self-reported smartphone addiction is associated with negative mental health outcomes, such as depression, anxiety, and impulsiveness, confirming our first hypothesis. However, there is increasing consternation about the validity of using self-reports as a proxy for smartphone use, especially when smartphones by default collect this data. These results demonstrate that logged and self-reported use are correlated (in contrast to our third hypothesis), but that self-reported smartphone usage is more strongly associated with smartphone addiction than actual behavior, supporting our second hypothesis. The present study concords with previous meta-analyses (Parry et al., 2021), albeit with minor caveats. The observed association between logged and self-reported behavior (r = 0.620) is greater than estimates calculated from previous meta-analyses (r = 0.38, *95% C. I.* = 0.33 - 0.42), but not outside the range of values observed in previous studies. Even with a latency of two weeks between estimated and logged behavior, a correlation of r = 0.438 was observed. This is not surprising given the significant heterogeneity that has been observed in these associations (Parry et al., 2021), but less than one might expect for measures of the same activity. The association between logged behavior and smartphone addiction is weaker. The observed findings (T1 r = 0.354, T2 r = 0.282) are similar to those observed in Parry et al. (2021) (r = 0.25, *95% C. I.* = 0.20–0.30). The correlations between smartphone use and smartphone addiction were weaker than the relationships between smartphone addiction and mental health (e.g. depression, anxiety), or other behavioral addictions (internet, social media). Furthermore, three sets of exploratory analysis: mediation models, correlations, and RSAs demonstrated that perceived smartphone usage is more salient than actual behavior in relation to smartphone addiction. The mediation analyses found that perceived smartphone use mediated most of the association between logged behavior and smartphone addiction. The correlation analyses found that people who overestimate their smartphone use report higher levels of smartphone addiction. Moreover, it does not appear that people with disordered smartphone usage are less able to accurately record their smartphone use, as there was no correlation between absolute error and smartphone addiction. Finally, RSA indicated that there is a broad congruence effect, i.e. respondents reporting similarly high logged and perceived use report higher smartphone addiction. However, when they are incongruent, respondents with higher perceived use report greater addiction, but not *vice versa*. The key finding across these analyses is that perceived overuse of smartphones appears to be more important than actual overuse in predicting smartphone addiction.

The findings of this study suggest that a unitary model of smartphone addiction is difficult to empirically support despite its popularity. Even though smartphone addiction was correlated with smartphone use, the size of the correlation indicates there is limited evidence that excessive or problematic use is generalized. Markers of behavior that might plausibly be associated with a continuous schedule of reinforcement (i.e. notifications), or compulsive behaviors (i.e. pickups) were not associated with smartphone addiction or other individual differences associated with distress. Instead, alternative conceptualisations of the relationship between smartphone use and harm ought to be considered. Within an addictions framework, the spectrum hypothesis proposed by Baggio et al. (2018) is one possibility. Using network analysis to test overlap between four technological addictions (internet, smartphone, cybersex, and gaming), they found strong evidence that internet addiction, but less so for smartphone addiction, falls under an umbrella construct capturing multiple addictive behaviors. In this study, the SABAS correlated with internet addiction more than any other variable, which is consistent with this perspective. It is possible that smartphone addiction measures capture a range of impulsive behaviors facilitated by smartphone use, but do not make up the majority of smartphone usage or a specific addiction construct. However, there would be a need to differentiate such a construct from other individual differences in psychology, particularly related to mental health and distress (Davidson et al., 2022). Further research could also model how specific pathways of problematic smartphone usage are related to objective behavior, as has been proposed in theoretical models such as the Pathways Model (Canale et al., 2021). These possibilities notwithstanding, this study highlights how there are severe limitations with the use of addiction models in understanding technological harm, and there is a need to encourage a greater diversity of psychological perspectives when it comes to understanding these phenomena.

These findings challenge the idea that smartphone addiction and screen time are straightforwardly associated with disordered mood (e.g. depression, anxiety). Depression was univariately associated with screen time and smartphone addiction, but multivariate associations were inconsistent over time. In contrast, there was stronger support for negative urgency. Negative urgency is a facet of impulsivity (Whiteside & Lynam, 2001) combining neuroticism, low agreeableness, and low conscientiousness, characterised by the tendency to act rashly when experiencing distress (Settles et al., 2012). For externalising behaviors like addictions (Whiteside et al., 2005), it is not simply distress that is triggering these behaviors, but the combination of a greater susceptibility toward distress alongside a tendency to behave rashly or impulsively when experiencing distress (Settles et al., 2012). By focusing on depression without considering negative urgency, a crucial component of the association between negative affect and smartphone addiction has been missed. Further, given the inconsistent causal literature on problematic smartphone use and depression (Elhai et al., 2017), this account specifically hypothesises that the relationship between depression and smartphone addiction is driven by prior individual differences, rather than a consequence of smartphone engagement itself. In addition to theories such as uses and gratifications theory, this also concords with theoretical accounts that hypothesize that addictive smartphone use is caused by the combination of depressive and impulsive traits (Billieux, 2012; Billieux et al., 2015). Further research ought to incorporate multidimensional measures of impulsivity when collecting measures of negative affect.

