# Decoding Sleep Disorders Through Self-Reported Patterns*

**A Logistic Regression Approach to the NHANES 2017-March 2020 Sleep Data**

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This study uses logistic regression to analyze the relationship between self-reported sleep behaviors and the likelihood of reporting sleep troubles, using data from the NHANES 2017 to March 2020 Sleep Disorders dataset. We examine factors such as snoring frequency, daytime sleepiness, and sleep duration on weekdays and weekends. Findings indicate that excessive snoring and high daytime sleepiness are strongly associated with more reported sleep issues, while longer weekend sleep correlates with fewer reports. These results highlight the importance of good sleep hygiene for overall health and provide insights into how daily behaviors affect sleep quality.

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*Code and data supporting this analysis are available at https://github.com/TEJMaster/Sleep-Disorder-Analysis

# 1 Introduction

Sleep disturbances are increasingly recognized as a major public health issue, comparable to concerns surrounding mental health and chronic lifestyle diseases. The effects of sleep disorders extend beyond personal inconvenience, influencing public health, workplace productivity, and overall quality of life. Despite increased awareness, there is still a significant gap in understanding the behaviors and patterns linked to sleep disturbances. This study addresses this gap by analyzing self-reported data on sleep behaviors and their impact on health outcomes, and by developing tools for individuals to predict potential sleep issues.

Utilizing the National Health and Nutrition Examination Survey (NHANES) dataset from 2017 to March 2020 (CDC 2021), our research examines how various sleep behaviors—such as snoring frequency, daytime sleepiness, and sleep regularity—correlate with the likelihood of reporting sleep issues to healthcare providers. The primary estimand of our analysis is the association between these behaviors and the probability of an individual reporting sleep disturbances, quantified through logistic regression. This approach provides a clearer understanding of the epidemiology of sleep problems and identifies key predictive factors.

Our findings pinpoint specific behaviors that significantly correlate with sleep disturbances. These insights are vital for healthcare professionals and policy makers, identifying potential areas for intervention to improve sleep health. The impact of our research is substantial, providing a basis for strategies to reduce the effects of sleep disorders on individuals and on society as a whole.

By establishing a direct link between certain sleep behaviors and reported sleep issues, our study contributes to ongoing efforts to address the silent epidemic of sleep disorders that affects a large segment of the population. It also offers individuals a valuable tool to assess their risk of sleep disturbances, promoting early detection and proactive health management.

The paper is structured to ensure a clear presentation of our research and findings: Section 2 (Data) describes our data collection and cleaning processes, providing a detailed overview of the NHANES dataset. Section 3 (Model) explains the logistic regression model, including the selection of predictors and the underlying rationale. Section 4 (Result) presents our main findings, supported by graphical representations for clearer understanding. Concluding the paper, Section 5 (Discussion) provides the implications of our research, recognizing limitations and suggesting future research directions.

# 2 Data

## 2.1 Raw Data

The dataset used in this analysis is derived from the National Health and Nutrition Examination Survey (NHANES), spanning from 2017 to March 2020. This public dataset includes responses from participants regarding their sleep patterns, incorporating 10,195 records initially. After some data cleaning, the dataset for analysis stands at 10,031 records, encapsulating variables critical to our research: the respondent's ID, usual sleep and wake times on both weekdays and weekends, total sleep duration, frequency of snoring, incidence of breathing pauses during sleep, and self-reported communication of sleep troubles to a health professional. The dataset provides a snapshot of Americans' sleep behaviors before the disruption caused by the COVID-19 pandemic (CDC 2021).

The survey participants' ages range widely, reflecting the diversity of the American population. Variables are finely tuned to capture the multifaceted nature of sleep, including aspects such as duration, disruptions, and subjective experiences of daytime sleepiness. The NHANES protocol ensures that this dataset is a robust and reliable source of information, assure ethical standards and data collection methods, as detailed in the NHANES Analytic Guidelines. For further information on the data cleaning specifics and validation checks, please see the supplementary material in Appendix.

## 2.2 Data Analysis Tools

Our analytical approach was completed using R (R Core Team 2022), utilizing the tidyverse (Wickham et al. 2019) for data manipulation and ggplot2 (Wickham 2016) for visualization. The readr (Wickham, Hester, and Bryan 2022), here (Müller 2020), and arrow (Apache Arrow Contributors 2024) packages were pivotal in handling data importation and directory management. Reproducible reporting was facilitated by knitr (Xie 2014) and kableExtra (Zhu 2021) for enhancing table presentations. Bayesian logistic regression modeling was conducted with rstanarm (Team 2024), while model diagnostics were visualized using bayesplot (Gelman, Gabry, and Ali 2024). These tools, which formed the backbone for this paper as well as the scripts, ensured efficient and reproducible analyses, culminating in a robust set of findings.

