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ORIGINAL PAPER

Media Use Is Linked to Lower Psychological Well-Being: Evidence from Three Datasets

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Abstract

Adolescents spend a substantial and increasing amount of time using digital media (smartphones, computers, social media, gaming, Internet), but existing studies do not agree on whether time spent on digital media is associated with lower psychological well-being (including happiness, general well-being, and indicators of low well-being such as depression, suicidal ideation, and suicide attempts). Across three large surveys of adolescents in two countries (n = 221,096), light users (<1 h a day) of digital media reported substantially higher psychological well-being than heavy users (5+ hours a day). Datasets initially presented as supporting opposite conclusions produced similar effect sizes when analyzed using the same strategy. Heavy users (vs. light) of digital media were 48% to 171% more likely to be unhappy, to be in low in well-being, or to have suicide risk factors such as depression, suicidal ideation, or past suicide attempts. Heavy users (vs. light) were twice as likely to report having attempted suicide. Light users (rather than non- or moderate users) were highest in well-being, and for most digital media use the largest drop in well-being occurred between moderate use and heavy use. The limitations of using percent variance explained as a gauge of practical impact are discussed.

Keywords Digital media · Electronic gaming · Social media · Psychological well-being · Happiness · Suicide

In recent years, children and teens have spent a substantial and increasing amount of leisure time online, using devices such as computers, smartphones, and tablets to engage in activities such as social media, computer use, gaming, and texting (commonly described using the term *digital media* [17, 56]). This shift in adolescents' time use has led to questions about possible associations between digital media use and mental health, especially as the increased use of

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electronic devices during the 2010s coincided with a marked rise in depression and suicide attempts among adolescents [30, 34, 54] as well as marked declines in happiness, life satisfaction, and self-esteem [55].

There is special concern about digital media use among adolescents, a population vulnerable to low psychological well-being that has come of age with smartphone technology allowing near-constant access to the Internet [53]. These concerns recently gained additional public attention when two major investors in Apple, Inc., the maker of iPhones and iPads, called on the company to give parents more options for limiting the time adolescents spend on digital media given the research on links between heavy use and mental health issues [5]. However, some researchers have publicly questioned whether associations between digital media use and well-being are large enough to merit such action [7, 13, 32, 58].

These views may be rooted in the mixed results of research examining digital media and well-being. Several studies find that digital media use and digital media use are linked to lower psychological well-being among children, adolescents, and adults [2, 23, 24, 27, 33, 37–41, 44], while other studies find no links [4] or enhanced well-being with more digital media use [10, 14, 59]. Some researchers argue that time spent on digital media activities per se is not related to well-being, with the quality of online interactions and activities – what people do with that time – significantly more important [4, 28, 43]. Thus, much debate still surrounds the question of whether a substantial association exists between time spent on digital media and lower psychological well-being (which we define here as including happiness, general psychological well-being, and indicators of markedly low well-being such as depression, suicidal ideation, and suicide attempts).

With many of these studies conducted on small and/or non-representative samples, on adult populations, or before smartphones became common, research using recently collected, large, nationally representative samples of adolescents was sorely needed. Fortunately, three recent studies by two different research groups examined samples fitting these criteria [35, 54, 55]. However, these studies came to opposite conclusions about the link between digital media and psychological well-being among adolescents, further muddying the waters. Przybylski and Weinstein [35] analyzed a large sample of 15-year-olds in the United Kingdom (UK) and found that high levels of digital media time "accounted for 1.0% or less of the observed variability in the mental well-being of the young people in the sample" (p. 210), which Przybylski later described as "literally the lowest quality of evidence that you could give that people wouldn't laugh you out of the room" [7]. Przybylski and Weinstein concluded that "the possible deleterious relation between media use and well-being may not be as practically significant as some researchers have argued" (p. 213). Przybylski and Weinstein suggest that the effect of digital media on well-being is so weak that medical professionals should reconsider giving parents advice about screen time: "Our findings also suggest the need for a careful cost-benefit analysis of existing professional advice—which at present supports allocating valuable pediatrician consultation time to discussing media use with caregivers" (p. 213). The perception of a link between digital media use and low well-being, Przybylski contends, is simply "a projection of our own fears" and "a big dog and pony show" [7].

Subsequently, two papers drawing from large U.S. surveys of adolescents came to the opposite conclusion. Based on data from the Youth Risk Behavior Surveillance System (YRBSS) survey administered by the Centers for Disease Control, Twenge et al. [54] found that adolescents who spent more hours a day on electronic devices were significantly more likely to have risk factors for suicide such as depression and suicidal ideation: "adolescents using devices 5 or more hours a day (vs. 1 hour) were 66% more likely to have at least one suicide-related outcome" (p. 8). They concluded that "new media screen time should be understood as an important modern risk factor for depression and suicide … it seems likely that the concomitant rise of screen time and adolescent depression and suicide is not coincidental" (p. 11, 13). Another paper from the same lab found correlations between unhappiness and hours spent online, texting, gaming, and on social media in another large U.S. survey of adolescents (Monitoring the Future: MtF), concluding that "The rapid adoption of smartphone technology in the early 2010s may have had a marked negative impact on adolescents' psychological well-being" ([55], p. 27).

Why did these studies – one in the UK and the other two in the U.S. – come to such different conclusions? One possibility is that, due to differences in population, culture, or other factors, the studies failed to replicate each other (i.e., show similar patterns of results). A second possibility is that differences in analytic strategy and interpretation, not the data itself, led to this stark difference in conclusions. The concept that analysis strategies may influence results has gained attention recently, often focusing on decisions about covariates [46]. However, the issue of analysis strategy also extends to calculations of effect sizes and interpreting how large or impactful effects are. This issue – whether the same data yields the same conclusions across research groups – is fundamental to reproducibility in psychological science, especially with the current recommendation of reporting effect sizes rather than null hypothesis significance testing *p*-values [9]. Without the (false) "yes or no" distinction of $p < .05$, interpreting the size of effects becomes paramount for drawing conclusions.

In the present research, we examine all three data sources using the same analysis techniques, a crucial step for reproducibility. This is also a crucial step for resolving the debate about the size of the associations between digital media use and psychological well-being, a debate that has now spilled from the research literature into the popular press with no clear resolution, partially due to the previous papers analyzing the large datasets coming to opposite conclusions [7, 13, 32, 58]. First, we briefly describe the underlying theoretical approaches and analytic approaches of the two groups.

Theoretical Approaches

Przybylski and Weinstein [35] argue for a *Goldilocks hypothesis*, with a moderate amount of digital media use optimal for well-being and light or heavy use harmful (although minimally so). Light digital media use may be harmful if adolescents miss out on social activity, and heavy use may be harmful if it displaces social activity. Although the term is not defined precisely, based on the way others have used the term "Goldilocks" to make specific predictions (e.g., [20], Fig. 2; [29]), this should produce a U-shaped curve with the highest levels of well-being in the middle and the harmful effects equally apportioned to the heavy and light sides of use – as the Goldilocks fable says, just right, too hot, too cold. This would resemble a classic curvilinear effect, with well-being peaking at moderate levels of use (perhaps 3 h a day, given that the measure of use in Przybylski and Weinstein ranged from 0 to 7 or more hours; see Fig. 1 for an illustration with hypothetical data).

