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Problematic media use, but not device time, tracks mental health issues: A four-wave cohort study in adolescents

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Abstract

Background.

Adolescent screen use has been linked to mental health issues, yet there remains confusion as to the respective role of time spent on media versus that of self-reported problematic use of media. Moreover, this work mainly focuses on average differences across adolescents, but rarely asks whether deviation in personal use actually impacts mental health down the line.

Methods.

We followed 550 German-speaking Swiss adolescents (median age 13 years, 295 girls) across four waves six months apart. At each wave they reported time spent on five device categories (mobile phone, computer, tablet, video game console, and television), problematic use on three different media (mobile phone - PMPU, social media - PSMU and video games — PVGU), as well as mental health issues spanning anxiety, depression, well-being and ADHD symptoms. For every variable pair, we fitted a cross-lagged panel model (CLPM) and a random-intercept version (RI-CLPM), adjusting for age, gender and socioeconomic status. Paths were interpreted when the mean standardized coefficient reached the medium benchmark ($|\beta| \geq .07$).

Results.

Cross-lagged panel models describe trends between adolescents. Here, as expected from the literature, on average smartphone time and PMPU predicted each other, as did console time and PVGU. Of note, problematic use, especially PSMU, showed strong reciprocal ties with mental health issues, whereas screen time was only weakly associated with mental health when considering mobile phones. Within adolescents, RI-CLPM models showed the same pattern, with mental health issues being only related to problematic use, especially PSMU, but none of the media time. Rising depressive symptoms and falling well-being each preceded higher PVGU without a reverse path. Interestingly, anxiety showed no within-person coupling.

Conclusions.

Time spent on devices indicated which adolescents reported problematic use but not whether a given adolescent's mental health deteriorated. Problematic use in contrast closely tracked mental health issues, particularly for depressive and ADHD symptoms. Screening that counts hours is at risk of missing mental health issues; rather, signs of impaired control over social media use, as well as mobile phone use are a more robust target.

Background

Adolescents in high-income countries now navigate digital environments for nearly everything they do, from schoolwork and friendships to entertainment and shopping [1, 2]. Mobile phones, social media platforms, streamed video, and video games are not single exposures. They are broad categories of activity that differ in content, social context, and timing, serve different motives, and demand different levels of self-regulation [3, 4]. The early claim that a generalized “screen time” crisis was driving adolescent mental health problems has given way to a more careful reading of the longitudinal evidence, in which associations are small, heterogeneous, and often depend on how use was measured and how the data were modeled [5, 6, 7, 8, 9, 10].

Two distinctions may help a better understanding of that heterogeneity. One concerns what is measured, especially distinguishing screen time from problematic use. The other concerns who is being compared, especially considering trends on average versus individual trajectories. The present study builds on a single cohort followed across four waves over 18 months to address the issue of the relationship between screen use and mental health.

Time spent and problematic media use are different constructs

Time spent on mobile phones, on social media, or in games can reflect efforts to keep up with friends, seek entertainment, or complete homework, or, in a minority of cases, escape from difficulty and displace other activities [11, 12]. In contrast, problematic media use captures impaired control, preoccupation, craving, withdrawal-like states, conflict with other obligations, and persistence despite negative consequences [13, 14, 15]. Whether these patterns are best framed as behavioral addictions or as difficulties anchored in particular online activities and platform designs remains debated [16, 17]. What is not debated is that problematic-use instruments ask about impairment and distress, whereas time-use instruments ask solely about consumption.

The empirical consequences of that difference are consistent across designs. A meta-analysis of 78 studies found that the duration of social media use was unrelated to positive well-being ($k = 37$, $r = 0.017$, 95% CI [−0.037, 0.070]), whereas problematic social media use was negatively related to it ($k = 31$, $r = −0.125$, 95% CI [−0.209, −0.040]), a contrast that also held in a longitudinal subset [12]. In a case-control meta-analysis of children and adolescents with a clinical ADHD diagnosis, time-based measures modestly separated cases from controls (SMD = 0.31, 95% CI [0.07, 0.55]), whereas problematic-use scales separated them roughly four times as strongly (SMD = 1.13, 95% CI [0.66, 1.60]) [18]. In the ABCD cohort, trajectories of addictive use of social media, mobile phones, and video games predicted later suicidal behaviors and internalizing symptoms, whereas baseline total screen time predicted none of these outcomes, and adjusting for it left the addictive-use associations intact [19]. A remote cohort study of young adults reached the same conclusion using device-logged data, in which self-reported problematic use tracked depressive and anxiety symptoms, but objectively recorded screen time, pickups, and notifications did not [20].

In line with this view, the meta-analysis most often cited as evidence that social media time is harmless reported a pooled effect of β = .061 across 79 estimates and, by design, excluded every study measuring problematic social media use [5]. Its conclusion is therefore about hours, not about the nature of the use. Meta-analytic estimates for problematic use itself are an order of magnitude larger, with pooled correlations of r = 0.318 for depression and r = 0.252 for anxiety in adolescent samples averaging 14.6 years [21]. One may argue that adolescents who reduced their social media consumption for one week did show decreases in depressive and anxiety symptoms, pointing to a clear causal role of consumption; yet, the largest reductions were among those reporting the most severe symptoms at baseline again pointing to problematic use [20]. School-based phone restrictions have been evaluated using similar logic [22].

Between-person and within-person effects

The second distinction concerns the comparison being made. Most longitudinal studies ask whether adolescents who on average use more media than their peers also report worse outcomes than their peers. This between-person question is the right one for identifying at risk groups. However, it is not the only question parents, teachers, and clinicians have in mind. Indeed, of high concern is whether a particular adolescent who starts using more media will subsequently do worse than that same adolescent usually does.

Cross-lagged panel models (CLPM) and random-intercept cross-lagged panel models (RI-CLPM) address these two questions with the same data. The CLPM estimates lagged paths in which all variance, whether it reflects durable differences between adolescents or fluctuations within one adolescent, contributes to the estimate. The RI-CLPM adds a random intercept for each variable, which absorbs each adolescent's own average level, so that the remaining lagged paths describe deviations from that personal average [23, 24]. Neither level is more dynamic than the other. They differ in what is held constant.

Studies that have made this separation have often found that associations between screen usage and mental health shrink or disappear at the within-person level. Houghton et al. [25] followed 1,749 adolescents and modeled depressive symptoms at three annual points. Between-person differences in screen time clearly separated the depressive-symptom trajectories. Within persons, total screen time and depressive symptoms predicted each other, though the effect was small enough that about 13 additional hours of screen time per day would be needed to move an adolescent from the average to the clinical range. Of the eight activity-specific within-person paths, only one differed from zero, which the authors treated as consistent with chance. Coyne et al. [26] reported little evidence over eight years that within-person increases in social media time preceded depression or anxiety. Puukko et al. [27], using an RI-CLPM in 2,891 Finnish adolescents, found that depressive symptoms preceded small increases in social media consumption (B = 0.13, 95% CI [0.01, 0.25]) while social media consumption did not precede depressive symptoms (B = 0.01, 95% CI [−0.05, 0.07]). Intensive designs point the same way,

with within-person effects of active and passive social media consumption on momentary well-being demonstrating close to zero on average and highly variable effects at the individual level [28, 29].

