SLEEP, 2025, **48**, 1–12
https://doi.org/10.1093/sleep/zsae172
Advance access publication 8 August 2024
Original Article

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Sleep disturbances across 2 weeks predict future mental healthcare utilization

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Abstract

Study Objectives: Insufficient sleep costs the US economy over $411 billion per year. However, most studies investigating the economic costs of sleep rely on one-time measures of sleep, which may be prone to recall bias and cannot capture variability in sleep. To address these gaps, we examined how sleep metrics captured from daily sleep diaries predicted medical expenditures.

Methods: Participants were 391 World Trade Center (WTC) responders enrolled in the WTC Health Program (mean age = 54.97 years, 89% men). At baseline, participants completed 14 days of self-reported sleep and stress measures. Mean sleep, variability in sleep, and a novel measure of sleep reactivity (i.e. how much people's sleep changes in response to daily stress) were used to predict the subsequent year's medical expenditures, covarying for age, race/ethnicity, sex, medical diagnoses, and body mass index.

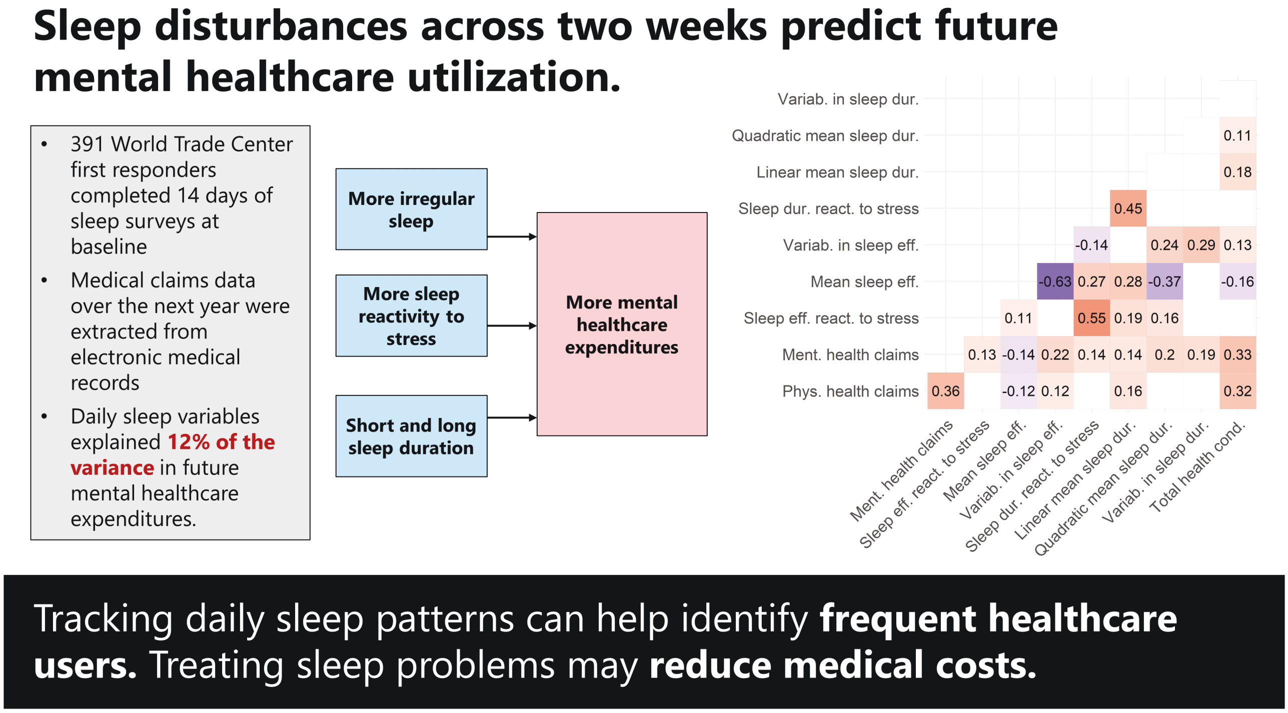
Results: Mean sleep efficiency did not predict mental healthcare utilization. However, greater sleep efficiency reactivity to stress (b = $191.75, p = .027), sleep duration reactivity to stress (b = $206.33, p = .040), variability in sleep efficiency (b = $339.33, p = .002), variability in sleep duration (b = $260.87, p = .004), and quadratic mean sleep duration (b = $182.37, p = .001) all predicted greater mental healthcare expenditures. Together, these sleep variables explained 12% of the unique variance in mental healthcare expenditures. No sleep variables were significantly associated with physical healthcare expenditures.

Conclusions: People with more irregular sleep, more sleep reactivity, and either short or long sleep engage in more mental healthcare utilization. It may be important to address these individuals' sleep problems to improve mental health and reduce healthcare costs.

Key words: sleep reactivity; medical claims; healthcare expenditures; World Trade Center; first responders; daily diary; sleep variability

Submitted for publication: May 3, 2024; **Revised:** July 22, 2024

Graphical Abstract



Statement of Significance

Sleep disturbances have significant economic costs. However, epidemiological studies often rely on one-time retrospective measures of sleep. We examined how daily sleep metrics captured from 14 days of sleep diaries were related to medical expenditures in World Trade Center responders. Greater sleep reactivity, more irregular sleep, and short and long average sleep predicted increased mental healthcare expenditures. Daily sleep metrics may help reliably detect who is at increased risk for frequent healthcare usage. These metrics may have better predictive utility than standard risk factors, although replication in other samples is needed. Understanding the modifiable factors associated with increased healthcare utilization can help identify people in greatest need of treatment and potentially reduce healthcare costs.

Sleep disturbances have an enormous economic cost worldwide. In the United States alone, it is estimated that insufficient sleep costs the US economy over $411 billion per year [1]. Sleep disorders and short sleep duration increase the utilization of office visits, emergency room visits, and prescription medications [2, 3]. Insufficient and poor quality sleep also are linked to more workplace absenteeism [4], lower productivity [5], and more injuries [6], as well as increased risk for developing other costly chronic health conditions (e.g. depression, cardiovascular disease) [7, 8] and premature mortality [9, 10].

Despite these well-established economic impacts of poor sleep, most studies rely on one-time measures of sleep disturbances (e.g. typical sleep patterns in the past 7 to 30 days, using a one-time self-report measure). While helpful for capturing general patterns, these measures may be prone to recall bias and cannot capture daily variability in sleep [11]. Sleep fluctuates substantially from night to night, even among healthy individuals [11–13]. Greater variability in sleep patterns appears to be a unique risk factor for adverse health outcomes, even after controlling for mean sleep patterns [11, 13]. Specifically, greater variability in sleep has been linked to increased risk for gastrointestinal issues and pain [13]; elevated levels of inflammation [14]; depression [15]; poorer cognitive function [16]; poorer cardiometabolic health [17]; and increased risk for mortality [18].

