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Journal of Adolescence

journal homepage: [www.elsevier.com/locate/adolescence](https://www.elsevier.com/locate/adolescence)

## Worldwide increases in adolescent loneliness

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### ARTICLE INFO

#### Keywords:

LONELINESS  
Psychological WELL-BEING  
MENTAL HEALTH  
Adolescence  
DIGITAL MEDIA  
SOCIAL MEDIA

### ABSTRACT

**Introduction:** Several studies have documented increases in adolescent loneliness and depression in the U.S., UK, and Canada after 2012, but it is unknown whether these trends appear worldwide or whether they are linked to factors such as economic conditions, technology use, or changes in family size.

**Methods:** The Programme for International Student Assessment (PISA) survey of 15- and 16-year-old students around the world included a 6-item measure of school loneliness in 2000, 2003, 2012, 2015, and 2018 ( $n = 1,049,784$ , 51% female) across 37 countries.

**Results:** School loneliness increased 2012–2018 in 36 out of 37 countries. Worldwide, nearly twice as many adolescents in 2018 (vs. 2012) had elevated levels of school loneliness. Increases in loneliness were larger among girls than among boys and in countries with full measurement invariance. In multi-level modeling analyses, school loneliness was high when smartphone access and internet use were high. In contrast, higher unemployment rates predicted lower school loneliness. Income inequality, GDP, and total fertility rate (family size) were not significantly related to school loneliness when matched by year. School loneliness was positively correlated with negative affect and negatively correlated with positive affect and life satisfaction, suggesting the measure has broad implications for adolescent well-being.

**Conclusions:** The psychological well-being of adolescents around the world began to decline after 2012, in conjunction with the rise of smartphone access and increased internet use, though causation cannot be proven and more years of data will provide a more complete picture.

### 1. Worldwide increases in adolescent loneliness

Beginning in the early 2010s, loneliness, depression, and self-harm increased sharply among U.S. adolescents (Keyes et al., 2019; Mercado et al., 2017; Mojtabai et al., 2016; Twenge, Cooper, et al., 2019; Twenge, Spitzberg, & Campbell, 2019), particularly among girls. Similar trends were reported in other English-speaking countries such as Canada and the UK (e.g., Bushnik, 2016; Patalay & Gage, 2019; for a review, see Haidt & Twenge, 2020). These trends were especially striking as loneliness and depression were unchanged or down for years or decades before these sharp increases beginning around 2012 (Clark et al., 2015; Keyes et al., 2019; Mojtabai et al., 2016; Twenge, Spitzberg, & Campbell, 2019).

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<https://doi.org/10.1016/j.adolescence.2021.06.006>

Received 25 January 2021; Received in revised form 21 June 2021; Accepted 22 June 2021

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However, there is mixed evidence on whether adolescent well-being also suffered in other countries around the world (Cosma et al., 2020; Dierckens et al., 2020). Thus, it remains to be discovered whether the sudden increase in loneliness and depression is limited to English-speaking countries or is instead a worldwide phenomenon.

To provide insight into this question, we draw from the Organisation for Economic Co-operation and Development (OECD) Programme for International Student Assessment (PISA) dataset of 15- and 16-year-olds around the world. More than one million students in 37 countries completed a measure of loneliness at school in 2000, 2003, 2012, 2015, and 2018. School loneliness (also known as school belonging or school connectedness in its inverse) is an established predictor of low well-being and depression among adolescents (Arslan, 2020; Mahon et al., 2006; Patalay & Fitzsimons, 2018), which are in turn associated with reduced quality of life, lower work productivity, and increased health care utilization (Cassano & Fava, 2002; Simon, 2003). However, prior analyses using the PISA dataset have focused on educational outcomes, not on trends in the loneliness items (e.g., Khine et al., 2020; Ma et al., 2019). This measure of school loneliness included on the world's only global educational survey might hold the key to assessing what could be a global increase in adolescent loneliness and depression. Given that other studies documenting trends in mental health have used dichotomous categorization (for example, for depression: e.g., Mojtabai et al., 2016), not just mean levels, it is also important to describe trends in the number of adolescents with high levels of loneliness, as they may be an at-risk population.

In addition to defining the scope of trends in loneliness, examining trends across many countries may help determine which cultural changes co-occur with any trends in adolescent well-being (although causation cannot be proven, given the impossibility of experimental research on cultural change). Some have speculated that the increases in adolescent loneliness and depression beginning around 2012 may be linked to the increasing use of digital media such as smartphones and social media (e.g., Luby & Kertz, 2019; Spiller, Ackerman, Spiller, & Casavant, 2019), given that 2012 was the first year when the majority of Americans owned a smartphone and that daily social media use among adolescents reached a critical mass in the early 2010s (Twenge, Martin, & Spitzberg, 2019).

Some studies find that individuals who spend more hours on digital media are more likely to be lonely and low in well-being (Primack et al., 2017; Song et al., 2014), while other studies find only a small or null effect (Nowland et al., 2017; Orben & Przybylski, 2019). However, these studies examined digital media and loneliness at the individual level, and digital media use may be associated with adolescent loneliness at the group level as well. For example, as smartphone adoption became widespread in the 2010s, adolescents spent less time interacting with each other in person and more time using digital media (Twenge, Spitzberg, & Campbell, 2019; Twenge & Spitzberg, 2020). Given that digital media does not produce as much emotional closeness as in-person interaction (Sherman et al., 2013), the result may be more loneliness in recent years.

Social interaction involves a group, not just an individual, and the average adolescent in 2018 had fewer opportunities to socialize in person and more opportunities to socialize online than the average adolescent in 2000 due to the shift in social norms. Thus, at the group level, they had less opportunity for an activity (in person social interaction) that protects against loneliness, and more opportunity for an activity that does not (digital media use; Twenge, Spitzberg, & Campbell, 2019). These social norm shifts may impact teens no matter how much or how little they personally use digital media. For example, social media may heighten feelings of missing out both when adolescents do not use it (as then they are cut off from communication) and when they do use it (as they may observe what their friends are doing without them and feel excluded: Covert & Stefanone, 2018; or they may experience cyberbullying: Dennehy et al., 2020). All of these experiences may lead to feelings of loneliness, and all were uncommon before 2010 when only a minority of teens used social media every day; by 2016, however, more than 83% of adolescents in the U.S. used social media every day (Twenge, Martin, & Spitzberg, 2019). In addition, smartphones may interfere with in-person interactions through "phubbing" (ignoring someone to look at one's phone; Roberts & David, 2016) and other distractions. This may explain why the accessibility of smartphones can dampen enjoyment of in-person social interactions among groups (Dwyer et al., 2018), which may in turn lead to feelings of loneliness. In the school setting specifically, smartphones may lead students to converse with each other less often or to interrupt face-to-face conversations to look at phones (Chotpitayasonondh & Douglas, 2016). These effects can occur whether an individual uses a smartphone or not, as long as other members of the group do.