In contrast, Twenge et al. [54, 55] argue for an *exposure-response curve hypothesis.* This hypothesis is modeled on research examining the effects of commonly used drugs such as alcohol and marijuana, in which progressively more use has increasingly negative consequences for well-being [8, 45]. If the same pattern appeared with digital media use, well-being would be progressively lower as digital media use moved from light to moderate to heavy. The

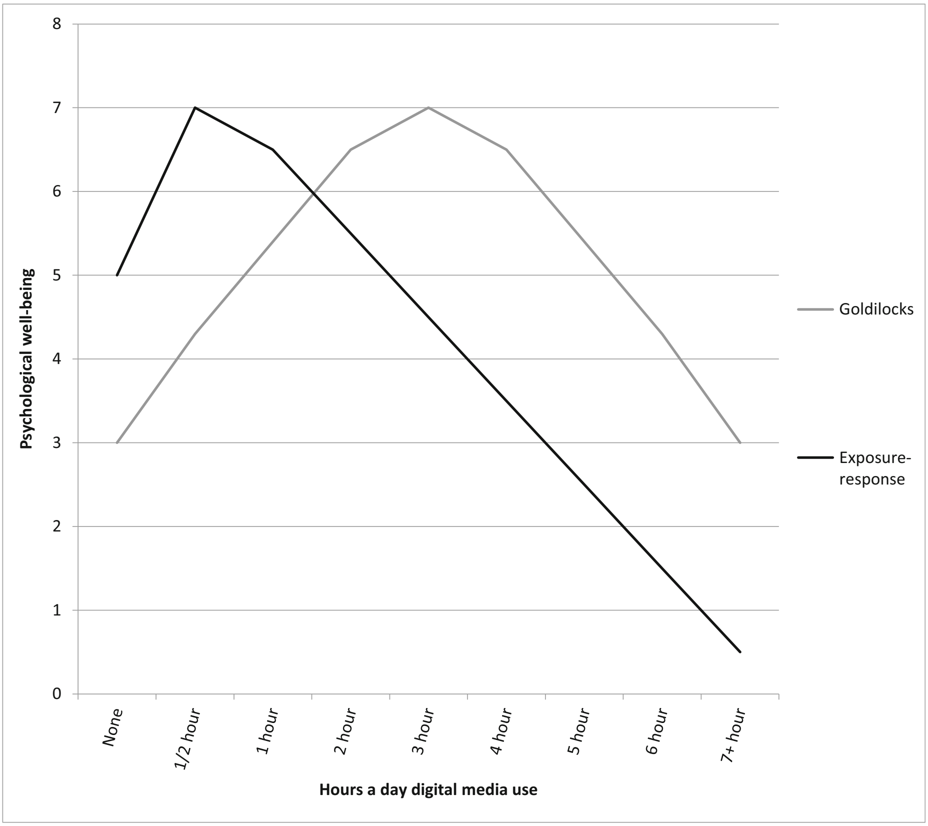

Fig. 1 Predictions (hypothetical data) for differences in psychological well-being based on hours per day of digital media use, Goldilocks hypothesis and exposure-response hypothesis

research on alcohol and marijuana also suggests that abstainers (here, non-users of digital media) may be lower in well-being (via social isolation, over-controlling parents, or other means). Thus, the response curve hypothesis predicts that well-being will peak at light use, not at non-use or moderate levels of use (see Fig. 1).

Analytic Approaches and Effect Size Estimates

All three previous studies reported a curvilinear association between digital media use and well-being but diverged on the description of those patterns. Curvilinearity presents challenges in interpretation of effect size. One approach gaining favor is to perform two linear regressions, one before the curve changes direction and one after; this is also known as segmented regression analysis, piecewise regression, or broken-stick regression, and yields better results than traditional quadratic or cubic analyses [47]. Effect sizes for differences in means between light, moderate, and heavy digital media use can also be compared to determine variations in well-being and test the models. For example, the Goldilocks hypothesis would posit higher well-being at moderate use compared to light use, or at least little difference, whereas the exposure-response curve model would expect lower well-being at moderate use compared to light use.

A second and related difference between a Goldilocks vs. exposure-response curvilinear pattern is that in the Goldilocks curvilinear pattern, light and heavy use should have the same association with well-being. In contrast, the exposure-response model suggests that the heaviest use should be associated with lower well-being than the lightest use (see Fig. 1).

Another analysis decision involves how effect sizes should be determined. For example, should we use percent variance explained, or compare means across groups? Percent variance explained may be appropriate if many possible associations that might explain variance are being measured, whereas comparing means may be more relevant if the focus is on the association with one particular factor. Another question is whether we should focus on mean well-being or the percentage scoring above or below certain cut-off points. Social-personality psychologists usually focus on means, whereas medical and other applied fields focus more on those falling above or below cutoffs. Cut-off scores are used in many clinical diagnoses, even with continuous variables such as blood pressure or depressive symptoms, because clinicians need to make a treatment decision. In the area of well-being, clinical practitioners are more interested in the minority of the population with depression – those most in need of intervention – than in the population average of depression scores.

The Present Research

Our goal in the present research is to examine the association between digital media time (smartphones, computers, electronic devices, time online, gaming, texting, and social media) and psychological well-being (including happiness, general well-being, and indicators of low well-being such as depression and suicide attempts) in three large samples. We use multiple analysis strategies including *d*, percent variance, linear *r;* and relative percent difference in those below a cut-off for well-being across those varying in their frequency of digital media use. Given the large sample sizes and potential practical applications of this data, a discussion of effect size is useful. By analyzing all three datasets using the same analytic techniques, we aim to provide a comprehensive view of the association between digital media use and psychological well-being and add insights to the debate surrounding the shape and size of the effects in this area. We also aim to address whether effect sizes comparing well-being between light and moderate digital media use differ from those comparing moderate use with heavy use, a question not addressed in previous analyses.

Method

Participants

Participants completed surveys as part of three large studies of adolescents that included time spent on digital media and a measure of well-being: 1) UK 15-year-olds ($n = 120{,}115$; data made available on the Open Science Framework by [35]), 2) the Youth Risk Behavior Surveillance System, or YRBSS, administered by the Centers of Disease Control, of U.S. 9th to 12th graders ($n = 59{,}115$, 2009–2015; used in [53]), and 3) Monitoring the Future, or MtF, administered by the Institutes for Social Research at the University of Michigan, of U.S. 8th, 10th, and 12th graders ($n = 41{,}866$, 2013–2016; used in [55]). Total $n = 221{,}096$.

Datasets are publicly available online at: 1) osf.io/49rmq/ 2) https://www.cdc.gov/healthyyouth/data/yrbs/data.htm and 3) http://www.icpsr.umich.edu/icpsrweb/NAHDAP/series/35/studies?archive=NAHDAP

YRBSS and MtF are designed to be nationally representative; Przybylski and Weinstein [35] described the UK sample as covering "150 local authorities across England, with the aim of making sufficient observations of English 15-year-olds to attain a +- .3% margin of error at a 95% confidence interval." Although data from these three data sources have been presented before, we conducted new analyses to compare them directly using the same analysis techniques and to examine differences between light use and moderate use, and moderate use and heavy use.

