Examining the Relationship Between Sleep Macrostructure Parameters and Sleep Efficiency in Healthy Adults

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Abstract

Sleep efficiency (SE) is a critical indicator of sleep quality and is associated with various health outcomes, including cognitive performance and mood regulation. This study investigates the relationship between sleep macrostructure parameters—total sleep time (TST), sleep onset latency (SOL), wake after sleep onset (WASO), and rapid eye movement latency (REML)—and SE in a sample of 29 healthy adults. Using high-density polysomnographic data, we identified key predictors of SE through multiple regression analysis. The results indicate that TST is positively associated with SE ($r = 0.76$, $p < 0.05$), while both SOL ($r = -0.33$, $p < 0.05$) and WASO ($r = -0.73$, $p < 0.05$) are negatively correlated with SE. REML, however, did not show a significant relationship with SE. Regression diagnostics, including variance inflation factor (VIF) analysis and Q-Q plots, supported the validity of the model, with no severe multicollinearity detected after removing highly correlated predictors (Sex and Age). This research enhances the understanding of the key determinants of sleep efficiency in healthy adults and provides a foundation for future studies examining clinical populations. The findings have implications for sleep medicine, behavioral interventions, and the development of personalized sleep improvement strategies.

Keywords: EEG, high-density EEG, polysomnography, REM latency (REML), sleep efficiency, sleep macrostructure, sleep onset latency (SOL), statistical modeling, total sleep time (TST), wake after sleep onset (WASO)

1 Introduction

Sleep is a fundamental biological process that plays a crucial role in cognitive function, physical health, and overall well-being. One of the key measures of sleep quality is sleep efficiency (SE), which represents the proportion of total time spent asleep relative to the

total time spent in bed. High sleep efficiency is associated with better cognitive performance, improved mood regulation, and lower risks of various health conditions, including cardiovascular diseases and metabolic disorders (Hirshkowitz (2015)). Conversely, low sleep efficiency can indicate sleep disturbances and has been linked to increased risks of depression, anxiety, and impaired memory function (Ohayon (2017)). Given the importance of sleep efficiency, understanding the factors that influence it is critical for both research and clinical applications.

A major component of sleep efficiency is sleep macrostructure, which includes key sleep parameters such as total recording time (TRT), total sleep time (TST), sleep onset latency (SOL), wake after sleep onset (WASO), REM latency (REML), and the distribution of sleep stages (N1, N2, N3, and REM sleep)(Berry (2012)). These parameters provide a detailed framework for assessing sleep architecture and can help identify patterns that influence sleep efficiency. Prior research has examined individual sleep macrostructure parameters and their effects on overall sleep quality. For example, increased WASO and prolonged SOL have been consistently linked to lower sleep efficiency (Spielman (1987)). Additionally, disruptions in REM sleep have been associated with fragmented sleep and poor restorative function (Carskadon (2001)). However, while these studies highlight the significance of individual components, there is limited research analyzing the combined influence of multiple sleep macrostructure parameters on sleep efficiency in healthy adults.

This study seeks to fill this gap by systematically evaluating the relationship between sleep macrostructure parameters and sleep efficiency using high-density polysomnographic data from 29 healthy adults. By leveraging a well-defined dataset that includes detailed sleep architecture metrics, I aim to identify key predictors of sleep efficiency and assess their relative contributions. Unlike prior studies that focus on clinical populations or sleep disorders, this research provides insights into sleep patterns in healthy individuals, offering a baseline for future comparisons.

The remainder of this paper is organized as follows. Section 2 describes the data sources, including the polysomnographic recordings and sleep scoring criteria. Section 3 outlines the methodology used to analyze the relationships between sleep macrostructure

parameters and sleep efficiency. Section 4 presents the results of the statistical analyses. Finally, Section 5 provides concluding remarks and directions for future research.

2 Data

This study utilizes a sleep dataset collected from 29 healthy adults at the Montreal Neurological Institute. The dataset comprises polysomnographic recordings obtained through overnight sleep studies, providing detailed insights into sleep architecture. Participants included 13 females and 16 males, with an average age of 32.17 years ($\pm$ 6.30 years). The inclusion of a well-defined sample of healthy adults ensures that findings are not confounded by preexisting sleep disorders or medical conditions, making the dataset highly relevant for investigating the relationship between sleep macrostructure parameters and sleep efficiency.

