SLEEP RESEARCH

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A global quantification of "normal" sleep schedules using smartphone data

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The influence of the circadian clock on sleep scheduling has been studied extensively in the laboratory; however, the effects of society on sleep remain largely unquantified. We show how a smartphone app that we have developed, ENTRAIN, accurately collects data on sleep habits around the world. Through mathematical modeling and statistics, we find that social pressures weaken and/or conceal biological drives in the evening, leading individuals to delay their bedtime and shorten their sleep. A country's average bedtime, but not average wake time, predicts sleep duration. We further show that mathematical models based on controlled laboratory experiments predict qualitative trends in sunrise, sunset, and light level; however, these effects are attenuated in the real world around bedtime. Additionally, we find that women schedule more sleep than men and that users reporting that they are typically exposed to outdoor light go to sleep earlier and sleep more than those reporting indoor light. Finally, we find that age is the primary determinant of sleep timing, and that age plays an important role in the variability of population-level sleep habits. This work better defines and personalizes "normal" sleep, produces hypotheses for future testing in the laboratory, and suggests important ways to counteract the global sleep crisis.

INTRODUCTION

Sleep is driven by an internal circadian clock that encodes our daily light exposure. Sunrise and sunset fix the window of sunlight available to this clock, whereas social factors, such as cultural norms or work obligations, modulate the amount of light reaching the clock through selective blocking of light during the day or the use of electric light at night. These same social factors also act on sleep through noncircadian pathways (for instance, by shortening sleep through alarm clocks). Understanding how these factors conspire to control sleep is of vital importance because impaired sleep presents an immediate and pressing threat to human health (*1*, *2*).

Although circadian effects on sleep have been studied extensively, precise characterization of social influences on sleep remains elusive. Quantifying these social effects is the next frontier in sleep research (*3*). The Munich ChronoType Questionnaire (*4*, *5*), launched in 2003, showed that the Internet can be used as a tool for large-scale scientific collection. The recent revolution in smartphone technology allows us to study these social effects on a similarly large scale, enabling fast and inexpensive data acquisition from many users and countries.

We released a free app for iOS and Android (in April and September 2014, respectively) that recommends optimal lighting schedules for adjusting to new time zones (*6*). The app, called ENTRAIN, asks users for "normal" sleep times, home time zone, and typical lighting. It can also record hourly light and sleep schedules, as well as subjective experiences of jet lag. Users may choose to send their anonymized data back to our servers. In what follows, we look at general demographics and normal sleep habits from those users who opted to submit their data. Our goals are both to demonstrate that mobile technology is a viable means of scientific collection and to quantify "real-world" social pressures on global sleep trends.

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RESULTS

A summary of the demographics of our data set can be found in Fig. 1. The responding population had more males than females, was more likely to report "indoor" light as typical than "outdoor" light, and had approximately symmetric distributions for age and day length (Fig. 1A). Respondents spanned the world (Fig. 1, B and E), as well as a range of sunrises, sunsets, and normal sleep habits (Fig. 1C). Typical sleep schedules for the long and short sleepers in our data set are shown in Fig. 1F. The results of regression analysis on all that follows can be found in tables S1 to S7.

Validating our collection method, we find a relationship between age and sleep scheduling that agrees with previous reports from both controlled laboratory studies of circadian factors and large-scale surveys (*7*–*9*). Age has a nonlinear relationship with sleep timing and sleep duration, with increasing age, in general, associated with shorter sleep duration and earlier wake times (Fig. 1D). Regression analysis shows that the nonlinearity can be primarily attributed to men and the population reporting indoor light as "typical" (tables S7 and S8). The trend begins around 20 to 24 years of age, is most drastic during middle age, and reverses around ages 50 to 60. That sleep in the youngest group (18 to 19 years of age) occurs earlier than in the 20- to 24-year-old group is consistent with previous reports (*8*); however, the reversal around ages 50 to 60 is not reported elsewhere.

Among all factors considered, age has the most dominant influence on the timing of midsleep, defined as the halfway point between bedtime and wake time. In contrast, user sex has the strongest influence on sleep duration. Women schedule more sleep at nearly every age group, by both going to bed earlier and waking up later (Fig. 1D). These differences are most pronounced for middle-aged users (30 to 60 years of age), similar to what is reported elsewhere (*10*). The effect on wake time and bedtime is relatively symmetric; thus, gender is not associated with a significant difference in midsleep (tables S2 and S4).

