

A Large Scale Test of the Goldilocks Hypothesis: Quantifying the Relations Between Digital
Screens and the Mental Well-Being of Adolescents

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Abstract

Although the time adolescents spend with digital technologies has sparked wide concerns their use might be negatively associated with mental well-being, these potential deleterious influences have not been rigorously studied. In line with a preregistered analysis plan, data from a representative sample of English adolescents ($n = 120,115$) provided evidence that the links between digital screen time and mental well-being follow quadratic functions. Further, these results showed that the relations with digital technology vary as a function of when it is used, suggesting that a full understanding of the impact of these recreational activities involves examining their functionality among other daily pursuits. Overall, evidence indicated that moderate digital technology use is not intrinsically harmful and may be advantageous in a connected world. Findings inform recommendations for limiting adolescents' technology use and provide a template for conducting rigorous investigations into the relations between digital technology and child and adolescent health.

Keywords: screen use, adolescents, mental well-being

A Large Scale Test of the Goldilocks Hypothesis: Quantifying the Relations Between Digital Screens and the Mental Well-Being of Adolescents

The proliferation of digital screens has fundamentally changed how humans work, play, and socialize. Rapid technological developments in high-speed Internet, flat panel displays, and mobile computing power have led to devices that now define and shape modern childhood (Lenhart, Smith, Anderson, Duggan, & Perrin, 2015). For example, in the span of a decade the amount of time adolescents spend online has more than doubled from an average of 8 hours per week in 2005 to 18.9 hours weekly today (Ofcom, 2015), and the time spent with these technologies, especially during childhood and adolescence, has sparked concerns their use might be negatively associated with mental and social well-being (for a review of this controversy see, Bell, Bishop, & Przybylski, 2015). Indeed, the American Academy of Pediatrics (AAP; Council on Communications and Media, 2013) has recommended that restrictions be placed on children's screen time, communicating that there are progressive costs of screen time for children's wellness, though this approach has been criticized by developmental (Linebarger & Vaala, 2010) and clinical (Ferguson & Donnellan, 2014) researchers.

The goal of the present research was to evaluate different ways of understanding how screen time is linked to mental well-being, and empirically quantify and define moderate engagement. To date, one view of digital screen effects predominates the literature, the displacement hypothesis (Neuman, 1988), which argues the harms of technology are directly proportional to exposure. Effects are negative because they supplant alternate activities such as socializing with peers and family, reading books, or exercising. We propose to test an alternate theory, implicit in the literature but not explicitly studied, which we label the 'digital' *Goldilocks hypothesis*, that digital screen use at moderate levels is not intrinsically harmful (Etchells, Gage,

Rutherford, & Munafò, 2016; Parkes, Sweeting, Wight, & Henderson, 2013; Przybylski, 2014) and may be advantageous in a connected world, whereas ‘overuse’ of screens may indeed displace activities, for example interfering with school, extracurricular, or other social activities (Valkenburg & Peter, 2009). In the tale, Goldilocks identifies that moderation (in porridge and beds) is “just right.” Similarly, it might be that “too little” tech use deprives young people of important social information and peer pursuits, whereas “too much” may displace meaningful analogue ones. Our Goldilocks hypothesis postulates there are empirically derivable balance points, moderate levels, that are “just right” for optimally connected young people.

To the extent that digital activities either enrich adolescents or displace more rewarding activities, we should see they have, respectively, positive or negative effects on mental well-being, where well-being can be understood as flourishing characterized by positive emotions, effective functioning including psychosocial functioning, and a sense of life satisfaction (Ryan & Deci, 2000; Tennant et al., 2007). For the displacement hypothesis the relationship between screen use is understood to be a negative monotonic one, as each “dose” of screen time takes the place of alternative pursuits which might be more edifying. Recent research suggests this account may not accurately describe the role of digital screens in everyday life. Indeed, adolescents must develop their identity and build life and social skills, and doing so fosters well-being (Luyckx, Soenens, Goossens, Beckx, & Wouters, 2008; Yarcheski, Mahon, & Yarcheski, 2001). If the Goldilocks hypothesis accurately describes the data, it may be because technology provides opportunities to pursue these developmental challenges in a satisfying way. For example, although many may think of gaming as a socially isolating activity, research indicates 38% of adolescent boys exchange online gaming handles as one of the first pieces of information they share when they meet someone with whom they would like to be friends (Lenhart et al., 2015).

Similarly, 83% of adolescents say social media makes them feel more connected to their friends, and 68% say they have received social support using these technologies in tough or challenging times (Lenhart et al., 2015). Taking this together, there is good reason to think digital engagement, in moderation, may not be disruptive, and that it may even be a supportive part of development.

Much of what is known regarding the possible influence of screens comes from the study of sedentary and non-sedentary activity in young people. Guided by the displacement hypothesis, existing research has compared activities in terms of physical health correlates such as body-mass index (Anderson, Economos, & Must, 2008; Boone, Gordon-Larsen, Adair, & Popkin, 2007), rigorous exercise (Anderson et al., 2008; Sisson, Broyles, Baker, & Katzmarzyk, 2010), or energy expenditure (Lanningham-Foster et al., 2006). Definitions and operationalizations of what constitutes engagement vary, but most test how doses of each relate to physical and psychological outcomes. Nearly all report statistically significant differences between sedentary and non-sedentary activities, identifying the former as deleterious, but patterns evident in the existing literature hint at a richer dynamic than the displacement account. First, these studies show weak links to health that suggest the possibility of a stronger alternative theoretical account (Anderson et al., 2008; Boone et al., 2007; Iannotti, Kogan, Janssen, & Boyce, 2009). Second, research indicates any detrimental effects of screen use on physical health depend on the type of digital activity, with some screen activities *promoting* physical activity (Lanningham-Foster et al., 2006). Third, studies examining physical outcomes (Anderson et al., 2008; Boone et al., 2007; Sisson et al., 2010), and preliminary work examining psychological ones, show inconsistent linear relations (Kremer et al., 2014), or use post-hoc bucketed predictors, and findings vary widely in their estimates for comparable types of screen use (Cao et al., 2011;

Hamer, Stamatakis, & Mishra, 2009; Mark Hamer, Stamatakis, & Mishra, 2010). A handful of recent large-scale studies focused on emotional and social functioning indicate that low to moderate levels of video gaming (Etchells et al., 2016; Przybylski, 2014) and watching films (Parkes et al., 2013) have little or no relations to functioning at levels below 2 to 3 hours per day, and may only have negative effects for young people at higher levels of use.