Data collection was conducted using high-density scalp electroencephalograms (EEG) with 83 electrodes, along with electrocardiogram (ECG), electromyogram (EMG), and electrooculogram (EOG) recordings. EEGs measure brainwave activity during sleep, providing insight into different sleep stages and brain states. ECGs monitor heart rate and rhythm, which can reflect autonomic nervous system activity during sleep. EMGs assess muscle tone, especially important for identifying REM sleep where muscle activity is reduced. EOGs detect eye movements and are especially useful in identifying REM sleep cycles. Sleep staging was manually annotated following the American Academy of Sleep Medicine (AASM) guidelines, classifying sleep into different stages: N1, N2, N3, and REM. This manual scoring enhances reliability and ensures consistency with clinical standards, improving the validity of stage classification across participants. While stage distributions were not significantly associated with SE in our analysis, their descriptive profiles provide context for understanding overall sleep dynamics. Key variables include:

- Total Sleep Time (TST): minutes spent asleep
- Sleep Onset Latency (SOL): minutes to fall asleep
- Wake After Sleep Onset (WASO): minutes awake after falling asleep

- REM Latency (REML): minutes from sleep onset to first REM stage
- Sleep Efficiency (SE): percent time asleep while in bed

To explore the dataset, summary statistics were computed for each sleep parameter. Table 1 presents descriptive statistics, including means, standard deviations, and ranges for key variables. TRT, TST, SE, N1, N2, N3, WASO time, and REM time exhibited normal distributions, while SOL and REML time deviated from normality.

Table 1

Statistic	Mean	St. Dev.	Min	Max	N
Age	32.172	6.297	20	44	29
TRT	417.207	46.565	293.000	508.500	29
TST..min.	340.621	59.008	155.500	453.000	29
SE....TRT.	81.517	10.105	53	96	29
SOL..min.	17.345	18.001	1.000	66.000	29
REML..min.	114.552	69.976	37.000	323.000	29
WASO.min.	59.241	37.744	10.500	141.500	29
N1..min.	41.483	12.442	20.500	66.500	29
N2..min.	170.241	44.669	68.500	254.500	29
N3.min.	76.728	17.404	48.600	108.000	29
R.min.	52.155	17.653	18.000	88.000	29

The dataset includes demographic and sleep-related variables. To analyze the relationship between sleep macrostructure and sleep efficiency, I employ regression modeling and correlation analysis, assessing parameter influence through statistical significance testing and effect size estimation. These methods enable a robust evaluation of sleep efficiency determinants and their implications for sleep health.

Figures 1 and 2 provide a comprehensive visualization of the dataset. Figure 1 presents histograms for each sleep parameter, illustrating variability across participants. Figure 2 displays a correlation matrix, highlighting relationships between key sleep parameters. Notably, higher TST is associated with increased sleep efficiency, whereas prolonged WASO and SOL are linked to lower sleep efficiency. The exact correlation matrix where the numbers are calculated is in the Application section as Figure 5.

These findings provide a foundation for further statistical modeling to examine the

