Behavioral Influences on Sleep Quality: A Multifaceted Analysis Using the MMASH Dataset

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Abstract

This investigation delves into the intersection of nocturnal behaviors, individual characteristics, and their collective impact on sleep quality amidst the digital age. Analyzing the MMASH dataset, the study employs a mixed-methods approach, utilizing Python for advanced data analysis, to explore the effects of physical activity and psychological stress on sleep patterns across different demographic profiles.

The research establishes a link between prolonged pre-sleep smartphone interaction, increased caffeine consumption, and the deterioration of sleep quality, with variations emerging across age and gender. Intriguingly, the study also highlights the differential impact of these factors on various psychophysiological responses, emphasizing the intricacy of sleep as a biopsychosocial phenomenon. The findings promote the notion of personalized sleep interventions, advocating for approaches that consider individual lifestyle patterns and psychosocial variables. Although the study is limited by the small sample size of the MMASH dataset, it offers a pioneering look at the daily influences on sleep quality and the potential benefits of customized sleep hygiene practices. These insights are poised to inform future research and practical applications in the realm of health and wellness.

Keywords: Sleep Quality, Bedtime Behaviors, Physical Activity, Psychological Stress, Individual Differences.

1. Introduction

The quest for restorative sleep is a fundamental human endeavor, intricately tied to a myriad of behaviors and moderated by individual characteristics. As the digital era reshapes our nightly routines, this research seeks to systematically quantify the influence of specific pre-sleep behaviors on the quality of sleep, with a secondary examination of the role played by individual differences. The study's cornerstone is the development of a computational model that rigorously analyzes and assigns weights to various behaviors, such as technology use and physical activity, in their contribution to sleep outcomes.

With the advent of omnipresent digital technology, behaviors like late-night screen time have become commonplace, potentially disrupting sleep patterns.[1] While acknowledging the role of individual traits, the primary aim of this research is to elucidate the proportional impact of each nocturnal activity on sleep quality, thereby offering a detailed behavioral sleep quality matrix. Leveraging the comprehensive MMASH dataset, this study employs advanced statistical methods to parse out the complex interactions between behaviors and sleep, providing a quantitative landscape of their interrelations.

Recognizing that individual characteristics such as age, gender, and personal health status may influence sleep, this investigation accounts for these variables without losing focus on the behavioral core of the research.[2][3][4][5][7][9][11][12] The project's novelty lies in its analytical rigor, capable of untangling and quantifying the myriad threads that weave the tapestry of sleep quality in our modern context.

This research is poised to make a significant contribution to sleep science by providing a quantified understanding of how behavior affects sleep quality. It holds the promise of guiding individuals towards evidence-based, behavior-focused sleep hygiene practices, potentially transforming nightly routines into a foundation for better health and well-being.

2. Literature Review

The contemporary investigation into sleep quality is increasingly focusing on the interplay between technology use, physical activity, and individual traits. The literature reveals a complex tapestry of factors influencing sleep, each contributing in multifaceted ways.

A pivotal study by Alshobaili & AlYousefi investigates the impact of smartphone use on sleep quality among non-medical workers. With a significant portion of the population engaging in pre-sleep smartphone usage, the study uncovers a correlation between extended screen time and poor sleep quality. The research also touches upon demographic variables in technology use, suggesting that younger individuals and females are more prone to use smartphones before sleep, potentially affecting their sleep patterns. This study sets a precedent for considering how modern lifestyle choices, particularly around technology, influence sleep quality.[1]

Further expanding on the theme of demographic influences, Chaput, Wong & Michaud delve into the sleep patterns of Canadians across various age and gender groups. Their findings highlight significant variations in sleep quality and duration based on gender, age, education, and income levels, prompting a deeper exploration into how these sociodemographic factors may interplay with sleep habits.[2]

O'Callaghan, Muurlink, & Reid's study on the effects of caffeine consumption provides another dimension to this intricate picture. Their comprehensive analysis reveals that caffeine intake, particularly in the evening, adversely affects sleep quality. They also emphasize the importance of individual differences, noting varying susceptibility to caffeine among individuals.[7]

These studies collectively underscore the necessity of a multifaceted research approach. Our study aims to build upon these insights, using wearable activity trackers and questionnaires to gather data on bedtime behaviors and physical indicators.[13] By examining how individual characteristics and physical activity independently and collectively influence sleep quality, the research aims to offer a more detailed understanding of the factors affecting sleep in today's fast-paced world.