The present research was the first to systematically test the presence of curvilinear relations on continuous measurements of screen use, keeping in mind type of screen use and day of the week. In line with the Goldilocks hypothesis, we expected to see curvilinear links with no costs to mental well-being for moderate use, and some detriments at high levels of use. A first for this area, we defined low and high use empirically by testing for local maxima, the inflection point, operationalized as the points at which the slopes relating screen use to well-being approach zero before reversing sign. This determined the point at which each type of media use shifted from having a null or positive relation to having a negative relation, indicating detrimental relations with mental well-being.

Methods

Participants

Participants were identified using the United Kingdom's Department for Education National Pupil Database. Fieldwork covered a total of 150 local authorities across England with the aim of making sufficient observations to attain a +/- 0.3% margin of error at a 95% confidence interval for English youths aged 15 years across the country. A pre-notification letter was sent to parents or carers of participants and gave them the opportunity to opt their child out of the survey. Providing this did not happen, written consent was collected directly from all participants. The original sampling frame for the study were 298,080 young people aged 15

years. Of these, 2,835 addresses were undeliverable or opted-out prior to fieldwork. A total of 120,115 participants responded with usable data through the use of paper ($n = 100,850$) or online questionnaire ($n = 19,265$).

Ethical Review

A comprehensive ethical review for the data collection was conducted by the United Kingdom's National Children's Bureau and the ethics review for data analysis was conducted by the research ethics committee at the University of Oxford (C1A16015).

Measures

Criterion variable – mental well-being. The Warwick-Edinburgh Mental Well-being Scale (Tennant et al., 2007), a 14-item self-report instrument validated for use in general population samples of those aged 13 years and above, was used to measure the happiness, life satisfaction, psychological functioning, and social functioning of participants. In line with past research using this instrument with young people (Stewart-Brown et al., 2009), the scale showed high internal consistency (Cronbach's $\alpha = .90$), and scores ranged from 14 to 70 ($M = 47.52$, $SD = 9.55$).

Explanatory variable – digital screen time. Participants were asked four questions regarding how they spend their free time using different kinds of digital screens. Specifically, participants were asked about their use of screens to watch (e.g., films, TV programs), play games (e.g., on computers and consoles), use computers (e.g., Internet, email), and use smartphones (e.g., social networking, chatting online).

Control and confounding variables. Past research has linked both the explanatory and criterion variables to gender (Clarke et al., 2011), economic factors and technology access (Helsper, 2010; Tennant et al., 2007), and ethnicity (Clarke et al., 2011; Eynon & Helsper, 2015;

UK Government, 2015). These were treated as control variable for the purposes of statistical modelling. If participants self-identified as being male they were coded 1; if not they were coded 0. Aggregate information derived from postcode data was used to identify if participants lived in a relatively deprived local authority district (UK Government, 2015). If a participant lived in an area in upper two quintiles of the multiple deprivation index, that is, an area that scores high on unemployment, crime, poor public services, and barriers to housing, they were coded 1, if they did not they were coded 0. Minority status as an individual difference variable was assessed by asking participants about their ethnic background, an identification based on many things such as skin color, culture, language, or family ancestry. In line with the approach taken by the United Kingdom Department of National Statistics (UK Government, 2015), participants who self-identified as White were coded as 0, whereas other ethnicities were coded 1.

Results

Data, Materials, and Analytic Strategy

The preregistered analytic strategy (osf.io/jkz9s) and the study materials, protocol, and data (osf.io/82ybd) are available using the Open Science Framework. Of note, there were three deviations from the registered analysis plan. First, two control variables the authors intended to include in statistical models were not available: (1) whether participants' parents were married, and (2) whether participants were born in the United Kingdom. Second, after plotting the data (see Figure 2), it was clear from interocular tests that there were no negative monotonic relationships between digital screen time and mental well-being. A negative linear trend could technically be fit onto the data but its suitability would be poor as outcome values increased across levels of the explanatory variables before decreasing. As such, our regression models considered trends with both linear and quadratic components. Finally, when examining the

distributions of total digital screen time, the sums of estimates, it was clear that many participants were reporting simultaneous screen use; approximately 20% of the sample reported a sum of more than 12 hours of engagement on weekdays and 35% of the sample reported a total of more than 12 hours on weekends. Given this finding was consistent with earlier research demonstrating these media are often used in parallel (Eynon & Helsper, 2015), testing the aggregate and individual reports, as planned, did not make theoretical or practical sense.

Exploratory Analyses

Digital screen engagement was quite popular with our sample, as more than 99.9% of those interviewed reported allocating some time to at least one form on a daily basis. Exploratory t-test analyses indicated adolescent girls reported spending more time using smartphones, computers, and watching videos, and boys devoted more time to computer and console games ($ps < 0.001$; Figure 1). Paired samples t-tests showed adolescents engaged digital screens between 25m and 1hr5m longer on weekends than weekdays and these differences were significant, all $ps < .001$. Repeated measures ANOVAs using within-subjects contrasts indicated smartphone screens were used most on weekdays whereas watching videos dominated free time on weekends, followed by computers and gaming, all $ps < .001$ (Figure 1).