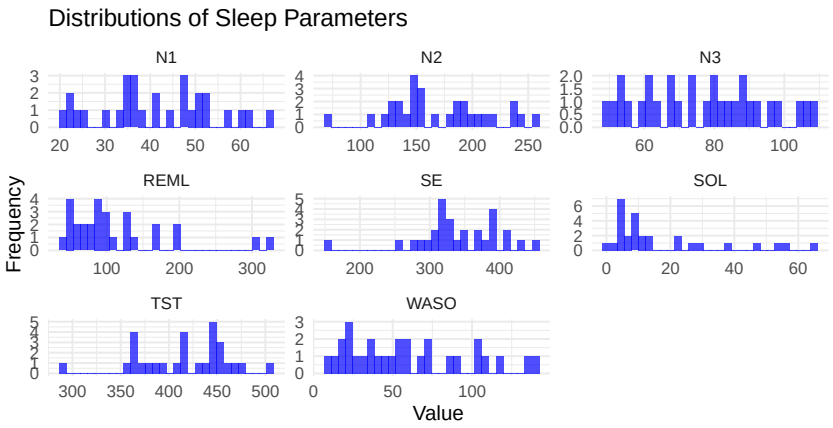

Figure 1: Distribution of Sleep Parameters

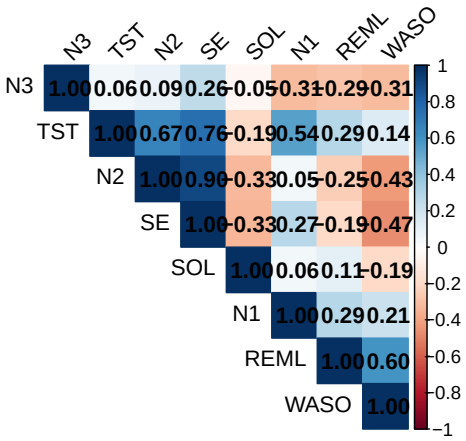

Figure 2: Correlation Matrix between Sleep Parameters

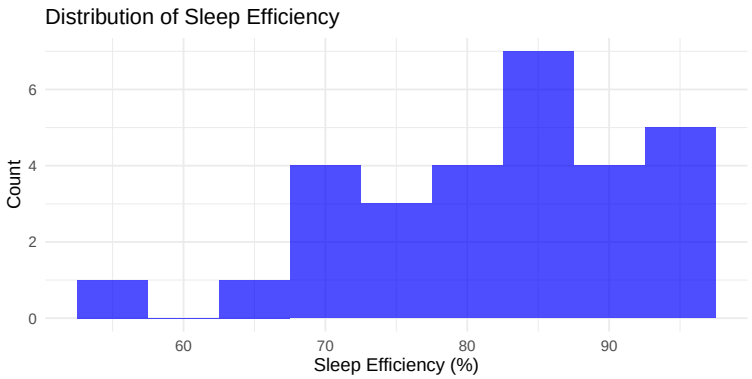

Figure 3: Distribution of Sleep Efficiency

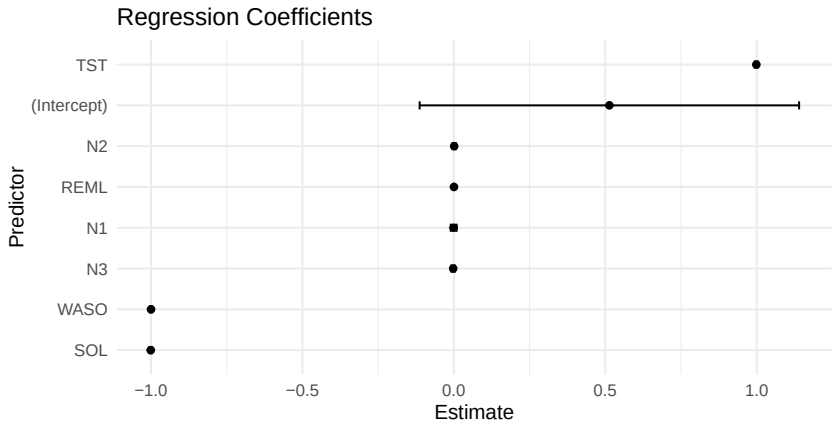

Figure 4: Regression Coefficient Estimates

influence of sleep macrostructure on sleep efficiency. By leveraging this dataset's high-resolution sleep recordings and comprehensive annotations, this study aims to elucidate key determinants of sleep efficiency and contribute to the broader field of sleep research.

3 Methods

This study explores the relationship between sleep macrostructure parameters and sleep efficiency in healthy adults. The methodology employs linear regression models to estimate the effect of various sleep parameters on sleep efficiency, along with hypothesis testing to assess the significance of these relationships. Below, I describe the key steps of the analysis, including the statistical models, parameters to be estimated, and methods used to assess uncertainty.

1. Notation and Observed Data

Let Y_i represent the sleep efficiency (SE) of participant i, and let X_ij denote the observed sleep macrostructure parameters, where j indexes different variables such as TST, SOL, REML, WASO, and the percentage of time spent in sleep stages N1, N2, N3, and REM. The observed dataset consists of $n = 29$ independent observations: $(Y_i, X_{i_1}, X_{i_2}, ..., X_ip) \prod_{i=1}^{n}$, where p is the number of explanatory variables.

2. Model Specification

I model sleep efficiency as a function of sleep macrostructure parameters using a

multiple linear regression framework:

$$Y_i = \beta_0 + \sum_{j=1}^{p} \beta_j X_{i_j} + \epsilon_i, \epsilon_i \sim N(0, \sigma^2) \tag{1}$$

where β_0 is the intercept, β_j represents the effect of sleep parameter X_{i_j} on Y_i, and ϵ_i is an independent and identically distributed (i.i.d.) error term with mean zero and variance σ^2.