Recent work has also identified another novel facet of daily sleep that is linked to adverse health outcomes, called "sleep reactivity." Sleep reactivity assesses how much an individual's sleep changes in response to stress. For example, some individuals demonstrate large disruptions in sleep following a stressful situation, whereas others are more resilient to these types of perturbations. Traditionally, sleep reactivity has been captured using one-time retrospective questionnaires, such as the Ford Insomnia Response to Stress Test (FIRST) [19], which asks individuals to report how much their sleep is typically impaired in response to or in anticipation of common stressors (e.g. "before an important meeting the next day"). Although measures like the FIRST are easy to administer and have good predictive validity for insomnia and other health outcomes [19–21], they may not provide a comprehensive assessment of how people's sleep is impacted by stressors in everyday life.

One alternative way to capture sleep reactivity is to use daily repeated measures of stress and sleep and multilevel modeling statistical techniques. Specifically, researchers can repeatedly assess daily stress and sleep patterns for several days using daily diary methods. Then a multilevel model can be estimated, using daily stress to predict that night's sleep, and extracting each person's individual random slope between these variables. These extracted variables represent how much an individual's sleep changes in response to daily stress, and can then be used to predict an outcome, such as risk for a particular health condition. Using this technique, greater sleep reactivity has been linked to several adverse health outcomes across various populations (e.g. insomnia [22], chronic medical conditions [23], and functional impairment [24]). However, no studies to the best of our knowledge have used these types of daily sleep reactivity metrics to predict more objective health outcomes, such as medical expenditures. This is an important gap to address, as determining who may be at increased risk of healthcare usage could help reduce medical costs and identify those in greatest need of treatment.

To address this gap and better understand the economic impacts of different types of daily sleep disturbances, we examined how several sleep metrics captured from 14 days of daily diaries were associated with medical expenditures over the course of the following year. We hypothesized that greater sleep reactivity to stress, greater mean sleep disturbances, and greater variability in sleep would each be associated with more yearly physical and mental healthcare expenditures.

Methods

Participants

Participants were 391 individuals enrolled in the larger World Trade Center (WTC) Personality and Health Study [25]. They were recruited from Stony Brook University WTC Health Program, which monitors WTC responders from Long Island, NY who responded to the September 11, 2001 (9/11) WTC attacks [25]. Participants enrolled in the study in 2017. Exclusion criteria included linguistic, cognitive, or physical limitations that would prevent completion of study procedures, such as the inability to understand survey questions, attend a baseline appointment, or complete surveys on a mobile device at home. The Institutional Review Board of Stony Brook University approved the study, and all participants provided informed consent prior to study enrollment. Most participants identified as male (88.5%, $n = 346$), non-Hispanic white (84.1%, $n = 329$), and currently working full-time (41.4%, $n = 162$). Most individuals (68.1%, $n = 263$) were working in law enforcement at the time of the 9/11 WTC attacks. Additional participant demographic information at baseline is presented in Table 1.

Procedure

After indicating informed consent, participants completed the baseline assessment, which included a physical exam to assess height and weight, and device training on how to complete the daily repeated measures surveys on a mobile device. The baseline visit was followed by 2 weeks of daily diary assessments of previous-night sleep (completed in the morning upon awakening) and previous-day stress (completed in the evening). A small proportion of participants completed additional morning surveys (6.1%; $n = 24$) or evening surveys (9.2%; $n = 36$) beyond the 2-week period, as surveys remained open to participants. To maximize reliability, all available survey data were used to calculate summary sleep variables. After completion of the daily diary portion of the study, participants' medical claims from the WTC Health Program were extracted from electronic medical records over the course of the following year.

Table 1. Participant Characteristics and Descriptive Statistics for Key Variables

	M (SD) or *n* (%)
Age	54.97 (8.60)
Body mass index	31.47 (6.05)
Sex	
Male	346 (88.5%)
Female	45 (11.5%)
Race	
White	351 (90.0%)
Black	30 (7.7%)
Asian	4 (1.0%)
American Indian/Alaskan Native	1 (0.3%)
Other or Multiracial	4 (1.0%)
Ethnicity	
Hispanic	27 (7.0%)
Non-Hispanic	360 (93.0%)
Education	
Less than a high school degree	2 (0.5%)
High school graduate	52 (13.3%)
Some college	171 (43.7%)
College graduate	103 (26.3%)
Professional academy graduate	19 (4.9%)
Some graduate or professional schooling	15 (3.8%)
Masters/doctoral or other advanced degree	29 (7.4%)
Current employment status	
Working full time	162 (41.4%)
Homemaker	1 (0.3%)
Full-time student	2 (0.5%)
Working part-time	43 (11.0%)
Laid off	2 (0.5%)
Retired	150 (38.4%)
Physical or psychiatric disability	28 (7.2%)
Unemployed	3 (0.8%)
World Trade Center-certified health conditions	
Anxiety	57 (14.6%)
Cancer	84 (21.5%)
Depression	43 (11.0%)
Extremity condition	3 (0.8%)
Gastroesophageal reflux disease	168 (43.0%)
Interstitial lung disease	9 (2.3%)
Obstructive airway disorder	113 (28.9%)
Posttraumatic stress disorder	57 (14.6%)
Substance abuse	7 (1.8%)
Spine condition	2 (0.5%)
Sarcoidosis	4 (1.0%)
Upper respiratory disease	212 (54.2%)
Total number of World Trade Center-certified health conditions	1.94 (1.60)

Table 1. Continued

	M (SD) or *n* (%)
Yearly medical claims	
Physical healthcare expenditures	\$1277.07 (\$1758.56)
Mental healthcare expenditures	\$597.16 (\$1783.53)
Daily sleep variables	
Sleep efficiency reactivity to stress	<0.01 (<0.01)
Sleep efficiency on a typical stress day	0.85 (0.08)
Sleep duration reactivity to stress	0.07 (0.10)
Sleep duration on a typical stress day	6.91 (0.90)
Mean sleep duration	7.14 (1.03)
Mean sleep efficiency	0.85 (0.09)
Variability in sleep efficiency	0.08 (0.05)
Variability in sleep duration	1.31 (0.57)

Percentages represent valid percentages (i.e. variables with missing data were not included in the total calculation). For daily sleep variables, the sleep on a typical stress day variables represent the random intercept extracted from multilevel models, and the sleep reactivity to stress variables represent the random slope extracted from multilevel models (i.e. each person's individual association between sleep and stress).

Measures

Daily sleep efficiency and sleep duration.

During the daily diary assessments, participants reported on their previous night's sleep each morning upon awakening, including when they got into bed with the intention of sleeping (bedtime), how long it took them to fall asleep (sleep onset latency), how much time they spent awake at night (wake after sleep onset), and when they woke up in the morning (wake time). Sleep duration was calculated as the time elapsed between bedtime and wake time, minus sleep onset latency and wake after sleep onset. Sleep efficiency was calculated as sleep duration divided by time in bed (i.e. time elapsed between bedtime and wake time)*100. For each person, we then calculated the intraindividual mean and intraindividual standard deviation for sleep duration and sleep efficiency. (For additional information on how sleep reactivity indices were calculated, see the Statistical Analysis Plan below).