Users were exposed to a wide range of sunrise and sunset times and represented a large pool of nationalities. We were thus able to examine the influences of solar information and home country on sleep scheduling. To approximate the effects of sunrise and sunset on sleep in

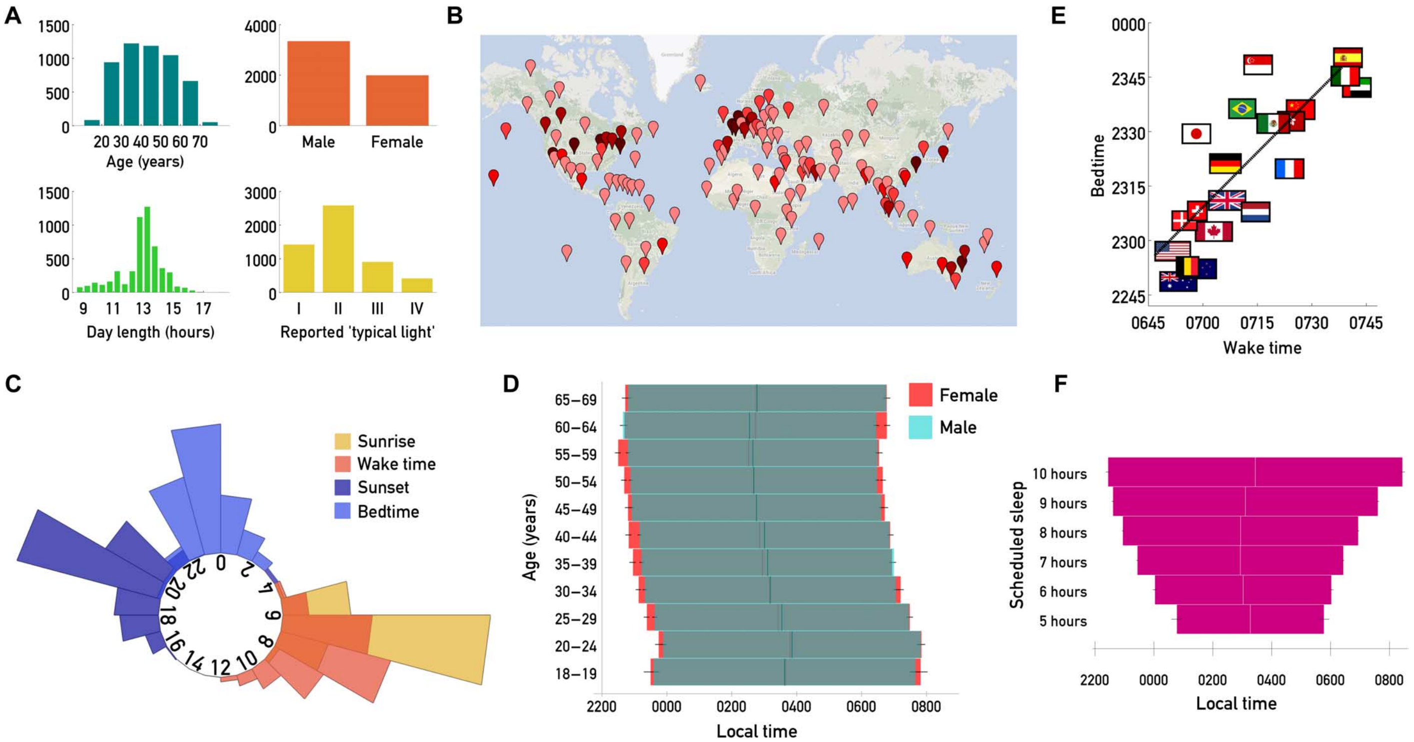

Fig. 1. Demographics of the surveyed set and validation. (**A**) Age, sex, day length, and lighting distributions from the user base. Lighting is divided into low indoor (I), bright indoor (II), low outdoor (III), and bright outdoor (IV). The vertical axis denotes the number of respondents in the cleaned data set. (**B**) Global spread of responses. One pin stands for every city that users could choose as their locale; darker colors indicate more responses from that location. Map data ©2015 Google. (**C**) The distribution of sunrise, sunset, wake time, and bedtime in the surveyed population, normalized and plotted on the circle. (**D**) Sleep scheduling by age and sex. We note a quadratic trend in sleep with age. We further note that women sleep more than men, through both earlier bedtimes and later wake times. (**E**) The 20 countries with the most respondents, plotted by mean wake time and bedtime. Geographically and culturally similar countries tend to cluster together. (**F**) Scheduled sleep and sleep duration, gauged by asking about normal habits. We note a significant quadratic trend in midsleep with sleep duration and that duration and timing are not independent variables in our data set (table S6).

the absence of social pressures, we used a mathematical model of the ascending arousal system coupled to a model of the circadian clock. The mathematical model of the circadian clock takes light as its input and provides an estimate of the circadian contribution to sleep and wake at different points in time (*11*, *12*).

Simulation predicts that both a later sunrise and a later sunset delay wake time and bedtime. This delay is more pronounced for light profiles with a higher maximum brightness (Fig. 2, A1 and B1). Through altered action of the circadian contribution to sleep drive, the model also predicts that later sunrises may slightly decrease sleep duration, whereas later sunsets and higher brightness should increase sleep duration (Fig. 2, C1 and C2).