Consistent with the idea of changes at the group level, increases in smartphone adoption and internet use preceded declines in adolescent well-being in U.S. samples in group-level Granger causality analyses (Twenge et al., 2018). If similar declines in well-being occurred around the world and not just in the U.S., that would be stronger evidence that a worldwide trend such as smartphone adoption – rather than factors unique to just a few countries – were operating. Given that smartphones did not exist in 2000 and 2003 and internet and social media use were limited during those years, anticipating a role for digital media use in school loneliness hypothesizes increases in loneliness in the PISA data occurring primarily between 2012 and 2018.

Other group-level factors may also be operating and must be considered as well. A global financial crisis began in 2008, just as smartphone ownership also began to spread. Thus, any attempt to identify causes of the increase in loneliness must adjudicate between these two global trends. Given connections between parental unemployment and adolescent low well-being (McLoyd et al., 1994), loneliness should be high when the economy is not performing well. Economic issues have been specifically suggested as a cause for the rise in adolescent depression in the U.S. during the 2010s (Mojtabai et al., 2016). Thus, we can examine co-occurrence with indicators of economic performance such as the unemployment rate and the gross domestic product (GDP). Other economic variables such as income inequality may also be important. Across 34 countries, happiness was lower when income inequality was higher, even during times of economic growth (Oishi & Kesebir, 2015). A meta-analysis also concluded that depression was higher when income inequality was higher across countries and time (Patel et al., 2018). These studies examined well-being among adults rather than adolescents; since adolescents are usually not supporting themselves economically, patterns may be different. However, if the same pattern holds for adolescents, school loneliness should be high during times of higher income inequality. Finally, trends in family size may have implications for feelings of loneliness among adolescents; smaller families and fewer siblings may mean more loneliness. Thus, we examined total fertility rate as a proxy for family size, again at the group (country) level.

**Table 1**School loneliness means, *d*'s, and 95% confidence intervals 2000–2018, within country, by region, and worldwide.

	2000	2003	2012	2015	2018	<i>d</i> (95% CI) 2000–2018	<i>d</i> (95% CI) 2012–2018
<b>Protestant Europe</b>							
Denmark	1.74 (.49)	1.76 (.46)	1.74 (.51)	1.88 (.61)	1.86 (.56)	.22 (.17, .27)	.22 (.18, .26)
5.6 million	2249	3776	4548	6440	6296		
Finland	1.77 (.47)	1.77 (.46)	1.80 (.51)	1.89 (.58)	1.96 (.59)	.35 (.30, .39)	.29 (.25, .33)
5.5 million	2620	5652	5526	5621	5102		
Germany	1.73 (.53)	1.68 (.51)	1.61 (.51)	1.81 (.64)	1.80 (.57)	.13 (.08, .18)	.35 (.30, .40)
82.3 million	2641	4091	2698	5353	3765		
Iceland	1.75 (.53)	1.72 (.54)	–	1.89 (.72)	1.96 (.69)	.33 (.27, .39)	–
.4 million	1785	3236		3150	2888		
Netherlands	1.76 (.40)	1.77 (.39)	1.76 (.43)	1.82 (.52)	1.82 (.49)	.13 (.06, .19)	.13 (.08, .18)
17.2 million	1336	3682	2797	5078	3689		
Norway	1.74 (.51)	1.67 (.49)	1.75 (.54)	1.85 (.63)	1.81 (.61)	.12 (.07, .17)	.10 (.06, .15)
5.4 million	2155	3733	2882	5093	5243		
Sweden	1.67 (.48)	1.65 (.47)	1.74 (.54)	1.97 (.74)	1.97 (.64)	.51 (.46, .56)	.38 (.33, .43)
10.1 million	2364	4346	2907	5071	4801		
Switzerland	1.70 (.51)	1.70 (.49)	1.63 (.50)	1.78 (.61)	1.83 (.56)	.24 (.19, .29)	.39 (.34, .42)
8.6 million	3059	7705	7166	5545	4827		
Region average	1.73 (.50)	1.70 (.49)	1.66 (.50)	1.83 (.62)	1.83 (.57)	.19 (.16, .20)	.32 (.30, .33)
	18209	36221	28524	41351	36611		
<b>Catholic Europe</b>							
Austria	1.69 (.54)	1.60 (.49)	1.51 (.50)	1.77 (.73)	1.78 (.66)	.15 (.09, .19)	.44 (.40, .49)
8.8 million	2495	4209	3023	6708	6113		
Belgium	1.90 (.48)	1.88 (.46)	1.82 (.48)	1.92 (.53)	1.94 (.52)	.08 (.04, .12)	.24 (.20, .27)
11.4 million	3529	8030	5271	8754	7338		
Czech Republic	1.91 (.41)	1.87 (.40)	1.89 (.46)	2.06 (.53)	2.10 (.52)	.39 (.34, .43)	.42 (.38, .46)
10.7 million	2860	5744	3336	6397	6199		
France	1.87 (.49)	1.85 (.47)	1.89 (.47)	1.96 (.50)	2.06 (.50)	.38 (.33, .43)	.35 (.31, .39)
67.0 million	2423	3990	2741	5312	5089		
Greece	1.81 (.46)	1.74 (.42)	1.79 (.50)	1.86 (.55)	1.93 (.55)	.23 (.18, .28)	.26 (.22, .31)
10.7 million	2419	4330	3300	5239	5815		
Hungary	1.72 (.45)	1.73 (.46)	–	1.91 (.61)	1.91 (.58)	.36 (.31, .40)	–
9.8 million	2672	4578		5341	4722		
Italy	1.79 (.45)	1.74 (.43)	1.77 (.49)	1.90 (.55)	1.92 (.54)	.25 (.21, .29)	.30 (.27, .32)
60.5 million	2680	11,118	20,077	10,815	10,182		
Luxembourg	1.79 (.56)	1.68 (.50)	1.71 (.55)	1.90 (.64)	1.93 (.58)	.24 (.19, .30)	.39 (.34, .43)
.6 million	1724	3548	3301	4925	4592		
Poland	2.00 (.45)	1.84 (.45)	1.86 (.49)	2.11 (.64)	2.11 (.57)	.20 (.15, .26)	.46 (.42, .51)
38.0 million	1659	4201	2991	4336	5343		
Portugal	1.76 (.41)	1.72 (.41)	1.73 (.48)	1.89 (.58)	1.87 (.52)	.23 (.18, .27)	.28 (.24, .32)
10.3 million	2405	4313	3708	6982	5325		
Spain	1.79 (.44)	1.68 (.44)	1.61 (.49)	1.70 (.63)	1.69 (.58)	-.18 (–.21, –.14)	.15 (.13, .16)
46.7 million	3273	10,084	16,275	6474	31,693		
Region average	1.85 (.46)	1.78 (.45)	1.78 (.48)	1.91 (.57)	1.94 (.54)	.18 (.16, .19)	.31 (.30, .32)
	28,139	64,145	64,023	71,283	92,411		
<b>Orthodox</b>							
Bulgaria	1.87 (.44)	–	1.89 (.52)	2.15 (.65)	2.13 (.57)	.50 (.44, .55)	.44 (.39, .48)
7.1 million	2246		3250	5143	3950		
Russia	1.90 (.43)	1.91 (.43)	1.94 (.46)	2.16 (.55)	2.21 (.55)	.61 (.56, .65)	.50 (.44, .57)
144.5 million	3452	5251	1142	5477	6631		
Region average	1.90 (.43)	1.91 (.43)	1.94 (.46)	2.16 (.55)	2.21 (.55)	.63 (.57, .64)	.53 (.48, .55)
	5698	5251	4392	10,620	10,581		
<b>Baltic</b>							
Latvia	1.96 (.44)	1.86 (.41)	1.85 (.48)	2.06 (.58)	2.12 (.57)	.30 (.25, .35)	.50 (.45, .55)
1.9 million	2019	4321	2769	4678	4829		
<b>English-speaking</b>							
Australia	1.82 (.47)	1.76 (.46)	1.91 (.52)	2.03 (.58)	2.09 (.58)	.48 (.44, .52)	.33 (.30, .35)
24.6 million	2746	11,888	9112	13,377	11,687		
Canada	1.76 (.52)	1.78 (.50)	1.83 (.54)	2.04 (.61)	2.08 (.61)	.56 (.54, .58)	.43 (.41, .45)
37.6 million	16,033	24,312	13,626	18,706	19,574		
Ireland	1.76 (.48)	1.73 (.43)	1.79 (.49)	1.94 (.56)	2.04 (.54)	.54 (.48, .59)	.48 (.44, .52)
4.8 million	2053	3448	3276	5473	5208		
New Zealand	1.80 (.47)	1.77 (.46)	1.88 (.50)	2.02 (.55)	2.08 (.56)	.52 (.47, .57)	.37 (.32, .42)
4.8 million	1936	4239	2703	4239	5725		
United Kingdom	1.74 (.47)	1.74 (.46)	1.82 (.50)	1.99 (.56)	2.09 (.56)	.66 (.62, .69)	.50 (.47, .53)
66.4 million	4944	8777	8092	13,082	12,192		
United States	1.85 (.54)	1935	–	1.85 (.53)	3168	1.99 (.60)	5414
327.2 million					2.11 (.60)	4487	.45 (.39, .50)
							.46 (.41, .50)