## 2.3 Variable Description

**Weekday Sleep Duration (SLD012)**: This variable measures the total number of hours respondents usually sleep on weekdays or workdays, with values ranging from 2 to 14 hours. It provides insight into their sleep patterns during the typical workweek.

**Weekend Sleep Duration (SLD013)**: Similar to the weekday sleep duration, this variable represents the total number of hours respondents usually sleep on weekends or non-workdays, also ranging from 2 to 14 hours. It helps in understanding the variation in sleep patterns during days off from work.

**Snoring Frequency (SLQ030)**: This variable records how often respondents snore while sleeping, with responses ranging from 0 (Never) to 3 (Frequently). Snoring is a common symptom of sleep disorders such as obstructive sleep apnea, making this variable relevant to the study of sleep health.

**Overly Sleep Frequency (SLQ120)**: This variable assesses how often respondents feel excessively or overly sleepy during the day, with values ranging from 0 (Never) to 4 (Almost always). It is an indicator of sleep quality and quantity, as well as potential sleep disorders.

**Reported Sleep Trouble (SLQ050)**: The dependent variable in this study, it indicates whether respondents have ever told a doctor or other health professional that they have trouble sleeping. It is treated as a binary outcome variable, with values of 0 (No report of sleep trouble) and 1 (Reporting sleep trouble).

## 2.4 Sample of Cleaned Sleep Disorder Data

Table 1: Sample of Sleep Disorder Data

| Respondent ID | Weekday Sleep Duration (hrs) | Weekend Sleep Duration (hrs) | Snoring Frequency | Breathing Pause Frequency | Overly Sleep Frequency | Reported Sleep Trouble |
|---|---|---|---|---|---|---|
| 109266 | 7.5 | 8.0 | 1 | 0 | 0 | 0 |
| 109267 | 8.0 | 8.0 | 0 | 0 | 2 | 0 |
| 109268 | 8.5 | 8.0 | 0 | 0 | 1 | 0 |
| 109271 | 10.0 | 13.0 | 0 | 0 | 3 | 1 |
| 109273 | 6.5 | 8.0 | 0 | 0 | 2 | 1 |
| 109274 | 9.5 | 9.5 | 1 | 0 | 0 | 0 |

Table 1 represents a subset of the broader NHANES sleep disorder dataset. Each row in the table corresponds to an individual participant, uniquely identified by their Respondent ID. The “Weekday Sleep Duration (hrs)” and “Weekend Sleep Duration (hrs)” columns quantify the number of hours slept during the weekdays and weekends, respectively, providing a snapshot of the individual’s sleep patterns. “Snoring Frequency” and “Breathing Pause Frequency” are categorical measures that reflect how often the respondents experience snoring and breathing pauses during sleep, common indicators of sleep disturbances such as sleep apnea. The “Overly Sleep Frequency” column indicates the frequency at which respondents report feeling overly sleepy during the day, a sign that can be indicative of inadequate sleep quality or quantity. Lastly, the “Reported Sleep Trouble” column is a binary measure showing whether the respondent has reported having sleep troubles to a health professional, with 0 signifying no reported trouble and 1 indicating reported trouble.

### 2.5 Measurement:

In this study, we utilized data from the National Health and Nutrition Examination Survey (NHANES), specifically focusing on the sleep disorders component which includes data collected between 2017 and March 2020. The NHANES program, a longstanding project conducted by the National Center for Health Statistics (NCHS), plays a critical role in assessing the health and nutritional status of adults and children in the United States. This dataset is pivotal in understanding public health and informs policy decisions through scientifically reliable data (CDC 2021).

The sleep disorders dataset within NHANES is enriched by questions adapted from the Munich ChronoType Questionnaire (Roenneberg, Wirz-Justice, and Merrow 2003), targeting various aspects of sleep behavior and disorders. The inclusion of these questions is instrumental in exploring the complex dynamics of sleep patterns among the U.S. population. Due to disruptions caused by the COVID-19 pandemic, the 2019-2020 data collection cycle was prematurely halted in March 2020, leading to its combination with the 2017-2018 cycle to ensure national representativeness and analytical robustness.

This combined dataset referred to as the NHANES 2017-March 2020 pre-pandemic data, offers valuable insights into the sleep habits of Americans before the pandemic. It is instrumental for researchers and public health officials aiming to understand baseline sleep behaviors and potential disturbances across a broad demographic spectrum.

To prepare the dataset for analysis, extensive data cleaning and processing were conducted. This included removing entries with missing, refused, or 'don't know' responses for critical variables such as sleep duration and frequency of snoring. Additionally, to address issues with data reliability and consistency, about 3% of the data underwent verification through audio recordings of the interviews. Moreover, for variables capturing sleep duration on weekdays (SLD012) and weekends (SLD013), reported times were meticulously reviewed, with outliers adjusted and rounded to the nearest half-hour, enhancing the data's accuracy and usability.