Measures

Well-Being In the UK sample, well-being was measured with the 14-item Warwick-Edinburgh Mental Well-Being Scale [51]. Internal reliability was $\alpha = .90$. In addition to examining mean well-being, we also recorded those scoring at the 15th percentile or lower on this measure as low in well-being.

In YRBSS, participants were asked four items about depression and other suicide risk factors: "During the past 12 months, did you ever feel so sad or hopeless almost every day for two weeks or more in a row that you stopped doing some usual activities?" "During the past 12 months, did you ever seriously consider attempting suicide?" "During the past 12 months, did you make a plan about how you would attempt suicide?" Response choices for these three items were "yes" or "no." Another item, "During the past 12 months, how many times did you actually attempt suicide?" was recoded to 0 times = "no" and one time, two or three times, four or five times, or six or more times = "yes." Participants who responded "yes" to any of the four items were recorded as having at least one suicide risk factor ($\alpha = .75$).

In MtF, participants are asked about their overall happiness: "Taking all things together, how would you say things are these days—would you say you're very happy, pretty happy, or not too happy these days?" with response choices coded 1, 2, or 3. In addition to examining mean happiness, we also examined the percentage who chose "not too happy" as an indicator of low well-being. As our focus was on digital media measured in hours of use, we were not able to examine other measures of well-being in MtF such as depressive symptoms and self-esteem, which are not asked of the same participants who answer the items about digital media use in hours.

Digital Media Time In the UK sample, Przybylski and Weinstein [35] report that "Participants were asked four questions regarding their engagement in different kinds of digital activities during their free time. Specifically, they were asked about watching films and other media (e.g., TV programs), playing games (e.g., on computers and consoles), using computers (e.g., Internet, e-mail), and using smartphones (e.g., social networking, chatting online)." As our focus was on digital media, we examined only the latter three items. Participants noted their frequency of use (ranging from none to 7 or more hours a day) separately for weekdays and weekends.

As the curve for well-being was similar for weekday and weekend use ([35], Fig. 1) and the U.S. datasets did not separate weekday and weekend use, we combined the weekday and weekend measurements into a single daily average (multiplying the weekday measurement by 5, the weekend measurement by 2, adding them together, and dividing by 7). We then recoded the daily average to correspond to the categories used in the original measure (coding .2599 or less = 0, .26 to .6499 = .5, .65 to 1.499 = 1, 1.50

to 2.499 = 2, 2.50 to 3.499 = 3, 3.50 to 4.499 = 4, 4.50 to 5.499 = 5, 5.50 to 6.499 = 6, and 6.50 and higher = 7).

We examined the YRBSS data from the years after smartphones were introduced, 2009–2015 (the iPhone was introduced in June 2007, after the 2007 data collection, and the YRBSS is only administered in odd-numbered years); these were also the years examined in previous research [53]. In 2009, YRBSS asked, "On an average school day, how many hours do you play video or computer games or use a computer for something that is not school work? (Include activities such as Nintendo, Game Boy, PlayStation, Xbox, computer games, and the Internet.)" In 2011, "On an average school day, how many hours do you play video or computer games or use a computer for something that is not school work? (Include activities such as Xbox, PlayStation, Nintendo DS, iPod touch, Facebook, and the Internet.)" In 2013 and 2015, "On an average school day, how many hours do you play video or computer games or use a computer for something that is not school work? (Count time spent on things such as Xbox, PlayStation, an iPod, an iPad or other tablet, a smartphone, YouTube, Facebook or other social networking tools, and the Internet.)" Response choices were "I do not play video or computer games or use a computer for something that is not school work;" "less than 1 hour per day;" "1 hour per day;" "2 hours per day;" "3 hours per day;" "4 hours per day;" and "5 or more hours per day."

Beginning in 2013, MtF began asking about hours per week spent on social media, adding it to items on hours per week texting, gaming, and general time online. Thus, we focused on the years 2013–2016. Time online was assessed with the following item: "Not counting work for school or a job, about how many hours a week do you spend on the Internet e-mailing, instant messaging, gaming, shopping, searching, downloading music, etc.?" Gaming was assessed with, "About how many hours a week do you spend … playing electronic games on a computer, TV, phone, or other device?" texting with, "About how many hours a week do you spend texting on a cell phone?" and social media with "About how many hours a week do you spend visiting social networking sites like Facebook?" Response choices were none, less than 1, 1–2 h, 3–5 h, 6–9 h, 10–19 h, 20–29 h, 30–39 h, and 40 h or more. We divided the average of these numbers by 7 to obtain a daily estimate.

Control Variables In the UK sample, demographic control variables included sex, race (white vs. non-white), and socioeconomic status (low, medium, and high based on postal code of residence). In the YRBSS sample, controls were sex, race (Black, Hispanic, and Other as dummy-codes), and grade (dummy coded); socioeconomic status was not measured. In MtF, controls were sex, race (Black and Hispanic as dummy codes), grade (dummy coded), and 6-level mother's education as a measure of socioeconomic status.

Results

First, we examined the overall pattern of the relationships between digital media use and well-being. We replicated the differences in mean well-being at levels of use of smartphones, computers, and gaming in the UK sample, finding, as Przybylski and Weinstein [35] and Twenge et al. [54, 55] did, that well-being rose from no use to light use use and then declined thereafter (see Fig. 2). This pattern is generally consistent with the exposure-response model.

A similar pattern appeared in the relationship between hours of electronic device use and having at least one suicide risk factor in YRBSS, as well as in the relationship between mean