Within-person effects of time-based measures are not always absent, and the exceptions are informative. Marciano, Schulz, et al. [30] found small within-person effects of internet-use duration on depressive symptoms among 981 Swiss early adolescents (β = .055 to .071). In the ABCD cohort, Nagata et al. [31] reported within-person effects of social media time on depressive symptoms across annual waves (β = .07 and .09), alongside a null between-person association, which is the mirror image of the pattern usually described. Orben et al. [32] identified narrow developmental windows in which higher-than-usual social media time preceded lower-than-usual life satisfaction, and a Swiss replication confined the effect to girls with lower parental education below age 18 [33]. Taken together, these results suggest that time-based within-person effects, where they exist, are small, conditional, and sample-specific.

Far less is known about problematic use at the within-person level. Boer et al. [34] used an RI-CLPM in 2,109 adolescents and found that problems with social media use preceded poorer mental health one year later, whereas intensity of consumption did not, in either direction. That result is the closest existing precedent for the question we ask here, and it concerns social media alone.

Considering the variety of media

Most longitudinal work focuses on a single platform, leaving open whether problematic use is platform-specific or reflects a broader difficulty regulating rewarding digital activity. The question matters practically. If problematic use spans platforms within the same adolescent, an intervention aimed at one platform may generalize or simply displace the behavior.

Mobile phones complicate this further because they are not themselves a source of reward. They deliver social media, games, messaging, and video, which is why some authors argue that “smartphone addiction” is a category error and that research should specify the reward and the behavior used to obtain it [15, 17]. A systematic review of 13 studies found correlations between problematic smartphone use and problematic social media use that were mostly medium to large, with several of these above 0.70 [35]. Such a pattern of results is consistent with a common underlying difficulty whichever media activity the mobile phone delivers. Here we measure problematic mobile phone, social media, and video game use in the same adolescents so as to prospectively address the contribution of each rather than having to infer it from cross-sectional overlap.

ADHD symptoms as a candidate cross-cutting process

ADHD symptomatology sits at the intersection of both distinctions: time spent vs. problematic use and between-person vs. within-person effects. Meta-analyses report moderate positive associations between ADHD symptoms and gaming disorder (r = 0.296, 95% CI [0.266, 0.326], 41 samples) [36] and between

ADHD symptoms and problematic social media use (r = 0.361, 95% CI [0.297, 0.421], 15 studies, N = 35,223) [37]. A systematic review of 28 longitudinal studies concluded that digital media use and ADHD symptoms are reciprocally associated, and that the associations are more consistent for problematic use than for screen time [38]. Two directions of influence are plausible and not mutually exclusive. Weak inhibitory and attentional control may make an adolescent more susceptible to designs built to prolong engagement, and heavy exposure to rapid rewards and frequent interruptions may, in turn, amplify impulsivity and inattention [39]. Unfortunately, almost all of this evidence is either cross-sectional or between-person, so whether ADHD symptoms and problematic use actually move together within individual adolescents remains unresolved.

The present study

We followed 550 German-speaking Swiss adolescents with a median age of 13 years across four waves spaced six months apart. At each wave, we measured time spent on five device categories (mobile phones, computers, tablets, TV and video gaming console), problematic use of three different media - mobile phones, social media, and video games, as well as anxiety (GAD-7), depressive symptoms (PHQ-9), well-being (WHO-5), and ADHD symptoms (ASRS). For every pair of variables, we fitted a CLPM and an RI-CLPM in parallel. This design lets us consider concurrently the triad of variables that are time spent on media, problematic media use and mental health. In particular, we can ask at both the between- and within-subject level what the relationships are between the two forms of media use - consumption and problematic use, as well as the relationships between mental health and each of these forms of media use. Critically we can do so over 4 waves with the granularity of five different devices and three different problematic media use scales.

Hypotheses

The literature supports reasonably firm predictions at the between-person level and much weaker ones within persons. Between adolescents, we expected higher problematic use of mobile phones, social media, or video games to precede (a) more time spent on the corresponding medium, (b) higher anxiety and depressive symptoms, (c) lower well-being, and (d) more ADHD symptoms, with reciprocal paths in the opposite direction. Within adolescents, we expected the coupling between problematic use and time spent to weaken or disappear, because the two constructs share stable individual differences more than they share short-term individual fluctuations, while the coupling between problematic use and symptoms should persist.

Methods

Design and participants

Data come from the Media Interactions, Cognition and Adolescent Health (MICAH) project, a school-based longitudinal panel study of Swiss adolescents. Participants were assessed at four waves (T1 to T4), spaced approximately six months apart, yielding an 18-month observation window. The design was prospective, observational, and fully repeated-measures. Adolescents were eligible if they were between 12 and 19 years old and had sufficient command of the local language to complete the questionnaires. No clinical exclusion criteria were applied.

Recruitment took place in secondary schools in the German-speaking part of Switzerland in September 2023. School directors who agreed to participate presented the study to their teaching teams, and volunteer teachers distributed a flyer and a consent form to adolescents and their legal guardians. Adolescents who returned a signed consent form and were present on the day of data collection were enrolled. At each wave, data were collected during two consecutive 45-minute school periods in a quiet classroom, supervised by two of the twelve assessors trained each year. Questionnaires were administered on a 10.1-inch tablet (Lenovo M10, Lenovo Group Ltd.). The same assessor team administered the protocol at all four waves to limit assessor-related variability.

The present analysis is restricted to the German-speaking sample. The two recruitment areas differed not only by canton and first language but also, unexpectedly, by age and sample size, making pooling inappropriate.

A total of 636 German-speaking adolescents began the study at T1. To allow longitudinal modeling, we retained participants with data at a minimum of three of the four waves, leaving 555 adolescents. Of these, 295 identified as female, 255 as male, two as “other,” and three as “prefer not to answer.” Gender was one of three a priori covariates, alongside age and socioeconomic status. The two “other” and three “prefer not to answer” responses were too few to model as a separate group, so these five adolescents were excluded. The analytic sample therefore comprised 550 adolescents (295 girls, 255 boys). At T1, age had a median of 13 years and a mean of 13.21 years (SD = 0.99, range 12 to 19). Because the age distribution was right-skewed, we report the median rather than the mean when describing the cohort.

Socioeconomic status was assessed at enrollment using a five-item proxy scale adapted from the Family Affluence Scale [40]: whether the adolescent has their own bedroom (no = 0, yes = 1), the number of family vehicles, the number of family holidays away from home in the past 12 months, the number of computers, laptops, and tablets in the household, and the number of bathrooms with a shower or bath (each scored 0 to 4 or more). Items were summed to create a composite score ranging from 0 to 17, with higher scores indicating greater family affluence. Because the items are concrete and observable, this proxy is generally more reliable in this age group than adolescent reports of parental occupation or income [40]. Observed scores ranged from 4 to 17 (mean = 10.77, SD = 2.09), indicating a sample drawn largely from moderately affluent families, with few adolescents at the low end of the scale. The distribution is shown in Supplementary Figure S1, and demographic characteristics are shown in Supplementary Table S1.

Power and sample size

Effect sizes were interpreted against the empirical benchmarks for cross-lagged coefficients derived by Orth et al. [41] from 1,028 CLPM and 302 RI-CLPM effects, with .03 considered small, .07 medium, and .12 large. Orth et al. recommend the same benchmarks for both model types. We report and interpret only paths that meet or exceed the medium benchmark, that is, mean $|\beta| \geq .07$. Coefficients below this threshold are provided in the supplementary results table for completeness but are not discussed.