Detailed descriptions of the variables used in this study, along with the specific adjustments made to the dataset, are available in Section 2.3. This section is designed to provide a comprehensive understanding of the origins, processing, and analytical framework applied to each variable relevant to this study.

## 2.6 Data Exploration:

In this section, we explore the distributions of key variables related to sleep patterns and disorders in the NHANES dataset. Histograms provide visual insights into the frequency of reported sleep duration, snoring, breathing pauses, daytime sleepiness, and reported sleep troubles.

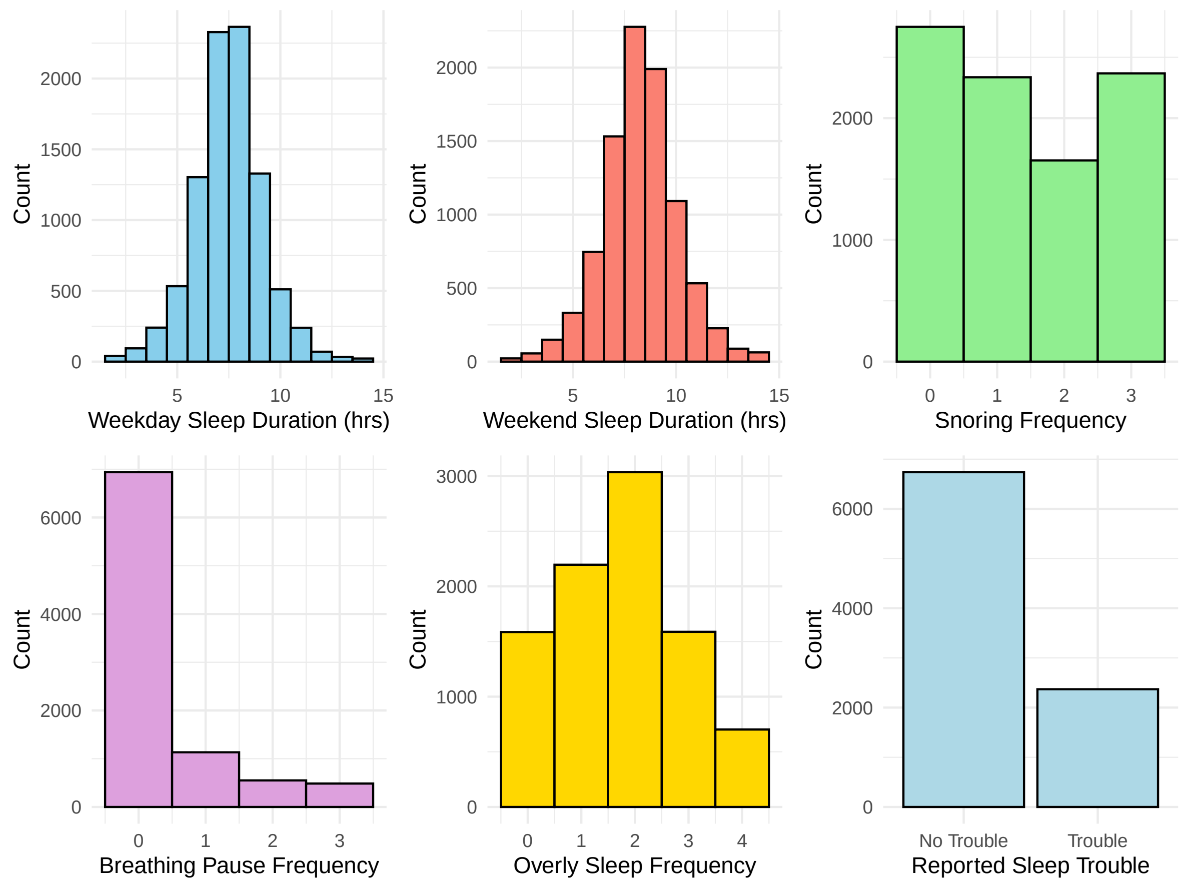



Figure 1: Distributions of sleep-related variables

**Weekday Sleep Duration (hrs)**: The histogram for weekday sleep duration exhibits a unimodal distribution, peaking around 7 to 8 hours, which aligns with the generally recommended sleep duration for adults. The symmetrical shape suggests a commonality in sleep patterns among individuals during the workweek.

**Weekend Sleep Duration (hrs)**: Similarly unimodal, the weekend sleep duration distribution also peaks around the same range as weekday sleep but shows a noticeable tendency for slightly longer durations. This may suggest that individuals take the opportunity to sleep more on weekends, possibly compensating for the workweek.

**Snoring Frequency**: The snoring frequency histogram reveals a broad distribution, with the majority of respondents indicating they never or rarely snore. A significant count of individuals also reports frequent snoring, suggesting that the experience of snoring is quite varied among the respondents.

