# 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 investigates the potential relationship between individuals' sleep patterns and the self-reported incidence of sleep troubles as confirmed by a medical professional. Using logistic regression analysis on data from the NHANES 2017-March 2020 Sleep Disorders dataset, we examine how various factors such as sleep duration on weekdays and weekends, frequency of snoring, and daytime sleepiness are associated with the likelihood of reporting sleep problems to a doctor. The results revealed that certain behaviors such as excessive snoring and high levels of daytime sleepiness showed a positive correlation with sleep troubles, Moreover, the duration of sleep showed a contrasting pattern of association for sleep during weekdays and weekends. This analysis contributes to the broader understanding of sleep health and its complex interactions with daily functioning.

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

# 1 Introduction

The rhythm of our nightly rest is more than a personal habit; it's a public health pulse that captures the essence of well-being in our fast-paced society. The increasing prevalence of sleep disorders and their impact on daily life and overall health has become a point of societal concern, akin to the growing conversation around mental health and lifestyle diseases. The intimate link between quality of sleep and the vitality of an individual's life prompts a closer examination of sleep patterns within the populace. Drawing on the rich dataset from the National Health and Nutrition Examination Survey (NHANES) for the years 2017 to March 2020, our research delves into the self-reported instances of sleep disturbances and their association with various sleep behaviors.

This study is an explorative journey into the silent epidemic of sleep disorders that plague modern society, affecting productivity, mental health, and long-term wellbeing. The aim is to uncover the underlying patterns of sleep behavior that correlate with the reports of sleep troubles to medical professionals, thereby piecing together the nocturnal puzzle of restless societies. We explore the quantitative relationship between self-reported snoring frequency, feelings of daytime sleepiness, and the regularity of sleep hours during weekdays and weekends with the likelihood of reporting sleep issues to a doctor (CDC 2021).

Our analysis hinges on the application of logistic regression to the NHANES dataset, which presents a comprehensive view of American sleep habits. By interpreting the nuances of this rich dataset, we aspire to illuminate the factors that signal the need for medical attention in the domain of sleep health. The outcome of our investigation is poised to provide a scaffold for healthcare professionals and policymakers to base early intervention strategies, aiming to cultivate a well-rested population.

Following this introduction, the structure of the paper is laid out to facilitate a coherent flow of information and analysis. Section 2 (Data) provides a meticulous breakdown of the NHANES dataset, elucidating the data cleaning process and offering a descriptive overview of the key variables. Section 3 (Model) details the logistic regression model's design and the rationale behind the choice of predictors. Section 4 (Result) presents the findings, interpreted with precision and caution, alongside graphical representations for clarity. Concluding the paper, Section 5 (Discussion) reflects on the broader implications of the study, acknowledging limitations and proposing avenues for future research.

# 2 Data

## 2.1 Raw Data

The dataset underpinning 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 meticulous 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, encompassing 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, adhering to stringent 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 statistical exploration was conducted within the R programming environment (R Core Team 2022), leveraging its comprehensive ecosystem for data analysis. We utilized the tidyverse collection of R packages (Wickham et al. 2019) to streamline our data processing tasks. The ggplot2 package (Wickham 2016) was instrumental in crafting insightful visualizations that articulated the intricate relationships within our data. The dplyr package (Wickham et al. 2022) provided a syntax that facilitated the manipulation and transformation of our dataset, enabling us to prepare the data effectively for logistic regression analysis. Data importation was efficiently handled by the readr package (Wickham, Hester, and Bryan 2022), known for its quick and user-friendly approach to reading tabular data. Navigational simplicity within our project's directories was achieved with the here package (Müller 2020), which reliably managed file paths without the need for manual path setting. The reproducibility of our research was enhanced by the knitr package (Xie 2014), which seamlessly wove R code into our report, ensuring that our findings are transparent and replicable. For tabular data presentation, kableExtra(Zhu 2021) offered a suite of customization options that enhanced the readability and aesthetic appeal of our tables. The logistic regression model was developed using core functions in R, which provide robust methods for estimating the effects of various predictors on a binary outcome.

## 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 Fre-quency | 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.

