SLEEP, 2023, 46, 1–16
https://doi.org/10.1093/sleep/zsad220
Advance access publication 23 August 2023
Original Article

Original Article

Rest-activity rhythms across the lifespan: cross-sectional findings from the US representative National Health and Nutrition Examination Survey

Danielle A. Wallace[1,2,*], Dayna A. Johnson[3,4], Susan Redline[1,2,5], Tamar Sofer[1,2,5], Joe Kossowsky[1,6,7]

[1]Division of Sleep Medicine, Harvard Medical School, Boston MA, USA,
[2]Division of Sleep and Circadian Disorders, Departments of Medicine and Neurology, Brigham and Women's Hospital, Boston MA, USA,
[3]Gangarosa Department of Environmental Health, Rollins School of Public Health, Emory University, Atlanta, GA, USA,
[4]Department of Epidemiology, Rollins School of Public Health, Emory University, Atlanta, GA, USA,
[5]Department of Epidemiology, Harvard T.H. Chan School of Public Health, Boston, MA, USA,
[6]Department of Anesthesia, Harvard Medical School, Boston MA, USA and
[7]Department of Anesthesiology, Critical Care and Pain Medicine, Boston Children's Hospital, Boston MA, USA

[*]Corresponding author. Danielle A. Wallace, Brigham and Women's Hospital, Department of Medicine, 221 Longwood Ave, BL-252, Boston, MA 02115, USA. Email: dclarkson-townsend@bwh.harvard.edu.

Abstract

Study Objectives: Rest-activity rhythms (RAR) may mark development, aging, and physical and mental health. Understanding how they differ between people may inform intervention and health promotion efforts. However, RAR characteristics across the lifespan have not been well-studied. Therefore, we investigated the association between RAR measures with demographic and lifestyle factors in a US nationally representative study.

Methods: RAR metrics of interdaily stability (IS), intradaily variability (IV), relative amplitude (RA), and mean amplitude and timing of high (M10) and low (L5) activity were derived from 2011 to 2012 and 2013 to 2014 National Health and Nutrition Examination Survey (NHANES) actigraphy data. Population-weighted linear and logistic regression models were fit to examine the associations of age, gender, smoking, alcohol, season, body mass index (BMI), income-to-poverty ratio, and race/ethnicity with RAR. Significance was based on a false-discovery rate-corrected *P*-value of <0.05.

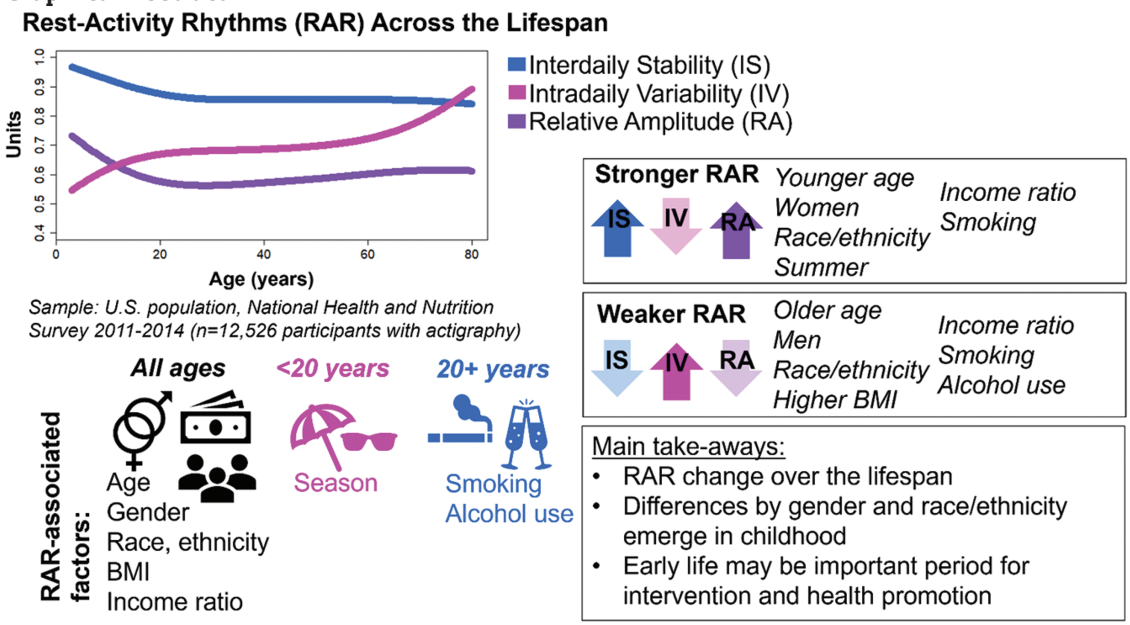
Results: Among n = 12 526 NHANES participants (3–≥80 years), IS (higher = greater day-to-day regularity) and RA (higher = greater rhythm strength) generally decreased with age and were lower among males, whereas IV (higher = greater rhythm fragmentation) increased with age ($p < 0.05$). Dynamic changes in RAR trajectories were observed during childhood and adolescence. Income, BMI, smoking, and alcohol use were associated with RAR metrics, as well as season among children and teenagers ($p < 0.05$). RAR also differed by race/ethnicity ($p < 0.05$), with trajectories initially diverging in childhood and continuing into adulthood.

Conclusions: RAR differed by demographic and health-related factors, representing possible windows for public health intervention and sleep health promotion. RAR differences by race/ethnicity begin in childhood, are evident in early adolescence, and persist throughout adulthood.

Key words: actigraphy; sleep; circadian; child; adolescent; adult; aged

Submitted for publication: March 27, 2023; **Revised:** August 15, 2023

Graphical Abstract



Statement of Significance

Rest-activity rhythms (RAR) are potentially useful markers for sleep and circadian health that are relatively inexpensive to collect at scale. Understanding their association with demographic and lifestyle factors can inform future public health research. This study builds on prior research to show that age, gender, income, smoking, alcohol use, BMI, season, and race/ethnicity are associated with RAR. The greatest change in RAR occurs during childhood and adolescence, with emergence of differences by gender and race/ethnicity beginning during childhood and persisting until adulthood. During adolescence and young adulthood, activity timing shifts later in the evening. Overall, men had worse rhythmicity metrics compared to women. Our data support future investigation of the root causes for RAR differences and research on interventions to improve sleep and chronobiological health across groups, with a special focus on RA during childhood and adolescence.

Introduction

Sleep is vital to growth and development [1] and necessary for metabolic [2–9], cognitive [10–14], reproductive [15, 16], and immunological [17–20] functioning. Likewise, sleep–wake rhythms are an important component of health, shaping (or shaped by) daily patterns in activity, meal timing, and general well-being. Sleep–wake patterns change over the lifespan, with changes likely related to normal developmental processes as well as aging and other factors that contribute to human health and disease [21]. Actigraphy measurement over multiple days and nights allows for assessment of rest-activity rhythms (RAR) without the need for sleep–wake annotation. Non-parametric measures can provide objective assessment of rest-activity behavior, which, while not measures of sleep per se, can serve as robust markers of circadian rhythmicity relevant to chronobiological health [22]. Because sleep is a two-part process regulated in part by the circadian system [23], RAR are also relevant to sleep health.

RAR measures capture different dimensions of behavioral rhythmicity. For example, interdaily stability (IS) reflects regularity in activity patterns between days, serving as a proxy for entrainment to a 24-hour cycle [24, 25]. Intradaily variability (IV), on the other hand, is a measure of within-day rhythm fragmentation [24, 26, 27]. Across days, the average amplitude and timing of the 5 consecutive hours of lowest activity (L5) and 10 consecutive hours of highest activity (M10) reflect bouts of rest/sleep and activity, respectively. Relative amplitude (RA) describes the strength of the difference between periods of high and low activity, with a higher amplitude indicating a larger difference between the least (L5) and the most (M10) active period during the day (i.e. a stronger rhythmicity) [28]. Like sleep patterns, these metrics may be useful markers and/or predictors for health outcomes, with the added benefit of ease of collection (low-cost, low impact for participants). For example, weakened rhythmicity of these measures (such as low RA, low IS, and/or high IV) has been linked to altered blood immune profiles [29], obesity [30], impaired metabolic health [31], and dementia risk [32]. RAR may also change in parallel with healthy developmental processes; for example, the consolidation of sleep that occurs in early childhood [33] and the influence of sex hormones on sleep and circadian rhythms [34] would be expected to be captured by RAR metrics. However, while these metrics hold promise as being informative, scalable, and harmonizable, characterization of these RAR metrics is underexplored.

Just as sleep patterns change with age and gender and differ between people, RAR may also differ with age, gender, substance use, socioeconomic status, race, and ethnicity and be a marker for underlying health. Prior studies have reported differences in non-parametric measures in a small pediatric sample (n = 58, ages 5–18) [28] and a nationally representative adult sample [35] by sex and gender, age, and race/ethnicity. In these studies,

adult females had more stable RAR patterns (higher IS, higher RA) and higher peak activities (higher M10 amplitude) than males [28]. Similarly, sex and gender differences are reported for sleep [36, 37] and circadian rhythms, which may be attributed to biological [38] as well as sociocultural factors [39]. However, little is known about gender differences in pediatric samples and RAR measures across a spectrum of ages, including children and teenagers. Recent studies have reported disparities in pediatric sleep duration which mirror adult populations [40] and suggest that sleep disparities can emerge in early life for certain demographic groups and become more or less severe across time [36], but less is known regarding disparities in RAR. Because infancy, childhood, and teenage years may represent distinct developmental windows of vulnerability, which can influence the trajectory for later life health and disease outcomes [41–43], characterization of RAR across the lifespan and how they differ between people can inform public health interventions and disease prevention. Additionally, how these metrics differ with sociodemographic and health-related variables is unclear. For example, smoking and alcohol use are known to interfere with sleep [44, 45], but less is known whether these substances also influence RAR, or whether RAR patterns influence substance use.

To address key gaps in our understanding of how RAR metrics differ by age, gender, and other factors at a population level, we investigated the association between RAR measures across pediatric and adult populations within US nationally representative National Health and Nutrition Examination Survey (NHANES) data with sociodemographic and health-related variables. Here, we adopt a lifespan approach to investigate age and developmental specificity of RAR. While further research is necessary, the reported differences may identify possible age-sensitive time periods for intervention and health promotion.

Methods

Study population

This analysis utilized data from NHANES, a cross-sectional study representative of the non-institutionalized US population conducted by the Centers for Disease Control and Prevention (CDC). NHANES included actigraphy measurements during the 2011–2012 and 2013–2014 cycles. Demographic and lifestyle information was collected via survey questionnaires and interviews and blood and physical measures were collected during physical examination in the Mobile Examination Center (MEC). Participants younger than 20 completed the questionnaires with a computer-assisted interview. NHANES was approved by the Ethics Review Board of the CDC National Center for Health Statistics, and all participants provided written informed consent.

Actigraphy measurement and data processing

Activity patterns were measured in NHANES using wrist-worn actigraphs (GT3X+ ActiGraph; ActiGraph, Pensacola, FL). Participants were asked to continuously wear the device across 9 days of measurement, beginning on the day of the MEC exam. Participants 6 years of age and older were included in the 2011–2012 cycle (n = 6917; physical activity (PA) Monitor protocol detailed here: https://wwwn.cdc.gov/nchs/data/nhanes/2011-2012/manuals/Physical_Activity_Monitor_Manual.pdf), and participants 3 years of age and older included in the 2013–2014 cycle (n = 7776; PA Monitor protocol detailed here: https://wwwn.cdc.gov/nchs/data/nhanes/2013-2014/manuals/2014-Physicial-Activity-Monitor-Procedures-Manual-508.pdf); therefore, all data for ages 3–5 are from the 2013–2014 cycle. Actigraphy data quality were reviewed and annotated by NHANES researchers, such as in the event of impossible values or contiguous minimum values (variable PAXFLGSM).