(continued on next page)

Table 1 (continued)

	2000	2003	2012	2015	2018	<i>d</i> (95% CI) 2000–2018	<i>d</i> (95% CI) 2012–2018
Region average	1.82 (.52) 29,647	1.76 (.47) 52,664	1.85 (.53) 39,977	2.00 (.59) 60,291	2.10 (.59) 58,873	.50 (.47, .51)	.45 (.43, .45)
<b>Latin America</b>							
Brazil	1.70 (.45) 209.3 million	1.71 (.46) 3630	1.85 (.50) 11,340	2.03 (.61) 18,276	2.06 (.58) 7813	.66 (.61, .70)	.39 (.36, .42)
Chile	1.71 (.51) 18.1 million	–	1.71 (.51) 4368	1.93 (.64) 6731	1.99 (.61) 6294	.48 (.43, .53)	.49 (.45, .53)
Mexico	1.75 (.46) 129.2 million	1.72 (.44) 27,002	1.74 (.49) 21,742	2.05 (.71) 7209	1.97 (.60) 5331	.40 (.34, .44)	.45 (.42, .48)
Peru	1.88 (.49) 32.2 million	–	1.88 (.43) 3449	1.04 (.55) 6535	2.01 (.53) 4062	.24 (.20, .30)	.25 (.22, .31)
Average	1.73 (.46) 9572	1.71 (.45) 30,632	1.81 (.49) 40,899	2.03 (.64) 38,751	2.02 (.58) 23,500	.53 (.51, .55)	.40 (.38, .42)
<b>Confucian</b>							
Hong Kong	1.98 (.39) 7.4 million	2.05 (.40) 4407	2.03 (.45) 3004	2.12 (.48) 5158	2.18 (.50) 5620	.43 (.38, .47)	.31 (.27, .36)
Japan	1.97 (.50) 126.8 million	2.04 (.48) 4561	1.84 (.53) 4121	1.96 (.54) 6404	1.96 (.54) 5838	-.02 (–.06, .03)	.22 (.18, .26)
South Korea	1.99 (.46) 51.5 million	1.96 (.44) 5368	1.87 (.47) 3342	1.84 (.48) 5443	1.82 (.54) 6529	-.33 (–.37, –.28)	-.10 (–.14, –.05)
Region average	1.98 (.48) 7848	2.02 (.47) 14,336	1.86 (.51) 10,467	1.93 (.52) 17,005	1.93 (.54) 17,987	-.10 (–.12, –.07)	.13 (.11, .15)
<b>South Asia</b>							
Thailand	1.92 (.39) 69.0 million	1.87 (.36) 5077	1.98 (.44) 4343	2.11 (.46) 7856	2.15 (.46) 8298	.52 (.48, .56)	.38 (.34, .41)
<b>African-Islamic</b>							
Indonesia	1.86 (.36) 264 million	1.90 (.33) 9088	1.88 (.40) 3598	1.76 (.35) 6223	1.96 (.48) 11,416	.22 (.18, .26)	.17 (.14, .21)
<b>Worldwide average</b>	1.83 (.46) 107,666	1.81 (.44) 221,735	1.84 (.48) 198,992	1.96 (.55) 258,058	2.02 (.55) 264,506	.36 (.35, .37)	.35 (.34, .35)

NOTES: 1. Numbers in cells are means, standard deviations (in parentheses), and *n*'s. 2. Region and worldwide averages are weighted by the population size of each country. 3. Dashes indicate that the survey or measure was not administered in that country in that year.

To determine associations between psychological well-being and digital media use and economic and family conditions at the group level, we take an ecological approach, a classic method for examining the drivers of cultural change (Cosma et al., 2020; Dierckens et al., 2020; Grossmann & Varnum, 2015; Santos et al., 2017). Thus, we match group-level indicators (smartphone access, internet use, unemployment rates, GDP, the GINI index of income inequality, and total fertility rate) within country and by year with mean school loneliness in an attempt to discover how indicators co-occur with trends in school loneliness. Although such analyses cannot prove causation, they can test whether cultural indicators can be ruled in or out. Assuming a relatively simple model, if an indicator is unrelated or related in the opposite direction than previous evidence would suggest, it seems unlikely to be the cause of the trends in loneliness. If it is related in the same direction as previous evidence would suggest, then it is more likely, though not proven, to be a cause of the trends.

### 1.1. Current research

In this study, we take several steps to address trends in adolescent well-being using the PISA dataset. As a preliminary step, we examine correlations between the measure of school loneliness and three other measures of well-being (positive affect, negative affect, and life satisfaction) included in the 2018 survey. This will demonstrate whether the school loneliness measure overlaps with other indicators of well-being and thus may be relevant for documenting worldwide trends in adolescent well-being. We also examine the measurement invariance of the loneliness scale across years. Next, we document trends 2000–2018 across 37 countries in school loneliness by country, region, and worldwide. Finally, we use multi-level modeling to examine associations between school loneliness and six group-level indicators: smartphone access, internet use, unemployment, GDP, income inequality, and total fertility rate.

