

Instructional approach, sleep, and perceived academic well-being in adolescents during COVID-19: Evidence from the NESTED study



Jared M. Saletin, PhD^{a,b,*}, Amy R. Wolfson, PhD^c, Kyla L. Wahlstrom, PhD^d, Sarah M. Honaker, PhD^e, Judith A. Owens, MD^f, Azizi A. Seixas, PhD^g, Patricia Wong, PhD^{a,b}, Mary A. Carskadon, PhD^{a,b}, Lisa J. Meltzer, PhD^h

^a Department of Psychiatry and Human Behavior, Alpert Medical School, Brown University, Providence, Rhode Island, USA

^b E.P. Bradley Hospital, East Providence, Rhode Island, USA

^c Department of Psychology, Loyola University Maryland, Baltimore, Maryland, USA

^d Department of Organizational Leadership, Policy, and Development, University of Minnesota, St. Paul, Missouri, USA

^e Department of Pediatrics, Indiana University School of Medicine, Indianapolis, Indiana, USA

^f Department of Neurology, Boston Children's Hospital; Harvard Medical School, Boston, Massachusetts, USA

^g Department of Psychiatry and Behavioral Sciences, University of Miami, Miami, Florida, USA

^h Department of Pediatrics, National Jewish Health, Denver, Colorado, USA

ARTICLE INFO

Article history:

Received 29 September 2023

Received in revised form 11 April 2024

Accepted 21 April 2024

Keywords:

COVID-19

Adolescence

School

Learning

Academics

Instructional format

ABSTRACT

Objectives: At the peak of COVID-19, adolescent life was disrupted as schools adapted their instructional approaches such as online, in-person, or hybrid instruction. We and others have previously commented on how these shifts facilitated longer, later and (more developmentally appropriate) sleep. Here, we report how sleep contributed to associations between remote instruction and broader academic well-being (e.g., cognitive function, school connectedness, and stress).

Methods: Adolescents from all 50 U.S. states (n = 4068) completed online self-report surveys in fall 2020. Instructional approach was operationalized from fully in-person instruction to fully asynchronous online education. Sleep parameters included sleep timing and duration, sleep disturbances, and sleep-related impairments. Perceived academic well-being was defined as cognitive function, school connectedness, and school-related stress. Sleep and perceived academic well-being are examined across instructional approaches, in their association, and in structural models.

Results: Sleep and perceived academic well-being differed between hybrid and online instruction groups. Less variable or disturbed sleep was associated both with in-person instruction, and with positive outcomes in cognitive function, school connectedness, and stress domains. Sleep mediated a substantial portion of variance in perceived academic well-being attributable to instructional approach.

Conclusion: These data highlight the need to protect both healthy sleep and in-person instruction. Appropriate sleep timing and duration, fewer sleep disturbances and sleep-related impairments accounted for a substantial degree of variance in the association between remote instruction on academic outcomes. While many students experienced “lost learning” because of COVID-19, this study joins a broader discussion of ensuring developmentally appropriate school-start times to support both sleep and achievement.

© 2024 National Sleep Foundation. Published by Elsevier Inc. All rights are reserved, including those for text and data mining, AI training, and similar technologies.

Introduction

In the fall of 2020, due to the COVID-19 pandemic, school districts nationwide used instructional approaches ranging from in-person to

fully on-line to protect health and safety while preserving education. Our Nationwide Education and Sleep in TEens During COVID (NESTED) study found that, compared to in-person instruction, online instruction was associated with later wake times (WTs) and longer sleep opportunities for adolescents¹ complementing other reports.^{2–4} Here, we expand our investigation to adolescents' perceived academic well-being.

While sleep opportunity may have benefited from online instruction, this reorganization of education led to a generational level of “lost learning.”^{5–7} How instructional approaches and sleep interact

* Corresponding author: Jared M. Saletin, PhD, E.P. Bradley Hospital Sleep Research Laboratory, 300 Duncan Drive, Providence, RI 02906, USA. Tel.: (401) 421 – 9440.

E-mail address: jared_saletin@brown.edu (J.M. Saletin).

to support student success is a question policymakers must weigh as education recovers.^{7–9} We returned to NESTED to test the hypothesis that sleep during the pandemic contributed to how adolescents' well-being fared in the face of destabilizing instructional approaches.

The links between sleep and learning are clear.^{10,11} Sleep supports attention,^{12,13} learning,¹⁴ recollection,^{10,11,15} and knowledge integration.¹⁶ Longer, more regular, and appropriately timed sleep supports grades^{17,18} and standardized test scores.¹⁹ Finally, delaying school start times in middle and high school increases sleep time, academics outcomes, and quality of life.^{20–27}

While the pandemic is no longer central in our lives, it led to a proliferation of hybrid instructional models, with some families continuing in virtual instruction.^{5,28} With this new status quo, the current study examined how sleep contributed to cognitive and academic function in adolescents across instructional approaches. Our analyses balanced data-driven and theoretically based exploratory modeling to examine: (1) how sleep and academic outcomes differed across instructional approaches; (2) whether sleep was correlated with academic outcomes; and (3) whether sleep was a significant mediator of the association between instructional approach and perceived academic well-being.

Participants and methods

Data acquisition

Data collection¹ occurred from October 8, 2020 to November 26, 2020 in adolescents in grades 6–12 across the United States, recruited over social media with a focus on geographic, ethnic, and racial representation. In October 2020, stay-at-home orders were lifted in all 50 states however restrictions on in-person school attendance varied significantly by state, region, and district. Informed consent and data collection occurred via REDCap. All procedures were approved by the BRANY SBER Institutional Review Board (#20-053-528) with a waiver of parental consent.

Measures

The NESTED¹ survey measured self-reported sleep patterns as a function of school start time and instruction approach along with demographic information, academic, physical health, and mental health outcomes, and social disparities with a retrospective lens of 1 week.

Instructional approach

Adolescents identified their instructional approach for each day of the week (Monday–Friday) yielding fifty-one distinct patterns. We categorized each child's report into one of 5 categories of instruction: (1) *In-Person* [5 days of in-person school]; (2) *Hybrid* [at least 1 day in-person]; (3) *Online/synchronous* [5 days with live online instruction or teacher interaction]; (4) *Online/mixed* [5 days online with at least one synchronous instruction day]; and (5) *Online Asynchronous/No-School* [No online synchronous or in-person instruction days]. Asynchronous and no-school were combined, as neither involved schedules that may govern sleep patterns.