Minute-epoch actigraphy files were downloaded from 2011 to 2012 and from 2013 to 2014 NHANES database website. Actigraphy data were trimmed to include the first 7 full 24-hour days (days 2–8) of measurement, excluding the first and last partial day of measurement. We evaluated the Monitor Independent Movement Summary triaxial minute values, a summary acceleration measure from the x-, y-, and z- axes, as a measure of activity. Using the NHANES-processed and annotated data (detailed for 2011–2012 here: https://wwwn.cdc.gov/Nchs/Nhanes/2011-2012/PAXMIN_G.htm#Data_Processing_and_Editing and for 2013–2014 here: https://wwwn.cdc.gov/Nchs/Nhanes/2013-2014/PAXMIN_H.htm; data quality flag summary table here: https://wwwn.cdc.gov/nchs/nhanes/Pam/Default.aspx), we created three quality control flags where activity Monitor Independent Movement Summary values were set to missing: (1) if a letter value for PAXFLGSM variable, (2) if PAXPREDM = 3 [46], or (3) if PAXMTSM value was "−0.01". We then imputed missing activity data using the "accelmissing" package [47] version 1.4 using predictive mean matching (pmm) under the zero-inflated Poisson Log-normal model (method="zipln.pmm"). The data was preprocessed with the following specifications: NAs were converted to 0; a flag matrix for missing data was created with a missing interval set to 60 minutes; a valid day was defined as 16 hours of wear time [28]; and participants with <4 valid days of data were excluded [29, 48].

Dependent variables

Five imputed activity datasets were generated and measures of IS, IV, RA, and start time and average activity for L5 and M10 were then derived from each using the "nparACT" package [49], version 0.8. RAR metrics were modeled as continuous outcomes in linear regression analyses and as dichotomized outcomes in logistic regression analyses. For the linear regression models, both untransformed RAR and Box-Cox transformed RAR (details in Supplementary Material) results are provided. For logistic regression models, RAR variables were dichotomized based on the median value (lower half = 0, ref; upper half = 1). More details regarding data processing methods are provided in Supplementary Material. Code for preprocessing data are available here: https://github.com/DWallace0/NHANES_RAR_across_lifecourse.

Predictor variables and covariates

Variables used in the analysis were based on data from NHANES questionnaires or physical examinations. NHANES derived a ratio of family income to federal poverty level, which we dichotomized as higher than federal poverty level (=0, ref) or at or below the federal poverty level (=1) and included in the analysis as a marker of socioeconomic status [50]. Body mass index (BMI) was measured using the formula: weight in kilograms/ height in meters [2] and modeled as a continuous variable. Gender was either reported by the NHANES interviewer based on perception or asked of the participant, but the options provided were "male", "female", "don't know" or "refuse"; here, the term "gender" is used to reflect the wording provided by NHANES, but we acknowledge that this variable may reflect sex and/or not appropriately capture gender identity. Likewise, the NHANES race/ethnicity variable was a self-report of NHANES-determined categories. Analyses of participants 20 and older included variables for current smoking and alcohol use (described in more detail in Supplementary Material); heavier alcohol use was

defined as having ≥3 drinks/day for males or ≥2 drinks/day for women [51]. Missing values for binary measures of income below the federal poverty level, current smoking, and heavier alcohol use were imputed using multiple imputation by chained equations (described in Supplementary Material) with the "mice" package [52]. We additionally performed linear regression with complete case analysis (with non-imputed income, smoking, and alcohol variables) and Box-Cox transformed outcomes in sensitivity analyses. Exploratory follow-up analyses included measures of education and occupation; A measure of high PA was derived from the imputed activity data. Pregnant participants were excluded. More details on covariates are provided in Supplementary Material.

Statistical analysis

All analyses utilized the appropriate NHANES sample survey weights using the "survey" package [53] to derive population-based estimates, except for the time-based circular variables M10 start and L5 start. Because actigraphy data were available across 2011–2014, 4-year MEC population weights were created according to CDC guidance (https://wwwn.cdc.gov/nchs/nhanes/tutorials/module3.aspx). Mean RAR measures and 95% confidence intervals were first examined in age and gender-stratified tables; within age strata, gender was modeled as a predictor in linear regression. RAR were then analyzed as continuous, continuous Box-Cox transformed, or as binary outcomes (median split) in linear and logistic regression models. Associations between demographic factors and RAR measures were analyzed in survey-weighted linear and logistic regression models. Visual inspection of RAR metrics plotted by age indicated age-specific inflection points around ages 20 and 60 years. Prior research has also suggested that the change in chronotype that occurs around age 20 signals the end of puberty [54]. Testing of model fit with and without natural spline terms for age (knots at 20 and 60 years) and interaction terms for age category (<20, 20–59, and ≥60 years) supported stratification by age categories to account for age-related non-linearity in the RAR metrics (more details in Supplementary Material). To account for developmental periods and biological shifts in sleep patterns, participants 19 years of age and younger were split into age brackets utilized by the CDC [55] and by the American Academy of Sleep Medicine [56] to capture preschool, childhood, and teenage years (3–5, 6–12, and 13–19 years old). Additionally, population-weighted estimates were calculated for each RAR metric and provided in age-stratified and gender-stratified tables; 95% confidence intervals were used to infer group differences. The multiple (n = 5) imputed datasets were analyzed according to Rubin's rule [57] to generate pooled effect estimates, standard errors, and confidence intervals for non-circular variables using the "mitools" package, version 2.4 [58] in order to account for uncertainty in the imputed values. For L5 start and M10 start variables, circular means and standard deviations for the first imputed sample are presented without population weights; existing software does not allow for the application of sample weights to circular variables. We also conducted sensitivity analyses defining a valid day as 20 hours of actigraph wear time and excluding participants with <6 days of valid data [59]. To account for multiple comparisons, P-values were corrected for false-discovery rate for each set of tests using the Benjamini and Hochberg method and considered statistically significant if false-discovery rate-corrected P-value <0.05. All analyses were performed in R version 4.1.1.

Results

Of the 14 693 participants with actigraphy data from 2011 to 2014, 2089 had <4 valid days of data, and 78 participants were pregnant, resulting in a total sample of 12 526 participants for analysis (Figure 1). Relative to the NHANES participants from the same cycle who did not have actigraphy measures, participants with actigraphy measures were more likely to be older, female, non-Hispanic (NH) White, have higher BMI, have higher income, and report heavier alcohol use (Supplementary Table 1). Compared to participants with actigraphy records but excluded from the analysis, included participants were more likely to be older, have higher BMI, have family income above the federal poverty level, are less likely to currently smoke, and are less likely to have heavier alcohol use (Table 1). Non-parametric measures for each individual were derived from actigraphy data (Supplementary Figures 1–3). The average start time of the 10 hours of highest activity (M10) was 9:37 am (median = 9:42 am, SD = 2.3 hours) and average start time of the 5 hours of lowest activity (L5), a marker of rest, was 12:45 am (median = 1:45 am, SD = 1.5 hours)(Table 2). It should be noted that both the M10 and L5 start times do not reflect wake time or sleep onset, but rather the window of averaged highest and lowest activity, respectively.

Continuous measures of RAR and timing differ by age and gender

There were age-specific and gender-specific patterns in IS, IV, and RA values. When visualized across the age spectrum, IS and RA decreased with age, with the greatest period of change occurring between the ages of 3 and 19, after which activity patterns reached a plateau and increased or decreased slightly with age. IV increased with age, with the greatest periods of change occurring between approximate ages of 3 and 19 and after the age of 60 (Figure 2, Supplementary Table 2). Women had higher mean M10 amplitude and lower mean L5 amplitudes than males.

Participants <20 years old

Among participants 19 years and younger, there were clear differences in activity patterns between age-stratified groups. Preschool-age children (ages of 3–5 years) had the highest levels of IS and lowest IV, followed by declining IS and rising IV over the course of adolescence and early adulthood, with teenagers

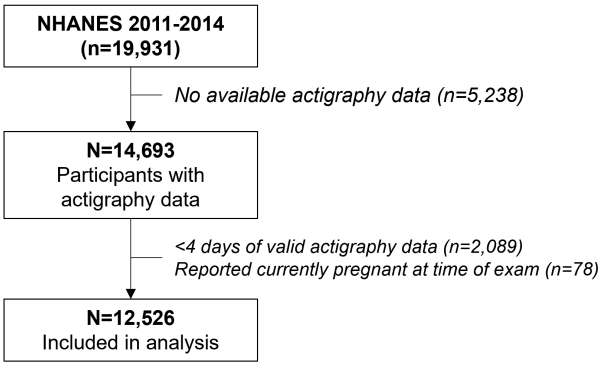


Figure 1. Flow chart depicting sample sizes of participants included in the analyses.

Table 1. Characteristics of 2011–2014 NHANES Participants With Actigraphy Measures Included and not Included in the Analysis

Variable	Excluded† (*n* = 2167)	Included† (*n* = 12 526)	*P*-value
Age, years (mean [SD])	31.06 (17.66)	40.93 (21.40)	<0.001
Gender, men (*n* [%])	1033 (46.19)	6155 (48.55)	0.17
Race/Ethnicity (*n* [%])			0.07
Mexican-American	269 (8.82)	1917 (10.14)	
Non-Hispanic Asian	284 (5.81)	1397 (4.70)	
Non-Hispanic Black	557 (13.13)	3092 (11.82)	
Non-Hispanic White	745 (62.65)	4402 (64.0)	
Other Hispanic	216 (6.25)	1224 (6.27)	
Other or Multiracial	96 (3.35)	494 (3.08)	
BMI (mean [SD])	26.68 (7.58)	27.46 (7.51)	0.003
Below federal poverty level (*n* [%])*	596 (21.27)	3238 (18.47)	0.03
Season of measurement, May 1–October 31 (*n* [%])	1188 (56.38)	6305 (54.16)	0.32
Current smoking (*n* [%])*	304 (23.01)	1637 (19.17)	0.0127
Heavier alcohol use (*n* [%])*	520 (51.46)	2616 (39.54)	<0.001

†Raw participant sample numbers (*n*=) are provided for variables with sample number (such as race/ethnicity) information; however, the percentages, means, and standard deviations provided in the table are all population-weighted; differences in population-weighted values were tested using *t*-tests or chi-squared tests.
*Numbers and percentages provided are for non-imputed data.

(13–19 years old) demonstrating the lowest IS and highest IV values (Supplementary Table 2). When comparing gender, girls had higher mean IS from 3 to 5 and 3 to 10 years and lower mean IV between the ages of 3 and 12 years compared to boys (Table 2, Supplemental Table 2). Boys had –0.02 units lower IS and 30% decreased odds of higher regularity, 0.03 higher IV and 35% increased odds of higher fragmentation, –0.01 lower RA and 28% decreased odds of higher amplitude, and 0.06 units higher L5 amplitude than girls (Table 3, Supplementary Tables 3–5). Participants 3–12 years of age also had the earliest mean L5 and M10 start times, with average activity timing becoming later in teenagers (Figure 3, Supplementary Table 2). As age progressed from childhood to adolescence, the difference in timing was greater for L5 values compared to M10 values, suggesting larger delays in sleep timing compared to activity timing. Boys had higher M10 amplitudes at ages 6–12 years and higher L5 amplitudes at ages 13–19 compared to girls.

Participants ≥20 years old.

Among those 20 years of age and older, women had higher IS from 31 to 60 years old (Table 2) and higher RA from 20 to 59 years compared to men (Table 2, Supplementary Table 2). Men had –0.03 lower IS and 28% decreased odds of higher regularity, 15% decreased odds of higher fragmentation, –0.02 lower RA and 30% decreased odds of higher amplitude, and –0.87 units lower M10 amplitude and 0.16 units higher L5 amplitude than women (Table 3, Supplementary Tables 3-5). Among women, M10 amplitudes were higher at ages 20 years and older and L5 values were lower from 20 to 59 years. Participants aged 20–59 had the greatest standard deviations in M10 start times, with the largest standard deviation at ages 41–50 (Table 2, Supplementary Table **2**). There were similar patterns for L5 start times, with latest L5 start and largest standard deviation at ages 21–30. When stratified by gender, men had greater variation (SD) in M10 and L5 timing across almost all age categories compared to women; within genders, the largest M10 variation for women occurred at ages 41–50 years, whereas the largest variation for men occurred at ages 21–30 years; the largest variation for L5 occurred at ages 21–30 for both men and women. Across all age ranges, there was a U-shaped curve in M10 and L5 timing (Table 2).