## 2. Method

### 2.1. Participants

Participants were students completing the OECD PISA survey, which obtains nationally representative samples of 15- and 16-year-olds enrolled in school in each country. Schools were required to have at least an 80% response rate for selected students. The survey was administered in the same language used for instruction in the school (OECD, 2020). The 2000, 2003, 2012, 2015, and 2018 surveys included a measure of school loneliness (see below). These items were asked in at least 4 of the 5 administrations of students in 37 countries around the world (see Table 1); total *n* = 1,049,784 (531,370 girls and 518,414 boys; 51% female). Most students (67%)

**Table 2**  
Percent high in school loneliness, 2000–2018, within country, by region, and worldwide.

	2000	2003	2012	2015	2018	% diff 2000–2018	% diff 2012–2018
<b>Protestant Europe</b>							
Denmark 5.6 million	12.85%	12.26%	13.85%	20.90%	20.93%	62.88%	51.12%
Finland 5.5 million	13.24%	11.69%	15.54%	20.83%	27.40%	106.95%	76.32%
Germany 82.3 million	14.73%	12.34%	10.97%	19.04%	20.05%	36.12%	82.77%
Iceland .4 million	14.68%	13.10%	–	23.49%	29.02%	97.68%	–
Netherlands 17.2 million	10.85%	8.61%	11.37%	13.19%	16.21%	49.40%	42.57%
Norway 5.4 million	13.97%	10.05%	14.50%	21.19%	21.36%	52.90%	47.31%
Sweden 10.1 million	11.42%	9.46%	16.37%	27.17%	28.31%	147.90%	72.94%
Switzerland 8.6 million	13.70%	11.71%	11.00%	17.39%	21.55%	57.30%	95.91%
Region average	13.75%	11.49%	11.88%	19.05%	20.69%	50.42%	74.21%
<b>Catholic Europe</b>							
Austria 8.8 million	14.87%	9.65%	8.60%	19.81%	21.14%	42.17%	145.81%
Belgium 11.4 million	19.44%	17.38%	14.93%	19.93%	23.13%	18.98%	54.92%
Czech Republic 10.7 million	17.31%	13.47%	15.89%	27.70%	32.44%	87.41%	104.15%
France 67.0 million	17.99%	15.24%	18.10%	24.06%	31.01%	72.37%	71.33%
Greece 10.7 million	15.13%	8.96%	15.61%	18.76%	24.16%	59.68%	54.77%
Hungary 9.8 million	10.55%	10.99%	–	22.77%	25.22%	139.05%	–
Italy 60.5 million	14.03%	9.47%	14.26%	21.56%	24.68%	75.91%	73.07%
Luxembourg .6 million	17.69%	12.09%	16.18%	23.90%	28.18%	59.30%	74.17%
Poland 38.0 million	29.29%	14.33%	16.68%	31.50%	35.39%	20.83%	112.17%
Portugal 10.3 million	10.35%	7.81%	12.81%	19.78%	20.15%	94.69%	57.30%
Spain 46.7 million	14.36%	8.27%	9.73%	13.79%	14.48%	0.84%	48.82%
Region average	17.33%	11.81%	14.69%	22.21%	25.93%	49.62%	76.55%
<b>Orthodox</b>							
Bulgaria 7.1 million	18.17%	–	23.75%	36.73%	43.72%	140.62%	84.08%
Russia 144.5 million	19.18%	17.31%	21.63%	35.88%	44.97%	134.46%	107.91%
Region average	19.13%	17.31%	21.73%	35.92%	44.91%	134.74%	106.69%
<b>Baltic</b>							
Latvia 1.9 million	22.29%	13.91%	16.00%	29.91%	37.36%	67.61%	133.50%
<b>English-speaking</b>							
Australia 24.6 million	14.09%	10.42%	20.54%	28.71%	34.43%	144.36%	67.62%
Canada 37.6 million	13.29%	12.19%	18.46%	30.03%	34.80%	161.85%	88.52%
Ireland 4.8 million	11.45%	8.61%	13.68%	21.93%	27.84%	143.14%	103.51%
New Zealand 4.8 million	12.65%	11.06%	17.72%	27.22%	32.19%	154.47%	81.66%
United Kingdom 66.4 million	10.03%	9.74%	15.39%	25.16%	32.85%	227.52%	113.45%
United States 327.2 million	18.55%	–	18.21%	27.50%	36.57%	97.14%	100.82%
Region average	16.54%	10.53%	17.90%	27.37%	35.65%	115.53%	99.16%
<b>Latin America</b>							
Brazil 209.3 million	9.96%	9.09%	19.10%	28.17%	34.83%	249.70%	82.36%

(continued on next page)

Table 2 (continued)

	2000	2003	2012	2015	2018	% diff 2000–2018	% diff 2012–2018
Chile 18.1 million	14.08%	–	13.60%	24.07%	30.98%	120.03%	127.79%
Mexico 129.2 million	13.04%	9.40%	13.29%	29.24%	26.71%	104.83%	100.98%
Peru 32.2 million	22.62%	–	16.65%	28.68%	27.40%	21.13%	64.56%
Region average <b>Confucian</b>	12.22%	9.21%	16.71%	28.38%	31.34%	156.36%	87.53%
Hong Kong 7.4 million	19.98%	25.19%	25.37%	32.22%	39.36%	97.00%	55.14%
Japan 126.8 million	25.90%	29.31%	20.31%	26.12%	27.56%	6.41%	35.70%
South Korea 51.5 million	27.29%	23.83%	18.79%	17.86%	20.48%	–24.95%	8.99%
Region average <b>South Asia</b>	26.05%	27.63%	20.09%	24.07%	26.07%	0.07%	29.75%
Thailand 69.0 million	18.74%	11.33%	25.58%	34.01%	42.81%	128.44%	67.36%
<b>African-Islamic</b>							
Indonesia 264 million	11.85%	10.16%	14.51%	6.70%	24.15%	103.80%	66.44%
<b>Worldwide average</b>	16.15%	13.21%	17.12%	24.03%	30.86%	91.05%	80.26%

NOTES: 1. For  $n$ 's within cells, refer to Table 1. 2. High loneliness is defined as a score of 2.22 or above on the 1–4 scale. 3. Percent difference is the relative percent increase or decrease in the number of adolescents with high loneliness between two years, calculated using formula B-A/A (with B the percent in the more recent year and A the percent in the less recent year). Percent difference is similar to relative risk (RR); for example, a percent difference of 100% is equivalent to  $RR = 2.00$ , or double the risk; a percent difference of 50% is  $RR = 1.50$ . 4. Region and worldwide averages are weighted by the population size of each country. 5. Dashes indicate that the survey or measure was not administered in that country in that year.

were 15 years old, with the rest 16 years old. The data are publicly available at <http://www.oecd.org/pisa/data/>

## 2.2. Measures

**School loneliness.** PISA asked six questions about loneliness at school: “I feel like an outsider (or left out of things) at school,” “I make friends easily at school” (reverse-scored), “I feel like I belong at school” (reverse-scored), “I feel awkward and out of place in my school,” “Other students seem to like me” (reverse-scored), and “I feel lonely at school.” Response choices were “strongly disagree,” “disagree,” “strongly agree,” and “agree,” scored from 1 to 4 with higher scores indicating more loneliness. Responses were added together and divided by 6 to calculate mean scores (Cronbach alpha = .82). We also examined trends in the number of adolescents with high levels of loneliness. We conducted a univariate normal mixture model using mixtools in R to estimate the presence of subgroups in our data (Benaglia et al., 2009); R Core Team, 2013). Using a 2-component mixture fit (low and high loneliness), we used the mean scores of our estimated subgroups to derive an appropriate cutpoint for low-high subgroups. This identified a cutpoint of 2.22 on the 1–4 scale (see Supplemental Fig. 1). We present only descriptive statistics for this dichotomous variable; all other analyses and models are based on the continuous measure of loneliness.