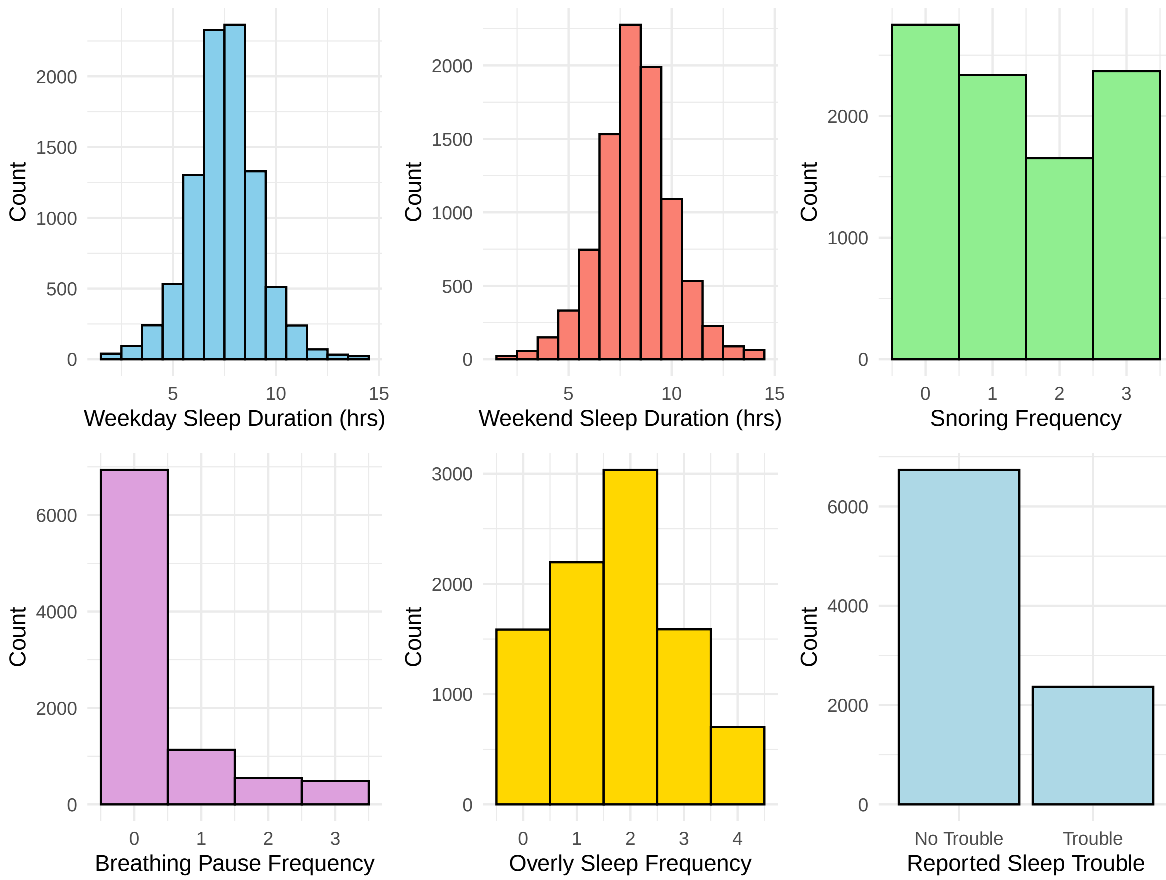



Figure 1: Distributions of sleep-related variables

**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 weekday sleep duration ($x_{i1}$), weekend sleep duration ($x_{i2}$), snoring frequency ($x_{i3}$), breathing pause frequency ($x_{i4}$), and daytime sleepiness ($x_{i5}$). The logistic regression model is formulated as follows:

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

The logistic regression model is defined using a Bayesian framework, implemented in R with the `rstanarm` package. This approach allows us to incorporate prior knowledge about the parameters and 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.

The priors for the intercept ($\beta_0$) and the slopes ($\beta_1$, $\beta_2$, $\beta_3$, $\beta_4$, $\beta_5$) are deliberately chosen to reflect initial neutrality or skepticism regarding the impact of each predictor on the likelihood of reporting sleep troubles.

Specifically, the intercept $\beta_0$ and the coefficients for weekday and weekend sleep duration, $\beta_1$ and $\beta_2$, are assigned Normal(0, 1) priors to maintain an unbiased stance before observing the data. This reflects an initial uncertainty about the base rate of sleep trouble in the population and acknowledges that the number of sleep hours could either positively or negatively influence sleep troubles, with only a modest expectation of effect size.

For the predictors related to snoring frequency, breathing pause frequency, and overly sleep frequency—$\beta_3$, $\beta_4$, $\beta_5$—the same Normal(0, 1) priors are utilized, which suggests that there are no preconceived notions regarding the magnitude or direction of their impact on reporting sleep troubles. This choice of priors allows the data 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 existing literature and plausible biological mechanisms:

**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 the predictors are held at zero. It suggests that, in the absence of any sleep issues or without considering any sleep behaviors, the baseline log odds of reporting sleep troubles to a doctor are negative, indicating a lower probability of reporting sleep troubles.

**Weekday Sleep Duration** ($\beta_1$): For the weekday sleep duration, the coefficient $\beta_1$ is 0.051, suggesting a slight increase in the log odds of reporting sleep troubles for each additional hour of sleep during the weekdays. This could be indicative of a situation where those who sleep more on weekdays might be doing so due to sleep issues that have led them to consult with a doctor.