These theoretical predictions qualitatively agree with many aspects of the data set. Sunrise, sunset, and light exposure do have marked effects on sleep timing (Fig. 2, A2 and B2), as in previous reports (*13*, *14*). Sunrises after 0630 are associated with later wake time and bedtime (Fig. 2, A2 and E). Later sunset is also associated with later wake time and bedtime, as well as longer sleep durations in the outdoor light population (Fig. 2D). Regression analysis confirms that sunrise, sunset, and typical lighting have significant associations with wake time, bedtime, and sleep duration (tables S1 to S4); however, the effect of sunset on sleep in the evening is weaker than what the model predicts. From this, we propose that solar cues do influence sleep but are being attenuated and/or ignored in the real world, particularly around bedtime.

Conversely, home country is more important to bedtime than wake time (Fig. 3), suggesting that people may be particularly receptive to social cues at night. Here, social cues reference those factors that cannot be explained by age, sex, light, sunrise, or sunset. For the 20 countries with the most respondents, average sleep duration is negatively correlated with bedtime but not correlated with wake time (Fig. 3, A and B). In agreement, regression analysis finds that average bedtime varies more among countries than average wake time and that average sleep duration does not vary significantly among countries when controlling for bedtime (tables S1 to S5).

Sensitivity to solar and social cues appears to vary with age and sex. Regression coefficients from a simple multiple linear regression show that the influence of sunrise and sunset on wake time and bedtime is particularly strong in specific groups in the population (Fig. 4A). For example, higher regression coefficients for women suggest they are more sensitive to changes in sunrise and sunset than men. Similarly, older users are more sensitive than younger users, and users reporting outdoor lighting are also more sensitive than users reporting indoor lighting.

Along with the differences in sleep habits already noted (Fig. 1), further distinctions between these groups can be observed. Sleep