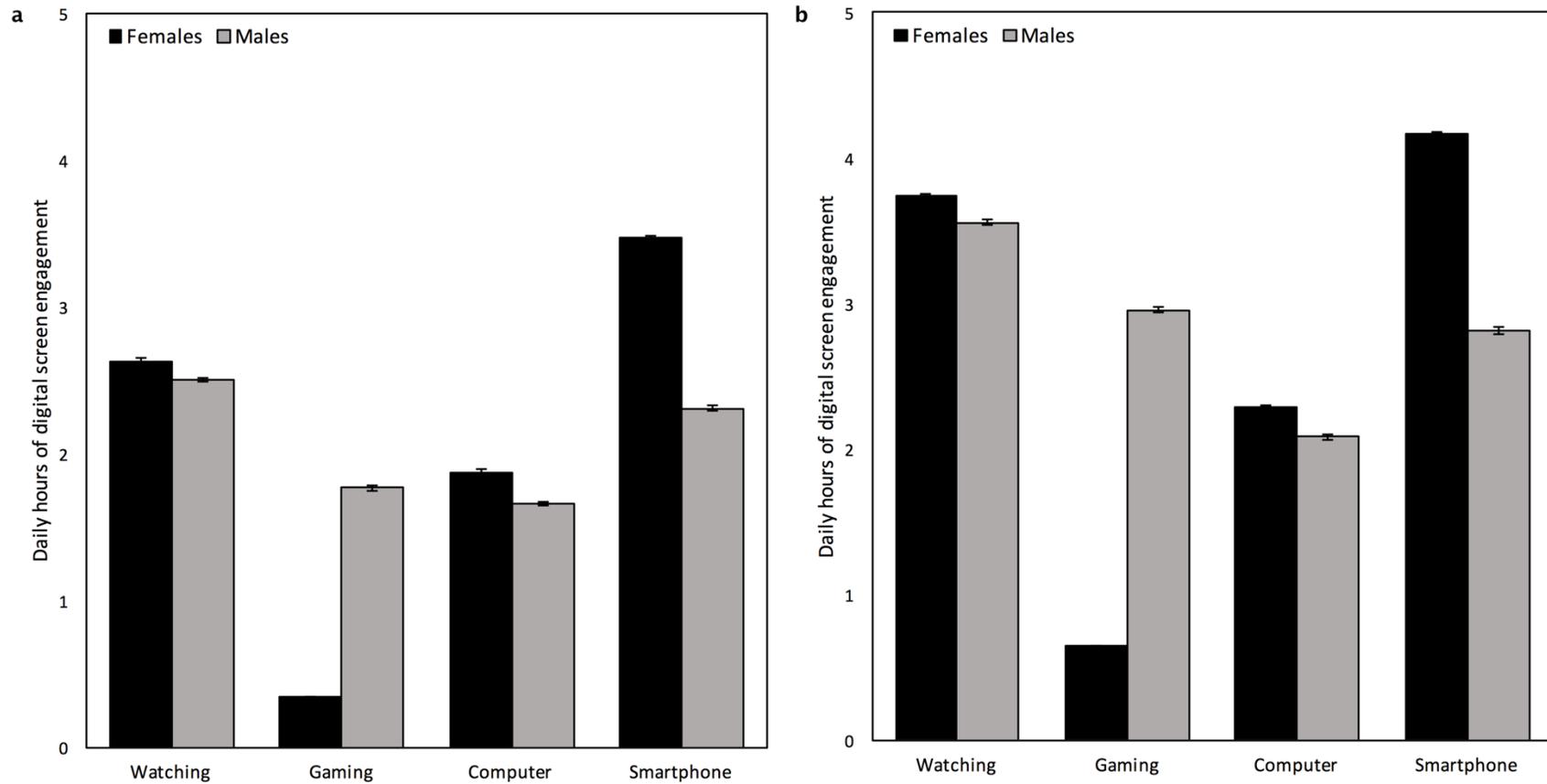


Figure 1. Daily digital screen time for male and female adolescents. **A.** Weekend digital screen time. **B.** Weekday digital screen time. Error bars denote the 95% confidence interval for the observed means. All male to female comparisons were statistically significant at the $p < 0.001$ level.

Confirmatory Analyses

In line with the preregistered analysis plan, a series of regression models tested weekday and weekend engagement with digital screens in comparison to a measure of mental well-being, assessed with the Warwick-Edinburgh Mental Well-being Scale (Clarke et al., 2011). Regression analyses considering linear and non-linear components (Table 1) indicated the quadratic trends evident in Figure 2 were statistically significant for all types of screen engagement. Looking at the direct links between screen use and mental health, concave down quadratic functions were in evidence for watching videos on weekdays, $b = -0.14$, $p < .001$, $|d| = 0.09$, and weekends, $b = -0.17$, $p < .001$, $|d| = 0.13$, playing games on weekdays, $b = -0.33$, $p < .001$, $|d| = 0.17$, and weekends, $b = -.026$, $p < .001$, $|d| = 0.20$, computer use on weekdays, $b = -0.17$, $p < .001$, $|d| = 0.11$, and weekends, $b = -0.18$, $p < .001$, $|d| = 0.14$, and smartphone use on weekdays, $b = -0.02$, $p = .019$, $|d| = 0.01$, and weekends, $b = -0.10$, $p < .001$, $|d| = 0.09$. Consistency across both weekdays and weekends and these forms of digital screens provided support for the Goldilocks hypothesis. The nature of the relation between screen use and mental well-being was qualitatively different at low levels versus high levels, a direct comparison which has not been, to our knowledge, made in previous work. Because past research has linked both the explanatory and outcome variables to gender (Ofcom, 2015; Clarke et al., 2011; Eynon & Helsper, 2015), economic factors and technology access (Clarke et al., 2011; Helsper, 2010), and ethnicity (Clarke et al., 2011; UK Government, 2015), these were treated as control variable for the purposes of statistical modelling. Results showed notable reductions in observed effects sizes but the direction and significance of effects remained unchanged after adjusting for variability in these factors (Table 2).

Table 1***Models Linking Mental Well-Being to Engagement Without Adjustments for Controls***

		<i>b</i>	Std. Error	95% CI	<i>p</i>	<i>d</i>
Watching						
Weekday	<i>x</i>	0.98	0.10	0.79 to 1.17	< .001	0.06
	<i>x</i> ²	-0.14	0.01	-0.16 to -0.12	< .001	0.09
Weekend	<i>x</i>	1.53	0.09	1.36 to 1.71	< .001	0.10
	<i>x</i> ²	-0.17	0.01	-0.18 to -0.15	< .001	0.13
Playing						
Weekday	<i>x</i>	3.56	0.11	3.34 to 3.77	< .001	0.19
	<i>x</i> ²	-0.33	0.01	-0.35 to -0.31	< .001	0.17
Weekend	<i>x</i>	3.16	0.08	3.00 to 3.32	< .001	0.22
	<i>x</i> ²	-0.26	0.01	-0.28 to -0.25	< .001	0.20
Computer						
Weekday	<i>x</i>	1.32	0.09	1.13 to 1.50	< .001	0.08
	<i>x</i> ²	-0.17	0.01	-0.18 to -0.15	< .001	0.11
Weekend	<i>x</i>	1.61	0.08	1.45 to 1.78	< .001	0.11
	<i>x</i> ²	-0.18	0.01	-0.19 to -0.16	< .001	0.14
Smartphone						
Weekday	<i>x</i>	-0.50	0.08	-0.65 to -0.35	< .001	0.04
	<i>x</i> ²	-0.02	0.01	-0.03 to -0.01	.019	0.01
Weekend	<i>x</i>	0.50	0.08	-0.35 to 0.65	< .001	0.04
	<i>x</i> ²	-0.10	0.01	-0.11 to -0.09	< .001	0.09

Watching = number of hours spent using screens to watch (e.g., films, TV programs), *playing* = number of hours spent playing games (e.g., on computers and consoles), *computer* = number of hours spent using computers (e.g., Internet, email), and *smartphone* = number of hours spent using smartphones (e.g., social networking, chatting online). *x* = linear relation, *x*² = quadratic relation. Quadratic relations were tested simultaneously controlling for linear relations. Cohen's *d* is the standardized effect size for the links between an activity and mental well-being during week-days, and week-ends, separately.