Measures of RAR and timing differ by race and ethnicity across ages

Race and ethnicity groups were significantly associated with RAR metrics in age-stratified linear and logistic regression models (Table 3, Supplementary Tables 3–5, Figure 4, Supplementary Figure 4). When visualized across ages, RAR metrics between racial and ethnic groups began to diverge during childhood, becoming progressively wider across ages (Figure 4, Supplementary Figure 4).

Participants <20 years old.

In participants 3–19 years old, race/ethnicity was significantly associated with RAR metrics (Table 3). The NH Asian, NH Black, and Other/Multiracial groups had –0.03, –0.03, and –0.02 units lower IS and the NH Asian and NH Black groups had 35% and 53% decreased odds, respectively, of higher regularity compared to the NH White group (Table 3, Supplementary Tables 3-5), suggesting greater irregularity among children and teenagers in these groups. Likewise, the Mexican-American, NH Asian, NH Black, and Other/Multiracial groups had 0.03, 0.07, 0.03, and 0.04 higher IV and 40%, 92%, 44%, and 67% increased odds of higher fragmentation compared to the NH White group (Table 3, Supplementary Tables 3–5). Additionally, the NH Asian and NH Black groups had lower RA and M10 values.

Participants ≥20 years old.

Among participants aged 20–59 years, IS values were lowest among the NH Black group and highest among the Mexican-American, Other Hispanic, and NH White groups. While the Mexican-American and Other Hispanic groups had –0.06 and –0.05 lower IV values and 39% and 32% decreased odds of higher fragmentation, the NH Asian group had the highest IV values from 20 to 59 years old (Table 3, Supplementary Tables 3–5). The Mexican-American and Other Hispanic groups also had the

Table 2. Population-Weighted RAR Measures (Mean (95% CI)) in NHANES 2011–2014 Participants 3–80+ Years Old, Stratified by Gender and Age Groups by 10-Year Categories: all Ages (*n* = 12526), 3–10 Years Old (*n* = 2085), 11–20 Years Old (*n* = 2313), 21–30 Years Old (*n* = 1231), 31–40 Years Old (*n* = 1336), 41–50 Years Old (*n* = 1441), 51–60 Years Old (*n* = 1430), 61–70 Years Old (*n* = 1427), and 71–≥80 Years Old (*n* = 1263)

	All	Men	Women
Interdaily Stability (IS)			
All ages (3–80)	0.591 (0.586–0.596)	**0.579 (0.573–0.586)**	**0.602 (0.597–0.607)**
3–10	0.699 (0.693–0.706)	**0.686 (0.677–0.695)**	**0.714 (0.708–0.721)**
11–20	0.567 (0.556–0.579)	0.561 (0.544–0.577)	0.574 (0.564–0.583)
21–30	0.541 (0.530–0.553)	0.533 (0.517–0.548)	0.551 (0.537–0.565)
31–40	0.568 (0.559–0.576)	**0.550 (0.536–0.563)**	**0.586 (0.576–0.595)**
41–50	0.575 (0.563–0.587)	**0.561 (0.549–0.574)**	**0.588 (0.574–0.602)**
51–60	0.591 (0.580–0.602)	**0.577 (0.564–0.591)**	**0.604 (0.590–0.617)**
61–70	0.616 (0.607–0.624)	0.604 (0.588–0.620)	0.625 (0.615–0.635)
71–80(+)	0.613 (0.603–0.624)	0.609 (0.596–0.622)	0.617 (0.604–0.629)
Intradaily Variability (IV)			
All ages (3–80)	0.698 (0.690–0.705)	0.697 (0.686–0.707)	0.698 (0.691–0.705)
3–10	0.567 (0.559–0.575)	**0.593 (0.584–0.601)**	**0.539 (0.528–0.550)**
11–20	0.688 (0.678–0.699)	0.693 (0.680–0.707)	0.683 (0.669–0.698)
21–30	0.680 (0.660–0.700)	0.669 (0.643–0.696)	0.692 (0.668–0.715)
31–40	0.683 (0.667–0.699)	0.679 (0.656–0.703)	0.686 (0.671–0.700)
41–50	0.691 (0.675–0.706)	0.675 (0.656–0.695)	0.705 (0.682–0.728)
51–60	0.696 (0.682–0.710)	0.708 (0.684–0.733)	0.684 (0.663–0.706)
61–70	0.726 (0.711–0.741)	0.727 (0.704–0.750)	0.725 (0.707–0.743)
71–80(+)	0.854 (0.837–0.872)	0.867 (0.844–0.890)	0.844 (0.818–0.871)
Relative amplitude (RA)			
All ages (3–80)	0.866 (0.862–0.869)	**0.858 (0.853–0.862)**	**0.874 (0.869–0.878)**
3–10	0.945 (0.943–0.947)	0.945 (0.943–0.947)	0.945 (0.943–0.947)
11–20	0.889 (0.883–0.896)	**0.882 (0.873–0.892)**	**0.895 (0.889–0.902)**
21–30	0.840 (0.833–0.848)	**0.828 (0.816–0.840)**	**0.855 (0.845–0.864)**
31–40	0.855 (0.847–0.863)	**0.842 (0.829–0.854)**	**0.868 (0.859–0.877)**
41–50	0.859 (0.851–0.867)	**0.846 (0.836–0.856)**	**0.871 (0.862–0.881)**
51–60	0.854 (0.845–0.862)	0.845 (0.833–0.858)	0.862 (0.849–0.874)
61–70	0.861 (0.852–0.870)	0.856 (0.842–0.870)	0.865 (0.856–0.873)
71–80(+)	0.844 (0.834–0.853)	0.837 (0.826–0.849)	0.848 (0.837–0.860)
Highest activity amplitude (M10)			
All ages (3–80)	15.230 (15.079–15.381)	**14.996 (14.797–15.195)**	**15.450 (15.284–15.617)**
3–10	23.561 (23.280–23.842)	23.700 (23.389–24.011)	23.407 (23.019–23.796)
11–20	16.744 (16.481–17.007)	16.727 (16.391–17.063)	16.761 (16.475–17.046)
21–30	15.322 (15.019–15.626)	15.091 (14.648–15.533)	15.585 (15.259–15.910)
31–40	15.158 (14.944–15.373)	**14.708 (14.396–15.021)**	**15.600 (15.327–15.873)**
41–50	14.777 (14.491–15.062)	**14.397 (14.013–14.781)**	**15.129 (14.772–15.485)**
51–60	14.041 (13.780–14.302)	**13.471 (13.111–13.832)**	**14.584 (14.210–14.959)**
61–70	13.021 (12.766–13.275)	**12.151 (11.785–12.517)**	**13.717 (13.370–14.063)**
71–80(+)	10.616 (10.337–10.895)	**10.154 (9.821–10.488)**	**10.975 (10.631–11.319)**
Lowest activity amplitude (L5)			
All ages (3–80)	1.043 (1.013–1.072)	**1.095 (1.052–1.139)**	**0.993 (0.957–1.029)**
3–10	0.653 (0.638–0.669)	0.656 (0.630–0.681)	0.651 (0.627–0.675)
11–20	0.962 (0.904–1.021)	**1.016 (0.934–1.098)**	**0.913 (0.847–0.978)**
21–30	1.343 (1.274–1.412)	**1.445 (1.325–1.564)**	**1.228 (1.143–1.313)**

Table 2. Continued

	All	Men	Women
31–40	1.212 (1.130–1.293)	**1.318 (1.181–1.454)**	**1.108 (1.029–1.187)**
41–50	1.117 (1.046–1.188)	**1.203 (1.101–1.304)**	**1.038 (0.959–1.117)**
51–60	1.091 (1.017–1.164)	1.110 (1.012–1.207)	1.073 (0.947–1.198)
61–70	0.932 (0.874–0.990)	0.903 (0.814–0.991)	0.956 (0.891–1.021)
71–80(+)	0.847 (0.802–0.893)	0.858 (0.796–0.919)	0.839 (0.779–0.900)
Start Time of Highest Activity (M10 Start), time (std in hours)*			
All ages (3–80)	9:37 am (2.27)	9:35 am (2.33)	9:38 am (2.21)
3–10	10:16 am (1.40)	10:08 am (1.42)	10:24 am (1.37)
11–20	10:38 am (1.97)	10:35 am (2.00)	10:41 am (1.93)
21–30	10:30 am (2.45)	10:27 am (2.70)	10:33 am (2.15)
31–40	9:46 am (2.45)	9:56 am (2.53)	9:36 am (2.36)
41–50	9:14 am (2.50)	9:17 am (2.59)	9:11 am (2.41)
51–60	8:50 am (2.29)	8:42 am (2.30)	8:56 am (2.28)
61–70	8:30 am (2.05)	8:26 am (2.07)	8:33 am (2.02)
71–80(+)	8:08 am (1.76)	8:04 am (1.84)	8:13 am (1.67)
Start Time of Lowest Activity (L5 Start), time (std in hours)*			
All ages (3–80)	12:45 am (1.53)	12:45 am (1.65)	12:45 am (1.42)
3–10	12:18 am (1.25)	12:18 am (1.22)	12:18 am (1.28)
11–20	1:09 am (1.40)	1:14 am (1.47)	1:04 am (1.33)
21–30	1:33 am (1.76)	1:39 am (1.95)	1:28 am (1.52)
31–40	12:45 am (1.42)	1:07 am (1.72)	12:50 am (1.43)
41–50	12:42 am (1.59)	12:41 am (1.77)	12:42 am (1.42)
51–60	12:31 am (1.55)	12:23 am (1.59)	12:39 am (1.49)
61–70	12:33 am (1.49)	12:26 am (1.55)	12:38 am (1.42)
71–80(+)	12:22 am (1.36)	12:15 am (1.52)	12:29 am (1.18)

*not population-weighted because appropriate software is not available for circular variables; circular means and standard deviations are provided in parentheses.
Population-weighted estimates and 95% CI were calculated with Rubin's rule for pooled estimates. For gender-stratified estimates, age groups where gender was significantly (FDR *P*-values <0.05) associated with non-circular RAR are bolded.

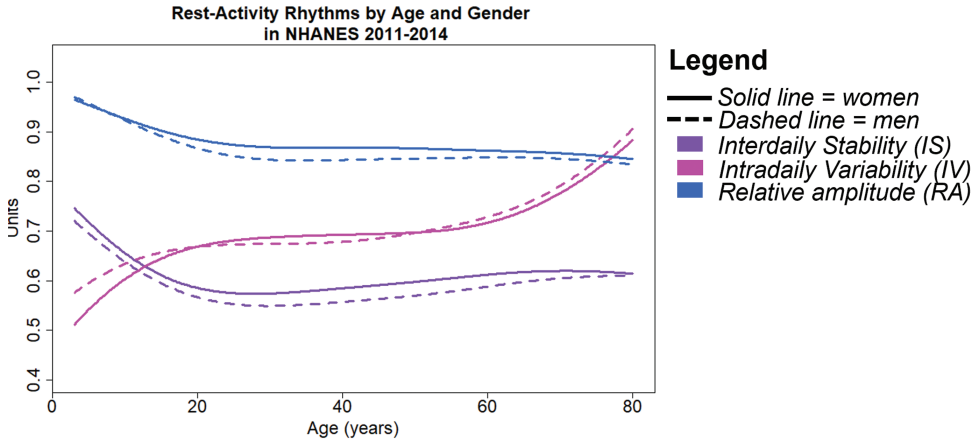


Figure 2. Plots of Interdaily stability (IS, purple), Intradaily variability (IV, magenta), and relative amplitude (RA, blue) by gender (solid line = women, dashed line = men) across ages 3–80 in NHANES 2011–2014.

highest M10 values. Similar to the race/ethnicity differences in RAR at earlier ages, the NH Asian and NH Black groups had 0.04 and 0.03 higher IV, –0.03 and –0.06 lower RA, and 0.16 and 0.52 higher L5 compared to the NH White group.