Sleep

Participants reported bedtime (BT, “what time did you try to fall asleep?”) and wake time (WT, “what time did you wake up in the morning?”) separately for nights before days with each instruction approach (in-person, online/synchronous, online/asynchronous, or no school). Sleep opportunity (elapsed time between BT and WT) served as an approximation for sleep duration; this proxy lacked sleep onset latency and wake after sleep onset which were not assessed. WT was chosen as our proxy for sleep timing as it is

immediately salient to school schedules. Data for each instructional approach were matched to days of the week and averaged to derive overall sleep estimates. Finally, variability in sleep patterns across the 5 days was computed using mean square successive differences (MSSD; e.g., Tuesday from Monday, Wednesday from Tuesday, etc.). A higher MSSD indicates greater variability. As sleep patterns were parsed by instruction, not by day, variability is zero for adolescents whose instructional approach was consistent.

Three items from each of the Patient-Reported Outcomes Measurement Information System (PROMIS) Pediatric Sleep Disturbance (SD) and Pediatric Sleep-Related Impairment (SRI) item banks were selected for this study²⁹ (SD: difficulty falling asleep, slept through the night, trouble sleeping; SRI: sleepy during the daytime, hard time concentrating because I was sleepy, hard time getting things done because I was sleepy). Items referenced the past 7 days, with a 5-point Likert response scale ranging from Never to Always. High Sleep Disturbance indicates difficulties falling, or remaining asleep, or poor-quality sleep whereas high Sleep-Related Impairment reflects daytime symptoms of concentration, fatigue or sleepiness consistent with insufficient or nonrestorative sleep. Both are expressed as t-scores (mean = 50; sd = 10) normed against a representative US sample.²⁹

Perceived academic well-being

Three measures probed perceived academic well-being. First, four items were selected from the PROMIS Pediatric Cognitive Function item bank (hard to pay attention to one thing for more than 5–10 minutes, forgot things easily, hard to concentrate in school, hard for me to learn new things). Response choices were on a 5-point Likert scale from either None of the Time to All of the Time, or Not at all to Very Much. T-scores were normed against a representative U.S. sample, with higher t-scores indicating better cognitive functioning.^{30–32} Second, a subset of six school-related questions from the Hemmingway Measure of Adolescent Connectedness^{33–35} was averaged to derive a school connectedness score, with higher scores indicative of greater school connectedness. Finally, we asked whether school was stressful compared to before the pandemic, on a 5-point Likert scale (a lot less to a lot more) reverse-coded such higher scores indicate less school-related stress.

Contextual variables and covariates

Our dataset was limited with respect to the number of demographic factors included. However, grade level, gender, race/ethnicity, and social vulnerability index are presented as analytic covariates. Age was not assessed; however, participants were asked to identify their grade in school (6–12) and were categorized into one of two grade levels: middle-school (grades 6–8) or high-school (grades 9–12). Self-reported gender was coded as male, female, or nonbinary/other. The latter category included those participants who chose not to respond. Race/ethnicity was coded as: White, Black, Hispanic/Latino(a/x), Asian, or Multiracial/Other. Unfortunately, no direct socioeconomic status variables were collected; however, we provide the Social Vulnerability Index (SVI)³⁶ as a proxy. The SVI, scaled 0–1, is a neighborhood-level factor derived from zipcode information and integrates census-level data on 4 risk factors: socioeconomic status, household composition, minority language presence, and transportation access. Participants were coded as low (≤ 0.25), low-moderate (0.25–0.5), moderate-high (0.5–0.75), or highest (> 0.75) SVI. Finally, participants were asked to identify the type of school they attended, with 94% indicating attendance at a public school.

Other contextual factors included rates of consistent room/space, computer access, and internet access as well as self-reported attention-deficit/hyperactivity-disorder (ADHD), autism, learning differences (LD), or an individualized education plan (IEP)/504.

Table 1
Sample demographics

	Overall N = 4068	In-person N = 868	Hybrid N = 1075	Online/Sync. N = 980	Online/Mixed N = 721	Asynch./No school N = 424	p-value ^a
Grade level							.14
Middle school	477 (12%)	122 (14%)	111 (10%)	116 (12%)	83 (12%)	45 (11%)	
High school	3591 (88%)	746 (86%)	964 (90%)	864 (88%)	638 (88%)	379 (89%)	
Gender identity							.059
Female	2125 (52%)	443 (51%)	561 (52%)	497 (51%)	387 (54%)	237 (56%)	
Male	1588 (39%)	365 (42%)	426 (40%)	386 (39%)	258 (36%)	153 (36%)	
N-b/other/prefer not to answer	355 (8%)	60 (7%)	88 (8%)	97 (10%)	76 (11%)	34 (8%)	
Race/Ethnicity							< .001
White	2700 (66%)	635 (73%)	821 (76%)	506 (52%)	444 (62%)	294 (69%)	
Black	167 (4%)	22 (2.5%)	25 (2%)	57 (6%)	42 (6%)	21 (5%)	
Hispanic/Latino(a/x)	668 (16%)	114 (13%)	118 (11%)	239 (24%)	125 (17%)	72 (17%)	
Asian	156 (4%)	13 (2%)	29 (3%)	75 (8%)	35 (5%)	4 (1%)	
Multiracial/other	377 (9%)	84 (10%)	82 (8%)	103 (11%)	75 (10%)	33 (8%)	
Social Vulnerability Index							< .001
Low	1221 (30%)	303 (35%)	293 (27%)	308 (31%)	244 (34%)	73 (17%)	
Low-oderate	1083 (27%)	231 (27%)	275 (26%)	265 (27%)	197 (27%)	115 (27%)	
Moderate	772 (19%)	135 (16%)	200 (19%)	235 (24%)	119 (17%)	83 (20%)	
Highest	992 (24%)	199 (23%)	307 (29%)	172 (18%)	161 (22%)	153 (36%)	
School-type							< .001
Public	3812 (94%)	789 (91%)	1014 (94%)	941 (96%)	689 (96%)	379 (89%)	
Private	195 (5%)	76 (9%)	52 (5%)	31 (3%)	18 (3%)	18 (4%)	
Other	61 (2%)	3 (< 1%)	9 (1%)	8 (1%)	14 (2%)	27 (6%)	
Consistent space for schoolwork?	3472 (86%)	718 (84%)	915 (86%)	860 (88%)	626 (88%)	353 (84%)	.043
Access to computer or tablet?	3952 (98%)	815 (96%)	1049 (98%)	967 (99%)	712 (100%)	409 (97%)	< .001
Reliable internet?	3581 (89%)	755 (89%)	951 (89%)	870 (89%)	631 (88%)	374 (89%)	.94
Report of ADHD	749 (18%)	165 (19%)	196 (18%)	158 (16%)	141 (20%)	89 (21%)	.10
Report of autism	183 (5%)	42 (5%)	50 (5%)	39 (4%)	31 (4%)	21 (5%)	.88
Report of an IEP							.22
No	2546 (63%)	532 (61%)	699 (65%)	622 (63%)	444 (62%)	249 (59%)	
Yes	634 (16%)	132 (15%)	164 (15%)	153 (16%)	121 (17%)	64 (15%)	
Not sure	887 (22%)	203 (23%)	212 (20%)	205 (21%)	156 (22%)	111 (26%)	
Report of a learning difference	200 (5%)	42 (5%)	44 (4%)	43 (4%)	39 (5%)	32 (8%)	.075

Abbreviations: ADHD, attention-deficit/hyperactivity-disorder; Asynch, asynchronous; IEP, individualized education plan; N-b, nonbinary; Sync., synchronous.