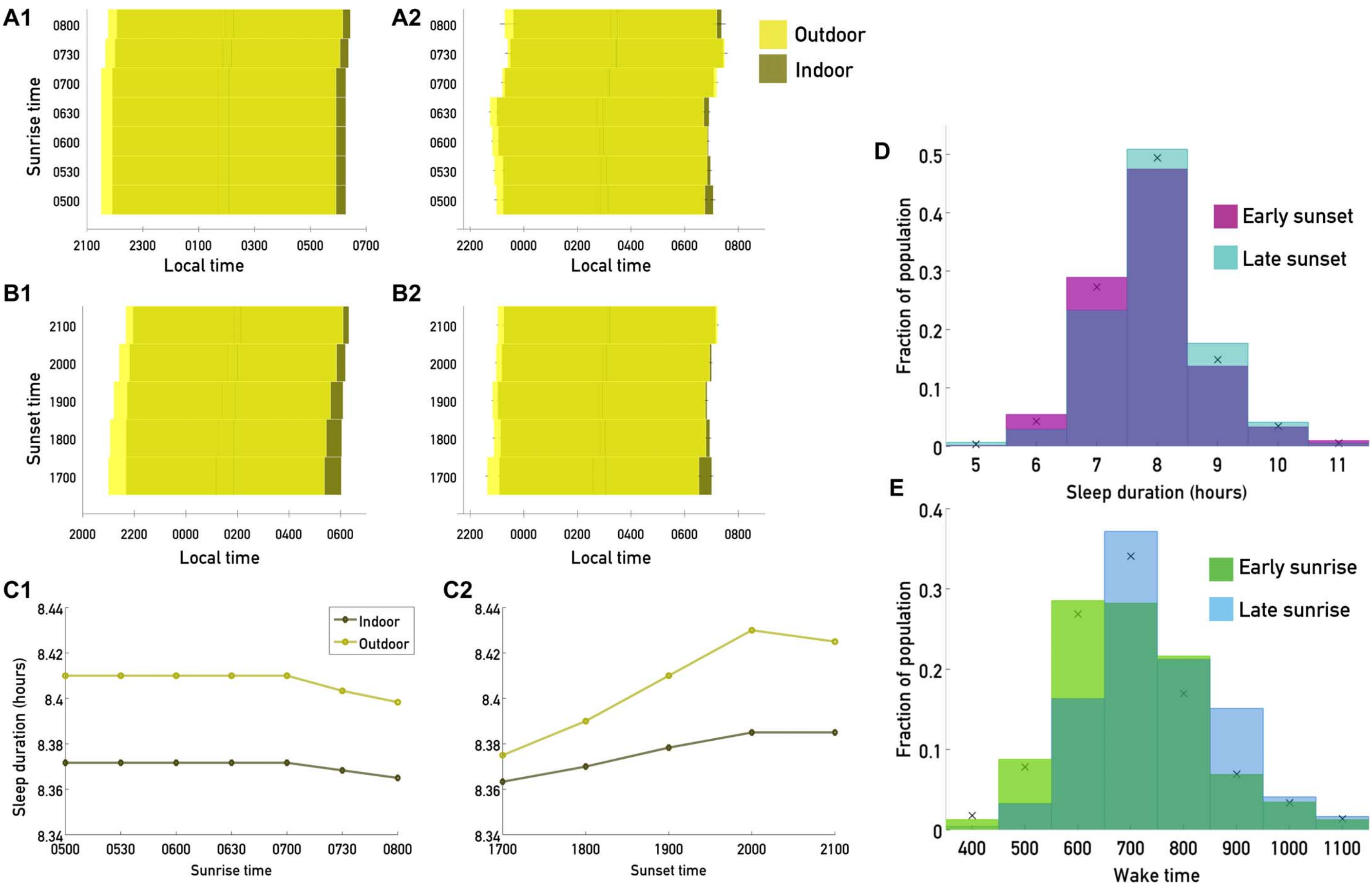

Fig. 2. Solar mediation of sleep. Light profiles with different sunrise and sunset times are simulated. Between sunrise and the population mean wake time, light from the sun is blocked. Between sunset and the population mean bedtime, light input is set to a low level representing indoor light. (**A1**) Model prediction of sleep scheduling for indoor (brown) and outdoor (yellow) light populations at varying sunrise times. (**A2**) Sleep scheduling for indoor and outdoor light populations at varying sunrise times from the data. As in the model, later sunrise times correspond to later wake times and bedtimes, with the trend being most pronounced after 0630. (**B1**) Model prediction of sleep scheduling for indoor (brown) and outdoor (yellow) light populations at varying sunset times. A pronounced shift in both bedtime and wake time is observed, particularly for the outdoor population. (**B2**) Sleep scheduling for indoor and outdoor light populations at varying sunset times from the data. Later sunsets correlate with later wake times in the outdoor light population. (**C1**) and (**C2**) Predicted sleep duration for varying sunrises (C1) and sunsets (C2). The increase in sleep duration with later sunset predicted by the model is seen in the data set. (**D**) Later sunset time increases sleep duration. The sunset distribution is divided into thirds; purple indicates the population experiencing the earliest third of the sunset range, and blue indicates the population experiencing the latest third. Black x's mark the overall population mean. To control for bedtime, only the population with the most frequent bedtime (2300) is plotted. (**E**) Later sunrises shift wake time later. Green, histogram of wake times for users experiencing early sunrises (before 0530); blue, histogram of wake times for users experiencing later sunrises (after 0730). Again, black x's indicate the overall population mean.