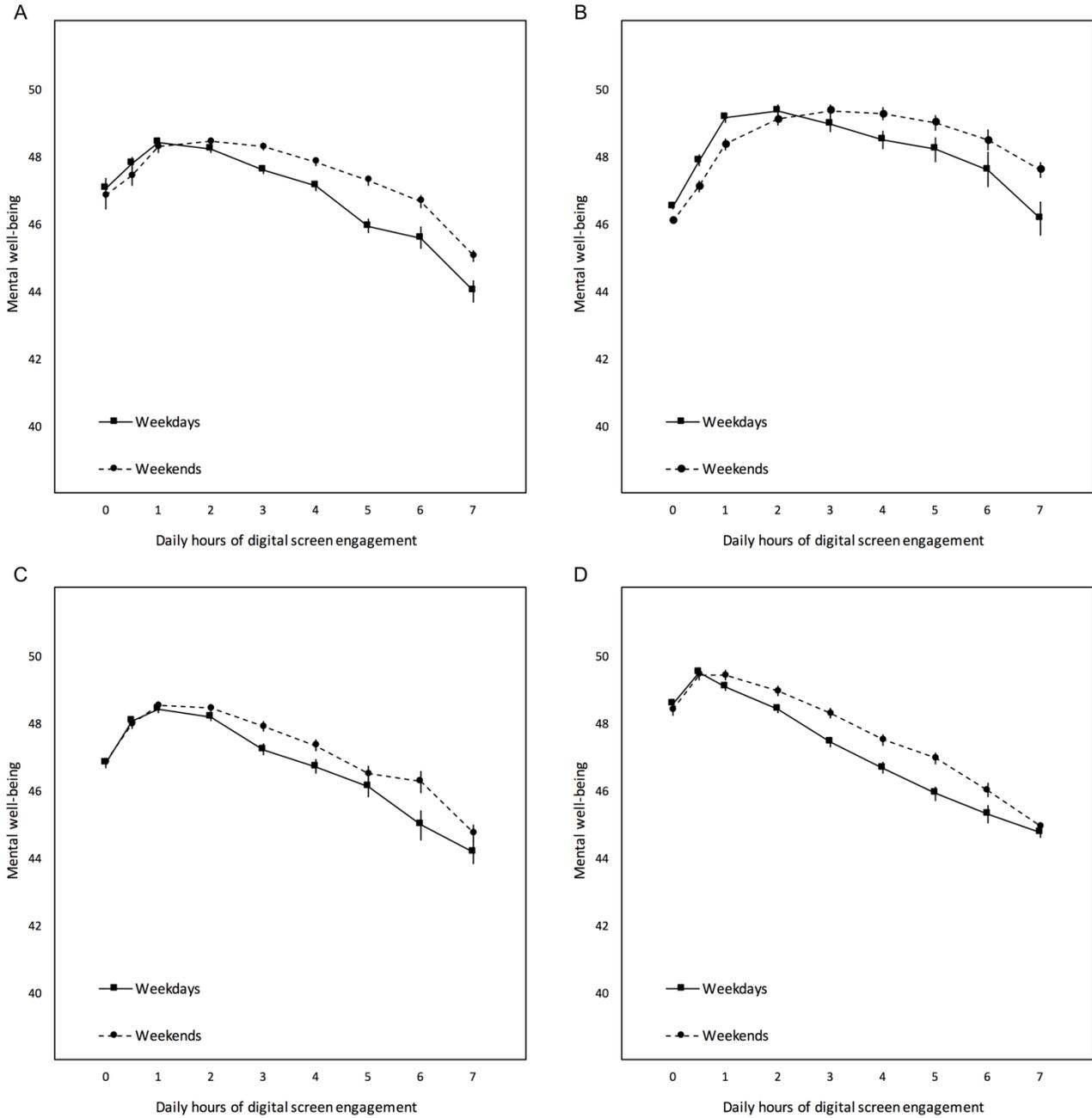


Figure 2. Curvilinear trends between daily digital screen time and mental well-being. **A.** TV and movies. **B.** Video games. **C.** Using computers **D.** Using smart phones. Error bars denote the 95% confidence interval for the observed means. All quadratic trends were significant at the $p < 0.001$ level.

Table 2***Models Linking Mental Well-Being from Engagement with Adjustments for Controls***

		<i>b</i>	Std. Error	95% CI	<i>p</i>	<i>d</i>	<i>Extremum</i>
Watching							
Weekday	<i>x</i>	0.95	0.09	0.77 to 1.13	< .001	0.06	3hr41m
	<i>x</i> ²	-0.13	0.01	-0.15 to -0.11	< .001	0.09	
Weekend	<i>x</i>	1.65	0.09	1.48 to 1.82	< .001	0.11	4hr50m
	<i>x</i> ²	-0.17	0.01	-0.19 to -0.16	< .001	0.13	
Playing							
Weekday	<i>x</i>	0.21	0.11	-0.01 to 0.43	.059	n/a	1hr40m
	<i>x</i> ²	-0.06	0.01	-0.09 to -0.04	< .001	0.03	
Weekend	<i>x</i>	0.57	0.09	0.41 to 0.74	< .001	0.04	3hr35m
	<i>x</i> ²	-0.08	0.01	-0.10 to -0.07	< .001	0.06	
Computer							
Weekday	<i>x</i>	1.43	0.09	1.25 to 1.61	< .001	0.09	4hr17m
	<i>x</i> ²	-0.17	0.01	-0.18 to -0.15	< .001	0.11	
Weekend	<i>x</i>	1.64	0.08	1.48 to 1.79	< .001	0.09	4h39m
	<i>x</i> ²	-0.18	0.01	-0.19 to -0.16	< .001	0.11	
Smartphone							
Weekday	<i>x</i>	0.23	0.08	0.08 to 0.38	.003	0.02	1hr57m
	<i>x</i> ²	-0.06	0.01	-0.07 to -0.05	< .001	0.05	
Weekend	<i>x</i>	0.98	0.08	0.83 to 1.12	< .001	0.07	4hr10m
	<i>x</i> ²	-0.12	0.01	-0.13 to -0.10	< .001	0.10	

x = linear relation, *x*² = quadratic relation between engagement and mental well-being. Engagement variables were defined at Step 2 of the model. *Watching* = number of hours spent using screens to watch (e.g., films, TV programs), *playing* = number of hours spent playing games (e.g., on computers and consoles), *computer* = number of hours spent using computers (e.g., Internet, email), and *smartphone* = number of hours spent using smartphones (e.g., social networking, chatting online). Cohen's *d* is the standardized effect size for the links between activity and mental well-being over and above controls.