Sample size was fixed before recruitment using the simulation results of Pan et al. [42] for a four-wave design with an intra-class correlation of 0.90, which returned 454 to 499 participants for a path coefficient of 0.14. We recruited 636 adolescents and retained 550. Because cross-lagged models have no closed-form power solution, and because software dedicated to the random-intercept model has appeared only recently [43], we repeated the calculation by Monte Carlo simulation in the metric we use for interpretation. With four waves and lagged paths constrained equal across waves, 550 participants give 80% power for a between-person coefficient of .07 and for a within-person coefficient of .12, respectively the medium and large benchmarks of Orth et al. [41]. Detecting .07 within persons would require roughly 1,600 participants. Standard errors in the fitted models ran wider than the simulation assumed, so these figures describe the best case for the design. Full details of the simulation are given in Supplementary Table S6.

Measures

Throughout, “time spent” refers to the self-reported duration of device use, and “problematic use” refers to the symptom-based scales described below. The two are never used interchangeably. The consumption item asked adolescents about “smartphone” use, and the problematic-use instrument is the Problematic Mobile Phone Use questionnaire. For consistency, we use “mobile phone” for both and note the wording of the original item here.

Time spent on devices

At each wave, adolescents separately estimated, for a typical weekday and a typical weekend day, how many hours they spent on each of five device categories: mobile phone, computer, video game console, television, and tablet. Response options were coded as: “I don’t use this” = 0, “Less than 1 hour” = 0.5, “1-2 hours” = 1.5, “3-4 hours” = 3.5, “5-6 hours” = 5.5, “7-8 hours” = 7.5, and “9 or more hours” = 10.5. Weekly time spent on each device was computed by weighting weekday hours by 5 and weekend hours by 2 [44].

Problematic media use

A separate instrument was used for each of the three media. Problematic mobile phone use was measured with the short form of the Problematic Mobile Phone Use questionnaire (PMPU), a 15-item scale rated on a four-point scale covering dependent, dangerous, and prohibited use, with scores

summed to a total ranging from 15 to 60 [45]. Problematic social media use (PSMU) was measured with the Social Media Disorder Scale, nine yes/no items mapping onto the nine DSM-5 Internet Gaming Disorder criteria as adapted to social media, with scores summed to a total ranging from 0 to 9 [46]. Problematic video game use (PVGU) was measured with a nine-item yes/no scale using the same nine criteria applied to video games, also ranging from 0 to 9. We deliberately matched the wording of the video game and social media items, using the phrasing of the social media scale, so that the two totals are directly comparable. Higher scores indicate more problematic use on all three scales.

Mental health, well-being and ADHD symptomatology

Anxiety was measured with the Generalized Anxiety Disorder 7-item scale (GAD-7, [47]), and depressive symptoms with the Patient Health Questionnaire 9-item scale (PHQ-9, [48]). Both ask respondents to rate symptom frequency over the past two weeks on a four-point scale from 0 (“not at all”) to 3 (“nearly every day”), with scores summed to totals ranging from 0 to 21 and 0 to 27, respectively. Both perform well in adolescent samples [49, 50].

Well-being was measured with the World Health Organization Five Well-Being Index (WHO-5), with a total range of 0 to 25 [51]. We treat well-being as part of mental health rather than as a separate domain, following the WHO definition of mental health as a state of well-being in which a person can realize their abilities, cope with ordinary stresses, work productively, and contribute to their community [52].

ADHD symptomatology was assessed with the six-item Adult ADHD Self-Report Scale short screener (ASRS), rated on a five-point frequency scale from 0 (“never”) to 4 (“very often”) [53]. Following the scoring rules for Part A of that instrument, each item was first dichotomised against its own threshold, a rating of 3 or higher for the first three items and of 4 or higher for the last three, and the six indicators were then summed to give a symptom count ranging from 0 to 6. Higher scores indicate a greater number of symptoms reaching the screening threshold. The instrument was developed for adults but has been used in adolescent samples with acceptable psychometric properties in this age range.

Statistical analysis

Analyses were conducted in R 4.5.2 [54] using lavaan [55]. Gender was coded 0 for boys and 1 for girls. All other variables, including time spent, problematic use, mental health, and ADHD measures, were standardized using the mean and standard deviation of the T1 distribution in the analytic sample, so that the T1 distribution has a mean of 0 and a standard deviation of 1, and later waves are expressed relative to it in the modeling performed.

Models were estimated with full-information maximum likelihood under a missing-at-random assumption, using all available observations across the four waves rather than restricting the analysis to complete cases. Missing data by construct and wave are reported in Supplementary Table S2.

For each pair of variables, we estimated two models. The CLPM provides the between-person estimate, in which lagged paths are estimated on the total variance. The RI-CLPM adds a random intercept for each variable, so that the lagged paths are estimated on structured residuals that describe each adolescent's deviation from their own expected level [23, 24]. The three covariates, gender, socioeconomic status, and age, were entered simultaneously and regressed on the T1 variables in the CLPM and on the random intercepts in the RI-CLPM. Autoregressive and cross-lagged coefficients were constrained to be equal across waves in unstandardized form, which assumes stationary dynamics and is reasonable given the approximately equal spacing of the four waves.

Constraining the unstandardized paths does not yield a single standardized coefficient because the variables' variances differ across waves. Each bivariate model therefore yields three standardized coefficients, one per time transition (one for T1→T2, one for T2→T3, and one for T3→T4) and per direction (three for X→Y and three for Y→X). We adopted the conservative rule of retaining a path only when all three standardized coefficients were significant at $p \leq .05$ in the same direction. The three values were then averaged to give the mean β reported throughout.

Model fit was evaluated using the criteria of Hu and Bentler [56], namely a comparative fit index (CFI) of at least .95 and a root mean square error of approximation (RMSEA) of at most .06. Following Mulder and Hamaker [24], we treat the comparison between the two models as informative about the level at which an association operates, with one important qualification. A path present in the CLPM and absent in the RI-CLPM indicates that the association is carried by differences between adolescents. A path present in both indicates that it operates at both levels. A path present in the RI-CLPM alone indicates within-person covariation that the CLPM obscured. The qualification is that a non-significant within-person path is not positive evidence of no within-person effect. Removing between-person variance leaves less variance to model and lowers power, and the design supports within-person coefficients of about .12 but not of .07, so within-person nulls are weaker evidence than between-person positives. We phrase all such results as an absence of evidence and read them against the effect sizes obtained at the other level rather than as a significant-versus-non-significant contrast.

Internal consistency

Internal consistency was estimated at each wave for every multi-item self-report scale among participants with complete data on that scale at that wave, using the psych package [57]. Reverse-keyed items were specified via a keying vector. We report Cronbach's α with 95% confidence intervals, interpreted against the conventional threshold of .70 while recognizing that such thresholds are rules of thumb rather than cutoffs [58, 59]. The six ASRS indicators are binary, so the same formula returns Kuder–Richardson 20. Because dichotomization attenuates inter-item covariance, we also computed ordinal α for that scale from the tetrachoric correlation matrix.

Results

We first report descriptive statistics and scale reliability, then the cross-lagged results in four blocks: time spent and problematic use, problematic use and mental health, time spent and mental health, and ADHD symptoms. Between-person estimates come from the CLPM, and within-person estimates come from the RI-CLPM. The two are reported side by side throughout. Only paths with mean |β| ≥ .07 are described. Figure 1 summarizes the full set of interpreted paths at both levels, and Table 2 gives their coefficients. The full model output, including coefficients that fell below the threshold and the fit indices for every model, is provided in Supplementary Table S5.