Bold p-values indicate statistical significance at $p < .001$.

^a Pearson's chi-square test with simulated p-values (2000 replications).

Sample selection

NESTED included 6577 adolescents in total. The current analyses were limited to participants with complete data on all sleep and academic variables and core contextual factors (grade level, gender, and race/ethnicity, SVI), yielding $n = 4068$ cases.

Statistical analyses

Analyses were conducted in R 4.3.1 with a significance threshold of $p < .001$.¹ One-way ANOVA or chi-square tests (2000 simulations to account for small cells) examined demographics across instructional approach. Primary analyses took a three-fold approach spanning from exploratory description to a structural model.

Step 1. Sleep and perceived academic well-being: Effects of instructional approach

We first examined independent associations of sleep and perceived academic well-being with instructional approach, using independent ANOVA or multinomial regression as appropriate. Instructional approach was entered as a categorical factor and grade level, gender, race/ethnicity, and SVI as covariates.

Step 2. Associations among individual sleep and academic variables

We next examined pairwise associations among sleep and academic variables, with Holm-Bonferroni correction. Stress-free school was treated as a continuous variable.

To reduce dimensionality, we used canonical correlation analysis (CCA), to identify orthogonal associations between sleep and perceived academic well-being. Inclusion in either the sleep or academic CCA variable set was based on the presence of at least one

significant pairwise association. Following CCA, the contributions to each canonical dimension were evaluated with Wilk's lambda. Canonical variables representing orthogonal sleep and academic constructs were forwarded to step 3.

Step 3. Sleep as a cross-sectional mediator of instructional approach and perceived academic well-being

To test our core hypothesis that sleep contributes to the association between instructional approaches and perceived academic well-being, we specified a structural equation model (SEM; lavaan 0.6-15) with bootstrapped ($n = 5000$) confidence intervals.

Our model effect-coded instructional approach as hybrid, online/synchronous, online/mixed, or asynchronous/no-school groups with in-person as reference. All three canonical variables from the CCA were entered as mediating (for sleep) or outcome (for academic) variables. As the canonical dimensions are orthogonal, this allows for three sets of direct and indirect paths between instructional approach to perceived academic well-being through sleep. Our primary focus is on the indirect effects through sleep. Judgments of mediation are made cautiously³⁷ using the bootstrapped indirect effect as core outcome. The cross-sectional nature of our data limits the interpretation of mediation as "variance accounted for" rather than causal. All paths covaried for grade level, gender, race/ethnicity, and SVI.

Sensitivity analyses: The impact of self-reported neurocognitive burden

While our study was not designed to examine the moderating impact of ADHD, autism, or other neurocognitive burden of these dynamics, rates of these endorsed conditions were high, nearly double national estimates.³⁸ We repeated the SEM analysis with

Table 2
Sleep and perceived academic well-being outcomes

	Overall N = 4068	In-person N = 868	Hybrid N = 1075	Online/Sync. N = 980	Online/Mixed N = 721	Asynch./No school N = 424	p-value ^a
Sleep opportunity							
Mean (h)	8.2 ± 1.4	7.6 ± 1.2	8.0 ± 1.2	8.1 ± 1.3	8.5 ± 1.3	9.4 ± 1.8	< .001
MSSD (h)	0.5 ± 0.9	0 ± 0	1.2 ± 1.1	0 ± 0	0.9 ± 1.0	0 ± 0	< .001
Wake time							
Mean (h)	7.5 ± 1.4	6.3 ± 0.7	7.4 ± 1.1	7.5 ± 1.1	8.2 ± 1.4	9.0 ± 2.0	< .001
MSSD (h)	0.6 ± 1.0	0 ± 0	1.5 ± 1.2	0 ± 0	1.0 ± 1.1	0 ± 0	< .001
PROMIS measures (t-scores)							
Sleep disturbance	62 ± 9	61 ± 9	61 ± 10	62 ± 9	63 ± 9	64 ± 9	< .001
Sleep-related impairment	64 ± 10	63 ± 10	63 ± 10	65 ± 10	64 ± 9	63 ± 11	.001
Cognitive function	41 ± 8	43 ± 8	42 ± 7	40 ± 8	40 ± 7	40 ± 8	< .001
Hemmingway school connectedness	3.5 ± 0.6	3.6 ± 0.6	3.6 ± 0.6	3.5 ± 0.6	3.5 ± 0.6	3.4 ± 0.6	< .001
How stressful is school (vs. pre-COVID)? ^b							< .001
A lot more	1730 (43%)	306 (35%)	460 (43%)	439 (45%)	316 (44%)	209 (49%)	
A little more	888 (22%)	216 (25%)	274 (25%)	188 (19%)	138 (19%)	72 (17%)	
About the same	594 (15%)	181 (21%)	133 (12%)	134 (14%)	95 (13%)	51 (12%)	
A little less	483 (12%)	101 (12%)	117 (11%)	128 (13%)	100 (14%)	37 (9%)	
A lot less	373 (9%)	64 (7%)	91 (9%)	91 (9%)	72 (10%)	55 (13%)	

Abbreviations: ADHD, attention-deficit/hyperactivity-disorder; Asynch, asynchronous; IEP, individualized education plan; N-b, nonbinary; Sync., synchronous.

Bold p-values indicate statistical significance at $p < .001$.

^a p-values from ANOVA or multinomial regression as appropriate.

^b Presented as n (%); all other data as mean ± SD.

each of these items as covariates. One participant did not provide health data and is excluded.

Results

Demographics

Table 1 describes the characteristics of our analytic sample parsed by instructional approach (21.1% in-person; 26.4% hybrid; 24.1% online/synchronous; 17.7% online/mixed; and 10.4% asynchronous/no-school). There was a relative balance of grade level and gender among instructional approaches. A significant effect of instructional approach emerged in race/ethnicity ($X^2 = 218.59$, $p < .001$) with white participants being overrepresented in the in-person and hybrid groups relative to non-white peers. SVI distinguished instructional approach ($X^2 = 110.65$, $p < .001$) with lower-risk teens disproportionately represented in the in-person group. While access to computers/tablets ($X^2 = 48.51$, $p < .001$) and rates of private/other types of school was higher for the online instruction groups ($X^2 = 126.37$, $p < .001$), these may reflect demand characteristics of attending school online. Neither rates of self-reported ADHD, autism, nor IEPs/504s or LD differed across groups.