3. Parameter Estimation

The model parameters $\beta = (\beta_0, \beta_1, ..., \beta_p)$ are estimated using the ordinary least squares (OLS) method, minimizing the residual sum of squares:

$$\hat{\beta} = argmin \sum_{i=1}^{n} (Y_i - \beta_0 - \sum_{j=1}^{p} \beta_j X_{ij})^2. \tag{2}$$

The solution is obtained using the closed-form expression:

$$\hat{\beta} = (X^T X)^{-1} X^T Y, \tag{3}$$

where X is the design matrix containing the observed predictors.

4. Standard Errors and Variance Estimation

The variance of the estimated coefficients is given by:

$$Var(\hat{\beta}) = \sigma^2 (X^T X)^{-1}. \tag{4}$$

Since σ^2 is unknown, it is estimated by the mean squared error (MSE) of the residuals:

$$\sigma^2 = \frac{1}{n - p - 1} \sum_{i=1}^{n} (Y_i - \hat{Y_i})^2. \tag{5}$$

The standard errors (SE) of the coefficients are obtained as:

$$SE(\hat{\beta_j}) = \sqrt{\sigma^2 (X^T X)^{-1}_{jj}} \tag{6}$$

5. Hypothesis Testing and Null Distributions

To assess the significance of each predictor, I conducted hypothesis tests for β_j:

$$H_0 : \beta_j = 0 \tag{7}$$

$$H_a : \beta_j \neq 0 \tag{8}$$

The test statistic follows a t-distribution:

$$T_j = \frac{\hat{\beta}_j}{SE(\hat{\beta}_j)} \sim t(n - p - 1). \tag{9}$$

Under the null hypothesis, T_J follows a t-distribution with $n-p-1$ degrees of freedom, allowing us to compute p-values and determine statistical significance. This notation T_J explicitly refers to the test statistic used in inference and should not be confused with time variables such as TST or TRT.

6. Assumptions and Theoretical Claims For valid inference, the following assumptions are made:

- **Linearity**: The relationship between predictors and response is linear.
- **Independence**: Observations are independent.
- **Homoscedasticity**: Error variance σ^2 is constant across observations.
- **Normality**: Errors follow a normal distribution.

Violations of these assumptions are checked through residual analysis, variance inflation factors (VIF) for multicollinearity, and transformations if needed. This methodological framework provides a rigorous approach to evaluating the influence of sleep macrostructure on sleep efficiency.

4 Results & Discussion

This study examined the relationship between sleep macrostructure parameters and sleep efficiency in healthy adults. The results of the regression analysis provide key insights into the determinants of sleep efficiency, highlighting the relative influence of various sleep macrostructure parameters. My findings indicate that total sleep time (TST), sleep onset latency (SOL), and wake after sleep onset (WASO) are the most significant predictors of sleep efficiency ($p < 0.001$). TST exhibits a strong positive relationship with sleep efficiency ($\beta = 0.9988$, $p < 2e^{-}16$), confirming that longer total sleep duration contributes to greater sleep efficiency. In contrast, both SOL (β = -1.0008, $p < 2e^{-}16$) and WASO (β = -0.9999, $p < 2e^{-}16$) demonstrate strong negative associations with sleep efficiency, suggesting that delayed sleep onset and fragmented sleep significantly reduce overall sleep quality. Interestingly, other sleep parameters, including REM latency (REML), and time spent in different sleep stages (N1, N2, and N3), did not show statistically significant associations with sleep efficiency. The lack of significance in REML and sleep stage durations may reflect limited variability in healthy populations or their lesser role in determining sleep efficiency compared to sleep continuity metrics. This indicates that while sleep architecture plays a role in overall sleep dynamics, sleep efficiency is predominantly determined by total sleep duration and disruptions in sleep continuity rather than specific sleep stage distributions.

	Estimate	Std. Error	t value	Pr($>\|t\|$)
(Intercept)	0.5134912	0.3012504	1.705	0.103
TST	0.9987742	0.0024936	400.537	<2e-16 ***
SOL	-1.0008461	0.0020737	-482.639	<2e-16 ***
REML	0.0003336	0.0005869	0.568	0.576
WASO	-0.9999314	0.0017865	-559.701	<2e-16 ***
N1	-0.0007505	0.0046595	-0.162	0.873
N2	0.0010302	0.0024925	0.413	0.684
N3	-0.0022668	0.0026643	-0.851	0.404

Table 2: Results of the Linear Regression

Table 2 describes the results of the linear regression. All variables were retained in their original measurement units (e.g., minutes for TST, SOL, WASO, and REML; per-