Daily stress.

During the daily diary assessments, participants also reported on their general stress levels in an evening survey by responding to the question: "Overall, how stressed did you feel today?" on a scale of 1 = none or not at all to 5 = extremely. Previous studies have used similar single-item measures to assess daily stress [22, 26, 27], which have good predictive validity for sleep and other health behaviors or health outcomes.

Medical expenditures.

As part of the WTC Health Program, participants receive free medical treatment for WTC-related conditions. Medical claims data include all paid pharmacy, inpatient, emergency department, and ambulatory care claims for these conditions. These administrative data include all services provided by WTC Health Program and affiliated providers in the community. Each claim is assigned to conditions treated and aggregated into physical and mental health claims according to condition. For more information on how WTC Health Program claims data are processed and compiled, see Azofeifa et al. [28]. For the current study, we examined the total cost of physical and mental healthcare expenditures during the 12 months following the study's baseline assessment. To control for outliers, expenditures data were Winsorized to the 97th percentile.

Covariates.

We included baseline body mass index (BMI), age, race/ethnicity (1 = Non-Hispanic white, 0 = any other racial/ethnic background), sex (1 = male, 0 = female), and total number of WTC certified medical conditions as covariates. The total number of WTC-certified medical conditions was calculated as the total number of the following 12 diagnoses certified by the program's physicians to be WTC-related: (1) posttraumatic stress disorder, (2) substance use disorder, (3) anxiety disorder, (4) depressive disorder, (5) musculoskeletal disorder of extremities (6) gastroesophageal reflux disease, (7) interstitial lung disease, (8) obstructive airway disorder, 9) spine condition, (10) sarcoidosis, (11) upper respiratory disease, and (12) cancer.

Statistical analysis plan

Computation of sleep reactivity indices.

Multilevel modeling analyses with random slopes were conducted to examine sleep reactivity indices based on daily covariation between stress and sleep efficiency or sleep duration. Sleep efficiency and sleep duration reactivity to stress were defined as an individual's change in sleep efficiency or sleep duration, respectively, predicted by changes in stress experienced on the previous day reported before bedtime. The reactivity scores were computed based on the methods employed by prior daily studies with multilevel models [22, 24, 29], where each individual's random slope (i.e. each person's deviation from the sample average slope between stress and sleep efficiency or sleep duration) is specified and extracted from the multilevel model to use as a predictor in subsequent models. Individual intercepts (i.e. each person's average sleep efficiency or sleep duration on a typical stress day [i.e. when person-mean centered stress = 0]) were also extracted from the multilevel models to use as covariates.

To compute reactivity indices, multilevel models were fitted using the *nlme* package [30] in R to obtain the reactivity of the two measures of sleep (i.e. sleep duration and sleep efficiency) to previous-day stress. For each reactivity index, the model fit was compared to an alternative model without the random slope to test whether there was meaningful variation between individuals in their daily sleep reactivity. The models were compared using a likelihood ratio test of model reduction [24]. All random slope coefficients were person-mean centered and multiplied by −1.00 to aid in interpretation across different measures. For additional information on the computation of reactivity indices, see Messman et al. [24].

Linear regression analyses

After the computation of the reactivity indices, intraindividual means, and intraindividual standard deviations, these variables were examined as predictors of medical expenditures in multiple linear regression models. Each pair of independent variables (i.e. intraindividual mean and standard deviation of sleep variables, or sleep reactivity slope and intercept) and each medical expenditures dependent variable (i.e. physical healthcare expenditures or mental healthcare expenditures) was examined in a separate model. This approach was taken in alignment with previous research [13, 14] and to examine the unique effects of sleep variability and sleep reactivity beyond mean or typical levels of sleep. Given substantial research showing quadratic effects of mean sleep duration on a variety of health outcomes [7, 31], we also included a quadratic term (i.e. the standardized intraindividual mean of sleep duration squared) in the mean sleep duration models. To ensure the robustness of effects, all analyses covaried for age, race/ethnicity, sex, BMI, and total number of WTC-certified health conditions. Given expected associations between the random intercept and random slope terms, as well as between the mean and variability in sleep parameters, variance inflation factors (VIF) were computed to test for potential multicollinearity. VIF values ≥3 were considered indicative of potential multicollinearity. To allow for interpretation across different sleep parameters, all sleep variables were standardized on the sample mean for regression models, so that the sleep parameters all had a mean = 0 and a standard deviation = 1. Therefore, unstandardized regression coefficients represent how much the medical expenditures increase or decrease in US dollars for every 1SD increase in the sleep variables, and the standardized regression coefficients represent by how many SDs the medical expenditures increase or decrease for every 1SD increase in the sleep variables.

Results

Preliminary descriptive results

On average, participants completed 12.79 morning surveys (median = 13, SD = 2.89, range = 1–26) and 13.29 evening surveys (median = 14, SD = 3.14, range = 1–28). Approximately 89.5% (n = 350) of participants completed at least 10 morning surveys, and approximately 89.8% (n = 351) of participants completed at least 10 evening surveys. There was a significant variation between individuals' daily stress and sleep reactivity (i.e. significant random slopes). Reactivity scores for each individual (i.e. within-person, random slope coefficients between previous-day stress and that night's sleep efficiency/duration) were therefore extracted for the subsequent analysis as predictors of medical expenditures. Average reactivity scores are displayed in Table 1. Positive reactivity scores indicated that on average, an increase in stress predicted a subsequent decrease in that night's sleep duration or sleep efficiency. For illustrative purposes, Figure 1 shows variability in sleep efficiency across the daily diary period for all participants, including an example of a participant with low versus high variability in sleep efficiency. Figure 2 shows sleep efficiency reactivity to stress for all participants, including an example of a participant with low versus high sleep efficiency reactivity to stress. Bivariate correlations for all key study variables are displayed in Figure 3, and all descriptives for medical expenditures and sleep variables are displayed in Table 1.

Mean and variability in sleep efficiency predicting medical expenditures

Mean sleep efficiency did not significantly predict mental or physical healthcare expenditures, covarying for age, race/ethnicity, sex, BMI, and number of certified WTC health conditions (Table 2). Greater variability in sleep efficiency significantly predicted more mental healthcare expenditures, but not physical healthcare expenditures, after covarying for the same variables described above (Table 2). Specifically, for every 1-SD increase in variability in sleep efficiency, yearly mental healthcare expenditures increased by $339.33 (β = 0.19, p = .002). VIF ranged from 1.04 to 1.68, indicating little multicollinearity between predictors.