It is important to reflect on the nature of 'screen time' at this point. This study only measured one facet of screen usage, on smartphones, over a short period. Screen time was relatively stable over the two measurements, but multivariate associations with individual differences were inconsistent. This study does not tell us whether aggregate screen use is stable in the longer term and whether self-reported behavior is more stable over time than actual behavior. Logged behavior captures usage over a pre-specified period (usually a week), whereas self-reported usage may use a longer reference point. Similarly, aggregate behavior may not be sufficiently sensitive to capture specific types of engagement associated with addiction related harms. There is also a need to consider the transactional relationship between devices. For instance, is a period of reduced smartphone use supplanted by increased PC, TV, tablet, or gaming time? Many individuals use multiple technologies at the same time, resulting in the missed measurement of overlapping behaviors due to difficulties in quantifying such habits – for example surfing the web whilst watching TV (Boase & Ling, 2013). Research often does not seek to understand the types of smartphone interaction, which could play a large role in predicting problematic smartphone use. For example, the difference between those who actively 'post' on social media and 'lurkers' (who passively 'scroll' through newsfeeds) is not captured in a timed log of daily use, yet represents a different type of interaction (Noë et al., 2019). Not to mention the act of watching TV on smartphones and whether it should be quantified as active or passive (Wilmer et al., 2017). Therefore, research collecting behavioral markers should differentiate between different goal directed behaviors (Kaye et al., 2020), and collect wider contextual data, both logged and self-reported, to understand if there are specific circumstances or cycles of behavior associated with harm.

It is important to consider the wider implications of these findings for how policymakers might seek to regulate and limit the effects of smartphone use on the population (Van Velthoven et al., 2018). Recommendations often focus on limiting screen time. Our findings suggest that such interventions are likely to be too broad and invasive, and ineffective at the same time. The relationship between logged smartphone use and smartphone addiction is not strong enough to suggest it would successfully mitigate harmful behavior. On top of this, there is relatively little information about the context of smartphone usage, which makes it difficult to identify specific markers that could be used to identify patterns of usage linked with harm. Collecting this data would be more likely to lead to more sophisticated interventions or measures, such as enabling people to restrict access to certain kinds of applications, rather than controlling smartphone usage in general. Research ought to be directed at identifying specific behaviors or features that are harmful, backed by behavioral data, rather than recommending controlling smartphone use in general.

There are a number of limitations with this study. Participants were asked to self-report their logged smartphone usage. This created the possibility for error by the participant, but also in processing the data as there is variance in the type of data received, especially for Android phones. However, the presence of a second time point mitigates much of this risk, as estimates were relatively consistent across the two time points. Other studies have asked participants to upload screenshots, which may reduce the margin for error (Hodes & Thomas, 2021). The data collected includes multiple measurements of smartphone behavior, but limited contextual information (Griffiths, 2018). For instance, respondents may use their phone extensively, but for passive use (e.g. listening to music, watching videos). Therefore, there may be additional sources of systematic variance in how phone developers and participants perceive and define 'screen time'. The analyses conducted here are cross-sectional. One of the strengths of the study was that the consistency of the associations could be tested in the two-wave data collection, but there is scope to model these longitudinally. There was however attrition between the first and second time points. Although the SABAS has been used considerably in the literature, other measures have been more widely used, and the lack of a gold standard in smartphone addiction measurement does limit any inferences we can make about addictive behavior.

In conclusion, this study demonstrates that smartphone addiction is better explained by self-reported use than logged phone activity and that smartphone addiction is more consistently associated with negative urgency than distress. This further challenges the idea that smartphone addiction can be defined principally by excessive or dependent use of a smartphone and that volume of use can solely be a predictor of subsequent harm. Instead, future research should either test between accounts that consider smartphone addiction as a spectrum disorder or identify specific patterns of harm associated with addictive behavior, or adopt an alternative model to understanding technological harm. In the interim, attempts to control smartphone related harms by restricting overall use are unlikely to be effective and both research and policy should instead focus on understanding the context in which smartphones are being used.

Credit author contributions

Conceptualization: LH, HJ, RJ, Data Curation: LH, HJ, RJ, Formal Analysis: RJ, LH, HJ, Investigation: LH, HJ, RJ, Methodology: HJ, LH, RJ, Project Administration: LH, HJ, RJ, Supervision: RJ, Funding Acquisition: RJ, Writing – Original Draft: LH, HJ, RJ, Writing – Review and Editing: HJ, LH, RJ.

Preprint

A preprint of this article is available at https://psyarxiv.com/tmhx5/

Data

The pre-registration, materials, data and analytic code for this study are available on the Open Science Framework at https://osf.io/2bw4q/.

Declaration of competing interest

There are no declarations of interest to report in relation to this research. Reimbursements for participant inconvenience were sourced from internal funds within the institution where the corresponding author is based. RJ is currently a principal investigator on research grants from the Academic Forum for the Study of Gambling, and Gambling Research Exchange Ontario, for projects investigating gambling disorder and gambling harms. These are unrelated to the research reported in this manuscript. LH and HJ have no conflicts of interest to declare.

Data availability

The data, code, and materials used in this manuscript are publicly available at https://osf.io/2bw4q/

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Appendix A. Supplementary data

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