**Breathing Pause Frequency**: The distribution for breathing pause frequency is steeply skewed towards 'Never', suggesting that breathing pauses during sleep are infrequently experienced or reported by the majority of respondents. The scant instances of frequent breathing pauses may indicate a lower occurrence or a lack of self-awareness of these events.

**Overly Sleep Frequency**: The distribution of daytime sleepiness frequency is right-skewed, with 'Sometimes (2-4 times a month)' emerging as the modal category. However, a notable proportion of respondents experience sleepiness during the day at least once a month, suggesting that daytime sleepiness is a common issue.

**Reported Sleep Trouble**: The binary distribution for reported sleep trouble shows a larger proportion of individuals reporting no sleep trouble compared to those reporting trouble, approximately threefold. This ratio highlights that while sleep trouble is present, it is not reported by the majority of participants in this sample.

# 3 Model

The aim of our model is to explore the relationship between various sleep-related factors and the self-reported incidence of sleep troubles. We employ a Bayesian logistic regression model to analyze the data from the National Health and Nutrition Examination Survey (NHANES). Further details and diagnostics of this model are provided in Appendix.

## 3.1 Model set-up

Let $y_i$ denote the binary outcome indicating whether an individual has reported sleep troubles to a doctor, with $y_i = 1$ for reported troubles and $y_i = 0$ otherwise. The predictors include continous variables like weekday sleep duration ($x_{i1}$), and weekend sleep duration ($x_{i2}$); ordinal categorical variables such as snoring frequency ($x_{i3}$), breathing pause frequency ($x_{i4}$), and overly sleep frequency ($x_{i5}$). The logistic regression model is formulated as follows:

$$
\begin{aligned}
y_i | p_i &\sim \text{Bernoulli}(p_i) && (1)\\
\text{logit}(p_i) &= \beta_0 + \beta_1 \times x_{i1} + \beta_2 \times x_{i2} + \beta_3 \times x_{i3} + \beta_4 \times x_{i4} + \beta_5 \times x_{i5} && (2)\\
\beta_0 &\sim \text{Normal}(0, 1) && (3)\\
\beta_1, \beta_2, \beta_3, \beta_4, \beta_5 &\sim \text{Normal}(0, 1) && (4)\\
& && (5)
\end{aligned}
$$

The logistic regression model is defined using a Bayesian framework, implemented in R with the `rstanarm` package. This approach enables the integration of prior knowledge about the parameters to estimate their posterior distributions based on the observed data.

In our model, the probability of an individual reporting sleep troubles, denoted by $p_i$, follows a Bernoulli distribution. The log odds of reporting sleep troubles are modeled as a linear combination of the predictors, with $\beta_0$ representing the intercept, and $\beta_1$ through $\beta_5$ representing the slopes for the respective predictors. Among these, $\beta_1$ (weekday sleep duration) and $\beta_2$ (weekend sleep duration) are continuous variables, reflecting the number of hours slept. In contrast, $\beta_3$ (snoring frequency), $\beta_4$ (breathing pause frequency), and $\beta_5$ (overly sleep frequency) are treated as ordinal categorical variables with numerically encoded categories.

The priors for the intercept ($\beta_0$) and the slopes are deliberately chosen to reflect initial neutrality or skepticism about each predictor's impact on the likelihood of reporting sleep troubles. Specifically, $\beta_0$ for intercept, $\beta_1$, and $\beta_2$ for the continous variables about sleep hours are assigned Normal(0, 1) priors to maintain an unbiased stance before observing the data, acknowledging that the number of sleep hours could either positively or negatively influence sleep troubles, with only a modest expectation of effect size.

For $\beta_3$, $\beta_4$, and $\beta_5$, which relate to ordinal categorical variables such as snoring frequency, breathing pause frequency, and overly sleep frequency are set to have the same Normal(0, 1) priors. This choice indicates no strong preconceived notions about the direction or magnitude of their impact, allowing the data itself to guide the inference about these predictors without the influence of strong initial assumptions.

## 3.2 Model Justification

Our Bayesian logistic regression model is designed to investigate the associations between various sleep-related factors and the likelihood of reporting sleep troubles. The priors for the coefficients are set with specific hypotheses in mind, informed by knowleged gained from the data exploration section:

**Weekday Sleep Duration ($\beta_1$)**: We initially hypothesize that there may be a complex relationship between sleep duration on weekdays and sleep troubles. Long sleep durations could indicate an attempt to compensate for poor quality sleep, potentially related to sleep disturbances. As such, the prior for this coefficient is centered around zero, allowing the data to indicate the direction of association.

**Weekend Sleep Duration ($\beta_2$)**: For sleep duration on weekends, we consider the possibility of a recuperative effect, where catching up on sleep may reduce the likelihood of reporting troubles. This hypothesis is tentative, hence a prior centered around zero with a conservative standard deviation, permitting data-driven insights into this relationship.

