

## Supplementary Online Content

Jaiswal SJ, Quer G, Galarnyk M, Steinhubl SR, Topol EJ, Owens RL. Association of sleep duration and variability with body mass index: sleep measurements in a large US population of wearable sensor users. *JAMA Intern Med*. Published online September 14, 2020.  
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### **eMethods.**

**eFigure.** Device users in data set based on device usage.

### **eReferences.**

This supplementary material has been provided by the authors to give readers additional information about their work.

## **eMethods**

### **Data source.**

Data were obtained through a collaborative arrangement with FitBit™ Inc., and have been previously used by our group to address important health questions.<sup>1,2</sup> The device used here utilizes a combination of a 3-axis accelerometer, green-light photoplethysmogram (for optical sensing), and altimeter to measure activity and heart rate to provide passively estimated daily sleep metrics, including sleep duration, time in bed, time to fall asleep, and “on-wrist”, or wear-time.<sup>3-5</sup> Individuals in this cohort used one of several models of activity trackers made by FitBit™. 65% of people used Charge HR™ (versions 1-3), 21% used Blaze™, 8% used Alta HR™, 3% used Ionic™, 2% used Surge™, and 1% used Versa™. A validated, proprietary algorithm is used to estimate sleep metrics that are provided to the user and which were stored for later analysis. Although different versions of the device were included in the data set, they all use the same physiological signals and algorithm to detect and measure sleep.

### **Device Validity.**

Sleep measurements from the device have been validated against polysomnography and actigraphy. Studies show generally good agreement, particularly for the metric of total sleep time that we report here.<sup>4</sup> A recent meta-analysis also showed that the newer devices which incorporate heart rate measurements into the algorithm (which are the devices from which our data came) had no significant difference between the total sleep time estimated from the devices and that determined by PSG.<sup>6</sup> Importantly, we note that FitBit™ is quite similar to actigraphy, which is the device that has been used in smaller samples published in the literature up until this point. Recently, Hagheyegh and colleagues showed there was no difference in total sleep time determined by actigraphy and that estimated from FitBit.<sup>7</sup> We emphasize that commercial activity trackers are not a replacement for PSG, which provides in-depth sleep information beyond the general metric of total sleep time.

## **Data analysis and statistics.**

All data analysis was completed using Python. The NumPy, pandas, and scikit-learn libraries were used with our own programming scripts designed for this data set.

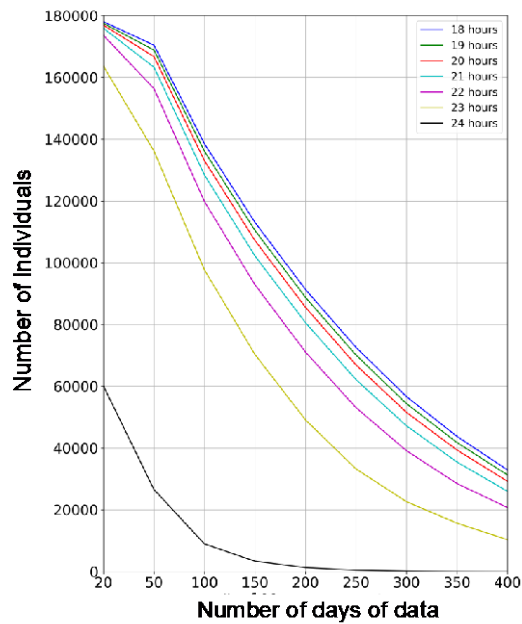
Mean sleep duration. Objective sleep durations, rounded to the nearest 15-minute hourly division, included the main sleep data available for each individual in a given 24-hour period. First, sleep durations were averaged for each individual, and then all individual averages were used to obtain a distribution of mean sleep duration for the entire cohort.

Individual sleep patterns. We graphically report all available sleep data for three individuals in distributions represented in intervals of 15 minutes. These individuals share the same overall mean sleep duration within 1 hour, and were manually selected to show a representation of the variability observed in our sample.

Sleep variability. Sleep variability was examined using the standard deviation of sleep duration. Given that sleep durations were rounded to closest 15-minute time point, a small quantization error is introduced in the calculation of the standard deviation of sleep duration. Since the typical variation in sleep among different days for a single person is larger than the corresponding quantization error, we simplified the quantization error as white noise uncorrelated with the sleep measure. The quantization error was modeled as a uniform distribution and its variance summed to the variance of the rounded sleep duration measures to obtain the total variance, from which we obtained the standard deviation of sleep duration presented in the manuscript. The additional variance calculated in this way was quite small, and its contribution in the calculation of the standard deviation could be neglected.

BMI and Sleep. Mean sleep duration and sleep variability are presented based on BMI. Line graphs were created from histograms using the center of each bin as a plot point. The associated 95% confidence interval in the estimation for each average was constructed and reported within the figures as standard error bars.

### eFigure



**eFigure. Device users in data set based on device usage.** Figure outlines the number of individuals in the data set based on both the number of days an individual wore the device, and the number of hours of wear time per day. We included data from users with at least 100 days of data that had at least 22 hours of wear time.

## eReferences

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