**Validation measures.** In 2018 only, PISA included a 5-item measure of positive affect (happy, proud, joyful, cheerful, lively; Cronbach alpha = .82) and a 4-item measure of negative affect (scared, miserable, afraid, sad; Cronbach alpha = .75), with response choices of never (1), rarely (2), sometimes (3), and always (4). Second, the survey included an item on general life satisfaction: “Overall, how satisfied are you with your life these days?” from 0 to 10, with higher numbers indicating more satisfaction.

**Smartphone access and internet use.** In 2012, 2015, and 2018 in 31 of the 37 countries with school loneliness data, students were asked, “Which of these is available for you to use at home? ... Cell phone with Internet access.” We recorded the percentage who answered “yes, and I use it” an indicator of smartphone access among respondents for each country. Students in these years were also asked, “On a typical weekday, for how long do you use the Internet outside of school?” with responses recoded to no time = 0, 1–30 min per day = .25, 31–60 min per day = .75, between 1 h and 2 h per day = 1.5, between 2 h and 4 h per day = 3, between 4 h and 6 h per day = 5, and more than 6 h per day = 7.

## 2.3. Procedure

We took two initial steps to examine the measurement properties of the school loneliness measure. First, we examined correlations between the continuous loneliness scale and three other measures of psychological well-being included in the 2018 dataset: positive affect, negative affect, and life satisfaction. We performed these analyses within countries to ensure that the results were not confounded by differences across countries.

Second, we examined the measurement invariance of the continuous school loneliness measure across the five time points of data collection within countries. This provides information about whether the measure has the same factor structure across time points of data collection. To do this, we used Multigroup Confirmatory Factor Analysis step-by-step through the three phases of measurement

invariance testing, beginning with configural invariance and then moving on to metric and scalar invariance. These analyses were conducted using the lavaan and SemTools packages in R (Hirshfeld, Gerrit & Brachel, 2014). Configural invariance was determined using the Comparative Fit Index (CFI), where  $CFI > 0.90$  was considered invariant, and metric and scalar invariance were then determined using Delta CFI, where  $\Delta CFI < \text{or equal to } 0.02$  was considered invariant (He et al., 2019).

For our primary research question, whether school loneliness changed over time, we report trends both for individual countries and in larger aggregates. We grouped countries into broad regions using the categories employed by the World Values Survey (Inglehart & Welzel, 2017; see Table 1). To obtain overall means and percentages by region and worldwide, we weighted by country population in 2018, so countries with a higher population in the region or the world counted proportionally more in the mean. This seemed more likely to be broadly representative and accurate than using unweighted means, which are influenced by arbitrary factors such as larger sample sizes in some countries in some years. We report means and percentages overall (see Tables 1 and 2) and separately by sex (see Supplemental Tables 1 and 2).

To determine which group-level factors covaried with loneliness as a continuous variable, we examined indicators of digital media use, economic performance, and family size at the level of countries and years. We obtained unemployment rate, GDP, income inequality (GINI index), and total fertility data by country and year from the World Bank website. Unemployment, income inequality, and GDP were entered for the current year, and total fertility rate at the approximate year of birth (15 years prior), as a proxy for family size at the time respondents' families were forming. Unemployment rates, GDP, and total fertility were available for all 37 countries, and the GINI index for income inequality was available up to 2017 or 2018 for 26 countries. Smartphone access and internet use by country and year came from the PISA dataset in 2012, 2015, and 2018 (see measures). Because of the nested nature of our data (years within countries), we used multi-level modeling with random intercepts (Bates et al., 2015) in R (R Core Team, 2015) to explore the main effects of smartphone access, internet use, unemployment, income inequality, GDP, and total fertility rate on school loneliness as a continuous variable. We also included year in our model to statistically control for the effects of time and correct for autocorrelation. Following multi-level model analysis convention (Hedeker & Gibbons, 2006; Singer, 1998; Snijders & Bosker, 2006), year was centered at  $t_0$  (first time point observation). To account for the variation of occasion in our data, we subdivided data based on the complete observations used in the model, then centered year based on the earliest year within the subset. For instance, the smartphone access variable began in 2012, therefore we centered on year at the 2012 timepoint for this model.

We examined both simple models (with each indicator and year predicting school loneliness) and comprehensive models (one with smartphone access, all other indicators, and year predicting school loneliness, and another with internet use, all other indicators, and year predicting school loneliness). For independent variable  $p$ -value calculations, we used the Satterthwaite's degrees of freedom approximation in lmerTest (Kuznetsova et al., 2017) which provides robust approximations in simulations (Luke, 2017). To ensure the

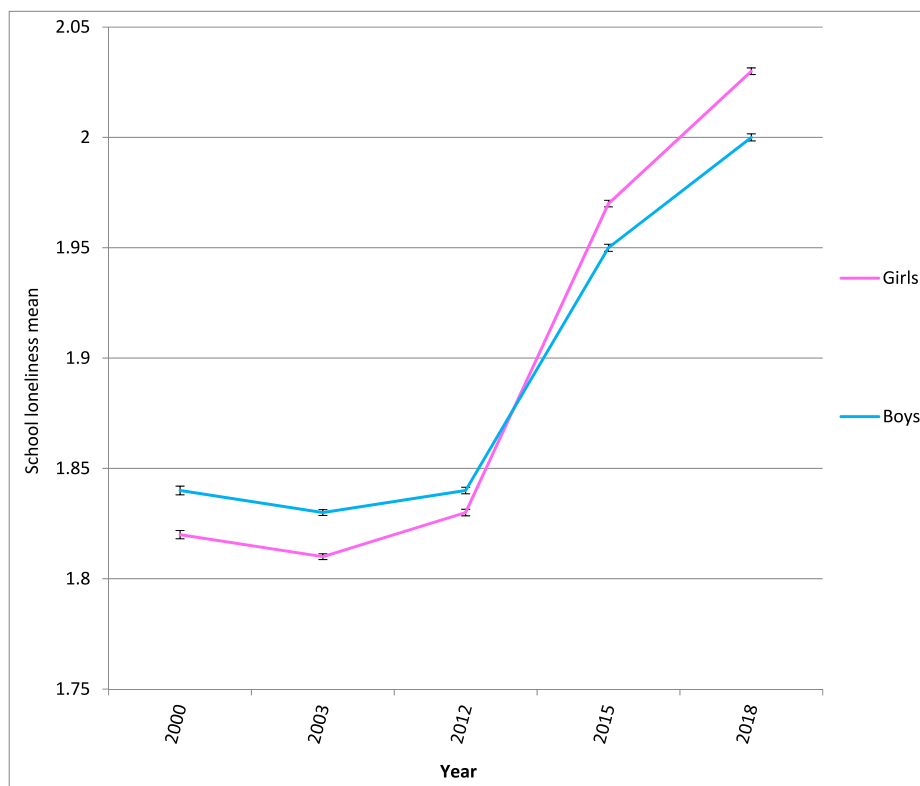


Fig. 1. School loneliness mean, worldwide, by sex. Error bars are plus or minus one SE.

most accurate variance and covariance estimation, we used “post-hoc” standardization techniques suggested by Hox et al. (2018) to report standardized effects. We also performed interaction models to examine the potentially complex patterns between these indicators and year.