In conclusion, the literature emphasizes the multifaceted nature of sleep quality, influenced by an array of factors including technological habits, sociodemographic elements, and individual physical characteristics. Our research seeks to expand on these findings, employing an integrative methodology to examine how various factors converge to shape sleep quality.[6][8][10]

3. Data Description and Methods

Our study harnesses the MMASH dataset to explore the relationship between bedtime behaviors and sleep quality. This dataset provides a comprehensive view, including metrics like heart rate, sleep quality, physical activity, and psychological states.

The MMASH dataset is compiled from data collected via wearable activity trackers, capable of monitoring physical activity, heart rate (HR), and sleep quality around the clock.[13] This amalgamation of data types is instrumental in developing tools to predict users' well-being, contributing to research across several fields by assessing the interrelations between physical, psychological, and physiological characteristics.

Data Description:
The MMASH dataset is structured into several files for each participant, encompassing diverse data types:

1. User_info.csv: Contains anthropometric characteristics like gender, height, weight, and age.
2. Sleep.csv: Provides information about sleep duration and quality, including metrics like latency efficiency, total sleep time (TST), wake after sleep onset (WASO), and sleep fragmentation indices.
3. RR.csv: Captures beat-to-beat interval data.
4. Questionnaire.csv: Contains scores from various psychological questionnaires, including MEQ, STAI, PSQI, and BIS/BAS.

5. Activity.csv: Lists daily activities categorized into sleeping, physical activities of varying intensities, screen usage, and consumption habits.

6. Actigraph.csv: Records accelerometer and inclinometer data throughout the day, including steps, heart rate, and body position.