Descriptive statistics

Descriptive statistics for all variables across all waves are presented in Table 1. We estimated the effect of wave on each repeated measure using linear mixed-effects models with a random intercept for participant, fitted with lme4 [60]. Wave effects were significant for mobile phone, computer, video game console, and television time (all $p < .05$), for all three problematic-media use scales (all $p < .01$), and for depressive symptoms ($p < .05$). Tablet time, anxiety, well-being, and ADHD symptoms did not change significantly across waves.

The direction of change is worth noting because it runs counter to a simple escalation account. Mobile phone time rose steadily, from 19.7 hours per week at T1 to 23.2 at T4. Console time fell over the same period, from 7.2 to 5.3 hours per week. All three problematic-use scores were low on average, and two declined, with PVGU falling from 1.13 to 0.71 and PSMU from 1.98 to 1.67 out of a possible 9, while PMPU rose slightly from 30.5 to 31.4 out of a possible 60. Depressive symptoms increased modestly, from 6.60 to 7.28.

[Table 1 near here. See the separate Tables and Figures file.]

Internal consistency

Internal consistency was good for the two symptom scales at every wave, with α ranging from .895 to .916 for the GAD-7, from .889 to .903 for the PHQ-9, and from .840 to .874 for the WHO-5. It was acceptable for PVGU (α = .786 to .851) and for PSMU (α = .720 to .755). The ASRS is scored as six binary indicators, so its coefficient is Kuder–Richardson 20, which was stable but modest across waves (.617 to .647). That figure is held down by the dichotomous scoring rather than by incoherent items, since ordinal α computed from the tetrachoric correlations reached .762 to .786, above the conventional threshold.

The PMPU was the weakest instrument in this sample. Its α was .332 at T1 and rose across waves to .549 at T4. This scale is explicitly multidimensional, with items distributed across sub-domains [45], whereas α assumes unidimensionality, so its internal consistency may be biased downward when applied to the total score. Even so, associations involving the PMPU are likely to be attenuated, and we

return to this in the limitations. Full reliability estimates are given in Supplementary Table S3, and the correlations between the PMPU total score and its sub-domains in Supplementary Table S4.

Time spent on devices and problematic media use

Between adolescents. As expected from the existing literature, the CLPM revealed reciprocal associations between time of use and problematic use. This was the case between mobile phone time and PMPU ($\beta_{TS\text{-}MP \rightarrow PMPU} = .133$, $\beta_{PMPU \rightarrow TS\text{-}MP} = .094$) and between mobile phone time and PSMU ($\beta_{TS\text{-}MP \rightarrow PSMU} = .070$, $\beta_{PSMU \rightarrow TS\text{-}MP} = .086$). Mobile phone time also preceded higher PVGU, with no return path ($\beta_{TS\text{-}MP \rightarrow PVGU} = .073$). Console time and PVGU predicted each other ($\beta_{TS\text{-}console \rightarrow PVGU} = .128$, $\beta_{PVGU \rightarrow TS\text{-}console} = .076$). Time spent on computers, televisions and tablets was unrelated to any problematic media use scales.

Mobile phone time was thus the only device measure to precede all three forms of problematic use.

The three problematic-use scales were themselves interdependent. PMPU and PSMU predicted each other (βPSMU→PMPU = .096, βPMPU→PSMU = .098), and each preceded higher PVGU (βPSMU→PVGU = .082, βPMPU→PVGU = .093). The reverse path was not significant for PSMU and fell below the interpretation threshold for PMPU. In contrast, time spent on one device did not predict time spent on any other.

Within adolescents. None of these paths survived. In the RI-CLPM, no cross-lagged association between a time-spent measure and a problematic-use measure reached the medium benchmark in either direction. The only path that remained among these eight variables ran from PSMU to PMPU (β = .140). When an adolescent's problematic social media use rose above their own usual level at one wave, their problematic mobile phone use was higher than their own usual level six months later. Interestingly, the reverse path was not significant.

Problematic media use and mental health

Between adolescents. Each of the three problematic-use scales was reciprocally associated with anxiety and with depressive symptoms (for anxiety, $\beta_{GAD\text{-}7 \rightarrow PMPU} = .087$ and $\beta_{PMPU \rightarrow GAD\text{-}7} = .096$, $\beta_{GAD\text{-}7 \rightarrow PSMU} = .191$ and $\beta_{PSMU \rightarrow GAD\text{-}7} = .204$, $\beta_{GAD\text{-}7 \rightarrow PVGU} = .077$ and $\beta_{PVGU \rightarrow GAD\text{-}7} = .088$; for depressive symptoms, $\beta_{PHQ\text{-}9 \rightarrow PMPU} = .090$ and $\beta_{PMPU \rightarrow PHQ\text{-}9} = .104$, $\beta_{PHQ\text{-}9 \rightarrow PSMU} = .201$ and $\beta_{PSMU \rightarrow PHQ\text{-}9} = .154$, $\beta_{PHQ\text{-}9 \rightarrow PVGU} = .106$ and $\beta_{PVGU \rightarrow PHQ\text{-}9} = .077$). The associations involving PSMU were the largest and exceeded the large-effect benchmark in both directions.

Well-being was also reciprocally and negatively associated with PSMU ($\beta_{WHO\text{-}5 \rightarrow PSMU} = -.095$, $\beta_{PSMU \rightarrow WHO\text{-}5} = -.159$). The other relationships were not reciprocal, with higher PMPU preceding lower WHO-5 scores (β = −.087) and higher WHO-5 scores preceding lower PVGU (β = −.077). Well-being

therefore appeared both as an antecedent of problematic use and as one of its consequences, depending on which problematic use scale was considered.

Within adolescents. Here associations were more limited and shifted from anxiety to depression. Depressive symptoms and PSMU reinforced each other (βPHQ-9→PSMU = .142, βPSMU→PHQ-9 = .106), as did depressive symptoms and PMPU ($\beta_{PHQ\text{-}9\rightarrow PMPU}$ = .103, $\beta_{PMPU\rightarrow PHQ\text{-}9}$ = .133). Depressive symptoms also preceded higher PVGU ($\beta_{PHQ\text{-}9\rightarrow PVGU}$ = .115) while lower well-being preceded higher PVGU ($\beta_{WHO\text{-}5\rightarrow PVGU}$ = −.125), in both cases without a return path. Anxiety showed no within-person association with any problematic-use scale in either direction. Anxiety, depressive symptoms, well-being and ADHD symptoms were themselves coupled, reciprocally at the between-person level for all six pairs. Within adolescents, only depressive symptoms and well-being predicted each other (βPHQ-9→WHO-5 = −.177, βWHO-5→PHQ-9 = −.110), and higher well-being preceded lower anxiety (β = −.115). These pairs are listed in Supplementary Table S5 and are not discussed further, since they concern the internal structure of the mental health measures rather than media use.

Time spent on devices and mental health

Between adolescents, mobile phone time preceded higher anxiety (βTS-MP→GAD-7 = .083) and higher depressive symptoms (βTS-MP→PHQ-9 = .092). These were the only associations between any time-spent measure and mental health measure, and the return paths from symptoms to mobile phone time fell below the medium benchmark. No time-spent measure was associated with well-being at either level.

Within adolescents, no cross-lagged association between a time-spent measure and a mental health measure reached the medium benchmark.