### 3. Results

#### 3.1. Validation of school loneliness measure with other measures of well-being

First, we examined correlations with other well-being measures within countries in the 2018 dataset to validate the measure of school loneliness. The school loneliness measure as a continuous variable correlated between  $r = 0.18$  and  $r = 0.46$  with negative affect, between  $r = -0.29$  and  $r = -0.47$  with positive affect, and between  $r = -0.20$  and  $r = -0.45$  with life satisfaction (see Supplemental Table 1). Thus, the school loneliness measure overlaps considerably with three other measures of psychological well-being.

#### 3.2. Measurement invariance

Next, we examined whether the school loneliness measure as a continuous variable demonstrated measurement invariance across the five time points of the survey. These analyses revealed that 12 countries displayed full measurement invariance (configural, metric, and scalar) across the five time points (Australia, Canada, the Czech Republic, Finland, Hungary, Iceland, the Netherlands, New Zealand, Norway, Sweden, the United Kingdom, and the United States; see Supplemental Table 2). Twelve countries demonstrated configural and metric invariance but not scalar invariance (Austria, Belgium, Chile, Denmark, Germany, Greece, Italy, Latvia, Poland, Portugal, Spain, and Switzerland). The remaining 13 countries did not pass configural invariance (Brazil, Bulgaria, France, Hong Kong, Iceland, Indonesia, Japan, Luxembourg, Peru, Mexico, Russia, South Korea, and Thailand). Thus, the factor structure was similar across years of data collection in some countries, but not in others. Given this span of outcomes, we will report trends in school loneliness within these categories of measurement invariance in the results.

#### 3.3. Trends 2000–2018 in school loneliness

School loneliness increased between 2000 and 2018, with nearly all of the increase occurring between 2012 and 2018. Adolescent loneliness increased after 2012 in 36 of 37 countries (see Tables 1 and 2, Figs. 1 and 2, and Supplemental Tables 3 and 4). Worldwide, nearly twice as many adolescents in 2018 scored high in loneliness than in 2000, with much of the increase occurring after 2012. Even with the recent increases, however, the majority of students did not report high levels of loneliness.

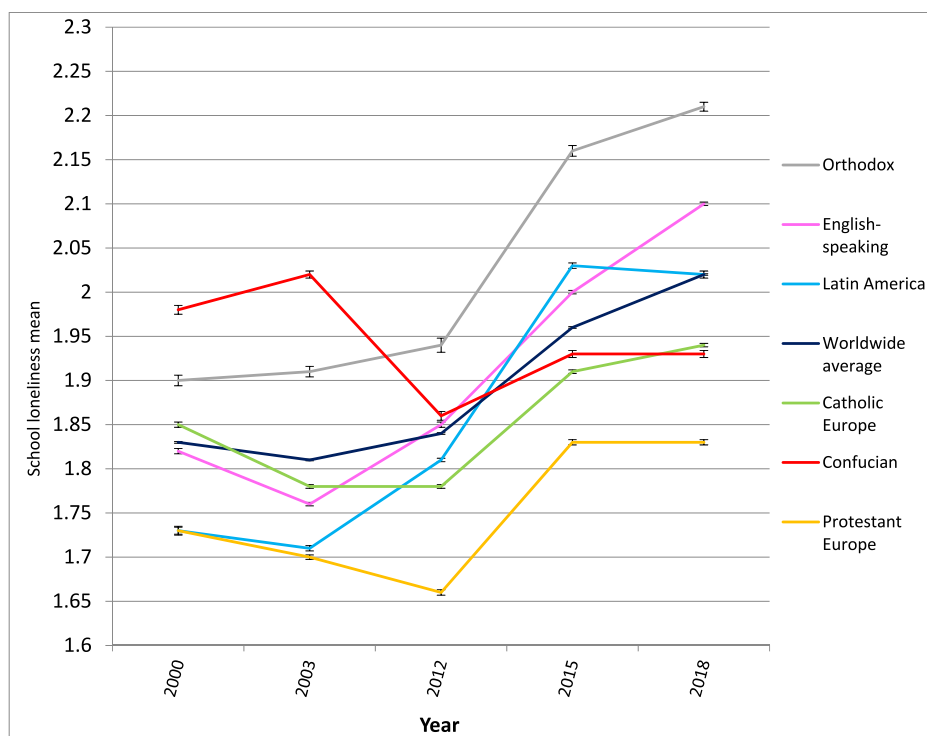


Fig. 2. School loneliness mean, by region. Error bars are plus or minus one SE.



By region, the largest increases in school loneliness appeared in Orthodox countries ( $d = 0.53$ , Bulgaria and Russia), Baltic countries ( $d = 0.50$ , Latvia), English-speaking countries ( $d = 0.45$ , Australia, Canada, Ireland, New Zealand, United Kingdom, United States), and Latin American countries ( $d = 0.40$ , Brazil, Chile, Mexico, and Peru). The smallest increases were in Confucian countries ( $d = 0.13$ , Hong Kong, Japan, and South Korea), primarily because school loneliness declined in South Korea, the only country of the 37 to not increase in loneliness. The loneliness increase since 2012 was somewhat larger among girls (93.41% and  $d = 0.38$ ) than among boys (66.45% and  $d = 0.31$ ),  $Z = 17.93$ ,  $p < .001$ .

The loneliness increase averaged  $d = 0.43$  from 2012 to 2018 among countries showing full measurement invariance on the loneliness scale,  $d = 0.31$  among countries with configural and metric invariance, and  $d = 0.32$  among countries without configural measurement invariance over time (weighted by population size). Thus, the countries with the most stable measurement had the largest increase in loneliness. Countries in all three categories of measurement invariance showed increases in school loneliness between 2012 and 2018 (see [Supplemental Fig. 2](#)).

**Table 3**

Multi-level modeling of group-level predictors of mean school loneliness as a continuous variable, fixed effects for each indicator and year.