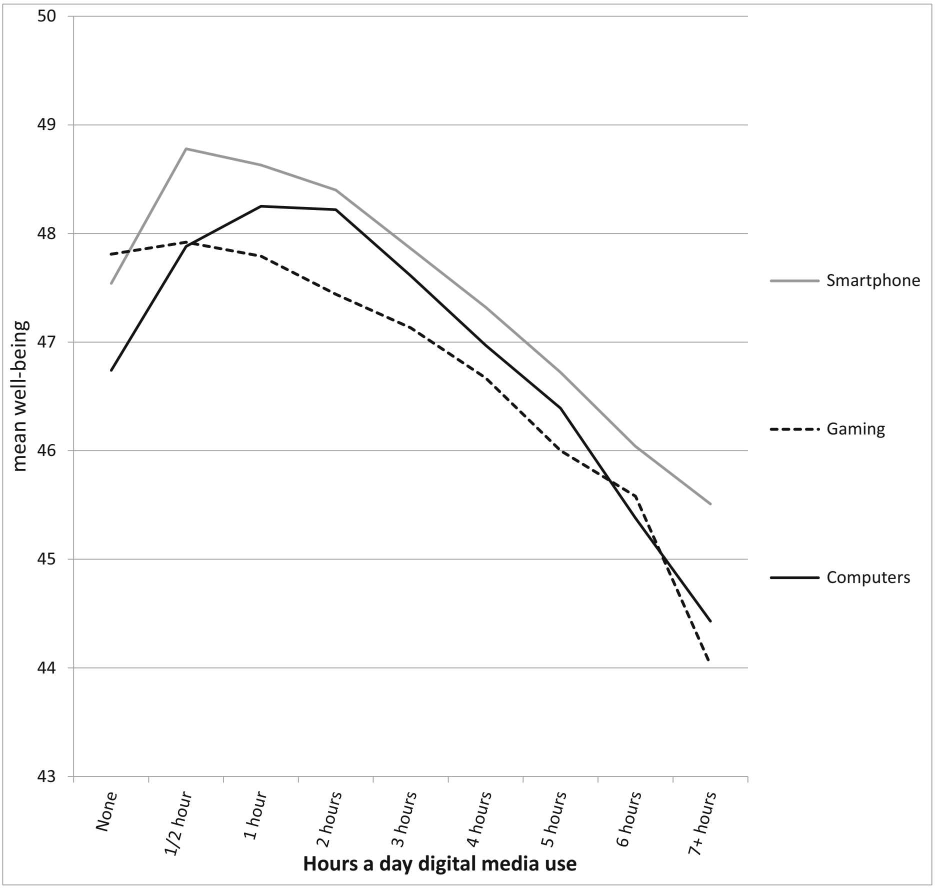

Fig. 2 Mean well-being by hours a day of gaming, smartphone, and computer use, UK sample of 15-year-olds, with controls

happiness and hours of texting, social media, gaming, and online time in MtF (see Fig. 3). Segmented regression analyses revealed positive *r*'s (and thus increasing well-being) from no use to light use, and negative *r*'s (and thus decreasing well-being) from light use to heavy use (see Table 1).

Effect sizes based on comparisons of teens using devices less than 1 h a day versus heavy use were quite similar in the three different datasets (see Table 1). The effect sizes (*d*) comparing mean well-being at light vs. heavy use ranged from small to moderate (.20 to .50), with effect sizes across the 8 measures of digital media use averaging .29 without controls and .31 with controls. Effect sizes were similar in the UK and U.S. datasets, despite the opposite conclusions reached by the previous papers examining this data [35, 54, 55].

Thus, links between digital media use and well-being replicate across several measures of well-being (a multi-item well-being measure, a single-item happiness measure, and a 4-item measure of suicide risk factors), different measures of digital media use (smartphone use, electronic device use, time online, computer use, gaming, texting, and social media) and in three datasets across two different countries (the UK and U.S.).

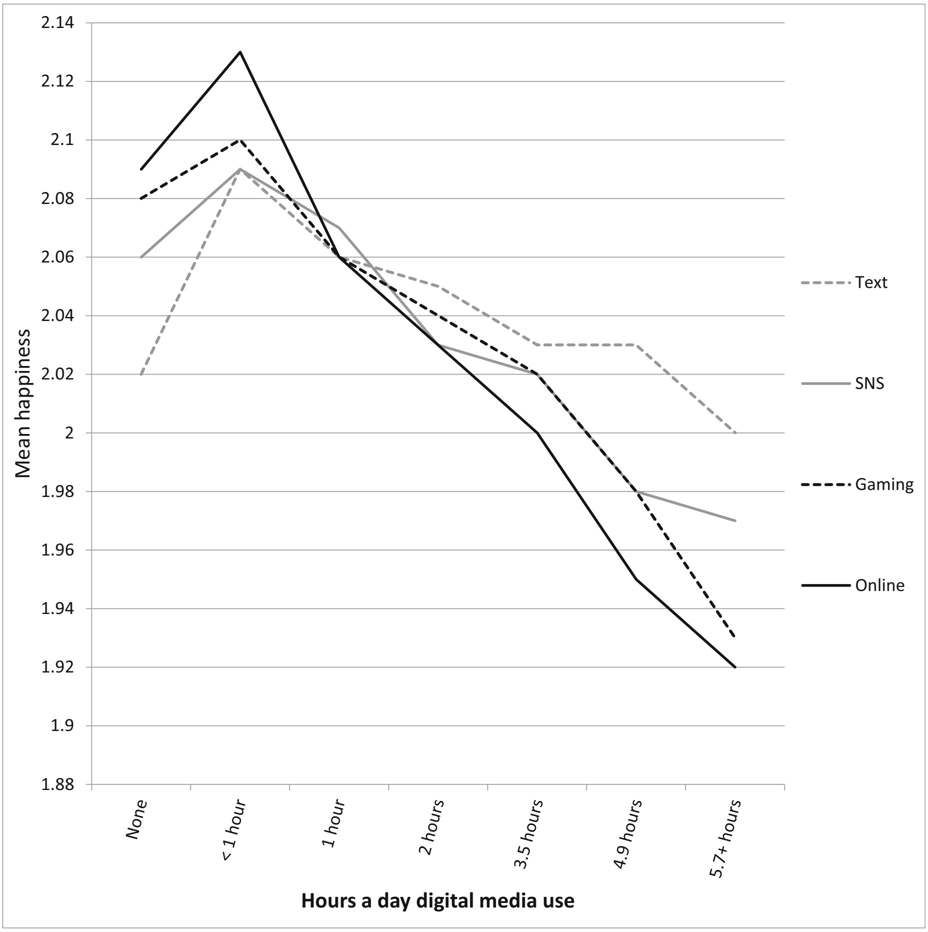

Fig. 3 Mean happiness by hours a day texting, social media, gaming, and online, 8th, 10th, and 12th graders, Monitoring the Future, 2013–2016, with controls

We then examined effect sizes across smaller intervals of use. First, we compared light (< 1 h) to moderate (3 h a day) use. The Goldilocks hypothesis posits higher well-being at moderate levels of use, whereas the exposure-response model instead predicts lower levels of well-being at moderate levels of use (see Fig. 1). As Table 2 shows, moderate digital media users generally had lower well-being than light users (see also Figs. 2 and 3), with effect sizes (with controls) ranging from .03 to .23, averaging .11 without controls and .12 with controls; this is contrary to the Goldilocks hypothesis positing higher well-being at moderate levels of use. However, these effect sizes were generally smaller than those comparing moderate levels of digital media use (3 h a day) with heavy use, with *d*'s ranging from .04 to .35, averaging .23 without controls and .20 with controls (see Table 3). Thus, well-being becomes progressively lower with more frequent digital media use, with the largest differences appearing between moderate and heavy use.