ADHD symptoms, time spent and problematic media use

Between adolescents. ADHD symptoms and PSMU were reciprocally associated, and strongly so ($\beta_{PSMU\rightarrow ADHD}$ = .190, $\beta_{ADHD\rightarrow PSMU}$ = .155). PMPU and PVGU each preceded higher ADHD symptoms (β = .130 and .093), with return paths that were significant but below the interpretation threshold. In contrast, time spent on computers, tablets, televisions and consoles fell below the benchmark in relation to ADHD symptoms, with only mobile phone time predicting ADHD symptoms and vice versa ($\beta_{TS\text{-}MP\rightarrow ADHD}$ = .111, $\beta_{ADHD\rightarrow TS\text{-}MP}$ = .082).

Within adolescents. Time-spent measures again dropped out entirely. PSMU and ADHD symptoms formed a reciprocal loop ($\beta_{PSMU\rightarrow ADHD}$ = .151, $\beta_{ADHD\rightarrow PSMU}$ = .111), and PMPU preceded higher ADHD symptoms (β = .156) with no significant reverse path. Problematic video game use, which predicted ADHD symptoms between adolescents, showed no within-person association with them.

Between adolescents, ADHD symptoms were reciprocally associated with anxiety (β = .147 and .126) and with depressive symptoms (β = .209 and .095). Neither association appeared within adolescents.

Convergence and divergence between the two levels

Across the variable pairs involving media use, 35 cross-lagged paths reached the medium benchmark in the between-person models and 10 in the within-person models. Eleven of the 35 between-person paths involved a time-spent measure. None of the 10 within-person paths did (Figure 1).

The two levels also differed in model fit. Thirty-five pairs include a time-spent measure. Across those pairs, the RI-CLPM met the Hu and Bentler criterion for CFI in every case (.953 to .998) and met the RMSEA criterion in 33 of 35 (.012 to .066). The CLPM met neither criterion for any of them (CFI .797 to .948, RMSEA .061 to .125). Fit was poorest for computer, console, and television time (CFI .797 to .880) and least poor for mobile phone and tablet time (CFI .896 to .948, RMSEA .061 to .086). Adding the random intercept improved fit in every pair, indicating that a large share of the covariance among these constructs is carried by durable differences between adolescents rather than by wave-to-wave co-movement. Fit indices for the remaining pairs are given in Supplementary Table S5.

[Figure 1 and Table 2 near here. See the separate Tables and Figures file.]

Discussion

We followed 550 adolescents with a median age of 13 years across four waves spanning 18 months, and modeled device consumption across 5 devices, problematic use across 3 media and mental health variables once with a cross-lagged panel model and once with a random-intercept version of the same model. While the first CLPMs ask whether adolescents who on average use media more than their peers report worse outcomes than their peers, the second RI-CLPM ask whether an adolescent who uses media more than they usually do subsequently reports worse outcomes than they usually do. Both questions are socially and clinically relevant and turned out to reveal associations that could differ.

Indeed, on average we found a strong and reciprocal effect between problematic social media use (and to a lesser extent problematic mobile phone use and problematic video game use) on all mental health variables, be it anxiety, depression, ADHD symptoms or well-being. In contrast, within adolescents all 3 problematic media use were associated with depression and to a lesser extent ADHD symptoms, but not with anxiety or well-being. Furthermore, the result highlights the complementary role of social media and video game use on mental health. In the case of problematic video game use, the within subject effects were limited to higher than individual baseline mental health issues predicting higher problematic video game use at the next wave, but not vice-versa. In contrast, for problematic social media use, reciprocal within subject associations were found with depression and ADHD symptoms, pointing to a mutually downward spiral of influence. Second, among the 5 device consumption we tracked, only time spent on mobile phone systematically impacted mental health, be it anxiety, depression or ADHD symptoms.

These effects were seen on average, but no effect of media time spent on mental health was detectable within adolescents.

Third, considering the relationships between our five device consumption and 3 problematic media use scales, we found the expected associations that, on average, time spent on mobile phone predicted greater problematic media use on all 3 problematic use scales, and reciprocally. In addition, time spent on console was also positively and reciprocally associated with problematic video game use. All of these associations were seen on average, but not at the individual adolescent level. Finally, within our 3 problematic social media use scales, problematic mobile phone use and problematic social media use were the most strongly associated both between and within subjects, in line with the literature. We discuss each result in turn below.

Time spent and problematic use are coupled between adolescents

Between adolescents, the two measures behaved as the literature would predict. Adolescents who reported more mobile phone time also reported more problematic mobile phone, social media, and video game use at the next wave, and the reverse held for phone and social media. Console time and problematic gaming predicted each other. Computer, television, and tablet time predicted nothing. Once each adolescent's own average level was removed, none of these paths survived, except one. That one link ran from problematic social media use to problematic mobile phone use. An adolescent whose social media use became more problematic than usual reported more problematic phone use six months later, whereas an adolescent who simply spent more time on their phone than usual did not. Considered alongside the between-person results, this suggests that the coupling between hours and impairment is largely a property of who an adolescent is rather than of what changes in them over six months.

This is consistent with the strongest existing within-person evidence on the same contrast. Boer et al. [34] fitted a random-intercept model to data from 2,109 adolescents and found that problems with social media use preceded poorer mental health a year later, whereas intensity of use did not, in either direction. It also fits a broader pattern in which the two constructs diverge whenever a study measures both. Duration of social media use is unrelated to positive well-being in a meta-analysis, whereas problematic use is negatively related to it [12]. Addictive-use trajectories in the ABCD cohort predict later suicidal behavior and internalizing symptoms, while baseline total screen time predicts neither [19]. Device-logged screen time in young adults is unrelated or weakly inversely related to symptoms, whereas self-reported problematic use tracks them clearly [20]. Among children and adolescents with a clinical ADHD diagnosis, time-based measures distinguish cases from controls about four times less strongly than problematic-use scales [18]. The meta-analysis most often cited as showing that social media time is harmless reached a pooled estimate of $\beta = .061$ after, by design, excluding every study that measured problematic use [5], which makes its conclusion a statement about hours rather than about impairment.

One recent result runs the other way and deserves attention. In the ABCD cohort, Nagata et al. [31] found within-person effects of social media time on depressive symptoms across annual waves (β = .07 and .09), together with a null between-person association, which is close to the inverse of what we observed. Several differences could account for this. Their participants were younger at baseline, with a mean age of 9.9 years against 13.2 here, so the two studies may be sampling different points on a developmental curve during which phone ownership and social media access are still being acquired. Their exposure was social media time specifically, whereas ours was time on different devices that could deliver social media among many other things. Their sample was more than twenty times larger, which matters for detecting within-person effects near the medium benchmark. Their waves were a year apart rather than six months. Mobile phone time was also the only device measure whose associations crossed platform boundaries, preceding problematic use of social media, games, and the phone itself. Phones are not a source of reward in the way that a game or a social feed is. They are the vehicle through which such rewards are delivered, which underpins the argument that "smartphone addiction" misnames the object of study and that research should specify the reward and the behavior used to obtain it [15, 17]. Our between-person results align with the predictions of that argument. Phone hours index access to many rewarding activities at once and therefore correlate with problematic engagement in several of them, while the within-person dynamics run between the problematic-use constructs themselves. The high overlap repeatedly reported between problematic smartphone use and problematic social media use, with correlations mostly in the medium-to-large range [35], is easier to interpret in this light.

Depressive symptoms, not anxiety, associate with problematic use within adolescents

Between adolescents, anxiety and depressive symptoms behaved almost identically. Both were reciprocally associated with all three problematic-use scales, with the anxiety-problematic social media use pair carrying the single largest coefficient in the study (β = .204). Within adolescents, anxiety disappeared from the model entirely, whereas depressive symptoms did not.