7. Saliva.csv: Details the concentrations of clock genes and hormones in saliva samples.

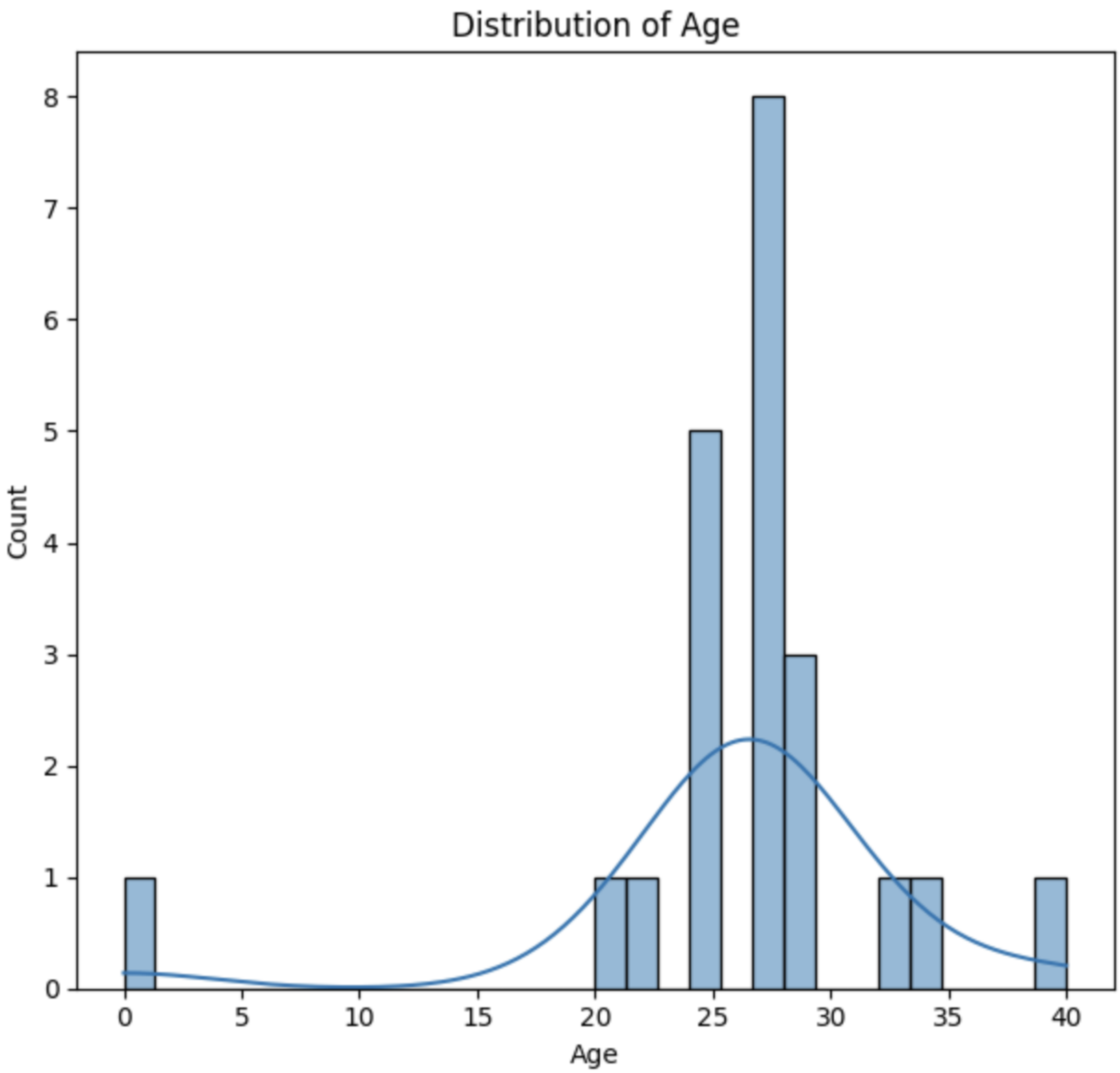

Figure 1: Distribution of Age

The age distribution of participants, as visualized in the histogram, indicates a concentration in the young adult age bracket, predominantly between 20 to 30 years. This peak suggests that the dataset primarily represents the physiological and behavioral patterns of this demographic. The presence of individuals in the broader age range, however, provides an opportunity to observe the variance in sleep quality across different life stages.

The Body Mass Index (BMI) is a standardized ratio of weight to height and is widely used as an indicator of body fatness, categorizing individuals into various weight status categories. The resulting value is used to classify the individual into categories that indicate a range of potential health outcomes:

Underweight: BMI less than 18.5
Normal weight: BMI 18.5–24.9
Overweight: BMI 25–29.9
Obesity: BMI 30 or greater