Mean and variability in sleep duration predicting medical expenditures

Greater quadratic mean sleep duration and greater variability in sleep duration both significantly predicted more mental healthcare expenditures, but not physical healthcare expenditures, after covarying for the same variables described above (Table 3). Specifically, for every 1-SD increase in quadratic mean sleep duration, yearly mental healthcare expenditures increased by $182.37 (β = 0.18, p = .001), suggesting that both short and long sleep duration predicted greater mental healthcare expenditures. For every 1-SD increase in variability in sleep duration, yearly mental healthcare expenditures increased by $260.87 (β = 0.15, p = .004). VIF ranged from 1.03 to 1.10, indicating little multicollinearity between predictors. Given the inclusion of both the linear and quadratic mean sleep duration terms (which were strongly correlated before standardizing [r = 0.99, p < .001]), we only interpreted the higher order quadratic mean sleep duration variable and not the linear mean sleep duration variable from these models.

Sleep efficiency reactivity to stress predicting medical expenditures

Greater sleep efficiency reactivity to stress predicted more mental healthcare expenditures, but not physical healthcare expenditures, after covarying for the same variables described above, as well as each person's mean sleep efficiency on a typical stress day (i.e. random intercept for sleep efficiency extracted from multilevel models; Table 4). Specifically, for every 1-SD increase in sleep efficiency reactivity to stress, yearly mental healthcare expenditures increased by $191.75 (β = 0.11, p = 0.027). Lower sleep efficiency on a typical stress day also predicted more mental healthcare expenditures (Table 4). Specifically, for every 1-SD decrease in sleep efficiency on a typical stress day, yearly mental healthcare expenditures increased by $204.98 (β = −0.11, p = 0.019). VIF ranged from 1.02 to 1.08, indicating little multicollinearity between predictors.

Sleep duration reactivity to stress predicting medical expenditures

Greater sleep duration reactivity to stress predicted more mental healthcare expenditures, but not physical healthcare expenditures, after covarying for the same variables described above, as well as each person's mean sleep duration on a typical stress day (i.e. random intercept for sleep duration extracted from multilevel models; Table 5). Specifically, for every 1-SD increase in sleep duration reactivity to stress, yearly mental healthcare expenditures increased by $206.33 (β = 0.11, p = .040). Sleep duration on a typical stress day did not significantly predict physical or mental healthcare expenditures (Table 5). VIF ranged from 1.02 to 1.38, indicating little multicollinearity between predictors.

All sleep variables predicting medical expenditures

On an exploratory basis, we also examined the change in the adjusted R^2 when examining all sleep variables as simultaneous predictors of medical expenditures, compared to a model with just the covariates as predictors of medical expenditures. The model with covariates alone explained 10% of the variance in physical health expenditures (Supplementary Table 1), and 12% of the variance in mental health expenditures (Supplementary Table 2). When all the sleep variables were added to the model, they explained 0% of the additional variance in physical health

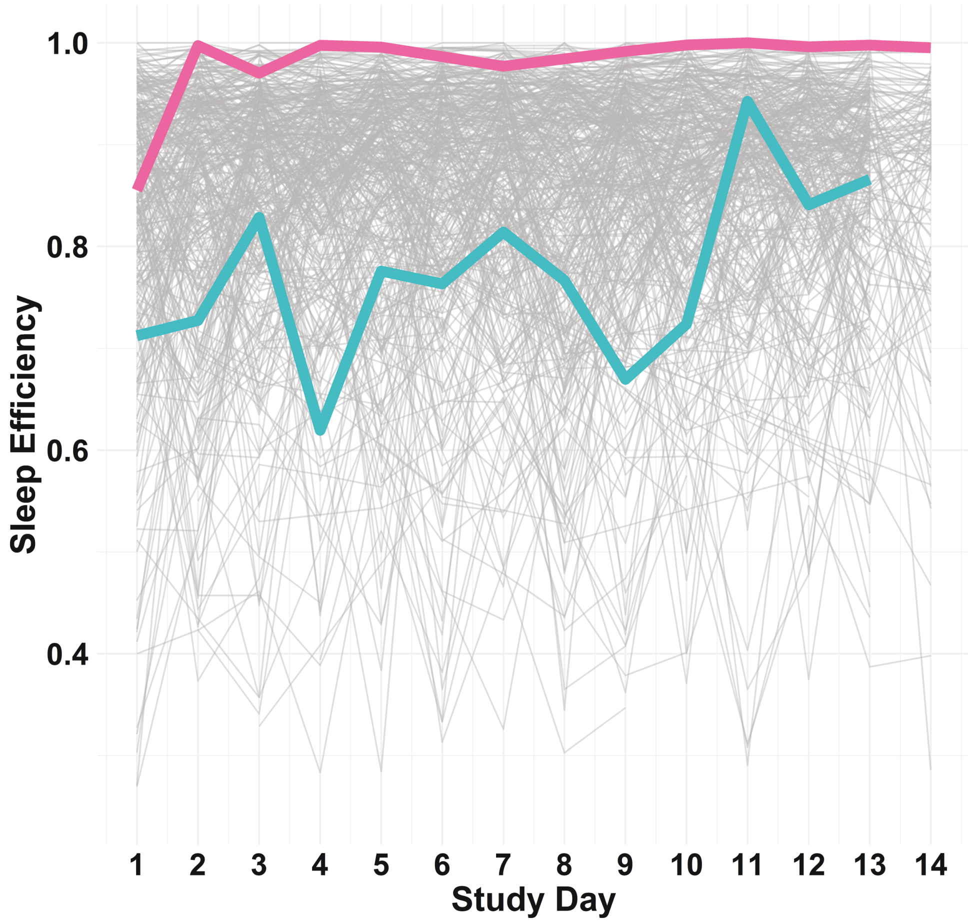


Figure 1. Intraindividual variability in sleep efficiency. The thinner lines (in gray) show sleep efficiency by study day for all study participants. The bottom thicker line (in turquoise) shows an example of a participant with high sleep efficiency intraindividual variability (i.e. relatively large fluctuations in sleep efficiency across the 14 days), and the upper thicker line (in pink) shows an example of a participant with low sleep efficiency intraindividual variability (i.e. relatively small fluctuations in sleep efficiency across the 14 days). For the y-axis, sleep efficiency is expressed as a decimal, where 0.4% = 40% and 1.0% = 100%.

expenditures (Supplementary Table 1), and 12% of the additional variance in mental health expenditures (Supplementary Table 2).

Discussion

Our study shows that daily sleep disturbances are an important predictor of increased mental healthcare expenditures. In particular, people who experience more irregular sleep, more sleep reactivity, and either short or long average sleep have more mental healthcare expenditures. Together, these sleep metrics explained 12% of the unique variance in mental healthcare expenditures. These results suggest that daily sleep metrics may have important predictive utility for determining who is at risk of frequent healthcare usage, even beyond standard risk factors such as age, race/ethnicity, BMI, sex, and number of medical conditions. It may be important to identify such individuals to proactively address their sleep problems and prevent downstream mental health conditions and costs on the healthcare system. Implications of these results in light of the current literature are discussed below.