The asymmetry suggests that anxiety marks which adolescents are prone to problematic use, without the two rising and falling together over a six-month period. Cross-sectional work is consistent with this reading. Social anxiety emerged as the most central node in a network linking gaming disorder to its risk and protective factors among 1,364 young adults, more central than fear of missing out or resilience [61]. Between-person associations between social anxiety and gaming disorder are partly accounted for by use motives and metacognitions [62], and a systematic review found dysfunctional metacognitive beliefs to be associated cross-sectionally with problematic use across gaming, internet, smartphone, and social networking [63]. These descriptions pertain to stable individual differences, which precisely aligns with the level at which anxiety manifested in our data.

Depressive symptoms operated at both levels. An adolescent who reported more depressive symptoms than usual reported more problematic phone and social media use six months later, and the reverse also

held. This is the pattern the I-PACE model describes as a reinforcement cycle, in which negative affect motivates use for mood regulation and escalating problematic use generates further negative consequences [16, 64]. It also extends what has been observed with time-based exposures. Puukko et al. [27] found that depressive symptoms preceded small within-person increases in social media use with no path in the reverse direction, and Marciano, Schulz, et al. [30] found small within-person effects of internet-use duration on depressive symptoms in a Swiss cohort of similar age. Our results add the reverse path and locate it in problematic use rather than in duration.

Problematic social media use and problematic video game use differentially impact mental health

Problematic gaming and problematic social media use behaved differently. Depressive symptoms preceded higher PVGU, and higher well-being preceded lower PVGU, both without a return path. Within-person increases in problematic gaming did not precede changes in mental health. Indeed, problematic gaming, which preceded ADHD symptoms between adolescents, showed no within-person association with them. This one-way pattern aligns with escape and compensation accounts, which predict that gaming intensifies when an adolescent feels worse than usual [65, 66]. It also converges with the direction reported in the ABCD cohort, where pre-existing psychopathology preceded the development of gaming disorder, while gaming disorder did not precede increases in psychopathology, with depressive symptoms the strongest single contributor [66].

In contrast to the limited impact of problematic video game use on mental health, problematic social media use had a much broader impact, with between-subject effect on anxiety, depression, ADHD symptoms and well-being as well as within-subject effect on depression, as just discussed above. Concerning ADHD, within adolescents, problematic social media use and ADHD symptoms reinforced each other. The between-person findings are consistent with meta-analytic estimates of r = 0.361 for ADHD symptoms and problematic social media use [37] and r = 0.296 for ADHD symptoms and gaming disorder [36]. The reciprocal within-person loop between problematic social media use and ADHD symptoms is the single result here with the clearest mechanistic interpretation, and it should be stated carefully. Rapid rewards, unpredictable reinforcement, and frequent interruptions plausibly amplify inattention and impulsivity over weeks and months, and weaker attentional control plausibly increases susceptibility to designs built to prolong engagement [14, 39]. Our design cannot separate these two directions of influence from a third possibility, namely that both sets of self-reports respond to a common fluctuating state, such as school stress, that we did not model here. Self-report also yields overlapping surface content for inattention and problematic use, since both ask about difficulty stopping and lapses in focus, and part of the coupling may reflect that overlap. The reciprocity is nonetheless specific to social media. It did not appear for gaming, which is the pattern one would expect if the relevant feature is the pull of a continuously updating social feed rather than screen exposure in general.

Implications

Two practical points follow, and neither requires the data to be causal.

When deciding who to worry about, hours are a poor guide. Time spent on devices identified a group of adolescents with more symptoms, but the coefficients were small, confined to mobile phones, and did not track when any individual adolescent got worse. In contrast, signs of impaired control tracked both. A screening approach based on duration thresholds will therefore flag many adolescents who are simply well connected and miss those whose use has become difficult to regulate.

When deciding when to act, the within-person results point to detectable warning signs. An adolescent whose problematic phone or social media use has risen above their own habitual level, or whose mood has dropped below it, is more likely at that moment to show the other change six months later. This is different from a population average, and it is the kind of information that parents, schools, and clinicians can act on. It also implies that measurement should shift toward indicators of dysregulation that platforms and researchers can observe, such as nighttime use, checking frequency, and responsiveness to engagement-prolonging design, rather than aggregate duration [14].

Strengths and limitations

The study has four strengths. Four waves at six-month intervals in a school-based sample of 550 adolescents enabled within-person modeling with limited attrition, as 555 of the 636 recruited adolescents completed at least three waves. Time spent was measured across five device categories, and problematic use was assessed across three interactive media in the same participants, which is uncommon in longitudinal work and enabled cross-platform questions. Every pair of variables was modeled twice with the same estimator and covariates, so the between-person and within-person estimates are directly comparable. Interpretation was anchored to published effect-size benchmarks for cross-lagged coefficients [41] and to a decision rule fixed in advance, rather than to significance alone.

Several limitations qualify the conclusions. First, time spent was self-reported in ranges, and self-reported estimates correspond only loosely to logged device use [67]. Some of the difference between our time-spent and problematic-use results may therefore reflect measurement error rather than construct validity, although the same contrast appears in studies using device logs [19, 20]. Future waves should incorporate logged use and data donation.

Second, the PMPU had low internal consistency, particularly at the first wave, which will have attenuated any association involving it. Because several conclusions rest on the PMPU, this matters. It is reassuring that the PSMU, which showed acceptable reliability at every wave, produced the same pattern and generally larger coefficients, so the conclusions are not carried by the weakest instrument. The ASRS is a six-item screener rather than a dimensional measure, and it is scored as binary indicators, which gives the summed score a Kuder–Richardson 20 of .617 to .647. Ordinal α of .762 to .786 indicates that the items themselves are reasonably coherent and that the shortfall comes from the scoring, but it is the

summed score that entered the models, so associations involving ADHD symptoms are likely to be attenuated.

Third, and most consequential for how these results should be interpreted, a within-person path that did not meet our threshold is not evidence that no such effect exists. Partialling out between-person variance leaves less variance to model, and our design supports within-person coefficients around the large benchmark of .12 rather than the medium benchmark of .07 that we adopted for interpretation. Power for a within-person coefficient of .07 was 25%, and detecting one reliably would have called for a sample roughly three times the size of ours. The contrast we draw is therefore between eleven between-person paths involving time spent, with coefficients of .070 to .133, and no within-person path involving time spent that reached the same threshold. It is not a demonstration that time spent has no within-person consequences. Two observations limit how far this qualification extends. Every within-person path that did emerge fell between .103 and .156 in absolute value, above the threshold the design could support, and no coefficient anywhere in the analysis landed in the narrow band where the two levels would be difficult to tell apart.

Fourth, models were fitted to pairs of constructs rather than as a single multivariate system, and we did not test mediation. The patterns described across sections are convergences across bivariate models and should be read as such. The poor fit of many CLPMs, in contrast to the good fit of the corresponding RI-CLPMs, is itself a reason to treat the between-person estimates with some caution.

Fifth, the six-month lag constrains what can be detected. Faster processes, such as the effect of an evening on a feed on the following day, and slower cumulative processes both fall outside this window, so within-person nulls should be read against this timescale.

Sixth, widely used problematic-use scales may partly capture intense but non-pathological engagement rather than genuine dysregulation [68], which argues against reading elevated scores as clinical problems.