schedules are more similar among older users (>55 years old) than among younger users (<30 years old). We find that both the SD and coefficient of variation in population wake time, bedtime, and sleep duration decrease with increasing age (Fig. 4B). We also note differences in the distributions of wake time and bedtime for older/younger populations and men/women (Fig. 4, C to E), and propose that differential sensitivity to solar and social cues could contribute to these differences.

DISCUSSION

Our results blend large-scale data collection with statistical and mathematical modeling. We find a number of trends that agree with previous large-scale surveys and laboratory studies, emphasizing that mobile technology is a reliable methodology for generating and testing scientific hypotheses in the real world.

Wake time is the primary vehicle through which age, sunrise, and sunset affect sleep. Yet, country differences in sleep timing were primarily explained by a difference in bedtime. Hence, mean sleep duration by country was predicted by bedtime and not by wake time. This points to the hypothesis that biological cues around bedtime are either weakened or ignored for societal reasons, thereby leading individuals to delay their bedtime and truncate their sleep duration as a result. Mathematical modeling echoes this hypothesis by predicting how sunrise, sunset, and light would influence sleep schedules in the absence of societal influences. Although there are key qualitative similarities between modeling and data, the model predicts more pronounced trends, primarily through an earlier bedtime.

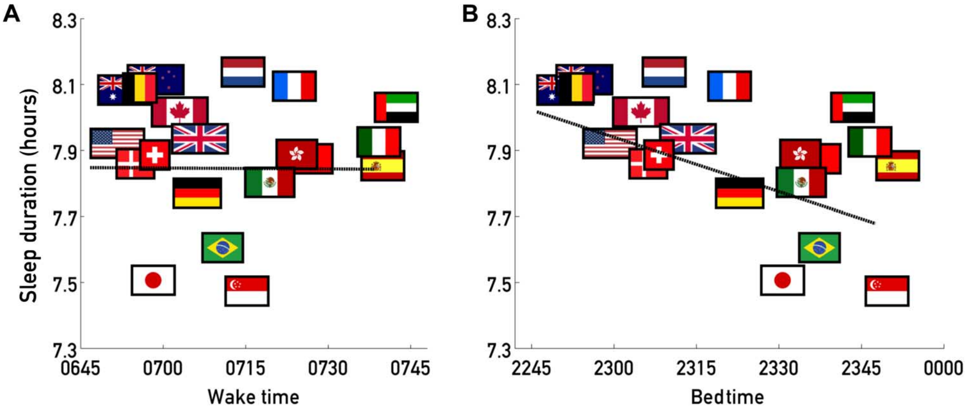

Fig. 3. Country effects on sleep duration act through bedtime. (**A**) Wake time and sleep duration for the 20 countries in the data set with the most respondents. (**B**) Bedtime and sleep duration for the same 20 countries. A significant trend appears only in bedtime.