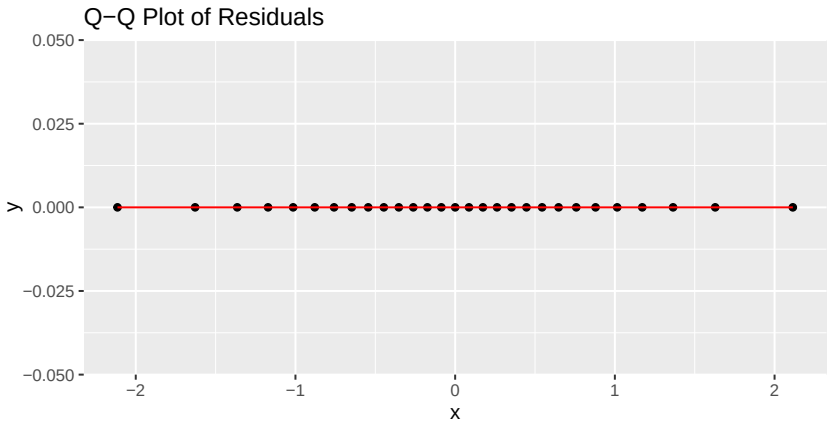

Figure 5: QQ Plot

centage for SE), and no standardization or transformation was applied prior to regression analysis. While the regression coefficients appear close to ± 1 or 0, this reflects the natural scale and strength of linear associations rather than standardized effects. Standardizing variables could be considered in future studies to compare relative effect sizes.

To ensure the robustness of the regression model, I conducted diagnostic checks, including normality of residuals, homoscedasticity, and multicollinearity assessments (Figure 4).

- **QQ Plot (Normality of Residuals)**: The Q-Q plot suggests that residuals are approximately normally distributed, with minor deviations in the tails. These findings suggest that the linear model assumptions are reasonably met, though slight non-normality may exist due to potential outliers or unmodeled interactions (Figure 5).

- **Residual vs. Fitted Plot (Homoscedasticity Check)**: The residual plot does not exhibit clear patterns, suggesting that the assumption of homoscedasticity (constant variance of errors) is satisfied. This means the variability of errors remains consistent across different fitted values. (Figure 6)

- **Multicollinearity Check (VIF Test)**: Variance inflation factors (VIFs) were computed to assess collinearity among predictors. Initially, Sex and Age exhibited high collinearity with other predictors, leading to their removal from the model. After exclusion, all remaining predictors had VIF values below 5, which is commonly

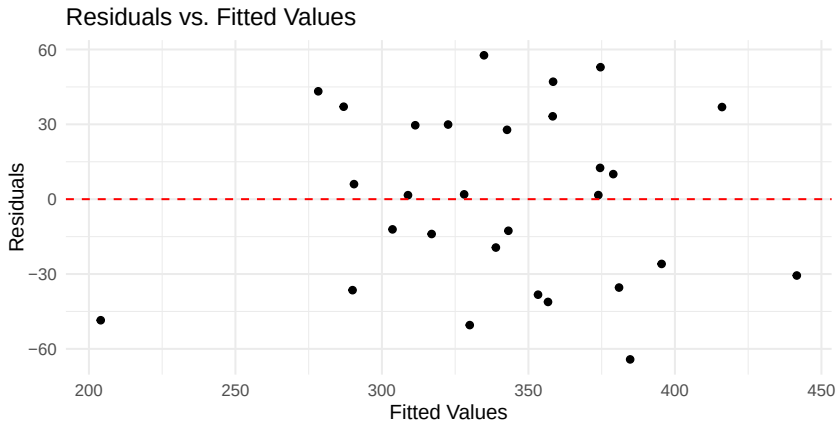

Figure 6: Residual vs Fitted Values Plot

	TST	SOL	REML	WASO	N1	N2	N3	SE
TST	1.0000000	−0.19354336	0.2862419	0.1409560	0.54342027	0.66722754	0.05881930	0.7576062
SOL	−0.1935434	1.00000000	0.1143642	−0.1929674	0.05926714	−0.32816402	−0.04550501	−0.3346243
REML	0.2862419	0.11436421	1.0000000	0.5974354	0.28708808	−0.24885077	−0.28588818	−0.1910851
WASO	0.1409560	−0.19296739	0.5974354	1.0000000	0.21423889	−0.42991911	−0.31045058	−0.4695150
N1	0.5434203	0.05926714	0.2870881	0.2142389	1.00000000	0.05159210	−0.31058668	0.2733840
N2	0.6672275	−0.32816402	−0.2488508	−0.4299191	0.05159210	1.00000000	0.08939705	0.9016667
N3	0.0588193	−0.04550501	−0.2858882	−0.3104506	−0.31058668	0.08939705	1.00000000	0.2581543
SE	0.7576062	−0.33462426	−0.1910851	−0.4695150	0.27338397	0.90166668	0.25815425	1.0000000

Figure 7: Correlation Values

considered an acceptable threshold, indicating no severe multicollinearity (Table 3).