Sociodemographic characteristics associated with RAR measures in logistic regression models

In linear and logistic regression models, age, BMI, family income to poverty ratio, smoking, alcohol use, and season of measurement

Table 3. Linear Regression Model Associations Between Demographic Characteristics and RAR Measures as Outcomes in NHANES 2011–2014 Participants Aged 3–80+ Years Old, Stratified into 3–19 Years Old (n = 4270) and 20–59 Years old (n = 5389), and 60+ (n = 2867); Population-Weighted Adjusted Estimates With Lower and Upper 95% CI in Parentheses are Provided

Variable*	Interdaily stability (IS)	Intradaily variability (IV)	Relative amplitude (RA)	Highest activity amplitude (M10)	Lowest activity amplitude (L5)
Participants aged 3–19 years					
Age (years)	**–0.02 (–0.017, –0.015)**	**0.01 (0.013, 0.016)**	**–0.01 (–0.006, –0.005)**	**–0.72 (–0.769, –0.67)**	**0.03 (0.019, 0.032)**
Gender					
Female	*ref*	*ref*	*ref*	*ref*	*ref*
Male	**–0.02 (–0.028, –0.01)**	**0.03 (0.015, 0.038)**	**–0.01 (–0.012, –0.002)**	0.18 (–0.084, 0.438)	**0.06 (0.014, 0.104)**
Race/Ethnicity					
Non-Hispanic White	*ref*	*ref*	*ref*	*ref*	*ref*
Mexican-American	–0.01 (–0.019, 0.006)	**0.03 (0.008, 0.045)**	0 (–0.006, 0.007)	–0.23 (–0.958, 0.488)	0.02 (–0.065, 0.106)
Non-Hispanic Asian	**–0.03 (–0.039, –0.012)**	**0.07 (0.05, 0.086)**	**–0.01 (–0.023, –0.006)**	**–2.14 (–2.649, –1.626)**	0.06 (–0.009, 0.124)
Non-Hispanic Black	**–0.03 (–0.044, –0.026)**	**0.03 (0.016, 0.045)**	**–0.02 (–0.023, –0.011)**	**–0.56 (–0.943, –0.173)**	**0.16 (0.096, 0.222)**
Other Hispanic	–0.01 (–0.026, 0.009)	0.02 (0.001, 0.035)	0 (–0.012, 0.008)	–0.26 (–0.746, 0.227)	0.04 (–0.056, 0.13)
Other/Multiracial	**–0.02 (–0.033, –0.005)**	**0.04 (0.017, 0.055)**	–0.01 (–0.019, 0.002)	**–1.39 (–2.089, –0.69)**	0.05 (–0.048, 0.139)
BMI	0 (–0.001, 0.001)	0 (–0.001, 0.001)	**0 (–0.002, –0.001)**	**–0.08 (–0.107, –0.047)**	**0.01 (0.005, 0.018)**
Below federal poverty level					
No	*ref*	*ref*	*ref*	*ref*	*ref*
Yes	0.01 (–0.003, 0.021)	**–0.02 (–0.03, –0.006)**	–0.01 (–0.017, 0.001)	0.36 (0.01, 0.705)	**0.1 (0.009, 0.184)**
Season					
November–April	*ref*	*ref*	*ref*	*ref*	*ref*
May–October	0 (–0.01, 0.009)	**–0.04 (–0.05, –0.021)**	0 (–0.008, 0.002)	**0.69 (0.257, 1.123)**	**0.05 (0.009, 0.099)**
Participants aged 20–59					
Age (years)	**0 (0.001, 0.002)**	0 (–0.001, 0.001)	**0 (0, 0.001)**	**–0.02 (–0.035, –0.014)**	**–0.01 (–0.01, –0.004)**
Gender					
Female	*ref*	*ref*	*ref*	*ref*	*ref*
Male	**–0.03 (–0.034, –0.02)**	–0.01 (–0.019, 0.009)	**–0.02 (–0.032, –0.017)**	**–0.87 (–1.114, –0.618)**	**0.16 (0.08, 0.231)**
Race/Ethnicity					
Non-Hispanic White	*ref*	*ref*	*ref*	*ref*	*ref*
Mexican-American	**0.02 (0.004, 0.028)**	**–0.06 (–0.087, –0.035)**	0 (–0.01, 0.016)	**2.32 (1.874, 2.775)**	**0.14 (0.014, 0.27)**
Non-Hispanic Asian	–0.02 (–0.036, –0.001)	**0.04 (0.018, 0.068)**	**–0.03 (–0.037, –0.014)**	**–0.71 (–1.115, –0.306)**	**0.16 (0.041, 0.269)**
Non-Hispanic Black	**–0.05 (–0.066, –0.039)**	**0.03 (0.006, 0.045)**	**–0.06 (–0.072, –0.047)**	–0.21 (–0.552, 0.122)	**0.52 (0.43, 0.605)**
Other Hispanic	0.01 (–0.005, 0.02)	**–0.05 (–0.072, –0.027)**	–0.01 (–0.021, 0.007)	**1.74 (1.186, 2.289)**	**0.19 (0.06, 0.329)**
Other/Multiracial	**–0.03 (–0.054, –0.011)**	0.02 (–0.019, 0.067)	**–0.04 (–0.055, –0.016)**	–0.34 (–1.062, 0.387)	**0.26 (0.085, 0.43)**
BMI	**0 (–0.001, 0)**	0 (–0.001, 0.002)	**0 (–0.003, –0.002)**	**–0.1 (–0.118, –0.078)**	**0.01 (0.009, 0.019)**
Below federal poverty level					
No	*ref*	*ref*	*ref*	*ref*	*ref*
Yes	–0.01 (–0.021, 0.011)	–0.02 (–0.042, 0.003)	**–0.02 (–0.035, –0.008)**	0.17 (–0.256, 0.591)	**0.19 (0.077, 0.308)**
Season					
November–April	*ref*	*ref*	*ref*	*ref*	*ref*
May–October	0 (–0.013, 0.009)	0.01 (–0.01, 0.028)	0 (–0.01, 0.007)	–0.18 (–0.441, 0.088)	–0.01 (–0.095, 0.071)
Current smoking					
No	*ref*	*ref*	*ref*	*ref*	*ref*
Yes	**–0.02 (–0.031, –0.004)**	**–0.06 (–0.082, –0.042)**	**–0.05 (–0.059, –0.035)**	–0.15 (–0.6, 0.293)	**0.4 (0.292, 0.507)**
Heavier alcohol use					
No	*ref*	*ref*	*ref*	*ref*	*ref*
Yes	**–0.02 (–0.026, –0.007)**	**–0.02 (–0.038, –0.005)**	**–0.01 (–0.024, –0.006)**	**0.36 (0.035, 0.677)**	**0.17 (0.084, 0.254)**

Table 3. Continued

Variable*	Interdaily stability (IS)	Intradaily variability (IV)	Relative amplitude (RA)	Highest activity amplitude (M10)	Lowest activity amplitude (L5)
Participants aged 60+					
Age (years)	0 (–0.002, 0)	**0.01 (0.009, 0.013)**	**0 (–0.003, –0.001)**	**–0.24 (–0.266, –0.208)**	0 (–0.009, 0.001)
Gender					
Female	*ref*	*ref*	*ref*	*ref*	*ref*
Male	**–0.02 (–0.034, –0.01)**	0.02 (–0.005, 0.039)	**–0.01 (–0.024, –0.005)**	**–1.26 (–1.549, –0.98)**	0.02 (–0.054, 0.085)
Race/Ethnicity					
Non-Hispanic White	*ref*	*ref*	*ref*	*ref*	*ref*
Mexican-American	0.01 (–0.008, 0.029)	**–0.05 (–0.088, –0.009)**	0 (–0.018, 0.014)	**1.36 (0.955, 1.765)**	0.14 (0.005, 0.27)
Non-Hispanic Asian	–0.01 (–0.034, 0.017)	**0.04 (0.008, 0.076)**	**–0.03 (–0.053, –0.015)**	0.4 (–0.169, 0.96)	**0.26 (0.131, 0.389)**
Non-Hispanic Black	**–0.07 (–0.08, –0.052)**	0.01 (–0.021, 0.036)	**–0.07 (–0.077, –0.056)**	–0.42 (–0.812, –0.037)	**0.45 (0.373, 0.517)**
Other Hispanic	–0.01 (–0.027, 0.015)	**–0.03 (–0.062, –0.008)**	–0.01 (–0.024, 0.003)	**0.94 (0.362, 1.509)**	**0.14 (0.057, 0.223)**
Other/Multiracial	–0.05 (–0.12, 0.018)	0.04 (–0.072, 0.154)	–0.05 (–0.123, 0.021)	0.07 (–1.122, 1.263)	0.48 (–0.226, 1.196)
BMI	**0 (–0.005, –0.002)**	**0.01 (0.005, 0.01)**	**0 (–0.004, –0.003)**	**–0.16 (–0.194, –0.127)**	**0.01 (0.007, 0.019)**
Below federal poverty level					
No	*ref*	*ref*	*ref*	*ref*	*ref*
Yes	**–0.02 (–0.029, –0.002)**	–0.01 (–0.043, 0.018)	**–0.02 (–0.038, –0.011)**	–0.46 (–0.931, 0.02)	**0.13 (0.042, 0.225)**
Season					
November–April	*ref*	*ref*	*ref*	*ref*	*ref*
May–October	0.01 (–0.008, 0.021)	–0.01 (–0.033, 0.022)	0 (–0.011, 0.011)	0.18 (–0.217, 0.584)	0.02 (–0.049, 0.087)
Current smoking					
No	*ref*	*ref*	*ref*	*ref*	*ref*
Yes	**–0.04 (–0.062, –0.018)**	0.04 (0.003, 0.083)	**–0.07 (–0.091, –0.047)**	**–1.82 (–2.337, –1.305)**	**0.3 (0.146, 0.46)**
Heavier alcohol use					
No	*ref*	*ref*	*ref*	*ref*	*ref*
Yes	0.02 (–0.003, 0.035)	**–0.03 (–0.066, –0.004)**	0.01 (–0.002, 0.021)	0.13 (–0.475, 0.739)	–0.06 (–0.146, 0.026)

*Estimates from linear regression models adjusting for all included covariates (age, gender, race/ethnicity, BMI, income ratio below federal poverty level, season; smoking and alcohol use are only adjusted for participants aged 20 and older).
Note: Population-weighted estimates and 95% CI were calculated with Rubin's rule for pooled estimates.
Association effect estimates with false-discovery rate P-values <0.05 are shown in bold.

were associated with each of the non-parametric measures (Table 3, Supplementary Tables 3-5).

Participants <20 years old.

In those 19 and younger, higher BMI was associated with decreased RA and M10 and increased L5, but not IS or IV (Table 3). Family income below the federal poverty level was also linked to –0.02 lower IV and 18% decreased odds of higher fragmentation, suggesting less rhythm fragmentation (Table 3, Supplementary Table 5). Differences in IV, M10, and L5 by season were only evident among those <20 years; measurement from May–October was associated with –0.04 units lower fragmentation and 0.69 and 0.05 higher M10 and L5 amplitudes (Table 3).

Participants ≥20 years old.

In participants aged 20–59 years, higher BMI was associated with weakened rhythmicity metrics (lower IS, RA, M10, and higher L5; Table 3). Having a family income ratio below the federal poverty level was also associated with 20% decreased odds of higher fragmentation, –0.02 lower RA and 33% decreased odds of higher amplitude, and 0.19 higher L5 activity (Table 3, Supplementary Table 5). To try to understand whether associations varied by education and occupation, we conducted an exploratory analysis including education or occupation as a covariate terms. The association between income ratio and fragmentation was no longer statistically significant after adjusting for education, with the odds ratio changing by more than 10%. When occupation was instead included as a covariate, the odds ratio also changed by more than 10%. Therefore, education and occupation may be confounders in the association between income ratio and IV (Supplementary Table 6).