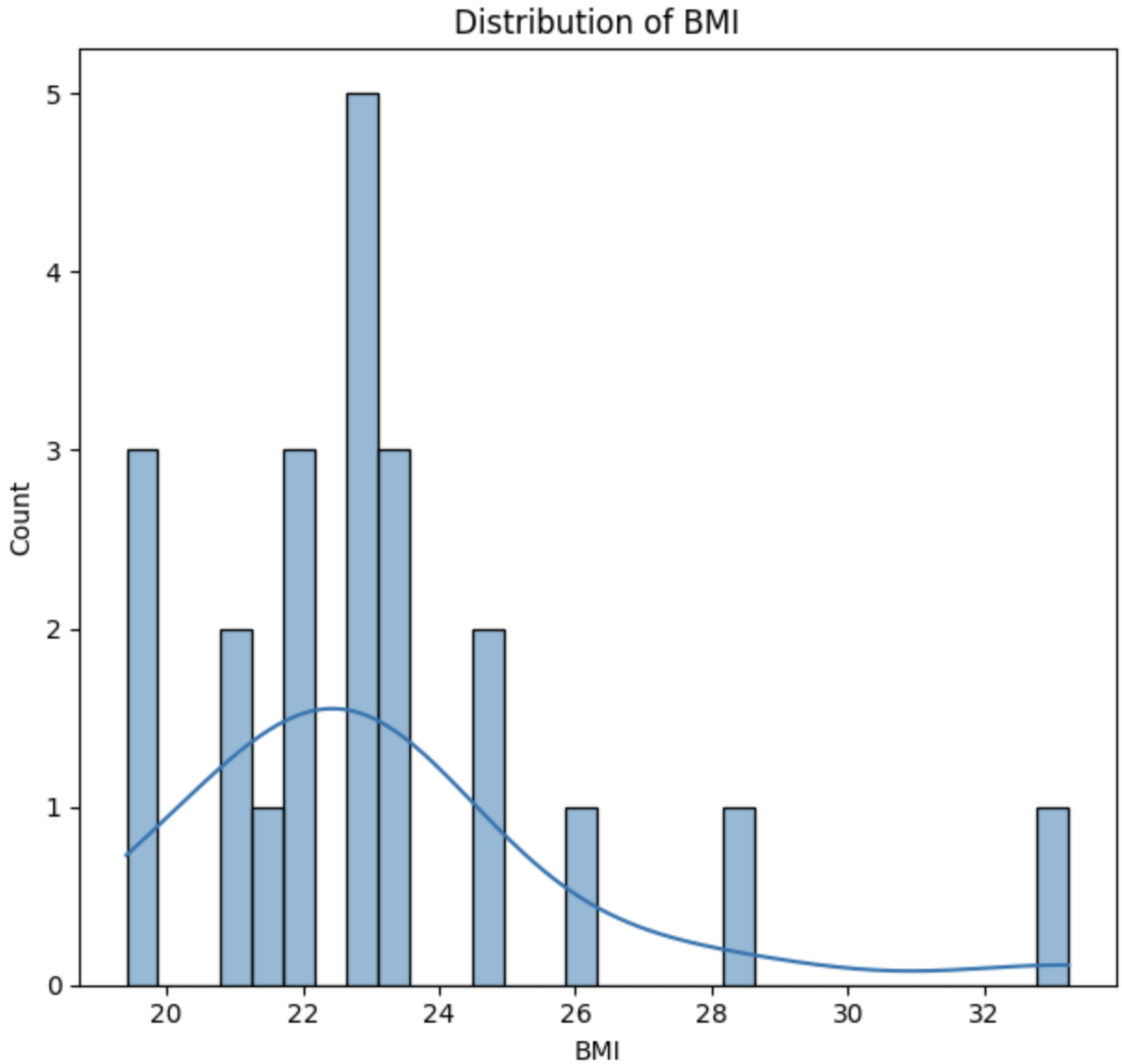

Figure 2: Distribution of BMI

The BMI of participants, calculated using the weight and height information provided in the dataset, is illustrated in the this histogram. The distribution of BMI values shows a central tendency around the 22 to 28 range, which typically falls within the normal to slightly overweight categories according to the World Health Organization's standards. The spread of the data indicates a diversity in body composition, offering a basis to explore potential correlations between BMI and sleep quality.

The histograms were generated using a kernel density estimate (KDE) to fit a smooth curve over the data, providing a clear visualization of the underlying distribution. These visualizations are a preliminary step in understanding the dataset's structure and ensuring that the models account for a representative sample of the population. They also serve as a tool to verify the normality assumption in the distribution of continuous variables, which can be important when applying certain statistical methods.

The MMASH dataset, with its comprehensive scope, allows researchers from various fields to investigate the relationship between psychophysiological responses and daily life aspects. This data can be used to develop machine learning algorithms for detecting daily activities, moods, emotions, and stress responses based on cardiovascular and actigraphy data. These algorithms hold potential for predicting routines and estimating well-being based on data from wrist-worn devices.

In the data preprocessing phase, we combined sleep quality scores, demographic details, and records of bedtime behaviors from individual CSV files. This involved transforming raw data into a format suitable for analysis. The Pittsburgh Sleep Quality Index (PSQI) score was extracted as a key measure of sleep quality, and bedtime behaviors were quantified. The next step was data integration and cleaning, forming a unified dataset for analysis.