**Weekend Sleep Duration** ($\beta_2$): Conversely, the coefficient for weekend sleep duration, $\beta_2$, is -0.131. This implies that for each additional hour of sleep during the weekends, there is a decrease in the log odds of reporting sleep troubles. It could be interpreted as those who manage to sleep more on weekends are less likely to report sleep problems, possibly because catching up on sleep may alleviate some of their weekday sleep deficits.

**Snoring Frequency** ($\beta_3$): The coefficient for snoring frequency, $\beta_3$, has a value of 0.032. While this is a positive value, suggesting that an increase in snoring frequency is associated with an increase in the likelihood of reporting sleep troubles, the effect size is relatively small.

**Breathing Pause Frequency** ($\beta_4$): The coefficient for breathing pause frequency, $\beta_4$, is 0.412, indicating a more substantial positive association with reporting sleep troubles. This aligns with clinical understanding, as breathing pauses are often associated with sleep disorders like sleep apnea, which can be a significant concern prompting medical consultation.

**Overly Sleep Frequency** ($\beta_5$): Lastly, the coefficient for overly sleep frequency, $\beta_5$, is 0.425, suggesting a strong relationship with the reporting of sleep troubles. This result is intuitive, as feeling excessively sleepy can be a direct symptom of poor sleep quality or a sleep disorder, leading to discussions with a healthcare provider.

**Interpretation**: The model indicates that various factors are related to the reporting of sleep troubles. While longer weekday sleep duration slightly increases the log odds of reporting sleep troubles, longer weekend sleep can reduce it. Frequent snoring has a smaller effect compared to breathing pauses and daytime sleepiness, which both have significant positive associations with reporting sleep troubles. These findings underline the complexity of sleep behavior and its impact on sleep quality and health consultations.

### 4.2 Model Equation

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

### 4.3 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 |

Interpretation of the Results From Table 3

**Logit(p)**: The computed logit(p) values reflect the aggregated effect of these variables. A positive value indicates a higher log-odds of reporting sleep troubles, while a negative value suggests lower odds. Jack's logit(p) value is positive, indicating a higher likelihood of reporting sleep troubles, possibly due to his poor sleep habits and symptoms indicative of sleep disorders. Conversely, Bob's negative logit(p) value suggests a lower probability of reporting sleep troubles, aligning with his generally healthier sleep patterns.

**Summary**: This analysis highlights how individual differences in sleep patterns and related symptoms can predict the likelihood of reporting sleep troubles. Jack's profile, characterized by frequent snoring, frequent breathing pauses, always feeling overly sleepy, and shorter sleep durations, aligns with a higher propensity for sleep disturbances. In contrast, Bob's healthier sleep habits and fewer symptoms suggest a lower risk of sleep troubles. This model effectively uses sleep-related metrics to provide insights into potential sleep health outcomes.

### 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

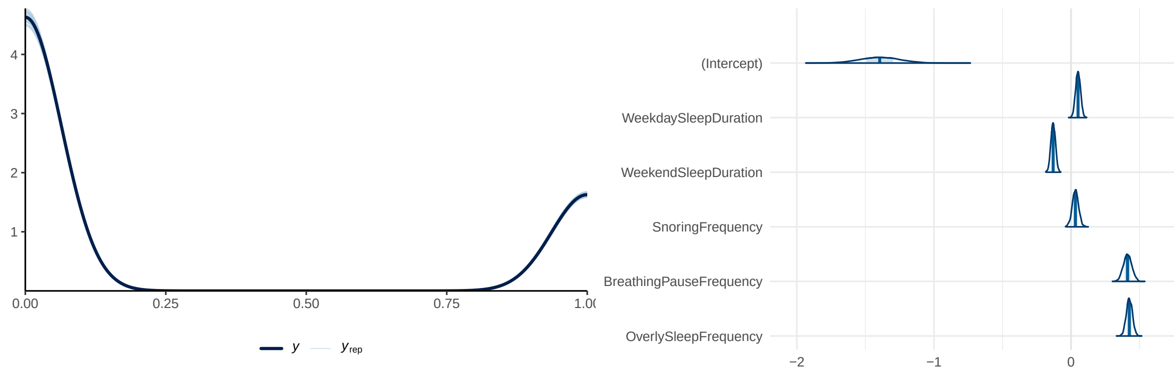
Following the cleaning phase, extensive data integrity tests were conducted to validate the quality and consistency of the cleaned data. The `testthat` package in R was employed to programmatically assert the following:

- 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 congruence indicates a model that adequately reflects the observed phenomena 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.

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