Sleep reactivity as a novel marker of healthcare usage

First, we found that greater sleep reactivity to stress was associated with increased mental healthcare expenditures. For every 1-SD increase in sleep efficiency or sleep duration reactivity to stress, yearly mental health claims increased by ~$200. Although these represent relatively small effects, the standardized effect sizes for these sleep reactivity variables were approximately one-third the size of the effect of a total number of certified health conditions on mental healthcare expenditures. Certified health conditions determine provision of care and no program expenditures are possible without them, so finding an effect of sleep reactivity above and beyond this variable represents a very stringent comparison. Our findings suggest that these sleep reactivity variables might have added predictive value for understanding who uses mental healthcare services more frequently.

Other studies using one-time retrospective measures of sleep reactivity (e.g. the FIRST) have similarly found that it is linked to a variety of adverse health outcomes, including increased risk for depression [21], anxiety [32], shift work disorder [33], and insomnia [34]. More recent papers using measures of sleep reactivity derived from daily measures have also found similar results. Greater daily sleep reactivity longitudinally predicts increases in insomnia symptoms [22], increases in chronic medical conditions [23], as well as declines in functional and social impairment [24]. Together, this evidence suggests that the tendency to experience more sleep disturbances in the face of stress may be uniquely associated with poor health outcomes. Our work extends these findings by showing these impaired health consequences of sleep reactivity also translate to increased healthcare expenditures.

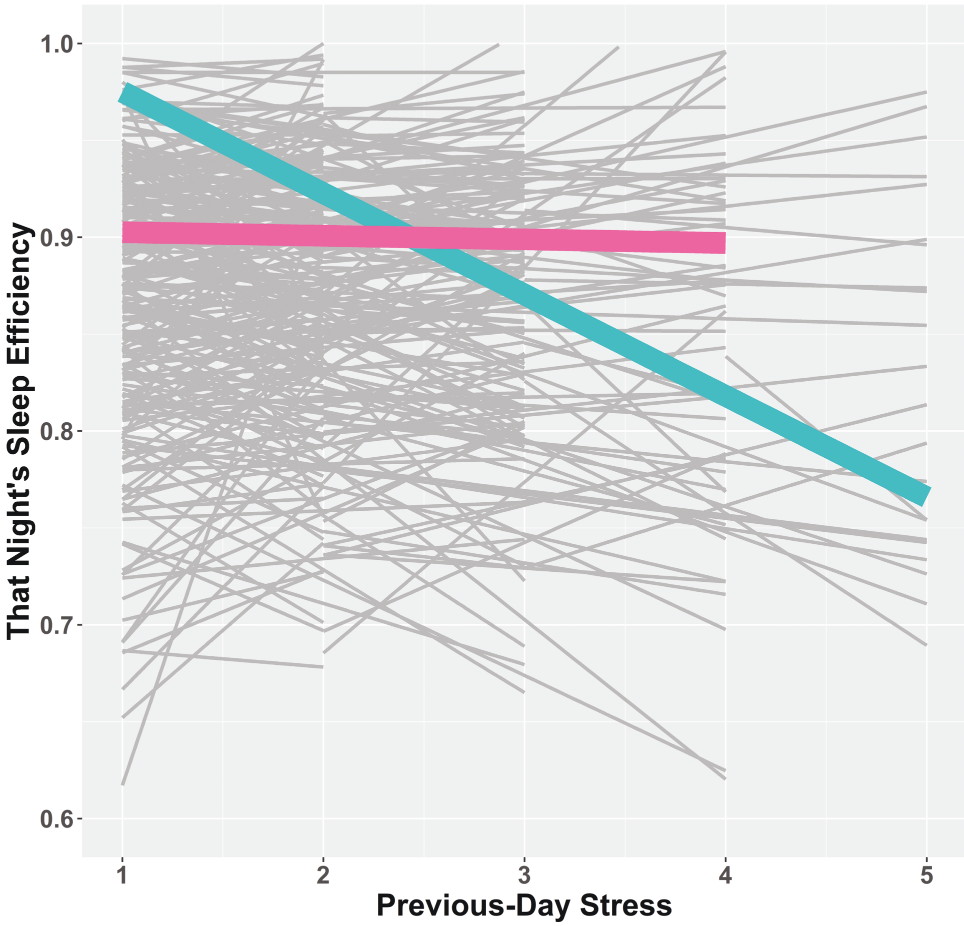


Figure 2. Sleep efficiency reactivity to stress. The thinner lines (in gray) show the individual, within-person random slopes between previous-day stress and that night's sleep efficiency for all study participants (i.e. the independent variable used in regression models to predict medical claims). The thicker upper line (in turquoise) shows an example of a participant with high sleep reactivity (i.e. a strong negative association between previous-day's stress and that night's sleep efficiency), and the thicker bottom line (in pink) shows an example of a participant with low sleep reactivity (i.e. weak association between previous-day's stress and that night's sleep efficiency). For the y-axis, sleep efficiency is expressed as a decimal, where 0.6% = 60% and 1.0% = 100%.

Identifying individuals with high sleep reactivity may allow for earlier detection of individuals at risk for poor health and frequent healthcare usage. Daily measures of sleep reactivity may provide a more ecologically valid and reliable measurement approach than one-time retrospective measures of sleep reactivity. However, formal validation studies on this topic have yet to be conducted. Future studies would benefit from comparing these different measures of sleep reactivity, as well as from incorporating more objective measures of sleep (e.g. actigraphy, ambulatory electroencephalography [EEG]). Experimental studies examining how sleep changes in response to more standardized stressful stimuli are also needed.

There are several potential explanations for how increased sleep reactivity may predict more frequent healthcare usage. First, individuals with high sleep reactivity may have other comorbid conditions (e.g. insomnia, depression, and cardiovascular disease) that necessitate medical treatment. Second, high sleep reactivity may be related to deficits in emotion regulation and/or stress regulation [35, 36] that cause physiological wear and tear (e.g. autonomic dysfunction, inflammation, oxidative stress, and accelerated biological aging). Over time, this dysregulation may lead to health problems that cause individuals to seek out medical treatment. Finally, it may be that individuals high in sleep reactivity are more sensitive to or aware of health issues, causing them to proactively seek out medical treatment. Interestingly, sleep reactivity appears to have both a strong genetic and environmental component, with a heritability of 29%–43% [20]. This suggests that although some individuals may be predisposed to higher sleep reactivity, environmental influences (e.g. exposure to traumatic events) may also play a crucial role in determining reactivity.