Finally, the sample was recruited in German-speaking Switzerland, drawn largely from moderately affluent families, with few adolescents at the low end of the socioeconomic range, and had a baseline median age of 13, so it speaks mainly to early-to-mid adolescence in a high-income setting. Retention required at least three of four waves, which may have selected for more engaged participants. Despite the longitudinal design and the separation of the two levels of variance, the data remain observational. Cross-lagged coefficients describe temporal order, not causal effect.

Conclusions

Across four waves among 550 Swiss adolescents, time spent on devices and problematic media use told two distinct stories about mental health. Between adolescents, both were linked to anxiety, depressive symptoms, and ADHD symptoms, and heavier users of a device reported more problematic use of the corresponding medium. Within adolescents, the time-spent associations did not appear, and a

narrower set of couplings remained. Depressive symptoms and problematic mobile phone and social media use reinforced one another. Declining mood and well-being preceded more problematic gaming, without a return path. Problematic social media use and ADHD symptoms formed a reciprocal loop, and problematic mobile phone use preceded ADHD symptoms.

The practical consequence is that counting hours answers a question about populations, not about children. Problematic patterns of use, together with depressive and ADHD symptoms, describe both which adolescents are vulnerable and when a given adolescent is deteriorating. Prevention and clinical attention are better directed at impaired control over phone and social media use than at total screen time, and research and platform accountability would be better served by indicators of dysregulation than by duration.

Abbreviations

ADHD: attention-deficit/hyperactivity disorder

ASRS: Adult ADHD Self-Report Scale

CFI: comparative fit index

CLPM: cross-lagged panel model

FIML: full-information maximum likelihood

GAD-7: Generalized Anxiety Disorder 7-item scale

ICC: intra-class correlation

I-PACE: Interaction of Person–Affect–Cognition–Execution model

MAR: missing at random

MICAH: Media Interactions, Cognition and Adolescent Health

PHQ-9: Patient Health Questionnaire 9-item depression scale

PMPU: Problematic Mobile Phone Use questionnaire

PMU: problematic media use

PSMU: Problematic Social Media Use scale

PVGU: Problematic Video Game Use scale

RI-CLPM: random-intercept cross-lagged panel model

RMSEA: root mean square error of approximation

SD: standard deviation

SES: socioeconomic status

TS: time spent

WHO-5: World Health Organization Five Well-Being Index

Declarations

Clinical trial number: not applicable.

Ethics approval and consent to participate

The study protocol was approved by the University Commission for Ethical Research at the University of Geneva (reference number CUREG-2023-05-71) and was conducted in accordance with the Declaration of Helsinki. Written informed consent was obtained from one legal guardian of each adolescent participant before enrollment, and all participating adolescents provided assent.

Use of artificial intelligence.

During the preparation of this manuscript, the authors used Claude (Anthropic) to restructure and rewrite text drafted by the authors, to improve clarity and concision, and to assist in preparing tables and figures. The tool was not used to generate data, to conduct or interpret the statistical analyses, or to produce results. All scientific content, including the study design, the analyses, the interpretation of the findings, and the selection of the cited literature, originates from and remains the responsibility of the authors. The authors reviewed and edited all AI-assisted text, verified the reported values against the analysis output and the citations against the primary sources, and take full responsibility for the content of the publication. All authors read and approved the final version of the manuscript.

Consent for publication

Not applicable.

Availability of data and materials

The datasets generated and analyzed during the current study are available from the corresponding author on reasonable request.

Competing interests

The authors declare that they have no competing interests.

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Authors' contributions

AND, MJ, FVH, GW, DB and BB contributed to the conceptualisation of the study. MJ and FVH performed the data collection. AND, PG, DB and BB carried out the statistical analysis. AND, DB and BB drafted the manuscript. FVH, GW, DB and BB supervised the project. AND, MJ, FVH and BB were responsible for study coordination. DB and BB acquired the funding. All authors read and approved the final manuscript.

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Tables

Table 1. Descriptive statistics for all study variables across four waves. Values are raw means, with standard deviations in parentheses. All variables were standardized to the T1 distribution before analysis.

Variable	T1 mean (SD)	T2 mean (SD)	T3 mean (SD)	T4 mean (SD)	Effect of wave
Time spent on devices, hours per week					
Mobile phone	19.69 (13.44)	21.23 (12.94)	22.78 (14.12)	23.24 (12.78)	$F(3, 2145.5) = 19.21$, $p < .001$
Computer	9.09 (10.97)	8.82 (10.88)	9.75 (12.25)	9.48 (11.30)	$F(3, 2148.7) = 3.28$, $p < .05$
Video game console	7.21 (10.15)	6.42 (10.86)	6.53 (10.19)	5.27 (9.03)	$F(3, 2145.4) = 14.47$, $p < .001$
Television	7.66 (6.93)	7.35 (7.22)	7.74 (8.53)	7.04 (7.86)	$F(3, 2155.5) = 4.24$, $p < .01$
Tablet	4.02 (5.74)	3.92 (6.13)	4.42 (7.11)	3.95 (6.45)	$F(3, 2166.0) = 1.07$, $p = .360$
Problematic media use					
PMPU total, 15–60	30.51 (6.07)	30.98 (6.78)	30.89 (6.51)	31.39 (6.47)	$F(3, 2027.0) = 22.98$, $p < .001$
PSMU total, 0–9	1.98 (1.98)	1.91 (1.99)	1.80 (1.98)	1.67 (1.96)	$F(3, 2117.1) = 3.84$, $p < .01$
PVGU total, 0–9	1.13 (1.79)	0.76 (1.59)	0.75 (1.56)	0.71 (1.64)	$F(3, 2070.3) = 12.00$, $p < .001$
Mental health, well-being and ADHD					
GAD-7 anxiety, 0–21	5.67 (4.90)	5.72 (4.91)	5.56 (5.17)	5.78 (5.14)	$F(3, 1975.3) = 0.86$, $p = .464$
PHQ-9 depression, 0–27	6.60 (5.84)	6.97 (5.92)	6.95 (5.88)	7.28 (6.03)	$F(3, 1958.2) = 3.55$, $p < .05$
WHO-5 well-being, 0–25	15.26 (5.52)	14.98 (5.07)	14.97 (5.38)	14.96 (5.22)	$F(3, 1953.6) = 1.45$, $p = .227$
ASRS total, 0–24	1.97 (1.66)	2.06 (1.64)	1.95 (1.66)	2.06 (1.67)	$F(3, 1987.0) = 0.47$, $p = .702$

PMPU, Problematic Mobile Phone Use questionnaire. PSMU, Problematic Social Media Use scale. PVGU, Problematic Video Game Use scale. GAD-7, Generalized Anxiety Disorder 7-item scale. PHQ-9, Patient Health Questionnaire 9-item scale. WHO-5, World Health Organization 5 Well-Being Index. ASRS, Adult ADHD Self-Report Scale, six-item short screener. Possible score ranges are given in parentheses after each scale name.

Table 2. Mean standardized cross-lagged coefficients for every pair of variables in which at least one direction reached the interpretation threshold, estimated between adolescents (CLPM) and within adolescents (RI-CLPM).