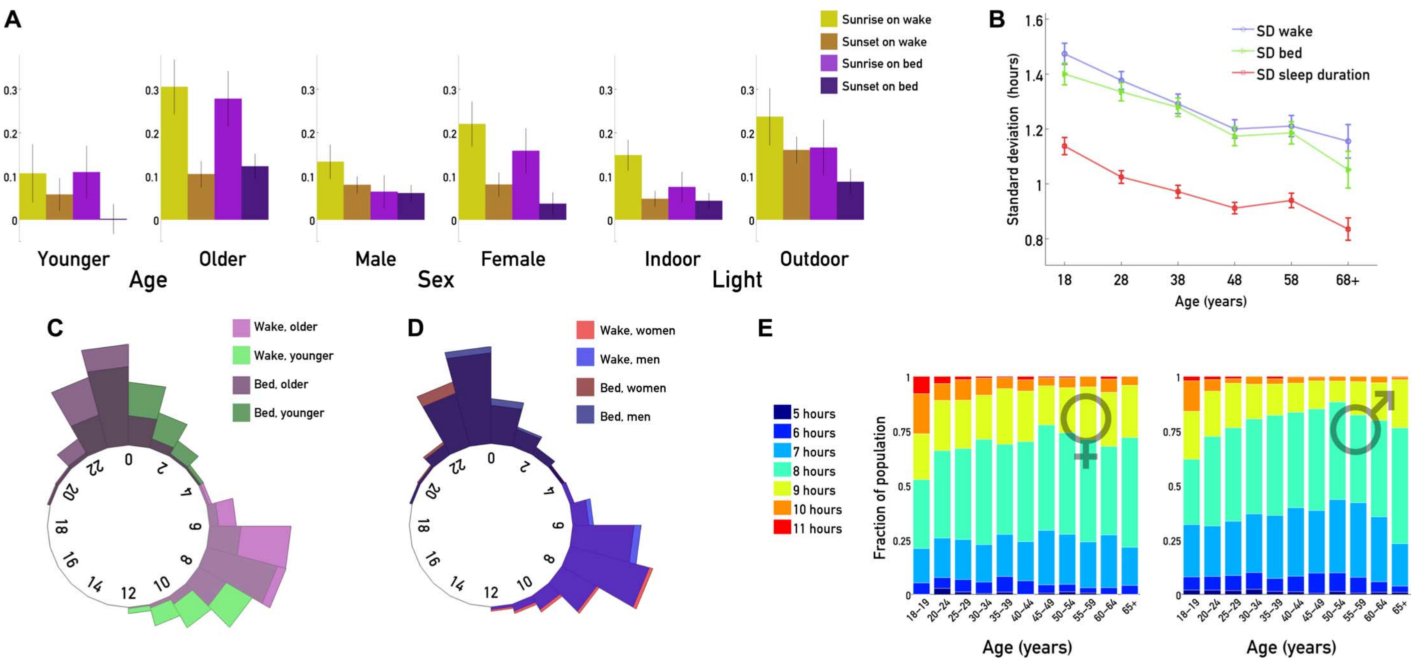

Fig. 4. Differential sensitivity to sunrise and sunset across subpopulations and population-level differences. (**A**) Regression coefficients resulting from multiple linear regression. This model assesses the contributions of sunrise and sunset to wake time and bedtime. For all groups, the coefficient corresponding to sunrise was higher than that for sunset for both wake time and bedtime. Generally, coefficients were higher for older populations (>55 years old), women, and those reporting outdoor light as "typical." Bars show SDs found through bootstrapping. (**B**) SD in population-level sleep habits decreases with increasing age. Bars show SDs found through bootstrapping. (**C**) Normalized histograms for the older population (>55 years old) versus the younger population (<30 years old), plotted on the circle. Younger individuals have much wider and later distributions of wake time and bedtime. (**D**) Normalized histograms on the circle for men and women. These distributions are much more similar than those for the older and younger populations, with the distribution for women skewed slightly earlier for bed and slightly later for wake. (**E**) Fraction of population in each sleep duration group, split up into men and women. Women are more likely to be long sleepers (>9 hours) and show less of a shift in sleeping habits with increasing age.

These discrepancies between theory and data argue that solar cues are present but weakened around bedtime, though it is unclear whether this weakening is through modulation of light exposure or increased social pressure to tolerate higher sleep pressure. Recent work has highlighted how activities before bedtime, for example, using eReaders, can affect sleep (*15*). Age and sex appear to influence the extent to which this weakening of solar information occurs, perhaps because of differences in sensitivity to solar and social cues across groups.

Age is also a critical determining factor in the timing and variability of sleep (Fig. 4), and the decrease in sleep habit variability with increasing age could reflect changes in the circadian clock due to aging. In particular, this result may provide real-world evidence for the previously reported age-related differences (*7*) in the likelihood of sleep at different circadian phases, with the hypothesis being that the older population is more homogeneous in their sleep habits because there is a narrower range of circadian phases at which they can readily sleep.