Table 1 Differences in well-being between less than an hour of use and heavy use (7+ hours a day, 5+ hours a day, or 5.7+ hours a day)

	Effect size (*d*) from means (with controls)	Percent variance explained (R^2) (with controls)	*r* before peak (with controls)	*r* after peak (with controls)	Average relative difference in low well-being with each hr./use (with controls)	% low in well-being	% low in well-being with controls	Relative difference based on % low in well-being (with controls)
Smartphone (UK)	−.50 (−.34) 14007, 16,220	6.25% (2.89%)	.06*** (.06***) 24,480	−.17*** (−.12***) 91,420	24% (14%)	8.9% vs. 24.1%	11.0% vs. 21.9%	171% (99%)
Smartphone (UK) 5+ highest	−.45 (−.29) 14007, 34,243	5.06% (2.10%)	.06*** (.06***) 24,480	−.16*** (−.11***) 91,420	28% (13%)	8.9% vs. 21.5%	11.0% vs. 19.4%	142% (76%)
Electronic devices and 1+ suicide risk factor (US, YRBSS) 2009–15	−.42 (−.41) 9572, 7102	4.41% (4.20%)	.05*** (.02**) 17,643	−.14*** (−.14***) 34,425	14% (14%)	28.3% vs. 48.2%	28.5% vs. 47.8%	70% (68%)
Electronic devices and depression (US, YRBSS), 2009–2015	−.36 (−.37) 10423, 8048	3.24% (3.42%)	.04*** (.01) 19816	−.13*** (−.13***) 38,167	14% (14%)	23.7% vs. 40.5%	23.9% vs. 40.7%	71% (70%)
Electronic devices and suicidal thoughts (US, YRBSS), 2009–2015	−.32 (−.32) 10427, 8049	2.56% (2.56%)	.02** (.01) 19817	−.11*** (−.11***) 38,153	18% (18%)	13.1% vs. 25.0%	13.0% vs. 24.9%	91% (92%)
Electronic devices and making a suicide plan (US, YRBSS), 2009–2015	−.30 (−.29) 10386, 7994	2.25% (2.25%)	.02** (.01) 19727	−.11*** (−.11***) 37,963	19% (19%)	10.6% vs. 20.9%	10.6% vs. 20.6%	97% (94%)
Electronic devices and past suicide attempts (US, YRBSS), 2009–2015	−.29 (−.24) 9648, 7212	2.10% (1.44%)	.04*** (.03***) 17,813	−.10*** (−.09***) 34,821	25% (25%)	5.8% vs. 13.0%	5.9% vs. 12.4%	124% (110%)
Electronic devices and 1+ suicide risk factor (US, YRBSS), 2013–15	−.45 (−.39) 3488, 4597	5.06% (3.80%)	.05*** (.02) 7451	−.16*** (−.15***) 17,071	15% (13%)	28.0% vs. 49.4%	29.5% vs. 48.3%	76% (64%)

Table 1 (continued)

	Effect size (d) from means (with controls)	Percent variance explained (R^2) (with controls)	r before peak (with controls)	r after peak (with controls)	Average relative difference in low well-being with each hr./use (with controls)	% low in well-being	% low in well-being with controls	Relative difference based on % low in well-being (with controls)
Online time (US, MtF)	−.37 (−.36) 6784, 3035	3.42% (3.24%)	.04*** (.03*) 9086	−.10*** (−.09***) 21,974	25% (25%)	10.8% vs. 24.4%	10.7% vs. 23.9%	127% (123%)
Computer use (UK)	−.43 (−.36) 20336, 3544	4.62% (3.24%)	.07*** (.07***) 61,462	−.13*** (−12***) 53,987	16% (13%)	12.7% vs. 27.0%	13.1% vs. 25.7%	113% (96%)
Computer use (UK) 5+ highest	−.30 (−.25) 20336, 11,779	2.25% (1.56%)	.07*** (.07***) 61,462	−.12*** (−11***) 53,992	15% (13%)	12.7% vs. 22.4%	13.1% vs. 21.5%	76% (64%)
Gaming (UK)	.20 (−.40) 14747, 1519	1.00% (4.00%)	.08*** (.01*) 66,952	−.05*** (−.10***) 48,792	5% (10%)	13.7% vs. 18.7%	13.7% vs. 23.6%	36% (72%)
Gaming (UK) 5+ highest	.02 (−.26) 14747, 7953	<1% (1.69%)	08*** (.01*) 66,952	−.04*** (−.09***) 48,792	−8% (8%)	13.7% vs. 13.3%	13.7% vs. 18.9%	−3% (38%)
Gaming (US, MtF)	−.29 (−.29) 8744, 2809	2.10% (2.10%)	.03** (.02) 12020	−.10*** (−.09***) 19,019	16% (16%)	12.8% vs. 23.3%	12.6% vs. 22.8%	82% (81%)
Texting (US, MtF)	−.20 (−.15) 8947, 4151	1.00% (<1%)	.06*** (.05***) 11,263	−.06*** (−.04***) 19,692	13% (9%)	12.0% vs. 19.8%	12.7% vs. 18.7%	65% (47%)
Social media (US, MtF)	−.27 (−.20) 9468, 3130	1.82% (1.00%)	.02** (.02*) 13,167	−.08*** (−.06***) 17,804	17% (13%)	12.1% vs. 22.2%	12.7% vs. 20.8%	83% (64%)

1. In the effect size column, n's are for the two groups being compared. In the r columns, n's for the r's are provided. 2. In the first four columns, suicide risk factors and the four individual items (depression, suicidal thoughts, making a suicide plan, and past suicide attempts) are reverse-scored, so that higher numbers represent higher well-being. 3. Percent variance explained is calculated from d; d's with controls are calculated using estimated marginal means and unadjusted standard deviations. 4. r's are based on all data before vs. after peak well-being as shown in Figs. 2 and 3. The division was <1 h and less vs. 1 h and more for all digital media activities except for computer use, where it was 1 h and less vs. 2 h and more. 5. The average relative difference column computes the increase in low well-being associated with each additional hour of digital media use beyond light use (less than 1 h). 6. * $p < .05$ ** $p < .01$ *** $= p < .001$

Table 2 Differences in well-being between less than an hour of use and 3 h a day of use

	Effect size (*d*) from means (with controls)	Percent variance explained (R^2) (with controls)	% low in well-being	% low in well-being with controls	Relative difference based on % low in well-being (with controls)
Smartphone (UK)	−.20 (−.10) 14007, 14,433	1.00% (.25%)	8.9% vs. 13.5%	11.0% vs. 13.1%	52% (19%)
Electronic devices, 1+ suicide risk factor (US, YRBSS) 2009–2015	−.15 (−.15) 9572, 6392	.56% (.56%)	28.2% vs. 34.9%	28.5% vs. 35.5%	23% (25%)
Electronic devices, depression (US, YRBSS), 2009–2015	−.12 (−.13) 10423, 6984	.36% (.42%)	23.6% vs. 28.6%	23.8% vs. 29.2%	21% (23%)
Electronic devices, suicidal thoughts (US, YRBSS), 2009–2015	−.10 (−.10) 10427, 6969	.25% (.25%)	12.9% vs. 16.3%	13.0% vs. 16.6%	26% (28%)
Electronic devices, making a suicide plan (US, YRBSS), 2009–2015	−.08 (−.08) 10386, 6956	.16% (.16%)	10.6% vs. 13.1%	10.6% vs. 13.3%	24% (25%)
Electronic devices, past suicide attempts (US, YRBSS), 2009–2015	−.06 (−.06) 9648, 6445	.10% (.10%)	5.7% vs. 7.2%	5.9% vs. 7.3%	26% (24%)
Electronic devices, 1+ suicide risk factor (US, YRBSS), 2013–15	−.14 (−.13) 3488, 3214	.49% (.42%)	28.2% vs. 34.6%	29.5% vs. 35.4%	23% (20%)
Online time (US, MtF)	−.21 (−.23) 6784, 2285	1.10% (1.32%)	10.8% vs. 17.7%	10.7% vs. 18.2%	64% (70%)
Computer use (UK)	−.06 (−.03) 20336, 13,529	.90% (.02%)	12.7% vs. 14.6%	13.1% vs. 14.2%	15% (8%)
Gaming (UK)	.14 (−.09) 14747, 9456	.49% (.20%)	13.7% vs. 10.0%	13.7% vs. 15.4%	−27% (12%)
Gaming (US, MtF)	−.12 (−.14) 8744, 1971	.36% (.49%)	12.8% vs. 15.9%	12.6% vs. 16.3%	24% (29%)
Texting (US, MtF)	−.14 (−.11) 8947, 2008	.49% (.30%)	12.0% vs. 16.0%	12.6% vs. 15.6%	33% (24%)
Social media (US, MtF)	−.16 (−.12) 9468, 1827	.64% (.36%)	12.1% vs. 17.0%	12.7% vs. 16.3%	40% (28%)