Empirically derived inflection points. To further define the quadratic patterns present in the data, local extrema were calculated for models statistically controlling for variance linked to potential confounds. If indeed the relations between mental well-being and digital screens are non-linear, systematically quantifying the point at which engagement shifts from benign to harmful is important (Nelson & Simonsohn, 2014). In line with the preregistered analysis plan, results from these analyses revealed clear inflection points relating engagement to well-being. Local extrema were at 1h40m for weekday video game play and 1h57m for weekday smartphone use. In contrast, watching videos and recreational computer use appeared less potentially disruptive at these levels, showing local weekdays maxima of 3hr41m and 4hr17m, respectively. Indeed, some digital activities might be better suited to weekday use than others. For example, it is relatively easy to switch between using computer for a range of tasks, whereas digital activities such as using a gaming console require more dedicated attention. On weekends, the derived inflection points ranged from 3hr35m for playing video games to 4hr50m for watching videos (Figure 3; Table 2). These findings indicated the pivot points between moderate and potentially harmful screen time were notably higher and less variable, suggesting again the nature and timing of engagement matter for understanding the relations between digital screens and mental well-being.

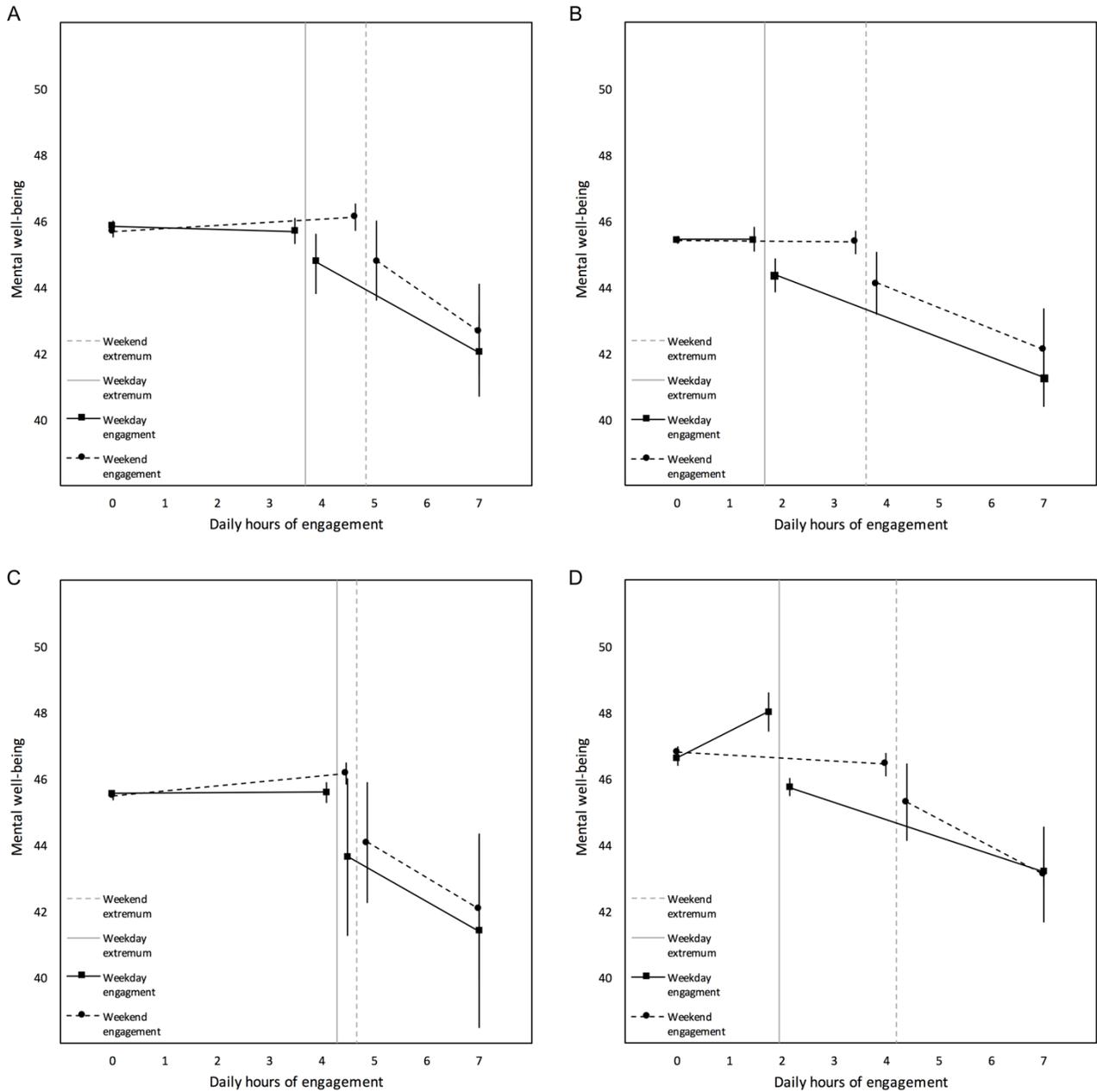


Figure 3. Linear trends daily digital screen time and mental well-being falling on either side of the local maxima for **A.** TV and movies. **B.** Video games. **C.** Using computers **D.** Using smart phones. Error bars denote the 95% confidence interval for observed slopes ($*p = 0.001$, $**p < 0.001$).

Below these thresholds (Figure 3; Table 3), the relations between screen engagement and mental well-being were largely flat ($ps > 0.183$), excepting positive links in the case of weekday watching ($b = 0.09, p = 0.001, |d| = 0.02$), weekend computer use ($b = 0.15, p < 0.001, |d| = 0.04$), and weekday smartphone use ($b = 0.80, p < 0.001, |d| = 0.07$), and a negative link with weekend smartphone use ($b = -0.10, p < 0.001, |d| = 0.03$). Above these thresholds, consistent negative monotonic relationships were in evidence for all forms of digital screen time ($bs > -0.53, ps < 0.05, |d| = 0.15$ to 0.20), indicating some detrimental relations linked to screen use. These findings further support a goldilocks hypothesis. It appears that with the exception of using smartphones during weekends, moderate digital activity as defined by the inflection points reported above does not displace other, more enriching activities essential for adolescents to experience mental well-being. Devoting time to smartphone screens during weekends may be an exception because socializing through virtual means when time is otherwise unstructured may be more susceptible to dysregulation or may indeed displace other beneficial week-end social activities (Ryan, Bernstein, & Brown, 2010).