Sleep and perceived academic well-being: Effects of instructional approach

Instructional approach distinguished sleep and perceived academic well-being (Table 2 and Appendix 1 [model outputs]). Sleep opportunity was progressively longer ($F(4, 4053) = 158.05$, $p < .001$; $\eta^2 = 0.14$ [medium/large effect]) and WT later ($F(4, 4053) = 415.51$, $p < .001$; $\eta^2 = 0.29$ [large effect]) for the hybrid, online and asynchronous/no-school groups compared to in-person instruction. Both variability (MSSD) in sleep opportunity ($F(4, 4053) = 595.93$, $p < .001$; $\eta^2 = 0.37$ [large effect]) and WT ($F(4, 4053) = 749.22$, $p < .001$; $\eta^2 = 0.43$ [large effect]) differed between groups. As three groups have no variability (by definition) pair-wise comparisons revealed higher variability in the hybrid compared to the online/mixed group for both sleep opportunity ($t(4053) = 10.56$, $p < .001$), $d = 0.55$) and WT ($t(4053) = 12.78$, $p < .001$; $d = 0.61$ [small effect]).

PROMIS-rated sleep disturbances were in the mild/moderate range (e.g., $t > 60$). A small main-effect of instruction group indicated subtly worse sleep disturbances in non-in-person groups ($F(4, 4053) = 8.28$, $p < .001$; $\eta^2 = 0.0081$ [small effect]). An effect on

PROMIS Sleep-Related Impairments did not reach our significance threshold ($F(4, 4053) = 4.49$, $p = .0013$; $\eta^2 = 0.0044$ [small effect]).

Our perceived academic well-being variables differed across instructional approaches. Online groups demonstrated nearly 3-point worse cognitive function than the in-person group ($F(4, 4053) = 22.21$, $p < .001$; $\eta^2 = 0.021$ [small effect]). School connectedness was also diminished for online groups ($F(4, 4053) = 12.79$, $p < .001$; $\eta^2 = 0.012$ [small effect]). Finally, while 65% of the overall sample rated school as more stressful compared to before the pandemic, school-related stress was most prominent in groups without consistent in-person instruction ($X^2 = 70.13$, $p < .001$).

Associations among individual sleep and academic variables

We next turned to pairwise correlations between sleep and perceived academic well-being (Fig. 1). We identified moderate within-domain associations (Perceived academic well-being: Pearson's Rs: 0.23 to 0.33; sleep: Pearson's Rs: 0.04 to 0.91). Between domains, later WTs, more variable sleep opportunity, and higher PROMIS-rated sleep disturbances and sleep-related impairments were associated with worse outcomes on at least 1 measure (Pearson's Rs: -0.57 to -0.07). Average sleep opportunity and WT MSSD lacked significant associations with any academic variable (Pearson's Rs: -0.06 to 0.04).

Fig. 1 makes evident overlapping associations between our variables. We therefore performed a CCA to reduce dimensionality and isolate orthogonal associations between sleep and perceived academic well-being. With no associations between average sleep opportunity or WT variability and any perceived academic well-being, these variables were excluded the CCA. The remaining variables were sorted into two sets: sleep (WT, sleep opportunity variability, PROMIS sleep disturbances, and PROMIS sleep-related impairments) and perceived academic well-being (stress-free school, cognitive function, and school connectedness).

The CCA (Fig. 2) revealed 3 dimensions of association between sleep and perceived academic well-being. The first dimension accounted for 97.99% ($\lambda[1-3] = 0.61$, $p < .001$) of the overall association between sleep and perceived academic well-being. Fig. 2A illustrates the significant positive correlation ($r = 0.62$, $p < .001$) between the first dimensions of sleep and perceived academic well-being. Examining the loadings of these canonical dimensions on individual items reveals that the first canonical sleep variable was negatively associated with scores for PROMIS sleep disturbance