In participants aged 20–59, heavier alcohol use was associated with –0.02 lower IS and 21% decreased odds higher regularity and –0.01 lower RA and 26% decreased odds higher amplitude (Table 3, Supplementary Table 5). Current smoking was also associated with –0.02 lower IS, –0.06 lower IV, and 45% decreased odds of higher fragmentation, and –0.05 lower RA and 50% decreased odds of higher amplitude (Table 3, Supplementary Table 5). To explore whether smoking associations varied by education and occupation, we compared model estimates with and without including education or occupation as covariate terms. When education was included as a covariate, the odds ratio for smoking changed by more than 10%, suggesting that education may be a confounder

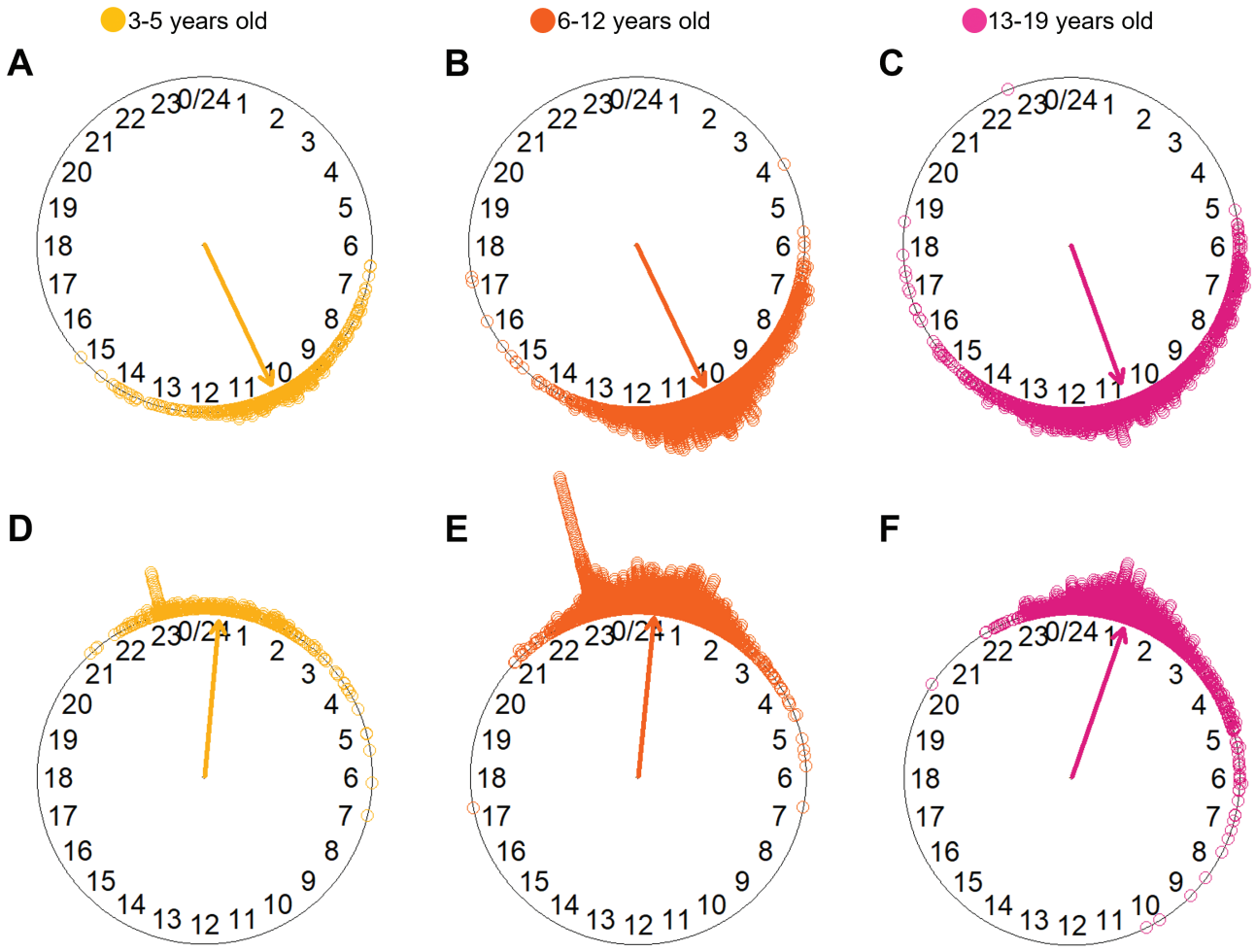


Figure 3. Circular plot of the start time of the 10 hours of highest activity (M10) for ages (A) 3–5 years old (n = 398) (B) 6–12 years old (*n* = 2281) and (C) 13–19 years old (*n* = 1591) and the start time of the 5 hours of lowest activity (L5) for ages (D) 3–5 years old (E) 6–12 years old and (F) 13–19 years old in NHANES. The arrows on the clockface represent the circular mean of the M10 and L5 times by age group.

in the association between smoking and IV. Lack of current occupation (not currently working) was also associated with increased fragmentation, but the odds ratio did not change by more than 10% when it was included as a covariate in the model (Supplementary Table 6). Because IV captures both the frequency and extent of rest-activity transitions within a day, we further explored whether increased IV could be driven by a spike in high PA, such as during exercise. Among participants aged 20–59 years, high PA was both uncommon among smokers and associated with increased odds of high IV. When high PA was included as a covariate, the odds ratio for smoking changed by more than 10%, suggesting that high PA may also be a confounder in the association between smoking and IV (Supplementary Table 7).

Sensitivity analysis results.

In the complete case analysis with non-imputed missing values for income, current smoking, and heavier alcohol use, results were largely the same for participants <60 years old, with more differences for participants ≥60 years old (who also had higher frequency of missingness, Supplementary Materials, Supplementary Table 8). In participants <20 years old, income ratio below the federal poverty level became associated with higher M10 and L5 amplitude, and gender was no longer associated with L5 amplitude. In participants 20–59, current smoking was no longer associated with IS. In participants ≥60, age became associated with lower L5, income ratio became associated with lower M10 amplitude, the NH Asian group was no longer associated with IV, the NH Black group was no longer associated with M10 amplitude, and the Other Hispanic group was no longer associated with L5 amplitude. Current smoking was no longer associated with IS and heavier alcohol use became negatively associated with IV (Supplementary Table 8).

Associations were largely similar in the sensitivity analysis using a more strict inclusion criteria for missingness (where a valid day was defined as ≥20 hours of wearing, with ≥6 valid days data), but there were some minor differences. Demographic characteristics of those included in the sensitivity analysis were similar except for lower frequency of heavier alcohol use (Supplementary Table 9). Among participants aged 3–19 years old, gender was no longer associated with RA or L5, family income ratio became associated with IS and M10 but was no longer associated with L5 amplitude, M10 was no longer associated with the NH Black group, the Other Hispanic group had higher IV and the Other/Multiracial group had lower RA compared to the NH White group, and season was no longer significantly associated with L5 amplitude when tested with linear regression (Supplementary Table 10); likewise, there were some minor differences in the logistic regression results (Supplementary Table 11). For participants 20–59 years old, the

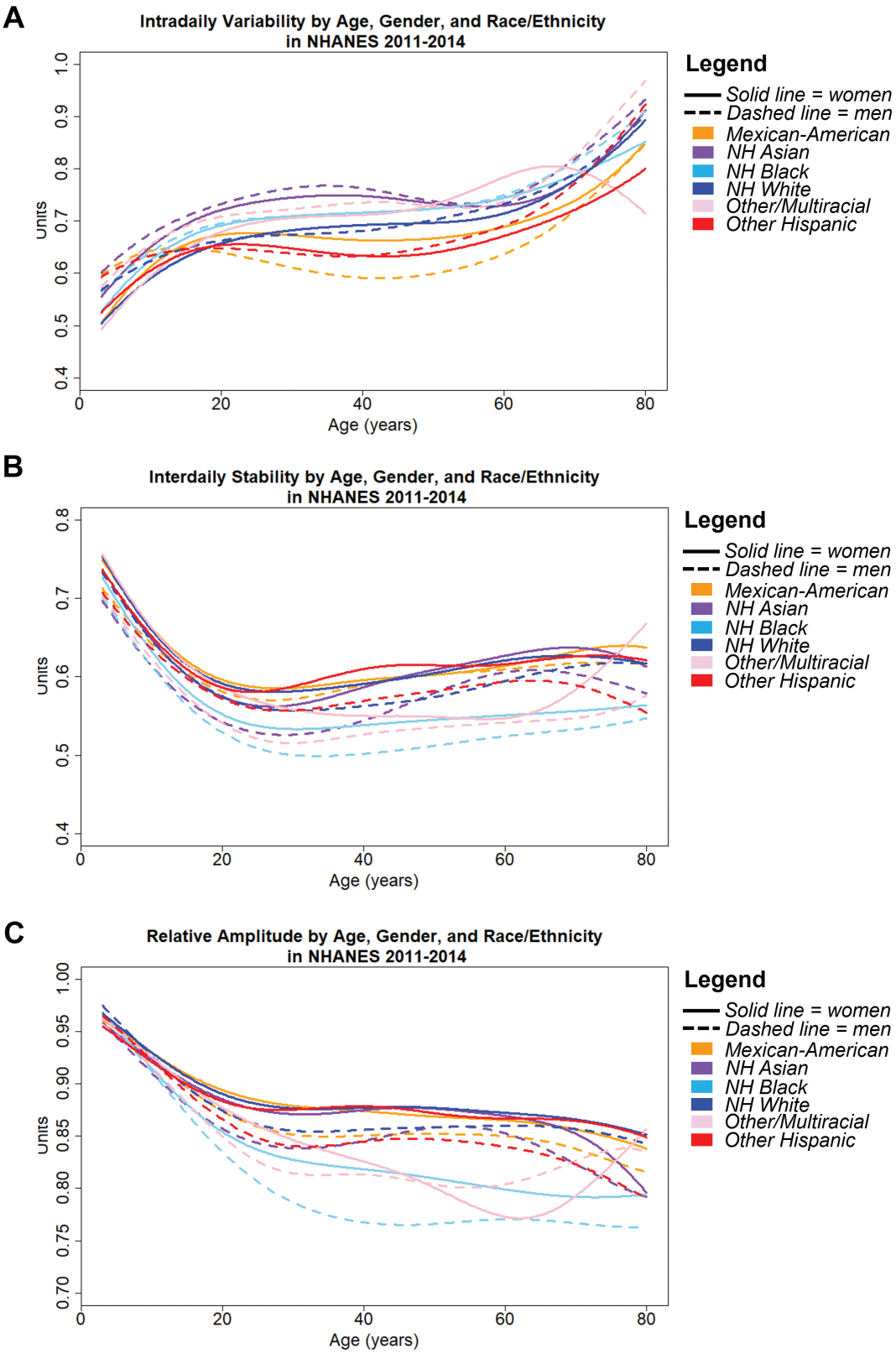


Figure 4. Plots of (A) interdaily stability (IS), (B) intradaily variability (IV), and (C) relative amplitude (RA) by race/ethnicity and gender as measured by actigraphy across ages 3–80 in NHANES 2011–2014. Solid line = women, dashed line = men, orange = Mexican-American, purple = NH Asian, sky blue = NH Black, dark blue = NH White, pink = Other/Multiracial, red = Other Hispanic.

Mexican-American group was no longer associated with IS and the NH Asian group became associated with lower IS. Among those 60 years and older, age became associated with lower IS, men were no longer associated with lower RA, the Mexican-American group became associated with higher L5, income ratio was no longer associated with IS, and heavier alcohol use was

no longer associated with lower IV in linear regression results (Supplementary Table 10).