Observed effect sizes. Although it is not typical for papers on digital screen effects to qualify statistically significant differences by reporting the amount of variability that is accounted for by these recreational activities, doing so is crucial for understanding the scope of the potential influence of screen time (Cumming, 2012). In this study, we found that average negative effect size (Cohen's d) of the slopes for engagement in excess of the inflection points was $d = 0.18$. In other words, these negative slopes accounted for 1.0% or less of the observed variability in the mental well-being of young people. Exploratory analyses examining links between individual difference measures in the data set and well-being provide some context to interpret these modest relationships. These indicated that the possible negative effects of excessive screen time are less than a third of the size of the positive associations between well-being and eating breakfast regularly ($d = 0.54$), getting regular

sleep ($d = 0.58$), or the variance associated with the control variables identified in our preregistered analysis plan ($d = 0.56$). Although the relations reported above are statistically significant, it is noteworthy that both the size of the linear and quadratic relations between screen time and well-being notably diminished once control factors were accounted for, and that the influence of incremental use above moderate levels accounts for very little of the variability we observed in mental well-being.

Table 3***Mental Well-Being Trends for Engagement Levels Below (\leq) and Above ($>$) Observed Extrema***

	<i>Extremum</i>	<i>b</i>	Std. Error	95% CI	<i>p</i>	<i> d </i>
Watching						
Weekday	\leq	-0.04	0.03	-0.11 to 0.02	.183	n/a
	$>$	-0.90	0.05	-1.00 to -0.80	< .001	0.20
Weekend	\leq	0.09	0.03	0.04 to 0.15	.001	0.02
	$>$	-1.09	0.06	-1.20 to -0.98	< .001	0.20
Playing						
Weekday	\leq	0.00	0.09	-0.18 to 0.18	.984	n/a
	$>$	-0.60	0.04	-0.67 to -0.53	< .001	0.19
Weekend	\leq	-0.02	0.03	-0.09 to -0.05	.519	n/a
	$>$	-0.63	0.05	-0.72 to -0.53	< .001	0.17
Computer						
Weekday	\leq	0.01	0.02	-0.04 to 0.06	.665	n/a
	$>$	-0.89	0.11	-0.11 to -0.67	< .001	0.15
Weekend	\leq	0.15	0.02	0.10 to 0.19	< .001	0.04
	$>$	-0.93	0.08	-1.09 to -0.77	< .001	0.16
Smartphone						
Weekday	\leq	0.80	0.11	-0.67 to -0.40	< .001	0.07
	$>$	-0.53	0.02	-0.56 to -0.49	< .001	0.20
Weekend	\leq	-0.10	0.02	-0.15 to -0.05	< .001	0.03
	$>$	-0.83	0.06	-0.94 to -0.74	< .001	0.14

Results for controls at Step 1 of the model presented in Table S2. Engagement variables were defined at Step 2 of the model. *Watching* = number of hours spent using screens to watch (e.g., films, TV programs), *playing* = number of hours spent playing games (e.g., on computers and consoles), *computer* = number of hours spent using computers (e.g., Internet, email), and *smartphone* = number of hours spent using smartphones (e.g., social networking, chatting online). Cohen's *d* is the standardized effect size for the links between mental well-being and high and low levels of the activity (above and below the extrema) over and above controls.

Discussion

In this study we show that the relationships between digital screen time and mental well-being are non-linear, and we find evidence that moderate use is not harmful. The presence of consistent concave down quadratic relations lends empirical support to our proposed Goldilocks hypothesis, indicating that post-hoc groupings oversimplify our understanding of the nature of the relations between digital screen use and adolescents' well-being. Our approach quantified moderate screen engagement and indicated screens are unlikely to present a material risk to mental well-being, whereas high levels of engagement may have a measurable, albeit small, influence. These are all firsts for a research area that uses omnibus measures that do not differentiate between the diverse types of digital screen uses (Sisson et al., 2010), and measures doses of screen-time based on arbitrary cut-offs (Hamer et al., 2009). Such approaches are limited because they discard informative variance and therefore pool non-harmful and potentially harmful amounts of engagement when estimating effects.

This research informs the field in a number of ways. First, it encourages us to consider the wider social and developmental contexts surrounding digital screen use. The relation between digital screens and well-being depended, in part, on whether they were used on weekdays or weekends. Compared to weekdays, adolescents could use screens on weekends between 22m and 2hr25min longer before we found evidence of negative effects. Second, we found evidence that not all screens are created equal. Those that were pervasive (i.e., smartphones) or required effortful task switching (i.e., game consoles) showed noticeably lower inflection points on weekdays. Taken together it is possible that some activities do interfere with other structured activities during weekdays. It is likely that adolescents are less likely to engage in academic responsibilities if overusing certain forms of media on weekdays (Junco, 2012; Upadaya & Salmela-Aro, 2013), and it may also be the case these adolescents are less engaged in structured after-school activities that support intrapersonal and social

development, and as a result promote well-being (Fletcher, Nickerson, & Wright, 2003). Despite these possibilities, statistical models suggested the possible harmful influence of screens on young people is fairly small, even assuming direct causal relations in these correlational data.

Avenues for future work. If indeed moderate engagement has little detrimental effect on, and even some positive correlates with, well-being, then such use may serve as a proxy for how technologies afford benefits to adolescents. These benefits may include avenues for communication, creativity, and development (Granic, Lobel, & Engels, 2014). In future work researchers should look more closely at how specific affordances intrinsic to digital technologies relate to benefits at various levels of engagement, alongside a systematic analysis of what is being displaced or amplified. For example, many popular games such as *Minecraft* provide a context for socializing and creativity, and smart-phone based activities like *Geocaching* provide motivation for undertaking physical activity and discovery (O’Hara, 2008). Engaging in these may not displace anything meaningful for development, whereas channel surfing and solitary reading might. Research building on these findings might examine non-linear effects over time, and could consider both those younger and older than the adolescents sampled in the present work. Finally, future studies should use convergent data sources from caregivers, peers, and teachers to evaluate the linear and non-linear relations between screen time and well-being. This approach would minimize the negative influence of extreme “mischievous responding” which might have exaggerated links between screen time and health (Robinson-Cimpian, 2014), particularly for our extreme responders who reported unrealistically high levels of technology use. More importantly, this would provide a further robust test of the goldilocks hypothesis (Cronbach & Meehl, 1955).