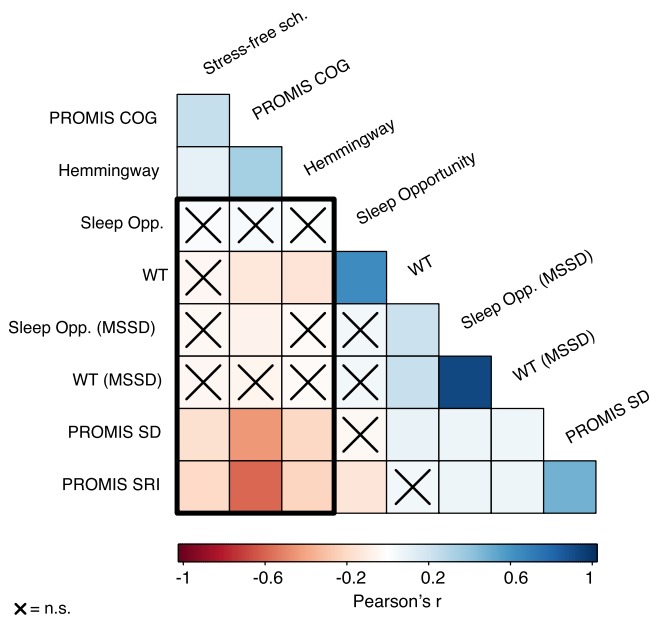


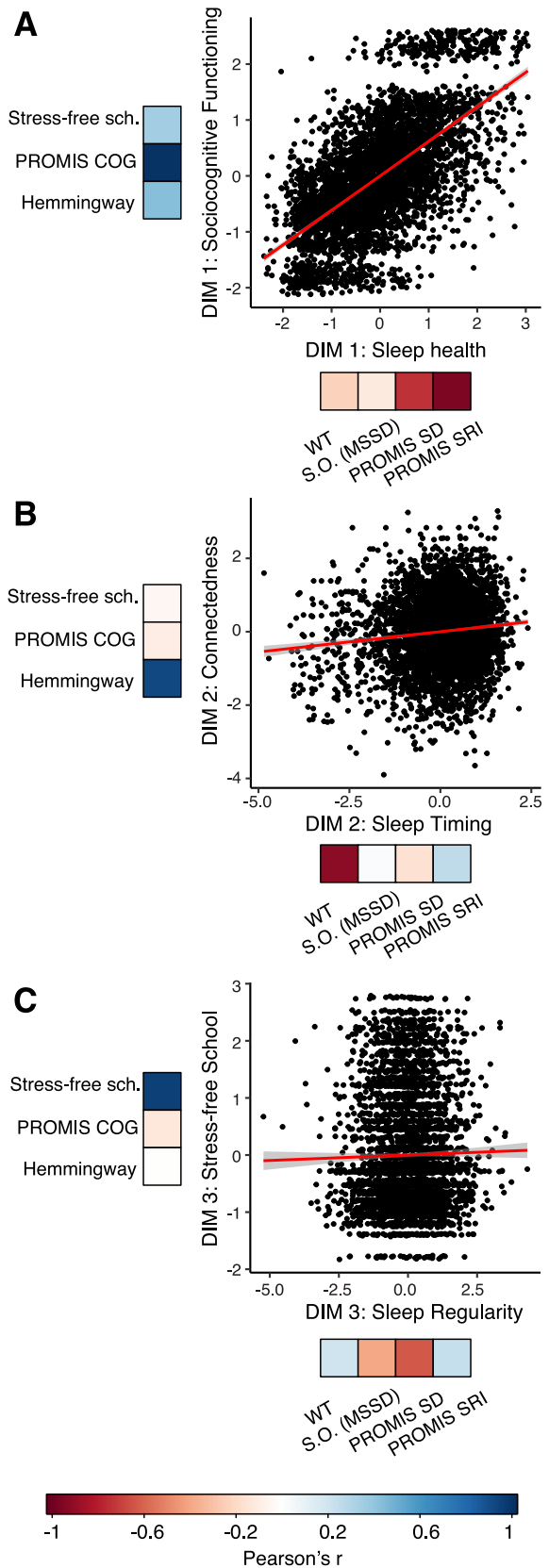
Fig. 1. Pairwise correlations between sleep and perceived academic well-being. Matrix of pairwise associations examined in analytic step 1. Color indicates the strength of Pearson's R correlations (red: negative, blue: positive). A black "x" indicates associations that were not significant at the $p < .001$ level. Abbreviations: MSSD, mean successive squared differences; PROMIS Variables: COG, cognitive function t-score; SD, sleep disturbances t-score; Sleep Opp., sleep opportunity; SRI, sleep-related impairments t-score; Stress Free sch., stress free school; WT, wake time

($r = -0.72$) and sleep-related-impairments ($r = -0.94$); we have labeled this variable "Sleep quality and consequences." The first canonical perceived academic well-being correlated most strongly with PROMIS cognitive-function ($r = 0.99$); we labeled this variable "Sociocognitive functioning." Taken together the canonical correlation reflects how less troublesome sleep is associated with better cognitive function in our sample.

The second canonical correlation (Fig. 2B) was also significant ($r = 0.11, p < .001$) yet accounted for only a small degree of additional variance ($1.98\%, p < .05, \lambda[2-3] = 0.99$). The second canonical sleep variable was negatively correlated with WT and ($r = -0.90$) positively correlated with PROMIS sleep-related impairment ($r = 0.25$). We have labeled this variable "sleep timing" to reflect the strong association with early wake times. The second canonical academic variable positively correlated with school connectedness ($r = 0.91$); thus, we labeled this variable "connectedness." The canonical correlation therefore reflects an association between early WTs and school connectedness which is orthogonal to the quality-by-cognition association described above.

The third canonical correlation (Fig. 2C) was not itself significant ($r = 0.020, p = .22$) and contributed only 0.06% of the overall association ($\lambda[3-3] = 1.00, p > .05$).

This CCA analysis suggests two frames through which sleep and perceived academic well-being are linked in our data: (1) a positive link between higher quality sleep and sociocognitive functioning; and (2) an association between appropriately earlier sleep timing and school connectedness. As earlier sleep times and higher quality sleep are also reflective of in-person school, these data indicate that sleep might be a mitigating or mediatory factor on the overall instruction-to-academic-well-being association: a possibility we explore below.



(caption on next page)

Fig. 2. Canonical correlation analysis: scatter plots for all 3 cardinal dimensions (panels A-C). Each scatterplot illustrates the association between the canonical variables identified for sleep (x-axis) and perceived academic well-being (y-axis). Each dimension is named based on its loadings on the underlying variables, as indicated by the red-blue grids underneath and to the left of the x- and y-axes, respectively. Linear regression lines with 95% confidence intervals are overlaid on each plot. Abbreviations: MSSD, mean successive squared differences; PROMIS Variables: COG, cognitive function t-score; SD, sleep disturbances t-score; Sleep Opp., sleep opportunity; SRI, sleep-related impairments t-score; WT, wake time

Sleep as a mediator of instructional approach and perceived academic well-being

A summary of our SEM illustrating the mediation of *instructional approach* and *perceived academic well-being* by *sleep* is illustrated in Fig. 3 (omitting covariate paths and collapsing across canonical dimensions). Full model estimates are included in Appendix II.

Overall, the model fit well (RMSEA = 0.040; CFI = 0.99; TLI = 0.85, AIC = 65,255.87, adjusted-BIC = 65,556.67). Summing across all three canonical dimensions, and across instructional approaches (coded in reference to *in-person*) our model showed evidence of full mediation. We identified a significant effect by which instructional approach impacts perceived academic well-being through sleep (− 1.012; [− 1.25, − 0.78]). The direct effects of *instructional approach* were no longer significant (summed direct-effect: − 0.288; [− 0.78, 0.20], *p* = .26). In summary, the less structured one's instructional approach, the worse their overall sleep, and in turn, the worse their academic outcomes. This effect was strong, with sleep mediating 77.8% ([54.3%, 125.3%], *p* < .001) the overall impact of *instructional approach* on *perceived academic well-being*.

The above omnibus paths can be decomposed by each dimension. In short (Appendix II), the first canonical dimension (driven by PROMIS scores) showed evidence for partial complementary mediation. That is, the indirect path of instructional approach to perceived academic well-being through sleep was significant (− 0.58; [− 0.75, − 0.40], *p* < .001), mediating 48.3% of the total effect ([36.6%, 61.3%], *p* < .001) while the direct effect remained significant (− 0.62; [− 0.85, − 0.38], *p* < .001). In the second canonical dimension, the indirect path through sleep (here driven mainly by WTs) was again significant (− 0.44; [− 0.59, − 0.29], *p* < .001), while the direct path was not (0.15 [− 0.18, 0.48], *p* = .37). As the signs of these effects differ, the proportion of the total effect mediated by sleep is greater than one (1.51; [− 1.95, 9.81]; *p* = .96). Finally, in the third canonical dimension, there was no evidence of indirect effects of sleep or direct effects of *instructional approach* (*p*'s > .26).