In sum, our results characterize normal sleep across sexes, ages, and countries; point to the suppression of circadian signaling at bedtime as an important target for clinical sleep intervention; and suggest that age-related differences in the window during which sleep can occur are evident on a global scale.

Moreover, we use mobile technology to collect a massive data set at essentially no cost. Advancing technology and wearables will soon increase the already substantial amount of human data available and will enable us to gain further insights into the toll that sleep deprivation is having on the population. In analyzing these large data sets, mathematical modeling will be key to generating useful predictions from the unstructured bulk collection, and will help us to further quantify the tug-of-war between solar and social timekeeping.

MATERIALS AND METHODS

App collection

The first version of the app, for iOS only, was released in April 2014. The second version for iOS was released in July 2014. An Android version was released in September 2014. The core functionality of the second version was largely unchanged from the first; however, the user interface was modified to improve usability. A total of 8070 users elected to submit their data in the first year of the app's release.

When the app is loaded, the first screen that loads asks users for their normal wake time and bedtime, home time zone, and "typical" amount of light exposure. The choices for wake time and bedtime are rounded to the nearest hour. In both the iOS and Android versions of the app, the cities and time zones that the user can choose from are those built into the app. The options for typical light are as follows: (i) low indoor (200 lux), (ii) bright indoor (500 lux), (iii) low outdoor (1000 lux), and (iv) bright outdoor (10,000 lux). In our analyses, "low indoor" and "bright indoor" are combined into a single category to minimize misclassification error; the same is done for "low outdoor" and "bright outdoor."

To submit their lighting data, users must provide answers to a demographics questionnaire that asks for their age, sex, and travel frequency. The options for sex are male, female, FtM (female to male), MtF (male to female), and intersex. For travel frequency, users can choose one of the following: "Several times a week (All the time)," "Several times a month (Very often)," "Once every couple of months (Often)," "Once or twice a year (Occasionally)," and "Less than once a year (Rarely)."

Users of the app can record their travel dates, their experiences of jet lag (using the Columbia Jet Lag Scale), and their lighting and sleep status for any current or past hour. When data are submitted to the server, the user's travel, lighting, sleep, and jet lag history are transmitted, along with their responses to the questionnaires. Using the home time zone and the time stamp recorded when the start screen questionnaire was filled out, the sunrise and sunset times at the time of survey completion could be determined and were included in the analysis. The top three countries contributing data were the United States (45%), Australia (9%), and Canada (5%). The top six European countries (UK, France, Spain, Netherlands, Denmark, and Germany) combined contributed 15% of responses, and China, Japan, and Singapore together made up 5% of responses. The remaining responses were contributed by countries that individually made up less than 2% of the total data set.

Outliers

Outliers were removed from the data set by applying the following exclusion criteria. Users were excluded if the difference between their wake times, bedtimes, or sleep duration and those quantities' respective peaks of 0700 local time, 2300 local time, and 8 hours of sleep exceeded 4 hours in magnitude. Hence, users reporting wake times strictly before 0300 or after 1100 were excluded, as well as users reporting bedtimes strictly before 1900 or after 0300 and sleep durations strictly less than 4 hours or greater than 12 hours. In addition, users strictly under the age of 18 or above the age of 85 were also excluded. It should be noted that most shift workers are likely to be excluded from our analysis. After this outlier removal, 5450 users remained in the dat a set.

SUPPLEMENTARY MATERIALS

Supplementary material for this article is available at http://advances.sciencemag.org/cgi/content/full/2/5/e1501705/DC1

Statistics

table S1. Fixed and random effects on scheduled bedtime and wake time.

table S2. Fixed and random effects on scheduled sleep duration and midsleep.

table S3. Fixed and random effects and their interactions on bedtime and wake time.

table S4. Fixed and random effects and their interactions on scheduled sleep duration and midsleep.

table S5. Moderation of wake time and bedtime on the relationship between regression terms and scheduled sleep duration.

table S6. Effect of scheduled sleep duration and the square of scheduled sleep duration on midsleep.

table S7. Main effects and interactions between fixed factors and age-squared on scheduled bedtime and wake time.

table S8. Main effects and interactions between fixed factors and age-squared on scheduled sleep duration and midsleep.

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