The importance of incorporating variability in sleep patterns

We also found that even after controlling for mean sleep parameters, greater variability in sleep duration and sleep efficiency across 14 days was associated with more mental healthcare expenditures. The effects of sleep variability on mental healthcare expenditures were slightly larger than the effects of sleep reactivity, and about half the size of the effect of the total number of medical conditions on mental healthcare expenditures. Instability in sleep patterns may be a cause or consequence of poorer mental health and increased healthcare usage. More irregular sleep is strongly associated with increased risk for depression, anxiety, and other mental health conditions across multiple samples [11], which may cause people to seek out medical care for these or related issues. Indeed, previous studies have shown that depression and anxiety are associated with increased healthcare

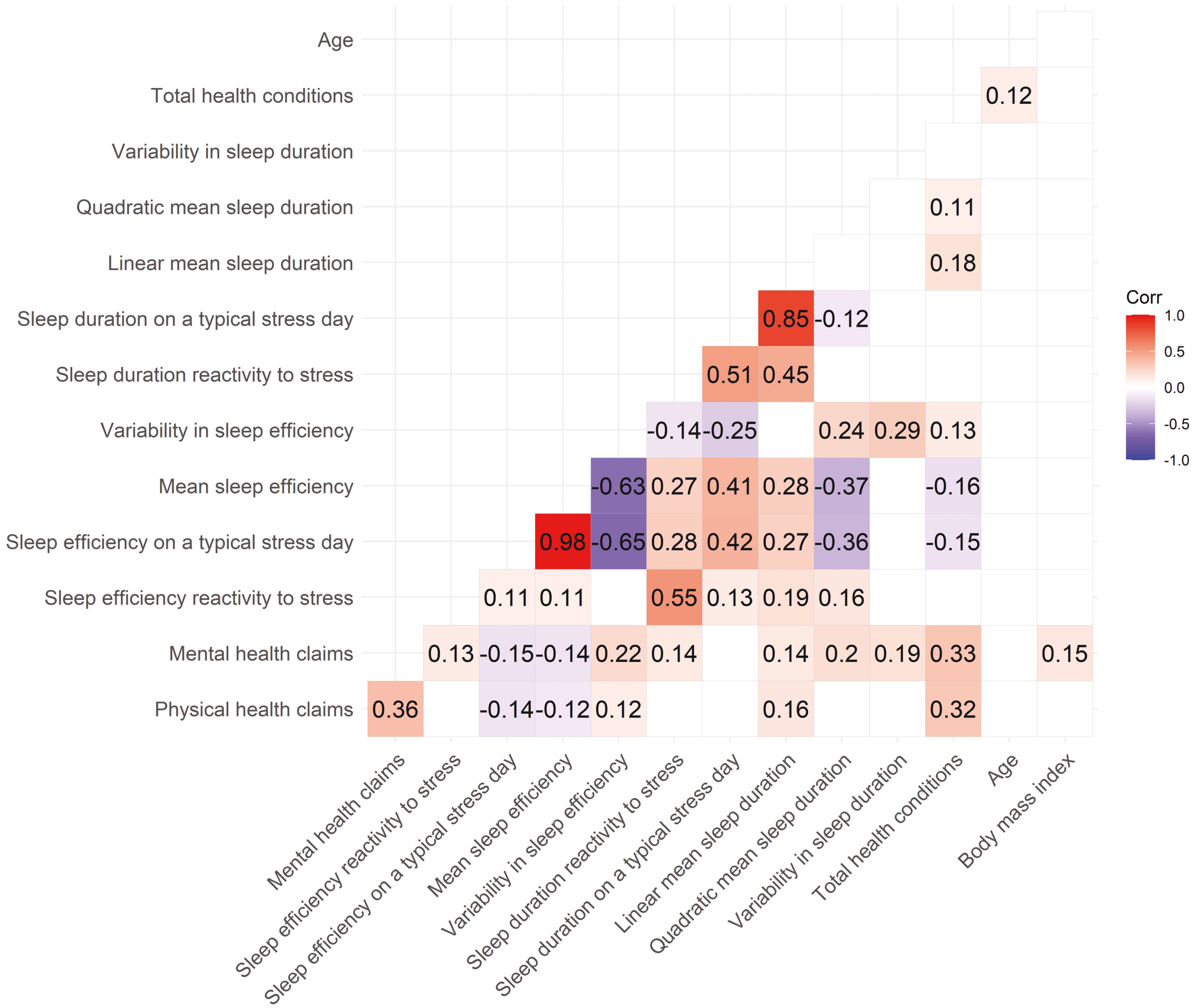


Figure 3. Significant bivariate correlations among key variables. Blank boxes in the lower diagonal represent correlations that are not statistically significant at the $p < .05$ level. Sleep reactivity to stress variables represent the random slopes extracted from multilevel models (i.e. each person's individual association between previous-day stress and that night's sleep); sleep on a typical stress day variables represent the random intercepts extracted from multilevel models (i.e. each person's individual mean sleep after a typical stress day, as stress was person-mean centered). Mean sleep represents the intraindividual means; variability in sleep represents the intraindividual standard deviations. All sleep variables are standardized, with a mean = 0 and a SD = 1.

utilization [37, 38]. However, mental health conditions (and by extension, seeking medical care for these issues) also may cause greater variability in sleep via circadian disruption, and/or disruption in social activities, coping skills, or health behaviors (e.g. excessive substance use, sedentary activity) that can accompany these conditions. Additional longitudinal and experimental work is needed to tease apart the direction of the effects between variability in sleep, mental health symptoms, and healthcare usage.

We also found that both short and long mean sleep durations were associated with increased mental healthcare expenditures. This finding supports research showing that both very short sleep (<6 hours per 24 hours) and very long sleep (>9 hours per 24 hours) are strong risk factors for poorer mental health outcomes [7]. Mental health conditions may cause short sleep due to trouble falling and staying asleep, but they may also lead to longer, but less restorative sleep [7, 39]. Both hypersomnia and hyposomnia are part of the diagnostic criteria for common mental health conditions such as depression and bipolar disorder [40], so it is somewhat unsurprising that a quadratic association between mean sleep duration and mental healthcare utilization emerged.

Clinical Implications

Our findings have some important potential clinical implications. First, our results suggest that daily sleep reactivity and variability measures may be important contributors to mental healthcare utilization, although this finding should be verified experimentally and across other samples [35]. Importantly, our results showed that these sleep metrics were often stronger predictors of healthcare utilization than other standard risk factors, such as age, race/ethnicity, BMI, or even number of diagnosed health conditions. The link between sleep and increased mental healthcare usage could be viewed as either a negative or a positive clinical outcome. On the one hand, sleep disturbances may

Table 2. Mean and Variability in Sleep Efficiency Predicting Physical and Mental Healthcare Expenditures