Examining our covariates revealed a series of associations (Appendix II), including worse sleep in high-school, better sleep in males and worse sleep in nonbinary participants compared to females, and worse sleep in Hispanic participants compared to white students. Likewise, for academic outcomes, we identified higher scores in high-school, worse scores for nonbinary and male participants relative to females, and lower scores in Hispanic adolescents compared to white students.

Sensitivity analyses: The impact of self-reported neurocognitive burden

We repeated our modeling to add ADHD, LD, IEP/504, and autism status as covariates, as each is known to negatively contribute to sleep and perceived academic well-being in adolescents. As before, the model fit well (RMSEA = 0.039; CFI = 0.99; TLI = 0.82, AIC = 652,041.97, adjusted-BIC = 65,436.74). Our core result remained. Once again, a significant overall indirect effect of sleep (− 0.99; [− 1.21, − 0.76], *p* < .001) was paired with a nonsignificant direct effect of *instructional approach* (− 0.32; [− 0.80, 0.18], *p* = .21), providing evidence of mediation, with the indirect effect accounting for 75.8% of the overall influence of *instructional approach* ([53.4%, 121.7%], *p* < .001). Reporting one of these conditions was uniformly associated with negative outcomes. Report of ADHD was negatively associated with scores on the first (− 0.30; [− 0.38, − 0.22], *p* < .001) and third (− 0.15; [− 0.23, − 0.073], *p* < .001) canonical sleep variables. Report of LD showed a similar negative association on the first canonical variable (− 0.30; [− 0.45, − 0.15], *p* < .001) and a response of “not sure” with respect to IEP/504 was associated with lower scores on the third (− 0.13; [− 0.21, − 0.058], *p* = .001). Similar patterns were found in the academic domain. Reports of ADHD (− 0.22; [− 0.29, − 0.16], *p* < .001) and LD (− 0.17; [− 0.28, − 0.054], *p* < .001) had a negative association with the first canonical academic variable. A “not sure” IEP/504 response was associated with lower scores on the second dimension (− 0.21; [− 0.28, − 0.13], *p* < .001).

Discussion

We¹ and others²⁻⁴ have reported that the change to online school during COVID-19 altered sleep patterns in adolescents. The current study findings highlight that varied instructional approaches were associated with adolescents' perceived academic well-being in addition to shifts in sleep. To that end, we report three main findings.

First, instructional approaches, other than fully in-person were associated with longer sleep opportunities and later WTs. However, they were also associated with more irregular and disturbed sleep. These nontraditional instructional approaches were associated with a loss of school connectedness, heightened school-related stress, and decreased cognitive function. Second, a strong association emerged between sleep and perceived academic well-being. Earlier morning WTs, less problematic sleep, and more regular sleep were associated with positive outcomes. Third, sleep mediated instructional approach and academic outcomes. Less disrupted and more regular sleep explained the associations between in-person instruction and more favorable perceived academic well-being.

While earlier WTs appear contradictory to typical adolescent sleep recommendations,³⁹ these data do not lend support for earlier school start times. Sleep—like so many adolescent behaviors—is ultimately structured by school schedules. Importantly, earlier morning WTs and more regular sleep were most commonly a result of in-person instruction. Thus, educators may seek to balance both healthy school start times (allowing for sufficient sleep duration) and in-person instruction (promoting academic well-being). The social vulnerability index distinguished instructional approaches, with those at lowest risk also being the most likely to be in-person. We must broadly consider structural forces underlying education policy in the US and abroad. The current study adds to this discussion by showing the contributing role of sleep on academic well-being for teens at the height of pandemic uncertainty.

We¹ and others²⁻⁴ have reported that the changes during the COVID-19 pandemic allowed for later wake times and increased sleep duration in adolescents. However, our results also indicate online instruction was associated with diminished academic well-being. A growing mental health crisis from social isolation⁴⁰⁻⁴³ joins

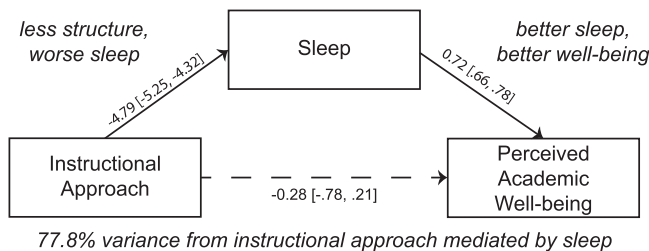


Fig. 3. Overall schematic of structural equation model. A construct-reduced path diagram illustrating the overall results of the structural equation model collapsed across canonical dimensions, across levels of online instruction with covariate-paths masked. Solid paths indicate significance at the *p* < .001 whereas dotted paths indicate nonsignificance

learning loss^{5–7,9,28} as significant concerns for school districts across the country.

These results join broader discussions of school start times to support developmentally appropriate sleep for adolescents.⁴⁴ However, online learning alone is not the solution. Rather, education leaders may be able to balance start times with protective aspects of in-person school,⁴⁵ such as stress-free education and social connectedness. In the current study, sleep regularity and wake time were particularly linked to school connectedness. Both were sensitive to the dissolution of a typical 5-day in-person school week. Stable routines were associated with both sleep consistency and a positive relationship to school. However, these findings should be considered within the context of the shorter sleep duration previously reported with unhealthy, early start times.^{1,46}

While districts work to recover achievement, adolescents are struggling not only from learning loss but a sense of lost community and higher rates of depression and anxiety.^{40,41,43} Simultaneously, many parents are taking advantage of new options including permanent asynchronous learning. In all cases, sleep must be considered. Our sleep-mediated effects extended not only to cognitive function but to school connectedness,^{33,35,45,47,48} a key component of adolescent socioemotional development which supports healthy relationships and mental health and was lost during the pandemic.⁴⁹ Sleep may not be the ultimate panacea but it can support resilience⁴² to otherwise deleterious effects when the standardized and social connected school environment is altered.

This study's limitations are endogenous to its design. Data collection was observational and cross-sectional and therefore cannot rule out all response or sampling biases which may influence these effects. Moreover, while able to parse associations in bivariate and multivariate frameworks, the ultimate directionality of these effects is probably complex and could not be ascertained.

Data collection was limited to a single self-reporter, introducing some expected covariance between items (an issue addressed with data reduction through CCA). An additional drawback was the lack of academic performance measures (e.g., grades). We note that grades in isolation omit the contextual factors of perceived academic well-being examined here, notably a student's orientation to their peers and their educational setting. Our recent parallel report indicated that healthy sleep and in-person education were also protective of depression and anxiety.⁵⁰ Together these studies highlight the importance of considering broad contributions to academic well-being in students in the post-COVID era.