Discussion

This lifespan analysis of RAR in a large, national sample of children and adults highlights inflection points relevant to age-related changes such as adolescence, early adulthood (~20 years old), and older adulthood/ menopause (~≥50) as times across development when rhythm patterns show the most change. This analysis also highlights differences in within and between-day rhythms associated with gender, race/ethnicity, and health-related and sociodemographic factors related to development and aging. The greatest change in RAR was found to occur during childhood and adolescence, with differences by gender and race/ethnicity emerging during childhood and persisting until adulthood. Compared to the NH White group, the Mexican-American and Other Hispanic groups generally had better RAR metrics, while the NH Asian, NH Black, and Other/Multiracial groups had worse RAR metrics (with differences by age and gender). Young children had the most stable rhythms, possibly due to more rigid daily routines in addition to biological factors. In comparison, teenagers had decreased RAR stability, possibly due to the confluence of school and work times, social commitments and social jet lag, and later chronotype due to hormonal changes [60]. The steep declines in IS and RA and increases in IV that occur in teenagers underscores this period of life as an important opportunity for chronobiological and sleep health promotion. After the age of 20 years, RAR stabilizes at about 20 years old and persists until approximately 60 years of age; RAR during this period may plateau, rather than improve or worsen, due to a holding pattern in daily schedules through occupational, family, social, and behavioral factors. Interventions during this period, particularly ones, which focus on occupational, health, and home-related factors, may also be effective at improving sleep health. However, after the age of 60 there is a steep rise in IV (but little change in IS or RA), which may represent an increase in napping frequency [61]. Sleep quality and duration tend to worsen with age due to age-related chronic disease, pain, rhythm dampening, and other factors, and napping may become more frequent to compensate for poor nighttime sleep [61]. Interventions for this age group which can treat the factors which drive nighttime sleep disruption may reduce daytime napping and rhythm fragmentation.

Our results align with and build upon prior research of RAR. These RAR differences may be due in part to biological aging, but they could also be due to environmental, behavioral, social, and occupational factors that change with age. The patterns of pediatric RAR timing, such as the delay in L5 timing during adolescence [62–64], are consistent with known biological shifts in chronotype that occur around puberty and persist until approximately 20 years of age [54, 65, 66], with slightly higher eveningness among men [66]. Likewise, a previous analysis of NHANES data reported shifts towards later sleep onset time during adolescence, a U-shaped pattern in sleep duration across age (reaching the minimum at age 40 and increasing again around age 50), and a gradual decrease in sleep efficiency across the lifespan, with differences by gender and race/ethnicity [48]. Our pediatric IS, IV, and RA results are comparable to previous findings in samples of Dutch children (n = 94) [67], which reported similar estimates and trends in non-parametric measures by pediatric age group; however, this study did not report any sex differences, possibly due to limited sample size. Our findings are also supported by a previous analysis of non-parametric RAR (actigraphy measured with same device model, ActiGraph GT3X+) in adults (n = 590) and children (n = 58) which reported lower IS, higher IV, and later M10 and L5 times in teenagers compared to younger children [28]; this study also did not report sex differences. The same study also reported higher IS, lower IV, and earlier M10 and L5 times in adults aged 30 and older compared to adults aged 18–29 [28], and lower IS and RA values in Black participants, similar to our findings. Furthermore, similar to our L5 and IS findings, an analysis of different NHANES actigraphy data, measured with a hip-worn accelerometer during 2003–2006 (n = 11 951 aged 6–≥80), showed greatest later time in bed midpoint on Fridays and Saturdays during later adolescence and early adulthood (approximately 16–26 years of age) [68]. Our results also support low variation (SD) in activity timing among children and high variation among ages of peak workforce employment (21–50 years). Another prior study of non-parametric measures in children ages 4–11 (n = 93) reported increasing RA with age and gender-related differences [69]; similarly, our findings show increasing RA at ages 3–10 years old, followed by a decline. This same study did not report age-related associations with L5 or M10 timing.

While many studies focus on the cardiometabolic consequences of disrupted sleep in older adults, children and younger adults may be equally or more vulnerable than older adults to the adverse health effects of sleep disruption [6, 70–72]. Our results indicated an association between higher BMI and lower RA and M10 in the 3–19 age group. Likewise, an analysis of adolescents (n = 778) in the Project Viva cohort reported an association between higher RA, but not L5 and M10, and lower measures of adiposity [73]. A study of young adults (n = 52) reported an association between greater regularity (IS) with lower blood lipids and greater fragmentation (IV) with higher C-reactive protein [74], a marker of inflammation. They also reported attenuation of associations between RAR and cardiometabolic metrics after adjusting for smoking and alcohol use [74], which may indicate substance use as possible upstream or downstream contributors on a causal path between RAR and health outcomes. Our results support associations between smoking and alcohol use and altered RAR. Among those aged ≥20 years old, current smoking was associated with reduced regularity, reduced amplitude, and higher L5, possibly due to the sleep-disrupting properties of nicotine [75, 76], as well as lower fragmentation in those aged 20–59; the combination of both reduced regularity and lower fragmentation with smoking are unexpected and may require further exploration. Education and other unmeasured contributing factors that are outside the scope of this analysis may also be confounding this association. Our results also supported associations between family income below federal poverty level and decreased fragmentation and amplitude, with education and employment status as possible confounders.

Rhythm fragmentation and regularity also differed by race/ethnicity and gender across ages. The Mexican-American and Other Hispanic groups had lower rhythm fragmentation while the NH Asian group had higher fragmentation compared to the NH White group. The high IS and low IV values of the Mexican-American and Other Hispanic groups is similar to previous research in Hispanic/Latino populations [77] and may be a relevant factor in the so-called "Hispanic paradox" [78], which describes a general trend for better cardiometabolic health and lower mortality rates among people of Hispanic origin in the United States, despite

disparities in adverse factors; social networks and decreased prevalence of smoking have been proposed as possible protective factors in these groups. Similarly, weaker rhythmicity metrics for men between ages 21 and 50 map onto broad trends in cardiovascular disease and may represent a marker for poorer health behavior and outcomes among men compared to women [79].

There is a growing body of data supporting disparities in sleep metrics, which may contribute to disparities in health outcomes. In the United States, disparities in sleep health [80–84] occur among historically marginalized groups due to structural violence and racism, resulting in a disproportionate burden of adverse social, political, environmental, and economic factors [85–89]. Because adverse sleep patterns are associated with inflammation [90–93], cardiovascular [94–96], and cardiometabolic disease [2, 5, 72, 97–101], it is hypothesized that sleep disparities may contribute to disparities in health outcomes [102]. However, disparities in RAR are less well-studied. Our data show patterns in RAR that differ by race and ethnicity, beginning in childhood and progressing into adulthood. These findings are consistent with the sleep literature that demonstrates sleep disparities emerge early in childhood, with earlier age of onset and greater severity [40, 103]. These differences in RAR support a need to better understand the social, occupational, and environmental exposures that may contribute to these racial/ethnic differences in rhythmicity metrics. If these differences are due to unjust exposures, early interventions may reduce disparities over time.

This study has multiple strengths, including use of a large, diverse dataset across a continuum of ages with population-weighted estimates for generalizability to the non-institutionalized US population. Additionally, a sensitivity analysis using strict quality criteria resulted in comparable findings to the primary analysis. Investigation of demographic characteristics associated with RAR were concordant with a prior analysis in NHANES in people aged 20 and older, which reported rhythm differences by age, gender, and race/ethnicity [35]. Our study includes a pediatric sample, adds description of factors associated with RAR (such as season, BMI, and smoking), and derives new measures of rest and activity timing (i.e. L5 and M10 start times) and how they differ with age and gender. We further address a limitation mentioned in the prior study with data preprocessing methods and imputation for more reliable estimates. However, our study also has limitations, which should be considered when interpreting the results. NHANES is a cross-sectional study and causality cannot be ascertained. Information regarding school start times, child bedtime routines, discrimination, stress, sleep timing, and shiftwork were not collected in the 2011–2012 or 2013–2014 cycles, so we are limited in our ability to account for these factors in our analysis. Individuals older than 80 years of age are specified as 80 years old in the NHANES data, and therefore the estimates for the 71–80(+) year old age group may include older individuals. Sample weights are not able to be applied to the circular, time-related variables of M10 and L5 start times, and therefore we are unable to derive population estimates for these measures. The findings between RAR metrics and season of measurement should also be interpreted cautiously because NHANES is designed to sample from northern parts of the US during warmer summer months, and southern parts of the US during colder winter months; therefore, any seasonal findings may be biased by study design. Additionally, participants with valid actigraphy measures differed in characteristics to those without actigraphy measures, suggesting results may be affected by selection bias.

Conclusion

We report population-based estimates of RAR across the lifespan; patterns differ by age, gender, race/ethnicity, income ratio, and health-related factors and behaviors. Differences in RAR measures by race/ethnicity emerge in childhood and progressively widen during adolescence to persist throughout adulthood. Adolescent and young adult men have worse rhythmicity measures compared to women. These findings suggest that sleep during early life may represent an important area for intervention and sleep health promotion. By mapping RAR trajectories across ages and evaluating associated factors, this analysis identifies possible drivers of RAR differences as well as sub-populations that may benefit from targeted interventions. Further research is necessary to investigate environmental, occupational, and social contributors to RAR differences.

Supplementary Material

Supplementary material is available at *SLEEP* online.

Funding

Supported by funding from the National Institutes of Health and National Heart, Lung, and Blood Institute(NIH-NHLBI T32HL007901 [to DW], R01 HL157954 [to DJ], R35 HL135818 [to SR], and K01DA057374 [to JK]). DW proposed the study. DW and JK designed the study, performed the analyses, created summary tables and figures, and wrote and edited the manuscript. DJ, TS, and SR contributed to results interpretation and synthesis. All authors reviewed and edited the manuscript.

Disclosure Statements

Financial disclosure: All authors have completed the ICMJE uniform disclosure form at www.icmje.org/coi_disclosure.pdf and declare grant support from the NIH for submitted work; DW reports a Travel Award from the Sleep Research Society; DJ reports consulting fees from Idorsia Pharmaceuticals; SR reports consulting fees from Jazz Pharma and Eli Lilly Inc, and paid participation on an advisory board for Apnimed. All other authors report no other relationships or activities that could appear to have influenced the submitted work. *Nonfinancial disclosure:* SR reports loaned equipment support from Philips Respironics and Nox Medical. All other authors report no other relationships or activities that could appear to have influenced the submitted work.

Data Availability

The dataset and information regarding study design, measurement, and variables used in this secondary analysis are publicly available online from the CDC's NHANES website: https://www.cdc.gov/nchs/nhanes/index.htm. Code for preprocessing the actigraphy data is available here: https://github.com/DWallace0/NHANES_RAR_across_lifecourse.