	<i>b</i>	<i>t</i> value	Std. <i>b</i>	LL	UL
<b>Smartphone access</b> ( $n = 83$ , $k = 31$ )					
Additive model					
Smartphone access	.0037***	3.72	.29	.0017	.0055
Year	.0171***	4.16	.28	.0100	.0249
Interaction model					
Smartphone access	.0031**	3.12	.24	.0012	.0051
Year	.0290***	4.94	.48	.0556	.2387
Interaction term	-.0013**	-2.72	-.10	-.0022	-.0004
<b>Internet use</b> ( $n = 83$ , $k = 31$ )					
Additive model					
Internet use	.0753**	2.97	.38	.0308	.1287
Year	.0137*	2.30	.23	.0011	.0247
Interaction model					
Internet use	.0807**	3.07	.41	.0287	.1303
Year	.0145*	2.41	.24	-.0049	.0557
Interaction term	-.0036	-0.85	-.02	-.0126	.0046
<b>Unemployment</b> ( $n = 179$ , $k = 37$ )					
Additive model					
Unemployment	-.0057*	-2.54	-.18	-.0101	-.0008
Year	.0094***	10.50	.47	.0074	.0111
Interaction model					
Unemployment	-.0017	-0.50	-.05	-.0082	.0053
Year	.0093***	10.32	.47	.0079	.0155
Interaction term	-.0004	1.53	-.02	-.0009	.0001
<b>Income inequality</b> ( $n = 123$ , $k = 26$ )					
Additive model					
Income inequality	-.0001	0.45	-.05	-.0054	.0034
Year	.0095***	8.86	.48	.0074	.0116
Interaction model					
Income inequality	-.0025	1.11	-.14	-.0070	.0018
Year	.0096***	9.14	.48	-.0119	.0080
Interaction term	.0003*	2.31	.02	.0001	.0006
<b>GDP</b> ( $n = 179$ , $k = 37$ )					
Additive model					
GDP	.0001	0.47	.05	.0074	.0112
Year	.0092***	10.06	.48	-.0001	.0001
Interaction model					
GDP	.0001	0.26	.05	-.0001	.0001
Year	.0092***	9.70	.47	.0070	.0112
Interaction term	-.0001	-0.02	-.01	-.0001	.0001
<b>Total fertility rate</b> ( $n = 179$ , $k = 37$ )					
Additive model					
Total fertility rate	.0037	0.17	.01	-.0369	.0463
Year	.0095***	8.93	.48	.0074	.0116
Interaction model					
Total fertility rate	-.0043	-0.04	-.01	-.0443	.0389
Year	.0097*	1.99	.34	.0001	.0128
Interaction term	.0017	0.92	.01	-.0018	.0056

NOTES: 1.  $n$ 's represent the total number of datapoints by  $k$  countries over time. 2. Data on smartphone access and internet use are only available 2012–2018. 3. Degrees of freedom for  $p$ -values were calculated using Satterthwaite's approximation method. 4. Parametric bootstrap analysis ( $n = 500$ ) confidence intervals were computed for the unstandardized coefficients such that lower level = LL and upper level = UL. 5. \*\*\* =  $p < .001$  \*\* =  $p < .01$  \* =  $p < .05$ .

### 3.4. Associations with group-level indicators

We employed multi-level modeling to examine group-level associations among school loneliness as a continuous variable, digital media use, economic conditions, and family size across countries over several years. In both additive and interaction models including year, school loneliness was high when smartphone access and internet use were high (see Table 3 and Fig. 3). Thus, digital media use predicts school loneliness above the monotonic effect of time. For smartphone access, there was also a significant interaction with year, with the increase in school loneliness larger in countries with initially lower smartphone access.

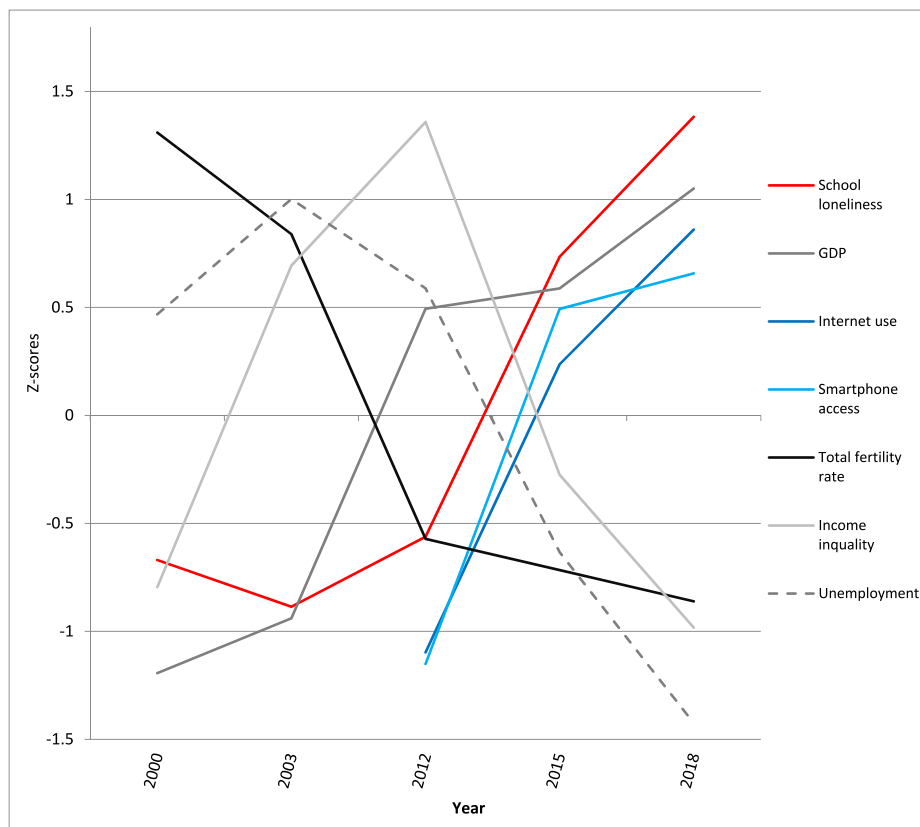
We also examined unemployment, income inequality, and GDP as possible economic determinants of school loneliness. If school loneliness were due to poor economic conditions, loneliness would be high in years when unemployment and income inequality are high and GDP is low. Instead, in the additive model, loneliness was high when unemployment was low – the opposite of predictions. School loneliness was not significantly related to income inequality or to GDP when matched by year (see Table 3).

If school loneliness were due to lower family size, loneliness would be high when total fertility was low; however, school loneliness was not significantly related to total fertility. This lack of convergence can be seen in Fig. 3: In worldwide data, unemployment and income inequality declined 2012–2018 when school loneliness increased, and the pattern of change for GDP and total fertility does not match that for loneliness.

We also examined comprehensive models predicting loneliness from all group-level social indicators and year. In a model including smartphone access, unemployment, income inequality, GDP, total fertility rate, and year, only smartphone access (Std.  $b = .26$ ) and year (Std.  $b = 0.29$ ) were significant predictors of school loneliness. In a model including internet use, unemployment, GDP, income inequality, total fertility rate, and year, only internet use (Std.  $b = .40$ ) was a significant predictor of school loneliness (see Table 4).