Regarding our operationalization of sleep, while our survey defined BT as trying to fall asleep rather than the time of getting into bed, we did not have access to sleep latency or wake after sleep onset. Thus, like in our original report¹ we pose sleep opportunity as a mere proxy for duration, but one that may mask disrupted sleep continuity (e.g., sleep latency, shut-eye latency, wake after sleep onset, and so forth). Our measure of variability, MSSD, is an approximation limited by the nature of our data collection which captured sleep related to specific instructional approaches rather than in reference to individual days of the week.

When considering our study's representativeness, we are limited by a narrow selection of demographic variables.¹ While no direct measure of socioeconomic status was included (with parents not assessed in the survey), zipcode data allowed us to compute the social vulnerability index (integrating factors such as transportation access, housing, and average regional income), with 43% of the sample carrying above moderate level scores. Ninety-four percent of students reported attending public school, slightly higher than a 2019 National Center for Education Statistics estimate of 91%.⁵¹ With respect to race and ethnicity, despite our best recruitment efforts, our sample included fewer Black participants (4.1%) than the U.S. Census (14.4%). With respect to geographical representation, data was acquired from all 50 U.S. states and two overseas jurisdictions;

thus, while representative of the broad U.S. population, these data lack international representation where other COVID-19 policies may have been in place. Finally, we note an intrinsic limitation to representativeness in our sample as each teen needed technological access and an active social media presence to engage with the survey. Taken together, these data may limit the generalizability of these findings to other similar samples. Ultimately, discussion across published datasets is warranted linking COVID-19's impact on school, sleep, and learning with social determinants of health including race-ethnicity-linked disparities. By engaging in such comparative literature, each study's deficits in representativeness may be overcome.

Conclusions

As society emerges from the pandemic, the discussion on school schedules continues at local, state, and national levels. Findings from this study do not support earlier school start times, but rather the benefits of in-person instruction coupled with healthy sleep and age-appropriate start times. In cases where school starts earlier than developmentally appropriate, our findings indicate that sleep may ultimately protect adolescents when their school structure is disrupted. This work joins a broader literature on sleep and academic success, supporting policies for later, healthy, and developmentally appropriate school start times.^{39,46}

Author contributions

Jared M. Saletin: Conceptualization, Methodology, Data curation, Formal analysis, Visualization, Writing – original draft, Writing – review & editing. **Amy R. Wolfson:** Conceptualization, Methodology, Writing – original draft, Writing – review & editing. **Kyla L. Wahlstrom:** Conceptualization, Methodology, Writing – review & editing. **Sarah M. Honaker:** Conceptualization, Methodology, Writing – review & editing. **Judith A. Owens:** Conceptualization, Methodology, Writing – review & editing. **Azizi A. Seixas:** Conceptualization, Methodology, Writing – review & editing. **Patricia Wong:** Conceptualization, Methodology, Writing – review & editing. **Mary A. Carskadon:** Funding acquisition, Conceptualization, Methodology, Writing – review & editing. **Lisa J. Meltzer:** Funding acquisition, Conceptualization, Methodology, Investigation, Data curation, Writing – original draft, Writing – review & editing. All authors have approved the final article.

Funding

The NESTED study did not receive any external funding. Support for MAC was received from the National Institute of General Medical Sciences, USA (P20GM139743). Other individual investigators were also supported by the National Institutes of Health, USA during the time of the study and/or preparation of this article (T32MH019927 to PW, K23HL150299 to SMH, K01MH109854 and R01HD103655 to JMS, and K01HL135452 and R01HL152453 to AS), as well as the Jacobs Foundation, Switzerland (to JMS) and the Rhode Island Foundation, USA (to JMS). The content is solely the responsibility of the authors and does not necessarily represent the official views of the National Institutes of Health.

Declaration of conflicts of interest

None.

Appendix A. Supporting information

Supplementary data associated with this article can be found in the online version at doi:10.1016/j.sleh.2024.04.006.