**Snoring Frequency ($\beta_3$)**: Frequent snoring is a recognized symptom of sleep disorders like obstructive sleep apnea, which can lead to disrupted sleep. We posit a positive association between snoring frequency and reported sleep troubles, reflected in the priors for this coefficient.

**Breathing Pause Frequency ($\beta_4$)**: Breathing pauses during sleep are indicative of sleep apnea, which is directly related to sleep troubles. We hypothesize a positive association for this coefficient, which is incorporated into the prior setting.

**Daytime Sleepiness ($\beta_5$)**: Excessive daytime sleepiness is often the result of inadequate or disrupted nighttime sleep. We hypothesize a positive relationship between daytime sleepiness and the reporting of sleep troubles, expecting that those experiencing higher levels of sleepiness will be more likely to report troubles.

These hypotheses are structured into our Bayesian model as informed priors, which, while reflecting our initial expectations, are sufficiently flexible to be shaped by the empirical data. This integration of prior beliefs and observed information will yield posterior distributions that convey a robust interpretation of how sleep behaviors relate to the reporting of sleep troubles.

# 4 Result

## 4.1 Model Coefficients Interpretation

Table 2: Summary Statistics for the Coefficients of the Logistic Model

| Term | Estimate |
|---|---|
| (Intercept) | -1.396 |
| WeekdaySleepDuration | 0.051 |
| WeekendSleepDuration | -0.131 |
| SnoringFrequency | 0.032 |
| BreathingPauseFrequency | 0.412 |
| OverlySleepFrequency | 0.425 |

Table 2 presents the key coefficients for understanding the influence of various sleep-related variables on the likelihood of reporting sleep troubles:

**Intercept ($\beta_0$)**: The intercept of the model, $\beta_0$, is estimated at -1.396. This value represents the log odds of reporting sleep troubles when all predictors are at their reference levels (minimal values). It suggests a lower likelihood of reporting sleep troubles in the absence of any problematic sleep behaviors.

**Weekday Sleep Duration ($\beta_1$)**: The coefficient $\beta_1$ is 0.051 for weekday sleep duration, indicating that each additional hour of sleep on weekdays slightly increases the log odds of reporting sleep troubles. This might suggest that individuals sleeping more on weekdays could be experiencing underlying sleep issues that lead them to consult a doctor.

**Weekend Sleep Duration ($\beta_2$)**: Conversely, the coefficient for weekend sleep duration, $\beta_2$, is -0.131. This implies that each additional hour of sleep during weekends decreases the log odds of reporting sleep troubles, supporting the idea that extra sleep on weekends might help reduce the chance of reporting sleep trouble.

**Snoring Frequency ($\beta_3$)**: The coefficient of 0.032 for snoring frequency indicates a positive but small effect on the likelihood of reporting sleep troubles. This relationship suggests that as snoring frequency increases, so does the likelihood of reporting sleep troubles, although the impact is relatively modest compared to other factors.

**Breathing Pause Frequency ($\beta_4$)**: A more substantial coefficient of 0.412 for breathing pause frequency reflects a significant increase in the likelihood of reporting sleep troubles. Breathing pauses are commonly associated with conditions like sleep apnea, which are often serious enough to warrant medical attention.

**Overly Sleep Frequency ($\beta_5$)**: Similarly, the coefficient for overly sleep frequency is 0.425, indicating a strong positive association with reporting sleep troubles. Frequent excessive daytime sleepiness is a critical indicator of poor sleep quality or underlying sleep disorders.

**Summary**: This analysis highlights the differential impacts of various sleep behaviors on the likelihood of reporting sleep troubles. Notably, while longer sleep on weekends appears protective, increased weekday sleep duration and higher frequencies of snoring, breathing pauses, and daytime sleepiness are linked with an elevated likelihood of reporting sleep troubles. These insights could guide clinical assessments and interventions aimed at improving sleep health.

### 4.2 Logistic Regression Model for Predicting Individual Sleep Disorder Probability

$$\text{logit}(\hat{p_i}) = -1.396 + 0.051 \times x_{i1} - 0.131 \times x_{i2} + 0.032 \times x_{i3} + 0.412 \times x_{i4} + 0.425 \times x_{i5} \quad (6)$$

$$\hat{p_i} = \frac{1}{1 + e^{-logit(\hat{p_i})}} \quad (7)$$

The above equation represents the logistic regression model used to estimate the probability ($\hat{p_i}$) of an individual reporting sleep troubles. In this model, $\text{logit}(\hat{p_i})$ is the log-odds of the individual reporting sleep troubles, which is calculated as a linear combination of several predictors. Here, $\beta_0 = -1.396$ is the intercept, which represents the log-odds of reporting sleep troubles when all predictors are at zero. The coefficients $\beta_1 = 0.051$, $\beta_2 = -0.131$, $\beta_3 = 0.032$, $\beta_4 = 0.412$, and $\beta_5 = 0.425$ represent the change in log-odds of reporting sleep troubles for each one-unit change in weekday sleep duration ($x_{i1}$), weekend sleep duration ($x_{i2}$), snoring frequency ($x_{i3}$), breathing pause frequency ($x_{i4}$), and daytime sleepiness ($x_{i5}$), respectively (Please check Section 2.3 for details). This model assumes that the probability of reporting sleep troubles increases or decreases with changes in these sleep-related behaviors and symptoms.