Closing Remarks

These findings underpin the need to revisit broad-stroke recommendations grounded in the displacement hypothesis (Brown, Shifrin, & Hill, 2015), and offer a new way for systematically defining the figures that underlie those recommendations. Our results indicated that the possible deleterious relations that media use has with well-being may not be as practically significant as some have argued (Strasburger, Donnerstein, & Bushman, 2014), and they highlight the continued need to critically reevaluate research claims that go beyond the available evidence (see Ferguson & Donnellan, 2014, for more on this). Our findings also suggest a careful cost-benefit analysis of existing professional advice – which at present supports allocating valuable pediatrician consultation time to discussing media use with caregivers – should be conducted. Future research and recommendations building on the goldilocks hypothesis would be sensitive to the various types and contexts of use, and based on peaks and drops in well-being as well as other meaningful outcomes identified systematically. If it is paired with open science practices, such as preregistration of statistical analyses that limits researcher degrees of freedom (Simmons, Nelson, & Simonsohn, 2011), the approach we take in this paper will form the basis for new robust studies in this area (Morey et al., 2016). Indeed, there is good reason to think that caregivers find enforcing existing digital screen guidelines extremely difficult (Houghton et al., 2015), and that other factors such as active caregiver-child co-use and engagement may be far more important for mental well-being.

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References

- Anderson, S. E., Economos, C. D., & Must, A. (2008). Active play and screen time in US children aged 4 to 11 years in relation to sociodemographic and weight status characteristics: a nationally representative cross-sectional analysis. *BMC Public Health*, *8*(1), 366. <http://doi.org/10.1186/1471-2458-8-366>
- Bell, V., Bishop, D. V. M., & Przybylski, A. K. (2015). The debate over digital technology and young people. *BMJ*, *351*, h3064. <http://doi.org/10.1136/bmj.h3064>
- Boone, J. E., Gordon-Larsen, P., Adair, L. S., & Popkin, B. M. (2007). Screen time and physical activity during adolescence: longitudinal effects on obesity in young adulthood. *International Journal of Behavioral Nutrition and Physical Activity*, *4*(1), 26. <http://doi.org/10.1186/1479-5868-4-26>
- Brown, A., Shifrin, D. L., & Hill, D. L. (2015). Beyond “turn it off”: How to advise families on media use. *AAP News*, *36*(10), 54–54. <http://doi.org/10.1542/aapnews.20153610-54>
- Cao, H., Qian, Q., Weng, T., Yuan, C., Sun, Y., Wang, H., & Tao, F. (2011). Screen time, physical activity and mental health among urban adolescents in China. *Preventive Medicine*, *53*(4–5), 316–320. <http://doi.org/10.1016/j.ypmed.2011.09.002>
- Children and parents: Media use and attitudes report 2015. (n.d.). Retrieved April 1, 2016, from <http://stakeholders.ofcom.org.uk/market-data-research/other/research-publications/childrens/children-parents-nov-15/>
- Clarke, A., Friede, T., Putz, R., Ashdown, J., Martin, S., Blake, A., ... others. (2011). Warwick-Edinburgh Mental Well-being Scale (WEMWBS): validated for teenage school students in England and Scotland. A mixed methods assessment. *BMC Public Health*, *11*(1), 487.

- Council on Communications And Media. (2013). Children, Adolescents, and the Media. *Pediatrics*, *132*(5), 958–961. <http://doi.org/10.1542/peds.2013-2656>
- Cronbach, L. J., & Meehl, P. E. (1955). Construct validity in psychological tests. *Psychological Bulletin*, *52*(4), 281–302. <http://doi.org/10.1037/h0040957>
- Cumming, G. (2012). *Understanding the new statistics: effect sizes, confidence intervals, and meta-analysis*. New York, NY: Routledge.
- Etchells, P. J., Gage, S. H., Rutherford, A. D., & Munafò, M. R. (2016). Prospective Investigation of Video Game Use in Children and Subsequent Conduct Disorder and Depression Using Data from the Avon Longitudinal Study of Parents and Children. *PLoS ONE*, *11*(1), e0147732. <http://doi.org/10.1371/journal.pone.0147732>
- Eynon, R., & Helsper, E. (2015). Family dynamics and Internet use in Britain: What role do children play in adults' engagement with the Internet? *Information, Communication & Society*, *18*(2), 156–171. <http://doi.org/10.1080/1369118X.2014.942344>
- Ferguson, C. J., & Donnellan, M. B. (2014). Is the association between children's baby video viewing and poor language development robust? A reanalysis of Zimmerman, Christakis, and Meltzoff (2007). *Developmental Psychology*, *50*(1), 129–137. <http://doi.org/10.1037/a0033628>
- Fletcher, A. C., Nickerson, P., & Wright, K. L. (2003). Structured leisure activities in middle childhood: Links to well-being. *Journal of Community Psychology*, *31*(6), 641–659. <http://doi.org/10.1002/jcop.10075>
- Granic, I., Lobel, A., & Engels, R. C. M. E. (2014). The benefits of playing video games. *American Psychologist*, *69*(1), 66–78. <http://doi.org/10.1037/a0034857>

- Hamer, M., Stamatakis, E., & Mishra, G. (2009). Psychological Distress, Television Viewing, and Physical Activity in Children Aged 4 to 12 Years. *PEDIATRICS*, *123*(5), 1263–1268.
<http://doi.org/10.1542/peds.2008-1523>
- Hamer, M., Stamatakis, E., & Mishra, G. D. (2010). Television- and Screen-Based Activity and Mental Well-Being in Adults. *American Journal of Preventive Medicine*, *38*(4), 375–380.
<http://doi.org/10.1016/j.amepre.2009.12.030>
- Helsper, E. J. (2010). Gendered Internet Use Across Generations and Life Stages. *Communication Research*, *37*(3), 352–374. <http://doi.org/10.1177/0093650209356439>
- Houghton, S., Hunter, S. C., Rosenberg, M., Wood, L., Zadow, C., Martin, K., & Shilton, T. (2015). Virtually impossible: limiting Australian children and adolescents daily screen based media use. *BMC Public Health*, *15*(1), 5. <http://doi.org/10.1186/1471-2458-15-5>
- Iannotti, R. J., Kogan, M. D., Janssen, I., & Boyce, W. F. (2009). Patterns of Adolescent Physical Activity, Screen-Based Media Use, and Positive and Negative Health Indicators in the U.S. and Canada. *Journal of Adolescent Health*, *44*(5), 493–499.
<http://doi.org/10.1016/j.jadohealth.2008.10.142>
- Junco, R. (2012). The relationship between frequency of Facebook use, participation in Facebook activities, and student engagement. *Computers & Education*, *58*(1), 162–171.
<http://doi.org/10.1016/j.compedu.2011.08.004>
- Kremer, P., Elshaug, C., Leslie, E., Toumbourou, J. W., Patton, G. C., & Williams, J. (2014). Physical activity, leisure-time screen use and depression among children and young adolescents. *Journal of Science and Medicine in Sport*, *17*(2), 183–187. <http://doi.org/10.1016/j.jsams.2013.03.012>
- Lanningham-Foster, L., Jensen, T. B., Foster, R. C., Redmond, A. B., Walker, B. A., Heinz, D., & Levine, J. A. (2006). Energy Expenditure of Sedentary Screen Time Compared With Active

Screen Time for Children. *PEDIATRICS*, 118(6), e1831–e1835.