1. In the effect size column, *n*'s are for the two groups being compared. 2. Percent variance explained is calculated from *d*; d's with controls are calculated using estimated marginal means and unadjusted standard deviations. 3. In first two columns, suicide risk factors and the four individual items (depression, suicidal thoughts, making a suicide plan, and past suicide attempts) are reverse-scored, so that higher numbers represent higher well-being

Table 3 Differences in well-being between 3 h a day of use and heavy use (7+ hours a day, 5+ hours a day, or 5.7+ hours a day)

	Effect size (*d*) from means (with controls)	Percent variance explained (R^2) (with controls)	% low in well-being	% low in well-being with controls	Relative difference based on % low in well-being (with controls)
Smartphone (UK)	−.31 (−.24) 14433, 16,220	2.40% (1.44%)	13.4% vs. 24.1%	13.1% vs. 21.9%	79% (67%)
Electronic devices, 1+ suicide risk (US, YRBSS), 2009–2015	−.27 (−.25) 6392, 7102	1.82% (1.56%)	34.9% vs. 48.1%	35.5% vs. 47.8%	38% (35%)
Electronic devices, depression (US, YRBSS), 2009–2015	−.26 (−.24) 6984, 8048	1.69% (1.44%)	28.6% vs. 40.6%	29.2% vs. 40.7%	42% (39%)
Electronic devices, suicidal thoughts (US, YRBSS), 2009–2015	−.21 (−.21) 6969, 8049	1.10% (1.10%)	16.3% vs. 24.8%	16.6% vs. 24.9%	52% (50%)
Electronic devices, making a suicide plan (US, YRBSS), 2009–2015	−.20 (−.20) 6956, 7994	1.00% (1.00%)	13.1% vs. 20.5%	13.3% vs. 20.6%	56% (55%)
Electronic devices, past suicide attempts (US, YRBSS), 2009–2015	−.19 (−.17) 6445, 7212	.90% (.72%)	7.2% vs. 12.7%	7.3% vs. 12.4%	76% (70%)
Electronic devices, 1+ suicide risk (US, YRBSS), 2013–15	−.30 (−.26) 3214, 4597	2.25% (1.69%)	34.6% vs. 49.4%	35.4% vs. 48.2%	43% (36%)
Online time (US, MtF)	−.16 (−.13) 2285, 3035	.64% (.42%)	17.8% vs. 24.4%	18.2% vs. 23.9%	37% (31%)
Computer use (UK)	−.35 (−.32) 13529, 3544	3.06% (2.56%)	14.6% vs. 27.0%	14.2% vs. 25.7%	85% (81%)
Gaming (UK)	−.35 (−.34) 9456, 1519	3.06% (2.89%)	10.0% vs. 18.7%	15.4% vs. 23.7%	87% (54%)
Gaming (US, MtF)	−.17 (−.15) 1971, 2809	.72% (.56%)	15.9% vs. 23.3%	16.3% vs. 22.8%	47% (40%)
Texting (US, MtF)	−.08 (−.04) 2008, 4151	.16% (.04%)	16.0% vs. 19.8%	15.6% vs. 18.7%	24% (20%)
Social media (US, MtF)	−.13 (−.09) 1827, 3130	.42% (.20%)	17.0% vs. 22.2%	16.3% vs. 20.8%	31% (28%)

1. In the effect size column, *n*'s are for the two groups being compared. 2. Percent variance explained is calculated from *d*; d's with controls are calculated using estimated marginal means and unadjusted standard deviations. 3. In first two columns, suicide risk factors and the four individual items (depression, suicidal thoughts, making a suicide plan, and past suicide attempts) are reverse-scored, so that higher numbers represent higher well-being

We also examined the percentage above or below cut-off points for well-being. In the UK data, more than twice as many teens who spent 7+ hours a day on smartphones (vs. spending a half-hour a day) were in the lowest 15% of well-being (24.1% vs. 8.9% without controls, and 21.9% vs. 11.0% with controls; see Table 1). Those who spent 7 or more hours a day on computers (vs. a half-hour) were also twice as likely to be low in well-being (see Fig. 4). The doubling or near-doubling of those low in well-being was still evident when demographic controls were included and when the highest category of use instead combined those spending 5, 6, or 7 or more hours a day (see Table 1). Including controls, the percentage of adolescents low in well-being increased by 14% with each additional hour of smartphone use (see Table 1).

Similar effects appeared in the U.S. datasets, with a 70% difference in the number with at least one suicide risk factor among those using electronic devices 5 or more hours a day compared to less than an hour, and more than twice as many unhappy adolescents among those spending 5 or more hours a day online vs. less than an hour (see Fig. 5). Including controls, the percentage of adolescents low in well-being increased by 25% with each additional hour of time online (see Table 1). Similarly, heavy users of social media (vs. light) were 83% more likely to say they were unhappy (64% with controls).