### 4.3 Example of Predict Sleep Disorder Through Self Reported Patterns

This section provides a detailed comparison of predicted sleep trouble probabilities for two hypothetical individuals, Jack and Bob, based on their sleep behavior statistics. The table below illustrates the significant differences in their sleep patterns and how these patterns potentially influence the logistic regression model's predictions regarding their sleep troubles.

Table 3: Comparison of predictive factors for Jack and Bob

| Statistic | Jack | Bob |
|---|---|---|
| Weekday Sleep Duration | 5 hours | 8 hours |
| Weekend Sleep Duration | 8 hours | 10 hours |
| Snoring Frequency | 3 (Frequently) | 0 (Never) |
| Breathing Pause Frequency | 3 (Frequently) | 0 (Never) |
| Overly Sleep Frequency | 4 (Always) | 1 (Rarely) |
| Logit(p) | 0.843 | -1.873 |
| Probability(p) | 0.699 | 0.133 |

Interpretation of the Results From Table 3

**Logit(p) and Probability(p)**: The values calculated from the logistic regression model indicate the log-odds and probability of reporting sleep troubles for each individual. A positive logit(p) value, such as Jack's 0.843, suggests higher log-odds of reporting sleep troubles, which translates to a probability of 69.9%. This indicates a substantial likelihood of sleep issues, possibly reflecting Jack's problematic sleep patterns and symptoms indicative of sleep disorders, such as frequent snoring, regular breathing pauses, and constant daytime sleepiness.

Conversely, Bob's logit(p) value of -1.873 presents negative log-odds, correlating with a much lower probability of 13.3% of reporting sleep troubles. This outcome aligns with his healthier sleep behaviors, such as less frequent snoring and almost no daytime sleepiness, which likely contribute to a significantly reduced risk of sleep disturbances.

**Summary**: This analysis shows the influence of individual sleep behaviors and symptoms on the probability of reporting sleep troubles. Jack's profile, marked by severe symptoms and less restful sleep, is predictive of a higher likelihood of experiencing sleep-related issues. In contrast, Bob's minimal sleep disturbances and healthier sleep habits are associated with a lower probability of sleep troubles. This modeling approach effectively leverages sleep-related metrics to provide insights into potential sleep health outcomes, emphasizing the predictive power of individual sleep patterns and behaviors in identifying potential sleep problems.

### 4.4 Model Performance

Table 4: Count Metrics of the Model Performance

| Metric | Count |
|---|---|
| True Positives | 363 |
| True Negatives | 6493 |
| False Positives | 245 |
| False Negatives | 2006 |

Table 4 showcases how well the model predicts reported sleep troubles with counts of true positives and true negatives indicating correct predictions for the presence and absence of sleep trouble, respectively. Conversely, false positives and false negatives highlight where the model predicts incorrectly, either by overestimating (predicting sleep trouble where there is none) or underestimating (failing to detect reported sleep trouble) the condition. These counts are essential for assessing the model's performance accuracy, balancing the sensitivity to detect actual cases against the specificity to dismiss non-cases.

Table 5: Rate Metrics of the Model Performance

| Metric | Rate |
|---|---|
| Accuracy | 0.753 |
| True Positive Rate | 0.153 |
| True Negative Rate | 0.964 |
| False Positive Rate | 0.036 |
| False Negative Rate | 0.847 |

Table 5 shows the performance indicators of the model. The accuracy stands at 75.3%, denoting the proportion of predictions that the model got right. The true positive rate is 15.3%, reflecting the model's efficiency in correctly predicting actual instances of sleep trouble. Impressively, the true negative rate is 96.4%, indicating the model's strong capability to recognize individuals without sleep trouble. Conversely, the false positive (type I error) rate is minimal at 3.6%, suggesting that the model seldom incorrectly flags sleep trouble where there is none. However, the model's potential area for improvement is highlighted by the false negative (type II error) rate of 84.7%, which points to a substantial number of actual sleep trouble cases that the model fails to detect. These metrics are instrumental for evaluating the model's precision and guiding further refinements.

# 5 Discussion

## 5.1 Advantages of Self-Reported Data in Sleep Health

Using self-reported patterns to predict sleep troubles offers a valuable, accessible means for identifying individuals who may require medical intervention. This approach leverages personal sleep logs and questionnaires, which are cost-effective and can be implemented on a large scale, enhancing the reach of health monitoring. Self-reported data provide insights into an individual's sleep duration, frequency of disturbances like snoring and breathing pauses, and subjective feelings of sleepiness, all of which are crucial for diagnosing sleep disorders.