	Physical healthcare expenditures (USD $)					Mental healthcare expenditures (USD $)				
Predictors	***Est.***	***Std. β***	***CI***	***Std. CI***	***P***	***Est.***	***Std. β***	***CI***	***Std. CI***	***P***
(Intercept)	83.27	−0.00	−1385.43 to 1551.97	−0.10 to 0.10	.911	−621.01	0.00	−2087.90 to 845.88	−0.09 to 0.09	.406
Non-Hispanic white	−17.33	−0.00	−470.78 to 436.13	−0.10 to 0.09	.940	−228.60	−0.05	−681.50 to 224.29	−0.14 to 0.05	.322
Age	4.37	0.02	−15.58 to 24.32	−0.08 to 0.12	.667	−10.27	−0.05	−30.19 to 9.66	−0.14 to 0.05	.312
Body mass index	8.80	0.03	−19.25 to 36.86	−0.07 to 0.13	.538	35.31	0.12	7.29 to 63.33	0.02 to 0.21	.014
Sex	63.96	0.01	−471.59 to 599.51	−0.09 to 0.11	.814	188.82	0.03	−346.07 to 723.71	−0.06 to 0.13	.488
Total health conditions	322.90	0.30	216.34 to 429.47	0.20 to 0.39	<.001	361.84	0.32	255.41 to 468.27	0.23 to 0.42	<.001
Mean sleep efficiency	−85.53	−0.05	−299.90 to 128.85	−0.17 to 0.07	.433	38.59	0.02	−175.52 to 252.70	−0.10 to 0.14	.723
Variability in sleep efficiency	81.81	0.05	−131.97 to 295.59	−0.08 to 0.17	.452	339.33	0.19	125.81 to 552.85	0.07 to 0.31	.002
Observations	387					387				
R^2/R^2 adjusted	0.107/0.091					0.166/0.151				

Est. = regression estimate (where the sleep variables were standardized to have a mean = 0 and a SD = 1); Std. β = standardized regression estimate; 95% CI = 95% confidence interval; Std. 95% CI = standardized 95% confidence interval; *p* = *p*-value; R^2 = percentage of variance explained; R^2 adjusted = percentage of variance explained, adjusted for the number of independent variables in the model. Non-Hispanic white is coded as 1 = identifies as white race and non-Hispanic ethnicity, 0 = identifies as any other racial/ethnic background. Sex is coded as 1 = male, 0 = female. Mean sleep efficiency = the intraindividual mean of sleep efficiency for each person. Variability in sleep efficiency = the intraindividual standard deviation of sleep efficiency for each person.

Table 3. Mean and Variability in Sleep Duration Predicting Physical and Mental Healthcare Expenditures

	Physical healthcare expenditures (USD $)					Mental healthcare expenditures (USD $)				
Predictors	***Est.***	***Std. β***	***CI***	***Std. CI***	***P***	***Est.***	***Std. β***	***CI***	***Std. CI***	***P***
(Intercept)	80.78	−0.00	−1617.16 to 1778.73	−0.11 to 0.11	.925	−1347.92	−0.00	−2857.25 to 161.41	−0.10 to 0.10	.080
Non-Hispanic white	−119.03	−0.02	−676.18 to 438.11	−0.13 to 0.09	.674	16.85	0.00	−478.41 to 512.10	−0.10 to 0.11	.947
Age	6.52	0.03	−17.03 to 30.08	−0.08 to 0.14	.586	−0.44	−0.00	−21.37 to 20.50	−0.11 to 0.10	.967
Body mass index	4.27	0.01	−29.48 to 38.03	−0.10 to 0.13	.803	34.22	0.12	4.21 to 64.23	0.01 to 0.23	.026
Sex	236.72	0.04	−395.44 to 868.88	−0.07 to 0.16	.462	108.05	0.02	−453.88 to 669.99	−0.09 to 0.13	.705
Total health conditions	306.23	0.28	185.17 to 427.29	0.17 to 0.40	<.001	300.61	0.30	192.99 to 408.22	0.19 to 0.40	<.001
Linear mean sleep duration	256.88	0.14	54.65 to 459.10	0.03 to 0.25	.013	233.53	0.14	53.77 to 413.30	0.03 to 0.24	.011
Quadratic mean sleep duration	73.39	0.07	−41.86 to 188.64	−0.04 to 0.18	.211	182.37	0.18	79.92 to 284.82	0.08 to 0.29	.001
Variability in sleep duration	45.78	0.03	−151.41 to 242.97	−0.08 to 0.13	.648	260.87	0.15	85.58 to 436.15	0.05 to 0.26	.004
Observations	303					303				
R^2/R^2 adjusted	0.128/0.105					0.217/0.196				

Est. = regression estimate (where the sleep variables were standardized to have a mean = 0 and a SD = 1); Std. β = standardized regression estimate; 95% CI, 95% confidence interval; Std. 95% CI = standardized 95% confidence interval; *p* = *p*-value; R^2 = percentage of variance explained; R^2 adjusted = percentage of variance explained, adjusted for the number of independent variables in the model. Non-Hispanic white is coded as 1 = identifies as white race and non-Hispanic ethnicity, 0 = identifies as any other racial/ethnic background. Sex is coded as 1 = male, 0 = female. Linear mean sleep duration = the intraindividual linear mean of sleep duration for each person. Quadratic mean sleep duration = the intraindividual quadratic mean of sleep duration for each person (i.e. the squared linear mean; standardized before creating the quadratic term to reduce multicollinearity). Variability in sleep duration = the intraindividual standard deviation of sleep duration for each person.

Table 4. Sleep Efficiency Reactivity to Stress Predicting Physical and Mental Healthcare Expenditures

	Physical healthcare expenditures (USD $)					Mental healthcare expenditures (USD $)				
Predictors	***Est.***	***Std. β***	***CI***	***Std. CI***	***P***	***Est.***	***Std. β***	***CI***	***Std. CI***	***P***
(Intercept)	62.42	−0.00	−1398.51 to 1523.34	−0.10 to 0.10	.933	−796.74	0.00	−2268.44 to 674.97	−0.09 to 0.09	.288
Non-Hispanic white	−26.01	−0.01	−482.34 to 430.33	−0.10 to 0.09	.911	−231.62	−0.05	−691.32 to 228.09	−0.14 to 0.05	.322
Age	4.86	0.02	−15.04 to 24.77	−0.07 to 0.12	.631	−7.62	−0.04	−27.67 to 12.43	−0.13 to 0.06	.455
Body mass index	8.35	0.03	−19.65 to 36.35	−0.07 to 0.13	.558	36.55	0.12	8.34 to 64.76	0.03 to 0.22	.011
Sex	90.48	0.02	−444.68 to 625.65	−0.08 to 0.12	.740	196.46	0.04	−342.65 to 735.57	−0.06 to 0.13	.474
Total health conditions	323.17	0.30	216.16 to 430.17	0.20 to 0.40	<.001	358.21	0.32	250.41 to 466.00	0.22 to 0.41	<.001
Sleep efficiency on a typical stress day	−170.52	−0.10	−340.78 to −0.25	−0.20 to −0.00	.050	−204.98	−0.11	−376.50 to −33.46	−0.21 to −0.02	.019
Sleep efficiency reactivity to stress	74.24	0.04	−93.86 to 242.34	−0.05 to 0.14	.386	191.75	0.11	22.41 to 361.09	0.01 to 0.20	.027
Observations	385					385				
R^2/R^2 adjusted	0.112/0.096					0.158/0.143				