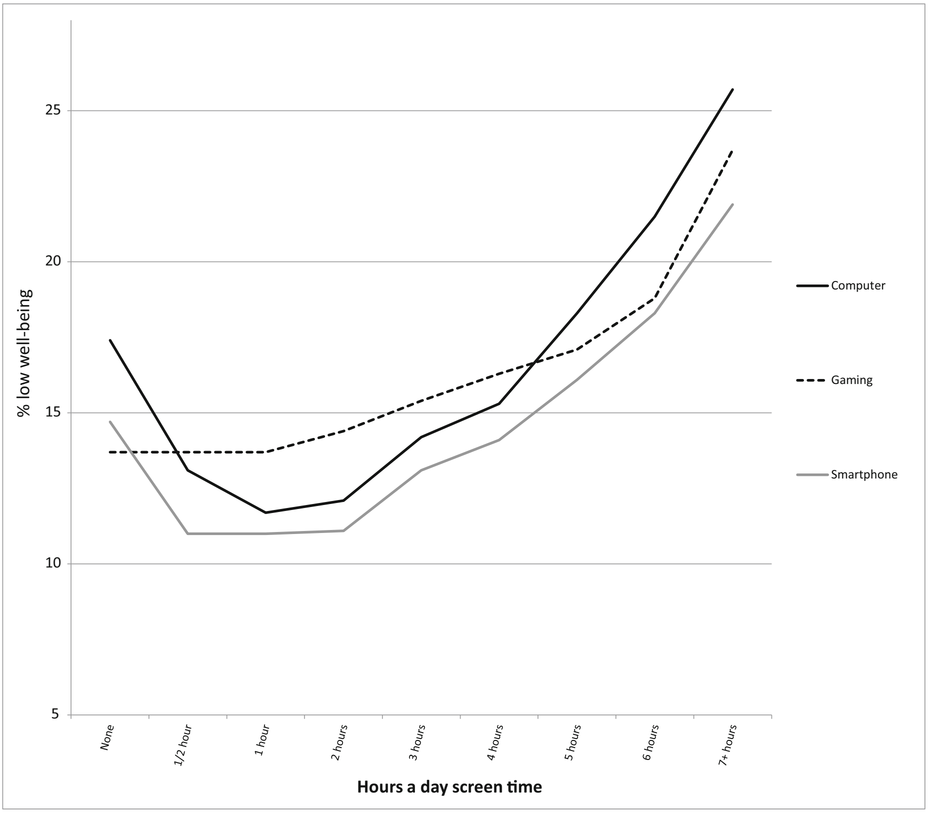

Fig. 4 Percent of adolescents low in psychological well-being by hours a day of computer, gaming, or smartphone use, UK sample of 15-year-olds, with controls

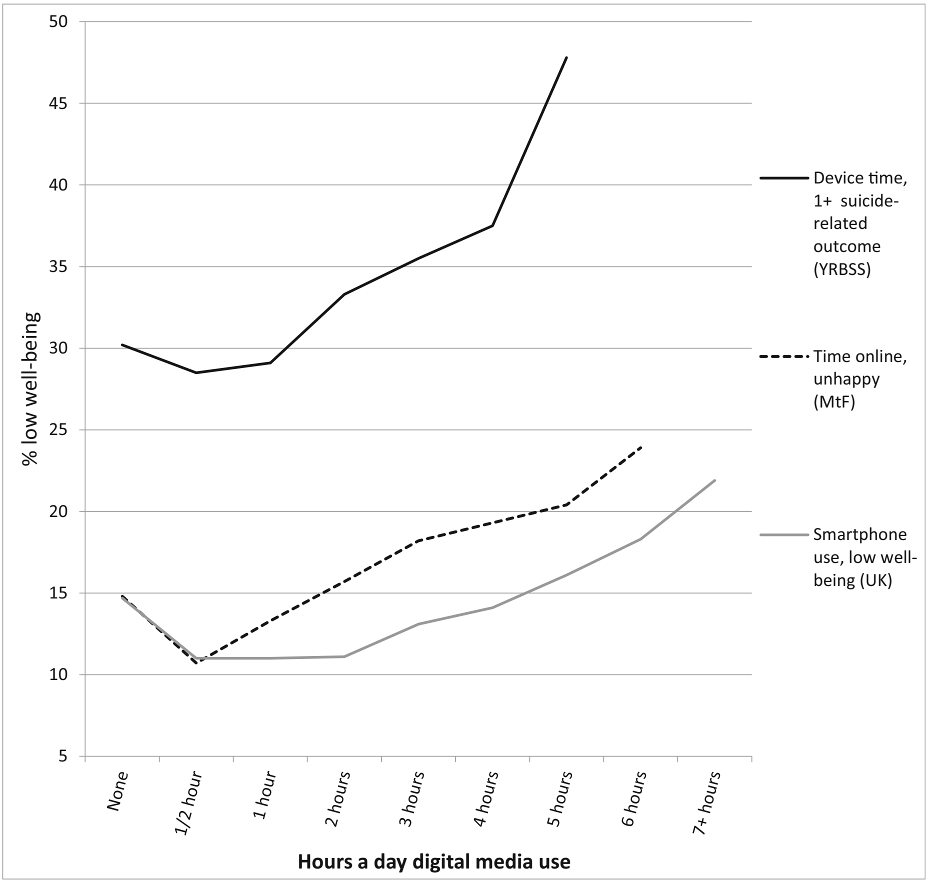

Fig. 5 Percent of adolescents low in psychological well-being by hours a day of digital media use, YRBSS 9th–12th graders, MtF 8th, 10th, and 12th graders, and UK sample of 15-year-olds, with controls

Similar results appear when examining the four suicide risk factors separately, which was not done in the previous papers (see Tables 1, 2 and 3 and Fig. 6). Light vs. heavy electronic device use was associated with a doubling of those who had suicidal thoughts, made a suicide plan, or who had attempted suicide. Similar to the analyses using means, relative percentage differences were smaller when comparing light to moderate use than when comparing moderate to heavy use (see Tables 2 and 3 and Fig. 6).

Discussion

Across three large surveys of adolescents in two countries, those who spent more time on digital media reported lower well-being. Adolescents using digital media an hour or less a day reported the highest levels of well-being, and those using digital media 5 or more hours a day reported the lowest levels of well-being. In many cases, heavy users of digital media were twice as likely to experience compromised psychological well-being (including suicide risk

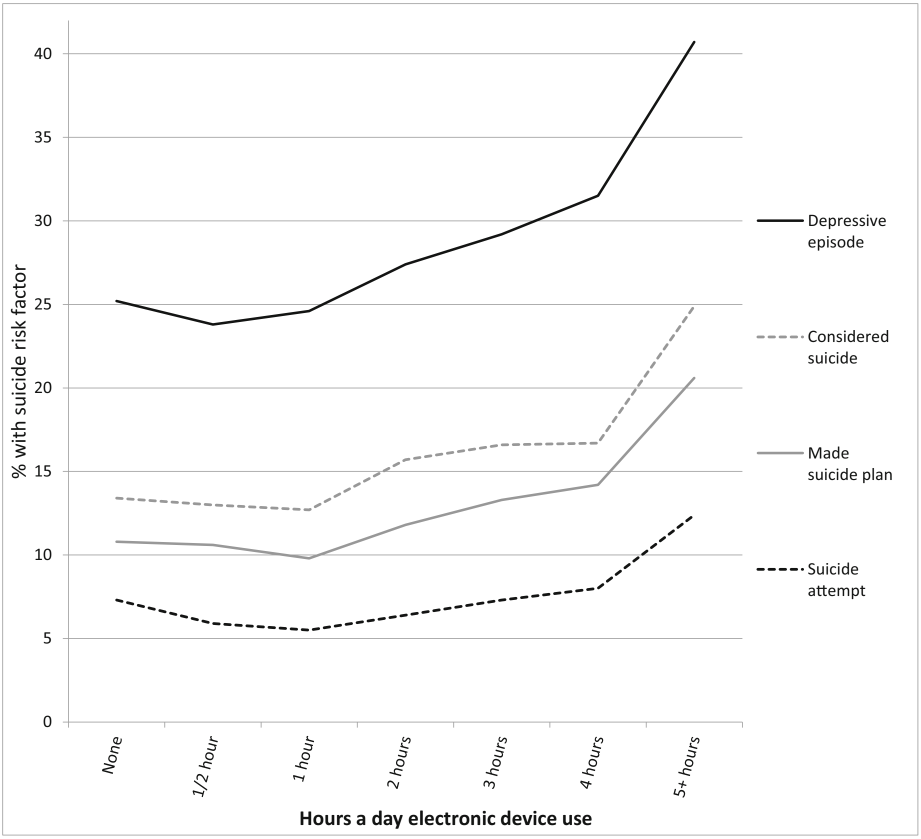

Fig. 6 Percentage of adolescents with suicide risk factors by hours a day of electronic device use, 9th–12th graders, YRBSS, with controls