Pair (X, Y)	Between X→Y	Between Y→X	Within X→Y	Within Y→X
Time spent and problematic use				
Mobile phone time, PMPU	.133	.094	ns	ns
Mobile phone time, PSMU	.070	.086	ns	ns
Mobile phone time, PVGU	.073	ns	ns	ns
Console time, PVGU	.128	.076	ns	ns
Problematic use with problematic use				
PMPU, PSMU	.098	.096	ns	**.140**
PMPU, PVGU	.093	(.045)	ns	ns
PSMU, PVGU	.082	ns	ns	ns
Time spent and mental health, ADHD and well-being				
Mobile phone time, GAD-7 anxiety	.083	(.051)	ns	ns
Mobile phone time, PHQ-9 depression	.092	(.052)	ns	ns
Mobile phone time, ASRS ADHD	.111	.082	ns	ns
Problematic use and mental health, ADHD and well/being				
PMPU, GAD-7 anxiety	.096	.087	ns	ns
PMPU, PHQ-9 depression	.104	.090	**.133**	**.103**
PMPU, WHO-5 well-being	−.087	(−.047)	ns	ns
PSMU, GAD-7 anxiety	**.204**	**.191**	**ns**	**ns**
PSMU, PHQ-9 depression	**.154**	**.201**	**.106**	**.142**
PSMU, WHO-5 well-being	**−.159**	**−.095**	**ns**	**ns**
PVGU, GAD-7 anxiety	.088	.077	ns	ns
PVGU, PHQ-9 depression	.077	.106	ns	**.115**
PVGU, WHO-5 well-being	ns	−.077	ns	**−.125**
PMPU, ASRS ADHD	.130	(.065)	**.156**	ns
PSMU, ASRS ADHD	**.190**	**.155**	**.151**	**.111**
PVGU, ASRS ADHD	.093	(.063)	ns	ns

Note. Each row is one bivariate model pair. X and Y follow the order given in the first column, so “Between X→Y” for the row “PMPU, PHQ-9 depression” is the between-person path from problematic mobile phone use to depressive symptoms at the following wave. Values in bold are the within-person paths, shown in bold to make the contrast between the two levels visible. Pairs in which no direction reached the threshold at either level are not listed. All pairs, all sub-threshold coefficients and the fit indices for every model are given in Supplementary Table S6. PMPU, Problematic Mobile Phone Use questionnaire. PSMU, Problematic Social Media Use scale. PVGU, Problematic Video Game Use scale. GAD-7, Generalized Anxiety Disorder 7-item scale. PHQ-9, Patient Health Questionnaire 9-item scale. WHO-5, World Health Organization Five Well-Being Index. ASRS, Adult ADHD Self-Report Scale short screener. CLPM, cross-lagged panel model. RI-CLPM, random-intercept cross-lagged panel model.

Figures

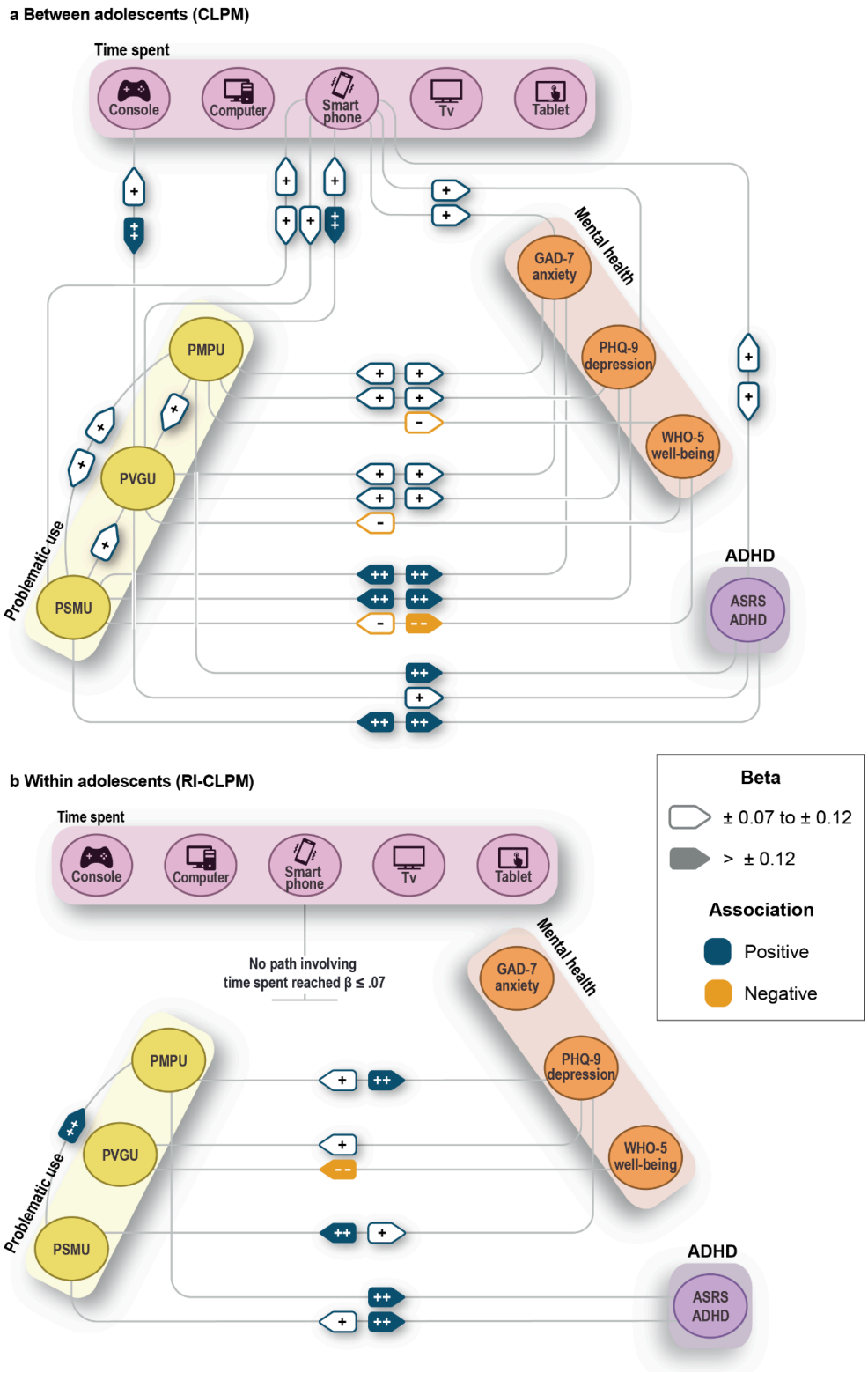


Figure 1

Cross-lagged paths between time spent on devices, problematic media use, mental health and ADHD symptoms, estimated between adolescents (**a**, CLPM) and within adolescents (**b**, RI-CLPM). Node groups: time spent on five device categories (pink), problematic use of mobile phones, social media and video games (yellow), anxiety, depressive symptoms and well-being (orange), and ADHD symptoms (purple). A line is drawn whenever at least one direction reached the medium benchmark. Arrowheads

mark the direction of each path, and the badge nearest an arrowhead gives the effect in that direction. Badge colour and symbol give the sign of the coefficient, dark blue with “+” for positive and orange with “−” for negative. One symbol indicates .07 ≤ |β| < .12 and two symbols indicate |β| ≥ .12, following the medium and large benchmarks of Orth et al. [41]. Open badges mark coefficients below .12 and filled badges those of .12 or above. Paths with mean |β| below .07, and paths for which at least one of the three wave-to-wave coefficients was not significant at p ≤ .05, are not shown. TS, time spent. PMPU, Problematic Mobile Phone Use questionnaire. PSMU, Problematic Social Media Use scale. PVGU, Problematic Video Game Use scale. GAD-7, Generalized Anxiety Disorder 7-item scale. PHQ-9, Patient Health Questionnaire 9-item scale. WHO-5, World Health Organization Five Well-Being Index. ASRS, Adult ADHD Self-Report Scale.

Supplementary Files

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