## 5.2 Impact of Sleep Patterns on Reported Sleep Troubles

The analysis presented in this paper underscores the complex interplay between various sleep behaviors and the likelihood of individuals reporting sleep troubles. Our model's findings align with existing literature suggesting that both insufficient sleep duration and poor sleep quality are significant predictors of sleep disorders (State 2024). In particular, the rates of false negatives indicate a substantial portion of individuals experiencing sleep issues that the model failed to capture, possibly reflecting the nuanced and subjective nature of sleep disturbances.

## 5.3 The Role of Breathing Irregularities and Daytime Sleepiness

Breathing irregularities and excessive daytime sleepiness emerged as strong predictors in our model, pointing towards conditions such as sleep apnea, which remains underdiagnosed in the general population (Foundation 2021). The high false negative rate may partly result from such conditions' subtler signs, which individuals may not report or may attribute to other causes.

## 5.4 Assessing Model Performance and Clinical Implications

While the model demonstrated robust true negative rates, indicating a strong ability to correctly identify individuals without sleep troubles, the high false negative rate poses significant concerns. Clinically, this could lead to missed diagnoses and a delay in treatment for those with unreported sleep disorders. Future iterations of the model might benefit from incorporating additional predictors or employing different statistical techniques to enhance sensitivity.

## 5.5 Limitations and Future Directions

### 5.5.1 Limitations

A significant limitation of this analysis was the sole reliance on self-reported data, which can introduce response bias and affect the accuracy of the findings. Additionally, the dataset may not adequately represent the entire population, as some demographics may be underrepresented. An inherent challenge also lay in the absence of a validation set, which could lead to an overfit model that doesn't generalize well to new, unseen data.

### 5.5.2 Future Directions

For future research, it would be beneficial to conduct longitudinal studies to understand the temporal aspects of sleep patterns better and their long-term health impacts. Utilizing a separate validation dataset would help in assessing the model's predictive power and in refining the classification threshold to balance the trade-off between sensitivity and specificity effectively. Incorporating objective data sources, such as wearable technology that provides sleep quality indicators, could greatly enhance the robustness of the findings. Additionally, employing advanced machine learning algorithms might reveal complex non-linear interactions and patterns within the predictors, offering richer insights than those obtainable from traditional logistic regression analysis. Emphasizing the development of predictive models that are both interpretable and accurate will be key to advancing our understanding of sleep health.

# Appendix

## A Additional Data Details

### A.1 Data Cleaning Process

The data cleaning procedure for the NHANES sleep disorder data was meticulous to ensure the reliability of the dataset for analysis. Initially, the raw data was imported using the `read_xpt` function, ensuring that all variables of interest were accurately read into R. The cleaning process included the following steps:

- Renaming variables for clarity.
- Removing entries with missing values or responses that indicated uncertainty (e.g., 'don't know' or 'refused').
- Selecting only relevant columns for the analysis.
- Recoding the `ReportedSleepTrouble` (outcome) variable to a binary format (0 and 1).
- Ensuring all identifiers were integers and that key sleep-related variables fell within reasonable and expected ranges.

The final dataset was saved in both CSV and parquet formats for accessibility and efficient analysis.

### A.2 Data Integrity and Validation

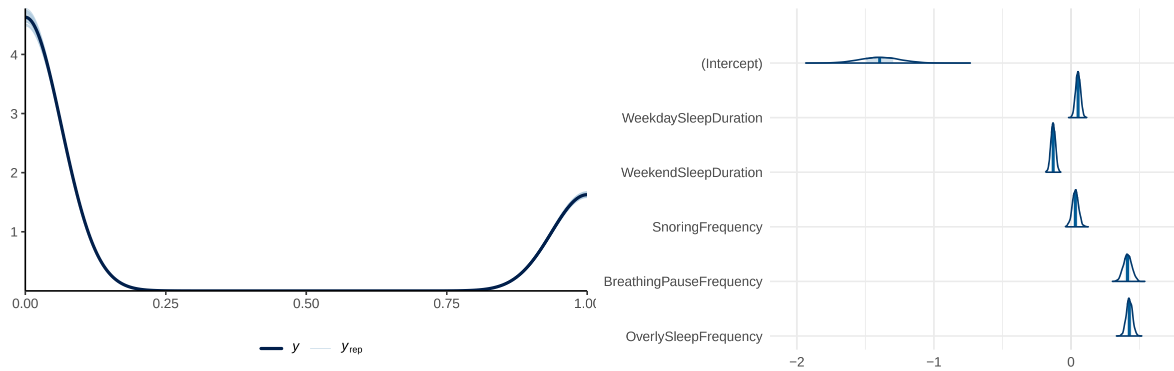
Following the cleaning phase, extensive data integrity tests were conducted to validate the quality and consistency of the cleaned data. The `testthat` package in R was employed to programmatically assert the following:

- Valid integer identifiers for each respondent.
- Logical ranges for sleep durations on both weekdays and weekends (2 to 14 hours).
- Appropriate categorization of snoring and breathing pause frequencies (0 to 3, indicating never to frequently).
- Binary coding of reported sleep trouble (0 for no trouble, 1 for trouble).
- Logical categorization of overly sleep frequency (0 to 4, indicating never to almost always).