<http://doi.org/10.1542/peds.2006-1087>

Lenhart, A., Smith, A., Anderson, M., Duggan, M., & Perrin, A. (2015). *Teens, Technology and Friendships*. Retrieved from <http://www.pewinternet.org/2015/08/06/teens-technology-and-friendships/>

Linebarger, D. L., & Vaala, S. E. (2010). Screen media and language development in infants and toddlers: An ecological perspective. *Developmental Review*, 30(2), 176–202.

<http://doi.org/10.1016/j.dr.2010.03.006>

Luyckx, K., Soenens, B., Goossens, L., Beckx, K., & Wouters, S. (2008). Identity Exploration and Commitment in Late Adolescence: Correlates of Perfectionism and Mediating Mechanisms on the Pathway to Well-Being. *Journal of Social and Clinical Psychology*, 27(4), 336–361.

<http://doi.org/10.1521/jscp.2008.27.4.336>

Morey, R. D., Chambers, C. D., Etchells, P. J., Harris, C. R., Hoekstra, R., Lakens, D., ... Zwaan, R. A. (2016). The Peer Reviewers' Openness Initiative: incentivizing open research practices through peer review. *Royal Society Open Science*, 3(1), 150547.

<http://doi.org/10.1098/rsos.150547>

Nelson, L. D., & Simonsohn, U. (2014, September 17). Thirty-somethings are Shrinking and Other U-Shaped Challenges. Retrieved June 29, 2016, from <http://datacolada.org/27>

Neuman, S. B. (1988). The Displacement Effect: Assessing the Relation between Television Viewing and Reading Performance. *Reading Research Quarterly*, 23(4), 414.

<http://doi.org/10.2307/747641>

- Ofcom. (2015). *Children and parents: Media use and attitudes report 2015*. Retrieved from <http://stakeholders.ofcom.org.uk/market-data-research/other/research-publications/childrens/children-parents-nov-15/>
- O'Hara, K. (2008). Understanding geocaching practices and motivations (p. 1177). ACM Press. <http://doi.org/10.1145/1357054.1357239>
- Parkes, A., Sweeting, H., Wight, D., & Henderson, M. (2013). Do television and electronic games predict children's psychosocial adjustment? Longitudinal research using the UK Millennium Cohort Study. *Archives of Disease in Childhood*, archdischild-2011-301508. <http://doi.org/10.1136/archdischild-2011-301508>
- Przybylski, A. K. (2014). Electronic Gaming and Psychosocial Adjustment. *Pediatrics*, 134(3), e716–e722. <http://doi.org/10.1542/peds.2013-4021>
- Przybylski, A. K., & Weinstein, N. (2016a). Data and Code. Retrieved April 22, 2016, from https://osf.io/82ybd/?view_only=3fd66ff28ee5410d91dc095de3023909
- Przybylski, A. K., & Weinstein, N. (2016b). Fork of Digital Screen Time for Registration. Retrieved April 22, 2016, from https://osf.io/jkz9s/?view_only=f0777ef544414aee9cf871d04e955f19
- Robinson-Cimpian, J. P. (2014). Inaccurate Estimation of Disparities Due to Mischievous Responders: Several Suggestions to Assess Conclusions. *Educational Researcher*, 43(4), 171–185. <http://doi.org/10.3102/0013189X14534297>
- Ryan, R. M., Bernstein, J. H., & Brown, K. W. (2010). Weekends, Work, and Well-Being: Psychological Need Satisfactions and Day of the Week Effects on Mood, Vitality, and Physical Symptoms. *Journal of Social and Clinical Psychology*, 29(1), 95–122. <http://doi.org/10.1521/jscp.2010.29.1.95>

- Ryan, R. M., & Deci, E. L. (2000). Self-determination theory and the facilitation of intrinsic motivation, social development, and well-being. *American Psychologist*, *55*(1), 68–78. <http://doi.org/10.1037/0003-066X.55.1.68>
- Simmons, J. P., Nelson, L. D., & Simonsohn, U. (2011). False-Positive Psychology Undisclosed Flexibility in Data Collection and Analysis Allows Presenting Anything as Significant. *Psychological Science*, *22*(11), 1359–1366. <http://doi.org/10.1177/0956797611417632>
- Sisson, S. B., Broyles, S. T., Baker, B. L., & Katzmarzyk, P. T. (2010). Screen Time, Physical Activity, and Overweight in U.S. Youth: National Survey of Children’s Health 2003. *Journal of Adolescent Health*, *47*(3), 309–311. <http://doi.org/10.1016/j.jadohealth.2010.02.016>
- Stewart-Brown, S., Tennant, A., Tennant, R., Platt, S., Parkinson, J., & Weich, S. (2009). Internal construct validity of the Warwick-Edinburgh Mental Well-being Scale (WEMWBS): a Rasch analysis using data from the Scottish Health Education Population Survey. *Health and Quality of Life Outcomes*, *7*(1), 15. <http://doi.org/10.1186/1477-7525-7-15>
- Strasburger, V. C., Donnerstein, E., & Bushman, B. J. (2014). Why is it so hard to believe that media influence children and adolescents? *Pediatrics*, *133*(4), 571–573. <http://doi.org/10.1542/peds.2013-2334>
- Tennant, R., Hiller, L., Fishwick, R., Platt, S., Joseph, S., Weich, S., ... Stewart-Brown, S. (2007). The Warwick-Edinburgh mental well-being scale (WEMWBS): development and UK validation. *Health and Quality of Life Outcomes*, *5*(1), 1. <http://doi.org/10.1186/1477-7525-5-63>
- UK Government. (2015). English indices of deprivation 2015 - Publications - GOV.UK. Retrieved March 7, 2016, from <https://www.gov.uk/government/statistics/english-indices-of-deprivation-2015>

- Upadyaya, K., & Salmela-Aro, K. (2013). Development of School Engagement in Association With Academic Success and Well-Being in Varying Social Contexts: A Review of Empirical Research. *European Psychologist, 18*(2), 136–147. <http://doi.org/10.1027/1016-9040/a000143>
- Valkenburg, P. M., & Peter, J. (2009). Social Consequences of the Internet for Adolescents: A Decade of Research. *Current Directions in Psychological Science, 18*(1), 1–5. <http://doi.org/10.1111/j.1467-8721.2009.01595.x>
- Yarcheski, A., Mahon, N. E., & Yarcheski, T. J. (2001). Social support and well-being in early adolescents: the role of mediating variables. *Clinical Nursing Research, 10*(2), 163–181.