Est. = regression estimate (where the sleep variables were standardized to have a mean = 0 and a SD = 1); Std. β = standardized regression estimate; 95% CI = 95% confidence interval; Std. 95% CI = standardized 95% confidence interval; *p* = *p*-value; R^2 = percentage of variance explained; R^2 adjusted = percentage of variance explained, adjusted for the number of independent variables in the model. Non-Hispanic white is coded as 1 = identifies as white race and non-Hispanic ethnicity, 0 = identifies as any other racial/ethnic background. Sex is coded as 1 = male, 0 = female. Average sleep efficiency on a typical stress day = the random intercept extracted from multilevel models (i.e. each person's sleep efficiency on a day when stress is at their individual mean). Sleep efficiency reactivity to stress = the random slope extracted from multilevel models (i.e. each person's individual association between previous-day stress and that night's sleep efficiency).

Table 5. Sleep Duration Reactivity to Stress Predicting Physical and Mental Healthcare Expenditures

	Physical healthcare expenditures (USD $)					Mental healthcare expenditures (USD $)				
Predictors	***Est.***	***Std. β***	***CI***	***Std. CI***	***P***	***Est.***	***Std. β***	***CI***	***Std. CI***	***P***
(Intercept)	39.65	−0.00	−1428.66 to 1507.97	−0.10 to 0.10	.958	−848.76	0.00	−2327.20 to 629.68	−0.09 to 0.09	.260
Non-Hispanic White	−38.80	−0.01	−497.87 to 420.27	−0.10 to 0.09	.868	−266.80	−0.05	−729.04 to 195.43	−0.15 to 0.04	.257
Age	4.70	0.02	−15.37 to 24.77	−0.08 to 0.12	.646	−6.70	−0.03	−26.91 to 13.52	−0.13 to 0.06	.515
Body mass index	10.66	0.04	−17.43 to 38.74	−0.06 to 0.14	.456	39.75	0.13	11.47 to 68.03	0.04 to 0.23	.006
Sex	21.29	0.00	−513.13 to 555.70	−0.10 to 0.10	.938	76.17	0.01	−461.92 to 614.27	−0.08 to 0.11	.781
Total health conditions	339.15	0.31	232.75 to 445.54	0.21 to 0.41	<.001	376.90	0.33	269.77 to 484.02	0.24 to 0.43	<.001
Sleep duration on a typical stress day	50.67	0.03	−144.64 to 245.98	−0.08 to 0.14	.610	−2.26	−0.00	−198.92 to 194.40	−0.11 to 0.11	.982
Sleep duration reactivity to stress	0.43	0.00	−195.08 to 195.94	−0.11 to 0.11	.997	206.33	0.11	9.47 to 403.19	0.01 to 0.22	.040
Observations	385					385				
R^2/R^2 adjusted	0.103/0.087					0.151/0.135				

Est. = regression estimate (where the sleep variables were standardized to have a mean = 0 and a SD = 1); Std. β = standardized regression estimate; 95% CI = 95% confidence interval; Std. 95% CI = standardized 95% confidence interval; *p* = *p*-value; R^2 = percentage of variance explained; R^2 adjusted = percentage of variance explained, adjusted for the number of independent variables in the model. Non-Hispanic white is coded as 1 = identifies as white race and non-Hispanic ethnicity, 0 = identifies as any other racial/ethnic background. Sex is coded as 1 = male, 0 = female. Average sleep duration on a typical stress day = the random intercept extracted from multilevel models (i.e. each person's sleep duration on a day when stress is at their individual mean). Sleep duration reactivity to stress = the random slope extracted from multilevel models (i.e. each person's individual association between previous-day stress and that night's sleep duration).

predict future mental health problems (a negative outcome). On the other hand, individuals with sleep problems may be more willing to seek treatment for related health concerns (a positive outcome).

Clinicians may consider adopting daily measures of stress and sleep to more accurately predict high healthcare utilizers or those in greatest need of treatment. Many clinicians who administer cognitive behavioral therapy for insomnia (CBT-I) ask participants to complete sleep diaries, to which measures of daily stress could be easily added to facilitate the calculation of naturalistic sleep reactivity. Our results also suggest equipping individuals with coping strategies (e.g. cognitive restructuring, mindfulness) may be important to break the cycle of stress and sleep disturbances. For example, psychological interventions targeting worry and rumination lead to small improvements in sleep [41]. Together, our results highlight the importance of assessing daily sleep patterns for understanding broader healthcare trends.

Limitations

Despite the multiple strengths of this study (daily repeated measures of stress and sleep; large sample; objective measures of yearly healthcare utilization), there are some limitations worth noting. First, our sample was mostly male, non-Hispanic white, and middle-aged. Women and racial/ethnic minorities experience disproportionately higher rates of insomnia and short sleep [42], and also use healthcare at different rates than white men [43]. Therefore, it will be important to assess these associations in more gender- and racially/ethnically diverse samples. Furthermore, the WTC Health Program mirrors several other health programs (e.g. VA health network), but its reimbursement structure likely does not generalize to all health systems. Therefore, the present results require replication in other settings. We also only used self-report measures of sleep. Calculating reactivity indices with more objective measures of sleep, such as actigraphy, may be an important next step for this research. For example, one study has shown that greater actigraphy sleep efficiency reactivity to a stressful task is associated with poorer cognitive performance [44]. Finally, although we covaried for the number of health conditions (including mental health conditions such as depression, anxiety, and PTSD), we did not screen for or exclude individuals with underlying sleep disorders or those engaged in shift work. These variables will be important to examine in future research, as both have been associated with increased healthcare expenditures [2, 3, 45].

Conclusion

Overall, our results suggest that the assessment of daily sleep regularity and sleep reactivity can aid in the detection of individuals at risk for frequent mental healthcare usage. These metrics may have better utility than other common risk factors. Our findings also help identify who may be in greatest need of sleep treatment or other clinical interventions. Accurately identifying the facets of sleep associated with increased healthcare usage may have important implications for improving mental health and reducing healthcare costs.

Supplementary material

Supplementary material is available at *SLEEP* online.

Data Availability

The data underlying this article cannot be shared publicly due to the privacy of individuals who participated in the study (i.e. medical claims data are protected by the HIPAA Privacy Rule). All R code used to run analyses is available in supplementary materials.

Disclosure Statement

Financial disclosure: This research was supported by the National Institute for Occupational Safety and Health (NIOSH) under Award Number U01OH011321 and R21OH012614 (PI: Roman Kotov). NIOSH had no role in the conduct of the study or preparation of the manuscript. The findings and conclusions in this article are those of the authors and do not represent the official positions of NIOSH. *Nonfinancial disclosure:* The authors report no conflicts of interest.

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