References

- Meltzer LJ, Saletin JM, Honaker SM, et al. COVID-19 instructional approaches (in-person, online, hybrid), school start times, and sleep in over 5,000 U.S. adolescents. *Sleep*. 2021;44(12):zsab180.
- Weingart R, Bryan C, Olson D, et al. Adolescent sleep duration and timing during early COVID-19 school closures. *Sleep Health*. 2021;7(5):543–547.
- Becker SP, Dvorsky MR, Breaux R, et al. Prospective examination of adolescent sleep patterns and behaviors before and during COVID-19. *Sleep*. 2021;44(8):zsab054.
- Sharma M, Aggarwal S, Madaan P, et al. Impact of COVID-19 pandemic on sleep in children and adolescents: a systematic review and meta-analysis. *Sleep Med*. 2021;84:259–267.
- Engzell P, Frey A, Verhagen MD. Learning loss due to school closures during the COVID-19 pandemic. *Proc Natl Acad Sci*. 2021;118(17):e2022376118.
- Azevedo JP, De Cojocar W, Montalva A, et al. COVID-19 School Closures, Learning Losses and Intergenerational Mobility. Policy Research Working Paper 10381. World Bank; 2023.
- Harmey S, Moss G. Learning disruption or learning loss: using evidence from unplanned closures to inform returning to school after COVID-19. *Educ Rev*. 2023;75(4):637–656.
- Gambi L, De Witte K. The resiliency of school outcomes after the COVID-19 pandemic. Standardised test scores and inequality one year after long term school closures. FEB Research Report Department of Economics; 2021.
- Skaraki E, Kolokotronis F. Preschool and early primary school age children learning of computational thinking through the use of asynchronous learning environments in the age of Covid-19. *Adv Mob Learn Educ Res*. 2022;2(1):180–186.
- Cunningham TJ, Stickgold R, Kensinger EA. Investigating the effects of sleep and sleep loss on the different stages of episodic emotional memory: a narrative review and guide to the future. *Front Behav Neurosci*. 2022;16:910317.
- Saletin JM, Walker MP. Nocturnal mnemonics: sleep and hippocampal memory processing. *Front Neurol*. 2012;3:59.
- Drummond SP, Gillin JC, Brown GG. Increased cerebral response during a divided attention task following sleep deprivation. *J Sleep Res*. 2001;10(2):85–92.
- Krause AJ, Ben Simon E, Mander BA, et al. The sleep-deprived human brain. *Nat Rev Neurosci*. 2017;18(7):404–418.
- Mander BA, Santhanam S, Saletin JM, Walker MP. Wake deterioration and sleep restoration of human learning. *Curr Biol*. 2011;21(5):R183–R184.
- Huber R, Born J. Sleep, synaptic connectivity, and hippocampal memory during early development. *Trends Cogn Sci*. 2014;18(3):141–152.
- Stickgold R. Parsing the role of sleep in memory processing. *Curr Opin Neurobiol*. 2013;23(5):847–853.
- Wolfson AR, Carskadon MA. Understanding adolescents' sleep patterns and school performance: a critical appraisal. *Sleep Med Rev*. 2003;7(6):491–506.
- Hysing M, Harvey AG, Linton SJ, Askeland KG, Siversten B. Sleep and academic performance in later adolescence: results from a large population-based study. *J Sleep Res*. 2016;25(3):318–324.
- Edwards F. Early to rise? The effect of daily start times on academic performance. *Econ Educ Rev*. 2012;31(6):970–983.
- Dunster GP, de la Iglesia L, Ben-Hamo M, et al. Sleepmore in Seattle: Later school start times are associated with more sleep and better performance in high school students. *Sci Adv*. 2018;4(12):eaau6200.
- Wahlstrom KL, Plog AE, McNally J, Meltzer LJ. Impact of changing school start times on teacher sleep health and daytime functioning. *J Sch Health*. 2023;93(2):128–134.
- Meltzer LJ, Plog AE, Wahlstrom KL, Strand MJ. Biology vs. ecology: a longitudinal examination of sleep, development, and a change in school start times. *Sleep Med*. 2022;90:176–184.
- Meltzer LJ, Wahlstrom KL, Plog AE, Strand MJ. Changing school start times: impact on sleep in primary and secondary school students. *Sleep*. 2021;44(7):zsab048.
- Wahlstrom KL, Owens JA. School start time effects on adolescent learning and academic performance, emotional health and behaviour. *Curr Opin Psychiatry*. 2017;30(6):485–490.
- Wahlstrom KL, Dretzke BJ, Gordon MF, et al. Examining the impact of later high school start times on the health and academic performance of high school students: a multi-site study; 2014.
- Wahlstrom, K., G. Wrobel, and P. Kubow. Minneapolis Public Schools start time study executive summary 1998; 1998.
- Yip T, Wang Y, Xie M, et al. School start times, sleep, and youth outcomes: a meta-analysis. *Pediatrics*. 2022;149(6):e2021054068.
- Kuhfeld M, Soland J, Tarasawa B, et al. Projecting the potential impact of COVID-19 school closures on academic achievement. *Educ Res*. 2020;49(8):549–565.
- Forrest CB, Meltzer LJ, Marcus CL, et al. Development and validation of the PROMIS Pediatric Sleep Disturbance and Sleep-Related Impairment item banks. *Sleep*. 2018;41(6):zsy054.
- Hinds PS, Nuss SL, Ruccione KS, et al. PROMIS pediatric measures validated in a longitudinal study design in pediatric oncology. *Pediatr Blood Cancer*. 2019;66(5):e27606.
- Irwin DE, Gross HE, Stucky BD, et al. Development of six PROMIS pediatrics proxy-report item banks. *Health Qual Life Outcomes*. 2012;10(1):13.
- Lai JS, Wagner LI, Jacobsen PB, Cella D. Self-reported cognitive concerns and abilities: two sides of one coin? *Psychooncology*. 2014;23(10):1133–1141.
- Coyne-Foresi M. Wiz Kidz: fostering school connectedness through an in-school student mentoring program. *Prof Sch Couns*. 2015;19(1) 1096–2409–19.1. 68.
- Karcher MJ. The Hemingway: Measure of Adolescent Connectedness—Validation Studies." Paper Presented at the Annual Conference of the American Psychological Association. San Francisco, CA; 2001.
- Karcher MJ. The effects of school-based developmental mentoring and mentors' attendance on mentees' self-esteem, behavior, and connectedness. *Psychol Sch*. 2005;42(1):65–77.
- Flanagan BE, Gregory EW, Hallisey EJ, Heitgerd JL, Lewis B. A social vulnerability index for disaster management. *J Homel Secur Emerg Manag*. 2011;8(1):0000102202154773551792.
- Zhao X, Lynch Jr JG, Chen Q. Reconsidering Baron and Kenny: myths and truths about mediation analysis. *J Consum Res*. 2010;37(2):197–206.
- CDC. Increasing prevalence of parent-reported attention-deficit/hyperactivity disorder among children: United States, 2003–2007. *Morb Mortal Wkly Rep (MMWR)*. 2010;59(44):1439–1443.
- Adolescent Sleep Working Group, Committee on Adolescence, Council on School Health. School start times for adolescents. *Pediatrics*. 2014;134(3):642–649.
- Meherali S, Punjani N, Louie-Poon S, et al. Mental health of children and adolescents amidst COVID-19 and past pandemics: a rapid systematic review. *Int J Environ Res Public Health*. 2021;18(7):3432.
- Tang S, Xiang M, Cheung T, Xiang Y-T. Mental health and its correlates among children and adolescents during COVID-19 school closure: the importance of parent-child discussion. *J Affect Disord*. 2021;279:353–360.
- Killgore WDS, Taylor EC, Cloonan SA, Dailey NS. Psychological resilience during the COVID-19 lockdown. *Psychiatry Res*. 2020;291:113216.
- Orben A, Tomova L, Blakemore SJ. The effects of social deprivation on adolescent development and mental health. *Lancet Child Adolesc Health*. 2020;4(8):634–640.
- Hirshkowitz M, Whiton K, Albert SM, et al. National Sleep Foundation's sleep time duration recommendations: methodology and results summary. *Sleep Health*. 2015;1(1):40–43.
- Lamblin M, Murawski C, Whittle S, Fornito A. Social connectedness, mental health and the adolescent brain. *Neurosci Biobehav Rev*. 2017;80:57–68.
- Ziporyn TD, Owens JA, Wahlstrom KL, et al. Adolescent sleep health and school start times: setting the research agenda for California and beyond. A research summit summary. *Sleep Health*. 2022;8(1):11–22.
- Widnall E, Winstone L, Plackett R, et al. Impact of school and peer connectedness on adolescent mental health and well-being outcomes during the COVID-19 pandemic: a longitudinal panel survey. *Int J Environ Res Public Health*. 2022;19(11):6768.
- Perkins KN, Carey K, Lincoln E, et al. School connectedness still matters: the association of school connectedness and mental health during remote learning due to COVID-19. *J Prim Prev*. 2021;42:641–648.
- Blakemore S-J. The social brain in adolescence. *Nat Rev Neurosci*. 2008;9(4):267–277.
- Wong P, Meltzer LJ, Barker D, et al. The associations between instructional approach, sleep characteristics and adolescent mental health: lessons from the COVID-19 pandemic. *Sleep Health*. 2024;10(2):221–228.
- Wang K, Rathbun A, Musu L. *School Choice in the United States*: 2019. NCES; 2019.