## 4. Discussion

The previously documented increase in adolescent depression and loneliness in English-speaking countries after 2012 appears to be a worldwide phenomenon. In a sample of one million adolescents, school loneliness increased between 2012 and 2018 in 36 out of 37 countries around the world. Nearly twice as many adolescents displayed high levels of loneliness in 2018 compared to 2012, an increase similar to that previously identified in clinical-level depression in the U.S. and UK (Mojtabai et al., 2016; Patalay & Gage, 2019; Twenge, Cooper, et al., 2019). Although countries varied in their degree of measurement invariance across time, the countries with the



**Fig. 3.** School loneliness, internet use, smartphone access, unemployment, income inequality, GDP, and total fertility rate (Z-scored), 2000–2018. NOTE: Z-scores are at the group level and are thus not associated with individual-level error bars.

**Table 4**

Multi-level modeling of group-level predictors of mean school loneliness, fixed effects for comprehensive additive models including A) smartphone access and all other indicators and B) internet use and all other indicators.

	<i>b</i>	<i>t</i> value	Std. <i>b</i>	LL	UL
<b>Comprehensive model A: Smartphone access and all other indicators (<i>n</i> = 61, <i>k</i> = 23)</b>					
Smartphone access	.0037**	3.03	.29	.0014	.0062
Unemployment	-.0033	-0.79	-.11	-.0117	.0046
Income inequality	.0078	1.73	.34	-.0009	.0169
GDP	-.0001	-0.93	-.14	.2079	.0841
Total fertility rate	-.0515	-0.73	-.13	-.0001	.0001
Year	.0173**	3.09	.27	.0056	.0278
<b>Comprehensive model B:</b>					
<b>Internet use and all other indicators (<i>n</i> = 61, <i>k</i> = 23)</b>					
Internet use	.0971*	2.61	.40	.0237	.1747
Unemployment	-.0057	-1.37	-.20	.0145	.0022
Income inequality	.0046	1.08	.20	.0042	.0120
GDP	-.0001	-0.68	-.10	-.0001	.0001
Total fertility rate	-.0504	-0.73	-.13	-.1794	.0776
Year	.0090	1.01	.14	.0098	.0276

NOTES: 1. *n*'s represent the total number of datapoints by *k* countries over time. 2. Data on smartphone access and internet use are only available 2012–2018. 3. Degrees of freedom for *p*-values were calculated using Satterthwaite's approximation method. 4. Parametric bootstrap analysis (*n* = 500) confidence intervals were computed for the unstandardized coefficients such that lower level = LL and upper level = UL. 5. \*\*\* = *p* < .001 \*\* = *p* < .01 \* = *p* < .05.

most stable measurement had the largest increases, suggesting that measurement variance was not the cause of the increase in school loneliness.

We were also able to gain some insight into which cultural trends co-occurred with the rise in loneliness. In multi-level models, school loneliness was higher when more students had access to smartphones and used the internet more hours per weekday, even when controlling for the monotonic effect of time. In contrast, school loneliness was higher when unemployment was lower, the opposite pattern than what would be expected if school loneliness was caused by economic troubles. Loneliness was not significantly correlated with GDP, income inequality, or total fertility rate (family size) when matched by year. Thus, school loneliness rose and fell in tandem with greater smartphone access and internet use, but not with unemployment, GDP, income inequality, or family size. The lack of connection with economic factors is surprising given previous research finding group-level links between lower income inequality and higher GDP and adult loneliness (Yang, 2019); adolescent loneliness may be more sheltered from economic factors than adult loneliness.

Although these analyses cannot prove causation, they demonstrate that loneliness grew among adolescents around the world in tandem with widespread smartphone and internet use. As smartphones became more widespread, adolescent social life shifted. Online interaction became more normative and in-person get-togethers less common (Twenge, Spitzberg, & Campbell, 2019; Twenge & Spitzberg, 2020) and smartphones interfered with social interaction (Dwyer et al., 2018). Social media in particular may create an exclusionary culture that increases loneliness at school, particularly among girls (Luby & Kertz, 2019; Viner et al., 2019). Although digital media carries many advantages for communication, it favors shallow ties rather than deep ones, which may result in loneliness (Sherman et al., 2013); however, digital media can prove crucial for coping in situations such as the COVID-19 pandemic when in-person social interaction was limited (Cauberghe et al., 2020). At the individual level, well-being is usually highest at low levels of digital media use, not at non-use (Twenge et al., 2018).

In interaction analyses, the increase in school loneliness was larger in countries with initially lower smartphone access. This suggests that the cultural effect of technology is strongest when adolescent smartphone access moves from low-majority levels to considerable majority levels (around 75%) rather than when it moves from high access to very high access. This may explain why South Korea did not show an increase in loneliness, as their smartphone access was already 87% in 2012 (however, smartphone access was also very high by 2012 in Denmark and Sweden, suggesting other cultural forces may also be at work). Thus, mean loneliness appears to shift the most when smartphone access crosses a critical level, suggesting the effect is due to group dynamics rather than high levels of access per se. Although we can only speculate, perhaps when smartphone use reaches approximately 3 out of 4 individuals, the social norm of digital vs. in-person interaction among adolescents becomes more entrenched. Future research should explore the critical level of smartphone or social media access that shifts the dynamic of social interaction in a group. This may include examining whether correlations between social media use and low well-being have grown weaker or stronger in recent years; this interaction suggests they may have grown weaker. This finding also suggests that adolescent loneliness may stop rising, as most countries had already reached high levels of smartphone access by 2018. However, events occurring after 2018, such as the COVID-19 pandemic and its associated impacts, may also impact trends in loneliness (Loades et al., 2020).

Overall, these results highlight how digital media use may influence adolescents at the group level (via emergent qualities of group dynamics), not just the individual level (in a dose-response manner). Although an individual's technology use may impact personal levels of well-being, the pervasive norm of smartphone and internet use may have an effect on adolescents no matter what their personal level of use. If true, solutions to curbing the concerning rise in loneliness and depression among adolescents should focus on group-level solutions, not just individual ones. For example, schools could consider not allowing students access to their smartphones

during the school day, a step France took for younger students beginning in fall 2018 (Ledsom, 2019). Future research should also explore aspects of group dynamics in social media use, such as increases in upward social comparison to social media influencers, cyberbullying, and fear of missing out, all of which may have a more pronounced effect on adolescents than on adults.

Although the school loneliness measure does not directly assess depressive symptoms, it is positively correlated with a measure of negative affect including emotions linked to depression (such as feeling miserable and sad) and negatively correlated with positive affect and general life satisfaction. Thus, school loneliness appears to have broader applicability to adolescent well-being as a whole. If so, the increase in depression among adolescents that has been documented in English-speaking countries may be occurring worldwide. If the data exist, future studies should examine worldwide trends in adolescent depression.

In conclusion, the PISA datasets demonstrate that adolescents around the world increasingly feel lonely at school. The rapid spread of smartphones and social media in the years since 2012 may be connected to this rise in loneliness, though causation cannot be proven.

## Appendix A. Supplementary data

Supplementary data to this article can be found online at <https://doi.org/10.1016/j.adolescence.2021.06.006>.

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