factors) than light users. These effects were primarily driven by differences between those engaging in moderate vs. heavy use, with heavy use especially problematic for well-being. Of note, those who did not engage in digital media activities at all were lower in well-being than light users. Consistent with an exposure-response model, well-being peaked not at moderate use (as posited by the Goldilocks hypothesis), but instead at light use. Despite the opposite conclusions reached in the previous papers relying on these datasets [35, 54, 55], effect sizes were similar in the UK and U.S. samples when analyzed using the same analytic strategy.

Implications

How these results are interpreted may partially depend on which effect size rubric is used. The choice of effect size rubric (for example, percent variance versus difference in well-being between levels of use) might vary with the question one wants to answer. Percent variance, the calculation of effect size relied on by Przybylski and Weinstein [35] and others, answers the question, "What percentage of the variation among individuals is linked to this factor and not others?" However, psychological well-being is influenced by many different factors, most of which (such as genetics) are not measured in studies of this type and are out of the individual's control and thus difficult to influence via intervention or lifestyle changes [25, 26]. Therefore, percent variance may not be particularly helpful for identifying lifestyle changes linked to improved well-being. The question clinicians and laypeople want answered instead is, "What is the difference in well-being associated with this activity?" Comparing the percentage low in well-being across different levels of use better answers this question than calculating percent variance explained. This viewpoint directly challenges the idea that effects explaining a relatively low percentage of variance are necessarily low in their impact. This is not a new observation; in fact, Rosnow and Rosenthal noted as far back as the 1980s [39, 40] that percent variance was not a good measure of practical impact. The doubling of low well-being from light to heavy use across all three datasets suggests a meaningful link between digital media use and well-being, despite the numerous public statements to the contrary by Przybylski and others [7, 13, 58].

Whether a given effect size is large enough to be meaningful is a matter of debate across several areas of study, including in research on gender differences [42, 62] and violent video games and aggression [16, 19]. The average effect size in social psychology is $r = .21$ (equivalent to $d = .42$; [36]). Ferguson [12] has argued that effect sizes should be $d > .40$ to be considered meaningful. In some fields, even small effect sizes are considered large enough to prompt widespread public health actions. For example, the effect size of secondhand smoke on lung cancer in North American samples (based on correlational data) is $d = .07$ [50], but this finding spawned bans on smoking in public places across the continent. Closer to the present research area are the effect sizes of treatments for depression. The effect of psychotherapy on youth depression is $d = .34$ in high-quality studies [61], and the effect of Internet-based cognitive behavioral therapy by itself is $d = .24$ [49]. Thus, the effect sizes found here for the association of digital media time and mean well-being are comparable in magnitude to several well-established intentional treatments for depression. Nearly half of the effect sizes comparing well-being at light vs. heavy use exceed or approach Ferguson's [12] $d > .40$ criteria. In addition, the doubling of those low in well-being at heavy vs. light digital media use suggests significant clinical relevance; that may be especially true for the doubling of suicide risk factors between light and heavy users.

These results suggest that time spent on digital media, not just quality of interaction online, is linked to psychological well-being. That was especially true at heavylevels of use, perhaps because heavy levels of use may displace time spent on activities beneficial for well-being such as sleep [60] and face-to-face social interaction [53]. These results suggest that experiments should be conducted to determine if restricting time spent on digital media leads to improvements in psychological well-being, perhaps via increased time spent on activities that positively predict well-being.

Limitations

All three of these datasets rely on correlational evidence, and thus cannot determine whether digital media time causes lower well-being or vice versa. However, several longitudinal studies have concluded that digital media use precedes declines in psychological well-being [2, 6, 24, 33, 37, 41], with two additional longitudinal studies showing that lower well-being does not lead to more social media use [21, 44]. At the cohort level, increases in time spent online preceded declines in adolescent happiness [55]. In addition, a random-assignment experiment showed that adults who gave up Facebook for a week ended that time higher in psychological well-being than those who did not [52], a natural experiment found that young adults required to delete their

Facebook accounts due to job requirements showed higher well-being than those who kept their accounts [1], and college students randomly assigned to limit their social media use over three weeks became less depressed and lonely [18]. A series of experiments have found that the presence of smartphones can interfere with enjoyment and meaning in social interactions (e.g., [11, 22]). Thus, limiting time spent on digital media might be considered as an intervention strategy for improving adolescents' psychological well-being. This conclusion is likely to be of interest to parents, clinicians, educators, technology companies, and adolescents themselves. However, the present research is not designed to test any intervention. Rather, it is an addition to a growing body of literature on this topic. We hope that intervention research is conducted.

There is still a great deal of work to be done on mechanisms of action. Przybylski and Weinstein [35] argue for a displacement effect (e.g., excessive digital media use taking up time from other beneficial activities). For example, digital media use may interfere with restful sleep [15] or may replace in-person social interaction [53, 57]. There may be other mechanisms, such as lack of enjoyment due to seeing the world as something to share online [3] or social comparison processes (e.g., FOMO; [31]).

The time use items in these surveys have limitations. First, they are retrospective, asking participants to reflect on past activities, rather than contemporaneous time-diary studies, the gold standard in time use research. Fortunately, comparisons of survey responses and experience sampling in the same individuals find that survey estimates are consistent with experience sampling results, especially for regularly occurring activities [48]. Second, participants were asked to estimate the number of hours they spent on each activity in broad groupings, which lacks precision. Overall, it is likely that adolescents underestimate the amount of time they spend on digital media, which may have implications for conclusions about time limits on use.

Another important challenge is to understand why non-users of digital media have lower psychological well-being than light users. Given the ubiquity of electronic devices, non-users are likely to be a different group of individuals, perhaps in terms of social isolation, special developmental needs, socioeconomic status, and/or academic performance, or (if parents have taken devices away as a punishment or out of concern) in delinquent behavior or predisposition to addictive behavior or depression. Future research should explore these questions.

In conclusion, three large representative datasets from two countries demonstrate a consistent relationship between digital media use and psychological well-being, with well-being steadily declining from light to moderate to heavy use and with slightly lower well-being among non-users. The effects are similar in size to other meaningful effects in social psychology and public health, with rates of low well-being doubling from light to heavy digital media use. Thus, despite the opposing conclusions reached in previous reports, moderate to heavy digital media use consistently co-occurs with lower psychological well-being in large samples of adolescents.

Compliance with Ethical Standards

Conflict of Interest Jean M. Twenge declares she has no conflict of interest. W. Keith Campbell declares he has no conflict of interest.

Ethical Approval This article does not contain any studies with human participants performed by any of the authors.

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