These tests are crucial for guaranteeing the analytical soundness of the dataset and were all passed successfully, adding a layer of assurance about the dataset's readiness for subsequent statistical modeling.

## B Model Details

### B.1 Posterior Predictive Check




(a) Posterior prediction check (b) Comparing the posterior with the prior

Figure 2: Examining how the model fits, and is affected by the data

From Figure 2, from the left plot the alignment of the observed data (solid black line) with the simulations from the model (lighter blue lines) suggests that the model captures the essential trends and variability in the data. This alignment indicates a model that adequately reflects the observed trend and provides assurance that the predictive capacity of the model is robust for the data in question.

The right plot displays the comparison between the posterior and prior distributions which offers insights into the influence of the data on our initial assumptions. The posterior distributions remain close to the priors, suggesting that the priors were well-calibrated and that the data has refined, rather than overturned, these initial beliefs. The spread of the posterior distributions signifies the inherent uncertainty and variability within the model, which is a fundamental aspect of statistical modeling and Bayesian analysis.

## C Shiny App

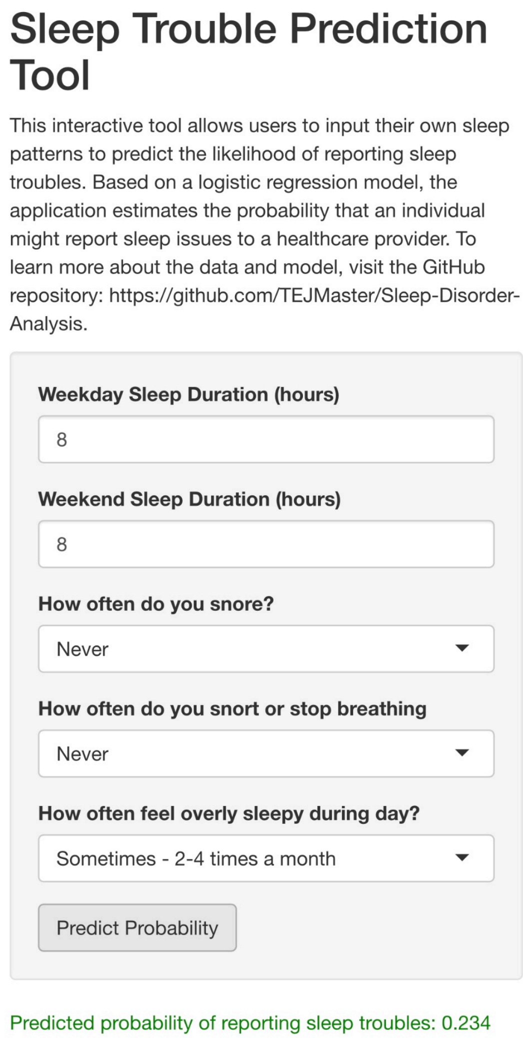



Figure 3: Demo of the shiny application

The Shiny app presented in Figure 3 is a user-friendly tool designed to help individuals understand their risk of having sleep troubles based on their self-reported sleep habits. Utilizing a pre-trained logistic regression model from this project, this application allows users to input various factors related to their sleep, such as weekday and weekend sleep duration, frequency of snoring, incidents of breathing pauses, and levels of daytime sleepiness.

To use the app, simply navigate through the input fields, providing accurate information about your regular sleep patterns. You can specify how many hours you typically sleep on weekdays and weekends, as well as how often you experience snoring, breathing pauses while sleeping, and excessive sleepiness during the day. These categories have predefined options ranging from 'Never' to 'Frequently' for snoring and breathing interruptions, and from 'Never' to 'Almost always' for feeling overly sleepy, making it straightforward to match your experiences to the app's metrics.

After inputting your data, click on the "Predict Probability" button. The app will process your inputs through the logistic regression model and return a probability score. This score represents your estimated likelihood of experiencing sleep troubles that you might report to a healthcare provider. The outcome is presented in a clear and concise manner at the bottom of the app, with the probability score highlighted in a color corresponding to the severity of the prediction: green for low, yellow for moderate, and red for high probability.

You can access the Sleep Trouble Prediction Tool (Shiny app) using https://3tbrto-terry0tu.shinyapps.io/shiny/ to explore your sleep patterns and their implications for your wellbeing.

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