Our analytical approach involved several regression models:

1. Linear Regression: The linear regression model predicts a continuous outcome based on one or more predictor variables, represented as:
   Y $=\beta_0 + \beta_1 X_1 + \beta_2 X_2 + ... + \beta_n X_n + \epsilon$
   Where:
   (a) Y is the dependent variable (e.g., PSQI score).
   (b) β_0 is the intercept.
   (c) $\beta_1, \beta_2, ..., \beta_n$ are the coefficients of the predictor variables $X_1, X_2, ..., X_n$.
   (d) ϵ is the error term.
2. Logistic Regression: Classifies sleep quality into binary categories, expressed as:
   $\log(\frac{p}{1-p}) = \alpha_0 + \alpha_1 X_1 + \alpha_2 X_2 + ... + \alpha_n X_n$
   Where:
   (a) p is the probability of the dependent variable belonging to a particular category.
   (b) α_0 is the intercept.
   (c) $\alpha_1, \alpha_2, ..., \alpha_n$ are the coefficients of the predictor variables $X_1, X_2, ..., X_n$.
3. Polynomial Regression: Polynomial regression allows for non-linear relationships between the dependent and independent variables, formulated as:
   Y$=\gamma_0 + \gamma_1 X + \gamma_2 X^2 + ... + \gamma_n X^n + \delta$
   Where:
   (a) Y is the dependent variable
   (b) X is the independent variable.
   (c) γ_0 is the intercept.
   (d) $\gamma_1, \gamma_2, ..., \gamma_n$ are the coefficients of X raised to the power of 1, 2, ..., n.
   (e) δ is the error term.

These models form the backbone of our analytical approach, enabling us to dissect and quantify the relationship between various behaviors and sleep quality. The linear regression model provides insights into how each behavior linearly affects sleep quality, while logistic regression categorizes sleep quality based on predictors. Polynomial regression reveals more complex, non-linear patterns in the data.

By applying these models, our study aims to deliver a nuanced understanding of sleep quality determinants, paving the way for more effective and personalized sleep management strategies.

4. Results and Discussion

	Linear Regression	Polynomial Regression	Logistic Regression	Average Impact
medium_5	0.865670	0.359890	0.375399	0.533653
small_screen_usage_8	0.329034	0.666667	0.206788	0.400830
sleeping_1	0.000167	0.500000	0.127000	0.209056
laying_down_2	0.187407	0.017639	0.321441	0.175496
sitting_3	0.056079	-0.109747	0.274842	0.073725
large_screen_usage_9	0.008061	-0.011905	-0.082056	-0.028633
eating_7	-0.084963	-0.229250	-0.008353	-0.107522
light_movement_4	0.579709	-1.583333	0.504238	-0.166462
alcohol_assumption_12	-0.363894	0.107182	-0.344267	-0.200326
caffeinated_drink_consumption_10	-0.321492	0.061111	-0.486611	-0.248998
smoking_11	0.286916	-0.823529	-0.232725	-0.256446
heavy_6	-0.682619	-0.033788	-0.722003	-0.479470

Figure 3: Impact Coefficients of Bedtime Behaviors on Sleep Quality from Multiple Regression Analyses

The analysis of the MMASH dataset via linear and polynomial regression models has shed light on the relationship between various daytime behaviors and sleep quality.

The linear regression model indicated that bedtime behaviors have a moderate influence on sleep quality, with an R-squared of 0.37. This suggests that while behaviors are significant, they are not the sole determinants of sleep quality. The logistic regression model corroborated this, demonstrating an 82% accuracy in predicting sleep quality classification, indicating a strong relationship between the behaviors examined and the likelihood of experiencing good or poor sleep.

In particular, medium-intensity physical activities such as fast walking and biking ('medium_5') emerged as a positive contributor to sleep quality across all models. This reinforces the beneficial role of moderate physical activity in promoting better sleep. Light physical activities ('light_movement_4'), which include slow/medium walking, chores, and work, displayed a more complex relationship with sleep quality, suggesting that the timing and context of these activities may be crucial.