References

1. Zielinski MR, McKenna JT, McCarley RW. Functions and mechanisms of sleep. *AIMS Neurosci*. 2016;**3**(1):67–104. doi: 10.3934/Neuroscience.2016.1.67

2. Huang T, Redline S. Cross-sectional and Prospective associations of actigraphy-assessed sleep regularity with metabolic abnormalities: the multi-ethnic study of atherosclerosis. *Diabetes Care*. 2019;**42**(8):1422–1429. doi: 10.2337/dc19-0596
3. McHill AW, Wright KP. Role of sleep and circadian disruption on energy expenditure and in metabolic predisposition to human obesity and metabolic disease. *Obes Rev*. 2017;**18**(suppl 1):15–24. doi: 10.1111/obr.12503
4. Depner CM, Stothard ER, Wright KP. Metabolic consequences of sleep and circadian disorders. *Curr Diab Rep*. 2014;**14**(7):507. doi: 10.1007/s11892-014-0507-z
5. Taylor BJ, Matthews KA, Hasler BP, *et al*. Bedtime variability and metabolic health in midlife women: the SWAN sleep study. *Sleep*. 2016;**39**(2):457–465. doi: 10.5665/sleep.5464
6. Buxton OM, Cain SW, O'Connor SP, *et al*. Adverse metabolic consequences in humans of prolonged sleep restriction combined with circadian disruption. *Sci Transl Med*. 2012;**4**(129):129ra43. doi: 10.1126/scitranslmed.3003200
7. Fritz J, Phillips AJK, Hunt LC, *et al*. Cross-sectional and prospective associations between sleep regularity and metabolic health in the hispanic community health study/study of latinos. *Sleep*. 2021;**44**(4). doi: 10.1093/sleep/zsaa218
8. Spiegel K, Leproult R, Van Cauter E. Impact of sleep debt on metabolic and endocrine function. *Lancet*. 1999;**354**(9188):1435–1439. doi: 10.1016/S0140-6736(99)01376-8
9. Leproult R, Van Cauter E. Role of sleep and sleep loss in hormonal release and metabolism. *Endocr Dev*. 2010;**17**:11–21. doi: 10.1159/000262524
10. Deak MC, Stickgold R. Sleep and cognition. *Wiley Interdiscip Rev Cogn Sci*. 2010;**1**(4):491–500. doi: 10.1002/wcs.52
11. Tai XY, Chen C, Manohar S, Husain M. Impact of sleep duration on executive function and brain structure. *Commun Biol*. 2022;**5**(1):201. doi: 10.1038/s42003-022-03123-3
12. Ma Y, Liang L, Zheng F, Shi L, Zhong B, Xie W. Association between sleep duration and cognitive decline. *JAMA Netw Open*. 2020;**3**(9):e2013573. doi: 10.1001/jamanetworkopen.2020.13573
13. Dijk DJ, Duffy JF, Czeisler CA. Circadian and sleep/wake dependent aspects of subjective alertness and cognitive performance. *J Sleep Res*. 1992;**1**(2):112–117. doi: 10.1111/j.1365-2869.1992.tb00021.x
14. Wright KP, Hull JT, Hughes RJ, Ronda JM, Czeisler CA. Sleep and wakefulness out of phase with internal biological time impairs learning in humans. *J Cogn Neurosci*. 2006;**18**(4):508–521. doi: 10.1162/jocn.2006.18.4.508
15. Leproult R, Van Cauter E. Effect of 1 week of sleep restriction on testosterone levels in young healthy men. *JAMA*. 2011;**305**(21):2173–2174. doi: 10.1001/jama.2011.710
16. Willis SK, Hatch EE, Wise LA. Sleep and female reproduction. *Curr Opin Obstet Gynecol*. 2019;**31**(4):222–227. doi: 10.1097/GCO.0000000000000554
17. Besedovsky L, Lange T, Born J. Sleep and immune function. *Pflugers Arch*. 2012;**463**(1):121–137. doi: 10.1007/s00424-011-1044-0
18. Besedovsky L, Lange T, Haack M. The sleep-immune crosstalk in health and disease. *Physiol Rev*. 2019;**99**(3):1325–1380. doi: 10.1152/physrev.00010.2018
19. Garbarino S, Lanteri P, Bragazzi NL, Magnavita N, Scoditti E. Role of sleep deprivation in immune-related disease risk and outcomes. *Commun Biol*. 2021;**4**(1):1304. doi: 10.1038/s42003-021-02825-4
20. Lange T, Dimitrov S, Fehm H-L, Westermann J, Born J. Shift of monocyte function toward cellular immunity during sleep. *Arch Intern Med*. 2006;**166**(16):1695–1700. doi: 10.1001/archinte.166.16.1695
21. Li J, Vitiello MV, Gooneratne NS. Sleep in normal aging. *Sleep Med Clin*. 2018;**13**(1):1–11. doi: 10.1016/j.jsmc.2017.09.001
22. Van Someren EJ, Swaab DF, Colenda CC, Cohen W, McCall WV, Rosenquist PB. Bright light therapy: improved sensitivity to its effects on rest-activity rhythms in Alzheimer patients by application of nonparametric methods. *Chronobiol Int*. 1999;**16**(4):505–518. doi: 10.3109/07420529908998724
23. Borbély AA, Daan S, Wirz-Justice A, Deboer T. The two-process model of sleep regulation: a reappraisal. *J Sleep Res*. 2016;**25**(2):131–143. doi: 10.1111/jsr.12371
24. Witting W, Kwa IH, Eikelenboom P, Mirmiran M, Swaab DF. Alterations in the circadian rest-activity rhythm in aging and Alzheimer's disease. *Biol Psychiatry*. 1990;**27**(6):563–572. doi: 10.1016/0006-3223(90)90523-5
25. van Someren EJ, Hagebeuk EE, Lijzenga C, *et al*. Circadian rest-activity rhythm disturbances in Alzheimer's disease. *Biol Psychiatry*. 1996;**40**(4):259–270. doi: 10.1016/0006-3223(95)00370-3
26. Luik AI, Zuurbier LA, Hofman A, Van Someren EJW, Tiemeier H. Stability and fragmentation of the activity rhythm across the sleep-wake cycle: the importance of age, lifestyle, and mental health. *Chronobiol Int*. 2013;**30**(10):1223–1230. doi: 10.3109/07420528.2013.813528
27. Musiek ES, Bhimasani M, Zangrilli MA, Morris JC, Holtzman DM, Ju Y-ES. Circadian rest-activity pattern changes in aging and preclinical alzheimer disease. *JAMA Neurol*. 2018;**75**(5):582–590. doi: 10.1001/jamaneurol.2017.4719
28. Mitchell JA, Quante M, Godbole S, *et al*. Variation in actigraphy-estimated rest-activity patterns by demographic factors. *Chronobiol Int*. 2017;**34**(8):1042–1056. doi: 10.1080/07420528.2017.1337032
29. Xu Y, Su S, McCall WV, Wang X. Blunted rest-activity rhythm is associated with increased white blood-cell-based inflammatory markers in adults: an analysis from NHANES 2011-2014. *Chronobiol Int*. 2022;**39**(6):895–902. doi: 10.1080/07420528.2022.2048663
30. Li J, Vungarala S, Somers VK, Di J, Lopez-Jimenez F, Covassin N. Rest-activity rhythm is associated with obesity phenotypes: a cross-sectional analysis. *Front Endocrinol (Lausanne)*. 2022;**13**:907360. doi: 10.3389/fendo.2022.907360
31. Sohail S, Yu L, Bennett DA, Buchman AS, Lim ASP. Irregular 24-hour activity rhythms and the metabolic syndrome in older adults. *Chronobiol Int*. 2015;**32**(6):802–813. doi: 10.3109/07420528.2015.1041597
32. Posner AB, Tranah GJ, Blackwell T, *et al*. Predicting incident dementia and mild cognitive impairment in older women with nonparametric analysis of circadian activity rhythms in the Study of Osteoporotic Fractures. *Sleep*. 2021;**44**(10). doi: 10.1093/sleep/zsab119
33. Lokhandwala S, Spencer RMC. Relations between sleep patterns early in life and brain development: a review. *Dev Cogn Neurosci*. 2022;**56**:101130. doi: 10.1016/j.dcn.2022.101130
34. Mong JA, Baker FC, Mahoney MM, *et al*. Sleep, rhythms, and the endocrine brain: influence of sex and gonadal hormones. *J Neurosci*. 2011;**31**(45):16107–16116. doi: 10.1523/JNEUROSCI.4175-11.2011
35. Li J, Somers VK, Lopez-Jimenez F, Di J, Covassin N. Demographic characteristics associated with circadian rest-activity rhythm patterns: a cross-sectional study. *Int J Behav Nutr Phys Act*. 2021;**18**(1):107. doi: 10.1186/s12966-021-01174-z
36. Saelee R, Haardörfer R, Johnson DA, Gazmararian JA, Suglia SF. Racial/ethnic and sex/gender differences in sleep duration trajectories from adolescence to adulthood in a US national sample. *Am J Epidemiol*. 2022;**192**:51–61. doi:10.1093/aje/kwac156
37. Mong JA, Cusmano DM. Sex differences in sleep: impact of biological sex and sex steroids. *Philos Trans R Soc Lond B Biol Sci*. 2016;**371**(1688):20150110. doi: 10.1098/rstb.2015.0110

38. Duffy JF, Cain SW, Chang A-M, *et al*. Sex difference in the near-24-hour intrinsic period of the human circadian timing system. *Proc Natl Acad Sci USA*. 2011;**108**(suppl 3):15602–15608. doi: 10.1073/pnas.1010666108
39. Burgard SA, Ailshire JA. Gender and time for sleep among U.S. Adults. *Am Sociol Rev*. 2013;**78**(1):51–69. doi: 10.1177/0003122412472048
40. Giddens NT, Juneau P, Manza P, Wiers CE, Volkow ND. Disparities in sleep duration among American children: effects of race and ethnicity, income, age, and sex. *Proc Natl Acad Sci USA*. 2022;**119**(30):e2120009119. doi: 10.1073/pnas.2120009119
41. Andersen SL. Trajectories of brain development: point of vulnerability or window of opportunity? *Neurosci Biobehav Rev*. 2003;**27**(1-2):3–18. doi: 10.1016/s0149-7634(03)00005-8
42. Rice D, Barone S. Critical periods of vulnerability for the developing nervous system: evidence from humans and animal models. *Environ Health Perspect*. 2000;**108**(suppl 3):511–533. doi: 10.1289/ehp.00108s3511
43. Soffer-Dudek N, Sadeh A, Dahl RE, Rosenblat-Stein S. Poor sleep quality predicts deficient emotion information processing over time in early adolescence. *Sleep*. 2011;**34**(11):1499–1508. doi: 10.5665/sleep.1386
44. Amiri S, Behnezhad S. Smoking and risk of sleep-related issues: a systematic review and meta-analysis of prospective studies. *Can J Public Health*. 2020;**111**(5):775–786. doi: 10.17269/s41997-020-00308-3
45. Roehrs T, Roth T. Sleep, sleepiness, and alcohol use. *Alcohol Res Health*. 2001;**25**(2):101–109.
46. John D, Tang Q, Albinali F, Intille S. An open-source monitor-independent movement summary for accelerometer data processing. *J Measure Physic Behav*. 2019;**2**(4):268–281. doi: 10.1123/jmpb.2018-0068
47. Lee JA, Gill J. Missing value imputation for physical activity data measured by accelerometer. *Stat Methods Med Res*. 2016;**27**(2). doi: 10.1177/0962280216633248
48. Su S, Li X, Xu Y, McCall WV, Wang X. Epidemiology of accelerometer-based sleep parameters in US school-aged children and adults: NHANES 2011-2014. *Sci Rep*. 2022;**12**(1):7680. doi: 10.1038/s41598-022-11848-8
49. Blume C, Santhi N, Schabus M. "nparACT" package for R: a free software tool for the non-parametric analysis of actigraphy data. *MethodsX*. 2016;**3**:430–435. doi: 10.1016/j.mex.2016.05.006
50. Chen C-Y, Chen J-H, Ree S-C, Chang C-W, Yu S-H. Associations between estradiol and testosterone and depressive symptom scores of the Patient Health Questionnaire-9 in ovariectomized women: a population-based analysis of NHANES data. *Ann Gen Psychiatry*. 2020;**19**(1):64. doi: 10.1186/s12991-020-00315-1
51. Snetselaar LG, de Jesus JM, DeSilva DM, Stoody EE. Dietary guidelines for americans, 2020-2025: understanding the scientific process, guidelines, and key recommendations. *Nutr Today*. 2021;**56**(6):287–295. doi: 10.1097/NT.0000000000000512
52. van Buuren S, Groothuis-Oudshoorn K. Multivariate imputation by chained equations in R. *J Stat Softw*. 2011;**45**(3):1–67. doi: 10.18637/jss.v045.i03
53. Lumley T. Analysis of complex survey samples. *J Stat Softw*. 2004;**9**(8):1–19. doi:10.18637/jss.v009.i08
54. Roenneberg T, Kuehnle T, Pramstaller PP, *et al*. A marker for the end of adolescence. *Curr Biol*. 2004;**14**(24):R1038–R1039. doi: 10.1016/j.cub.2004.11.039
55. Wheaton AG, Jones SE, Cooper AC, Croft JB. Short sleep duration among middle school and high school students - United States, 2015. *MMWR Morb Mortal Wkly Rep*. 2018;**67**(3):85–90. doi: 10.15585/mmwr.mm6703a1
56. Paruthi S, Brooks LJ, D'Ambrosio C, *et al*. Recommended amount of sleep for pediatric populations: a consensus statement of the american academy of sleep medicine. *J Clin Sleep Med*. 2016;**12**(6):785–786. doi: 10.5664/jcsm.5866
57. Rubin DB, ed. *Multiple Imputation for Nonresponse in Surveys*. New York: John Wiley & Sons, Inc.; 1987. doi: 10.1002/9780470316696
58. Lumley T. Package "mitools: Tools for Multiple Imputation of Missing Data". Version 2.4. Author Thomas Lumley. CRAN repository; 2022.
59. Patel SR, Weng J, Rueschman M, *et al*. Reproducibility of a standardized actigraphy scoring algorithm for sleep in a US hispanic/latino population. *Sleep*. 2015;**38**(9):1497–1503. doi: 10.5665/sleep.4998
60. Wittmann M, Dinich J, Merrow M, Roenneberg T. Social jetlag: misalignment of biological and social time. *Chronobiol Int*. 2006;**23**(1-2):497–509. doi: 10.1080/07420520500545979
61. Zhang Z, Xiao X, Ma W, Li J. Napping in older adults: A review of current literature. *Curr Sleep Med Rep*. 2020;**6**(3):129–135. doi: 10.1007/s40675-020-00183-x
62. Galland BC, Taylor BJ, Elder DE, Herbison P. Normal sleep patterns in infants and children: a systematic review of observational studies. *Sleep Med Rev*. 2012;**16**(3):213–222. doi: 10.1016/j.smrv.2011.06.001
63. Iglowstein I, Jenni OG, Molinari L, Largo RH. Sleep duration from infancy to adolescence: reference values and generational trends. *Pediatrics*. 2003;**111**(2):302–307. doi: 10.1542/peds.111.2.302
64. Gradisar M, Gardner G, Dohnt H. Recent worldwide sleep patterns and problems during adolescence: a review and meta-analysis of age, region, and sleep. *Sleep Med*. 2011;**12**(2):110–118. doi: 10.1016/j.sleep.2010.11.008
65. Carskadon MA, Vieira C, Acebo C. Association between puberty and delayed phase preference. *Sleep*. 1993;**16**(3):258–262. doi: 10.1093/sleep/16.3.258
66. Randler C. Age and gender differences in morningness-eveningness during adolescence. *J Genet Psychol*. 2011;**172**(3):302–308. doi: 10.1080/00221325.2010.535225
67. Rensen N, Steur LMH, Wijnen N, van Someren EJW, Kaspers GJL, van Litsenburg RRL. Actigraphic estimates of sleep and the sleep-wake rhythm, and 6-sulfatoxymelatonin levels in healthy Dutch children. *Chronobiol Int*. 2020;**37**(5):660–672. doi: 10.1080/07420528.2020.1727916
68. Urbanek JK, Spira AP, Di J, Leroux A, Crainiceanu C, Zipunnikov V. Epidemiology of objectively measured bedtime and chronotype in US adolescents and adults: NHANES 2003-2006. *Chronobiol Int*. 2018;**35**(3):416–434. doi: 10.1080/07420528.2017.1411359
69. Ferreira ABD, Schaedler T, Mendes JV, Anacleto TS, Louzada FM. Circadian ontogeny through the lens of nonparametric variables of actigraphy. *Chronobiol Int*. 2019;**36**(9):1184–1189. doi: 10.1080/07420528.2019.1636814
70. Duffy JF, Willson HJ, Wang W, Czeisler CA. Healthy older adults better tolerate sleep deprivation than young adults. *J Am Geriatr Soc*. 2009;**57**(7):1245–1251. doi: 10.1111/j.1532-5415.2009.02303.x
71. Zitting K-M, Münch MY, Cain SW, *et al*. Young adults are more vulnerable to chronic sleep deficiency and recurrent circadian disruption than older adults. *Sci Rep*. 2018;**8**(1):11052. doi: 10.1038/s41598-018-29358-x
72. Roenneberg T, Allebrandt KV, Merrow M, Vetter C. Social jetlag and obesity. *Curr Biol*. 2012;**22**(10):939–943. doi: 10.1016/j.cub.2012.03.038
73. Quante M, Cespedes Feliciano EM, Rifas-Shiman SL, *et al*. Association of daily rest-activity patterns with adiposity