The polynomial regression analysis highlighted the significant nonlinear influence of dietary habits ('eating_7') on sleep quality, with an R-squared of 0.28. This suggests that not just what or how much is eaten, but also when and in what context, can significantly impact sleep. High-intensity physical activities ('heavy_6') also displayed a substantial effect on sleep quality, suggesting that engaging in vigorous exercise may have a complex but notable impact on sleep, which requires careful timing relative to bedtime.

The impact of small screen usage ('small_screen_usage_8'), such as smartphones and computers, was notable with an R-squared value of 0.13 in the linear regression model, highlighting the disruptive potential of such devices on sleep. However, large screen usage ('large_screen_usage_9'), corresponding to watching TV and cinema, showed a negligible effect, which could suggest that these activities may not be as disruptive or may even be part of a relaxing pre-sleep routine for some individuals.

Interestingly, the effects of consuming caffeinated drinks ('caffeinated_drink_consumption_10'), smoking ('smoking_11'), and alcohol ('alcohol_assumption_12') were less pronounced in our models than might be expected given their recognized impact on sleep. This could reflect a limitation of the dataset or the multifaceted nature of sleep quality, where other unmeasured factors may also play a role.

In sum, our results delineate a nuanced landscape where behavioral patterns have varying degrees of impact on sleep quality. While moderate physical activity appears beneficial, the timing and intensity of exercise, alongside dietary habits and technology use before bedtime, are pivotal considerations. These insights advocate for personalized sleep strategies that account for the individual's full spectrum of daytime behaviors. Future research should aim to further unravel the complexities of these relationships and their implications for holistic sleep health.

5. Conclusions

The investigation into the interplay between daily behaviors and sleep quality, as analyzed through the MMASH dataset, has culminated in several key findings. The linear regression model's R-squared value of 0.37 indicates that while certain behaviors have a quantifiable impact on sleep quality, they do so alongside a constellation of other factors that also merit consideration. The behaviors captured in the dataset, therefore, should be viewed as part of a broader sleep quality ecosystem.

The logistic regression model proved to be highly effective, with an 82in classifying sleep quality. This robust performance illustrates the potential of behavioral data to serve as reliable indicators for sleep quality assessment. It paves the way for the development of predictive tools that could be incorporated into health applications or clinical practice to provide early warnings or personalized sleep improvement advice.

The polynomial regression model offered a more nuanced view, particularly highlighting the complex relationship between dietary habits ('eating_7') and sleep quality. The significant R-squared value attributed to 'eating' behavior underscores the influence of not just diet itself but the intricacies of dietary timing and composition on sleep. This insight has profound implications for nutritional counseling as part of sleep hygiene programs.

'Heavy physical activity' ('heavy_6') also displayed a significant, though nonlinear, association with sleep quality, suggesting that the benefits of vigorous exercise on sleep may be influenced by the timing of the activity relative to sleep. This finding echoes the delicate balance required in exercise regimens and their synchronization with the body's circadian rhythms.

Interestingly, the moderate impact observed from 'small screen usage' ('small_screen_usage_8') challenges the commonly held view that all screen time before bed is detrimental. It suggests a need for a more granular approach in evaluating the context and content of screen interactions in relation to their impact on sleep.

The relatively small coefficients associated with 'caffeinated drink consumption' ('caffeinated_drink_consumption_10'), 'smoking' ('smoking_11'), and 'alcohol assumption' ('alcohol_assumption_12') point towards a more intricate interplay of these behaviors with sleep quality than typically acknowledged. These results may indicate individual resilience factors or other lifestyle aspects that mitigate the expected negative impacts of these substances.

In sum, this study has painted a complex picture of the factors affecting sleep quality.

It reinforces the notion that interventions aimed at improving sleep should be multifactorial and tailored to individual behaviors and lifestyles. Our findings advocate for further research that could integrate a wider range of variables, including environmental and psychological factors, to build even more comprehensive models of sleep quality prediction. Such models would not only deepen our understanding of sleep hygiene but could also lead to more effective and personalized sleep improvement strategies.

6. References

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