and cardiometabolic risk measures in teens. *J Adolesc Health*. 2019;**65**(2):224–231. doi: 10.1016/j.jadohealth.2019.02.008
74. Hoopes EK, Witman MA, D'Agata MN, *et al*. Rest-activity rhythms in emerging adults: implications for cardiometabolic health. *Chronobiol Int*. 2021;**38**(4):543–556. doi: 10.1080/07420528.2020.1868490
75. Heishman SJ, Kleykamp BA, Singleton EG. Meta-analysis of the acute effects of nicotine and smoking on human performance. *Psychopharmacology (Berl)*. 2010;**210**(4):453–469. doi: 10.1007/s00213-010-1848-1
76. Jaehne A, Loessl B, Bárkai Z, Riemann D, Hornyak M. Effects of nicotine on sleep during consumption, withdrawal and replacement therapy. *Sleep Med Rev*. 2009;**13**(5):363–377. doi: 10.1016/j.smrv.2008.12.003
77. Gaston SA, Martinez-Miller EE, McGrath J, *et al*. Disparities in multiple sleep characteristics among non-Hispanic White and Hispanic/Latino adults by birthplace and language preference: cross-sectional results from the US National Health Interview Survey. *BMJ Open*. 2021;**11**(9):e047834. doi: 10.1136/bmjopen-2020-047834
78. Seicean S, Neuhauser D, Strohl K, Redline S. An exploration of differences in sleep characteristics between Mexico-born US immigrants and other Americans to address the Hispanic Paradox. *Sleep*. 2011;**34**(8):1021–1031. doi: 10.5665/SLEEP.1154
79. Bots SH, Peters SAE, Woodward M. Sex differences in coronary heart disease and stroke mortality: a global assessment of the effect of ageing between 1980 and 2010. *BMJ Glob Health*. 2017;**2**(2):e000298. doi: 10.1136/bmjgh-2017-000298
80. Caraballo C, Mahajan S, Valero-Elizondo J, *et al*. Evaluation of Temporal Trends in Racial and Ethnic Disparities in Sleep Duration Among US Adults, 2004-2018. *JAMA Netw Open*. 2022;**5**(4):e226385. doi: 10.1001/jamanetworkopen.2022.6385
81. Hale L, Do DP. Racial differences in self-reports of sleep duration in a population-based study. *Sleep*. 2007;**30**(9):1096–1103. doi: 10.1093/sleep/30.9.1096
82. Krueger PM, Friedman EM. Sleep duration in the United States: a cross-sectional population-based study. *Am J Epidemiol*. 2009;**169**(9):1052–1063. doi: 10.1093/aje/kwp023
83. Whinnery J, Jackson N, Rattanaumpawan P, Grandner MA. Short and long sleep duration associated with race/ethnicity, sociodemographics, and socioeconomic position. *Sleep*. 2014;**37**(3):601–611. doi: 10.5665/sleep.3508
84. Chen X, Wang R, Zee P, *et al*. Racial/Ethnic differences in sleep disturbances: The Multi-Ethnic Study of Atherosclerosis (MESA). *Sleep*. 2015;**38**(6):877–888. doi: 10.5665/sleep.4732
85. Johnson DA, Billings ME, Hale L. Environmental determinants of insufficient sleep and sleep disorders: implications for population health. *Curr Epidemiol Rep*. 2018;**5**(2):61–69. doi: 10.1007/s40471-018-0139-y
86. Billings ME, Cohen RT, Baldwin CM, *et al*. Disparities in sleep health and potential intervention models: A focused review. *Chest*. 2021;**159**(3):1232–1240. doi: 10.1016/j.chest.2020.09.249
87. Billings ME, Hale L, Johnson DA. Physical and social environment relationship with sleep health and disorders. *Chest*. 2020;**157**(5):1304–1312. doi: 10.1016/j.chest.2019.12.002
88. Jackson CL, Walker JR, Brown MK, Das R, Jones NL. A workshop report on the causes and consequences of sleep health disparities. *Sleep*. 2020;**43**(8). doi: 10.1093/sleep/zsaa037
89. Jackson CL, Powell-Wiley TM, Gaston SA, Andrews MR, Tamura K, Ramos A. Racial/ethnic disparities in sleep health and potential interventions among women in the united states. *J Womens Health (Larchmt)*. 2020;**29**(3):435–442. doi: 10.1089/jwh.2020.8329
90. Vallat R, Shah VD, Redline S, Attia P, Walker MP. Broken sleep predicts hardened blood vessels. *PLoS Biol*. 2020;**18**(6):e3000726. doi: 10.1371/journal.pbio.3000726
91. Dzierzewski JM, Donovan EK, Kay DB, Sannes TS, Bradbrook KE. Sleep inconsistency and markers of inflammation. *Front Neurol*. 2020;**11**:1042. doi: 10.3389/fneur.2020.01042
92. Irwin MR, Olmstead R, Carroll JE. Sleep disturbance, sleep duration, and inflammation: a systematic review and meta-analysis of cohort studies and experimental sleep deprivation. *Biol Psychiatry*. 2016;**80**(1):40–52. doi: 10.1016/j.biopsych.2015.05.014
93. Irwin MR. Sleep and inflammation: partners in sickness and in health. *Nat Rev Immunol*. 2019;**19**(11):702–715. doi: 10.1038/s41577-019-0190-z
94. Covassin N, Singh P. Sleep duration and cardiovascular disease risk: epidemiologic and experimental evidence. *Sleep Med Clin*. 2016;**11**(1):81–89. doi: 10.1016/j.jsmc.2015.10.007
95. Huang T, Mariani S, Redline S. Sleep irregularity and risk of cardiovascular events: the multi-ethnic study of atherosclerosis. *J Am Coll Cardiol*. 2020;**75**(9):991–999. doi: 10.1016/j.jacc.2019.12.054
96. Daghlas I, Dashti HS, Lane J, *et al*. Sleep duration and myocardial infarction. *J Am Coll Cardiol*. 2019;**74**(10):1304–1314. doi: 10.1016/j.jacc.2019.07.022
97. Tobaldini E, Fiorelli EM, Solbiati M, Costantino G, Nobili L, Montano N. Short sleep duration and cardiometabolic risk: from pathophysiology to clinical evidence. *Nat Rev Cardiol*. 2019;**16**(4):213–224. doi: 10.1038/s41569-018-0109-6
98. Parsons MJ, Moffitt TE, Gregory AM, *et al*. Social jetlag, obesity and metabolic disorder: investigation in a cohort study. *Int J Obes (Lond)*. 2015;**39**(5):842–848. doi: 10.1038/ijo.2014.201
99. Wong PM, Hasler BP, Kamarck TW, Muldoon MF, Manuck SB. Social jetlag, chronotype, and cardiometabolic risk. *J Clin Endocrinol Metab*. 2015;**100**(12):4612–4620. doi: 10.1210/jc.2015-2923
100. Rangaraj VR, Knutson KL. Association between sleep deficiency and cardiometabolic disease: implications for health disparities. *Sleep Med*. 2016;**18**:19–35. doi: 10.1016/j.sleep.2015.02.535
101. St-Onge M-P, Grandner MA, Brown D, *et al*.; American Heart Association Obesity, Behavior Change, Diabetes, and Nutrition Committees of the Council on Lifestyle and Cardiometabolic Health; Council on Cardiovascular Disease in the Young; Council on Clinical Cardiology; and Stroke Council. Sleep duration and quality: impact on lifestyle behaviors and cardiometabolic health: a scientific statement from the american heart association. *Circulation*. 2016;**134**(18):e367–e386. doi: 10.1161/CIR.0000000000000444
102. Jackson CL, Redline S, Emmons KM. Sleep as a potential fundamental contributor to disparities in cardiovascular health. *Annu Rev Public Health*. 2015;**36**:417–440. doi: 10.1146/annurev-publhealth-031914-122838
103. Smith JP, Hardy ST, Hale LE, Gazmararian JA. Racial disparities and sleep among preschool aged children: a systematic review. *Sleep Health*. 2019;**5**(1):49–57. doi: 10.1016/j.sleh.2018.09.010