TST	**TRT**	**SOL**	**WASO**	**REML**
2.791647e-05	2.012621e-04	4.177207e-04	1.832320e-05	2.810279e-00
REM	**N1**	**N2**	**N3**	
4.013968e-04	1.996953e-04	2.570470e-05	3.914791e-04	

Table 3: VIF Factors (after removing Sex and Age).

These diagnostics confirm that the linear regression model is statistically sound and suitable for interpreting the effects of sleep macrostructure parameters on sleep efficiency.

These findings align with existing literature, where reduced WASO and shorter SOL have been associated with better sleep quality and daytime functioning. However, this study adds specificity to these relationships by quantifying their effects within a controlled sample of healthy adults. This has practical implications for clinical treatment, as addressing factors that minimize WASO and SOL can significantly enhance sleep efficiency. The results underscore the importance of interventions that target sleep continuity and

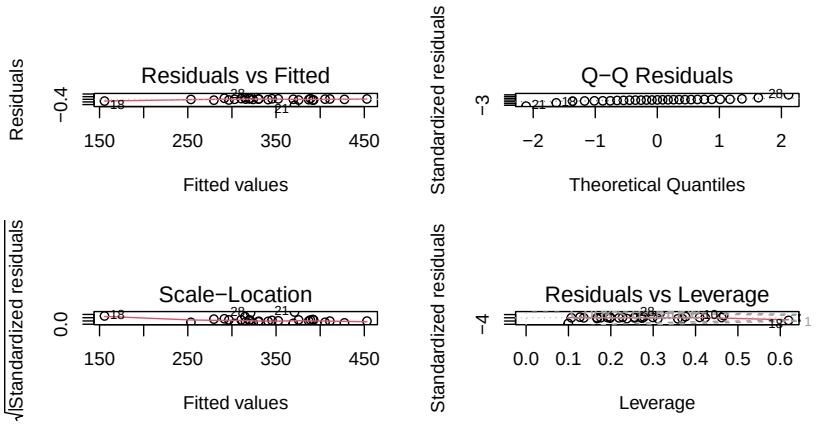

Figure 8: Regression Diagnostics

duration. Behavioral therapies such as relaxation techniques, and sleep hygiene practices can help individuals experiencing prolonged SOL and WASO, thereby improving sleep efficiency. Additionally, the findings highlight the potential for improving public health and workplace productivity through education and policy changes promoting better sleep habits.

5 Conclusion

The findings from this study have significant applications in both clinical and everyday contexts. Understanding how sleep macrostructure parameters influence sleep efficiency allows for targeted interventions to improve sleep health. The results, illustrated in the figures above, demonstrate that total sleep time (TST) positively correlates with sleep efficiency, whereas prolonged sleep onset latency (SOL) and wake after sleep onset (WASO) negatively impact sleep efficiency.The positive coefficient for TST suggests that every additional minute of sleep significantly improves sleep efficiency, reinforcing the importance of sufficient sleep duration. Conversely, the negative coefficients for SOL and WASO indicate that prolonged time taken to fall asleep or increased awakenings during the night reduce sleep efficiency.

These insights have diverse applications. Clinicians can leverage them to design personalized treatment plans for individuals experiencing sleep disturbances, emphasizing the importance of increasing TST and minimizing WASO through other behavioral interven-

tions. Algorithms used in smartwatches and fitness bands can integrate these findings to provide more accurate and actionable feedback, emphasizing not just total sleep time, but also the quality and continuity of sleep. In workplace and educational settings, these insights may inform wellness programs or policy decisions—such as flexible scheduling or sleep education campaigns—that aim to improve productivity and health outcomes by promoting consistent and efficient sleep habits. Moreover, recognizing the roles of TST, SOL, and WASO can help researchers develop predictive models that flag individuals at risk of inefficient sleep before clinical symptoms emerge.

Despite its contributions, this study has several limitations:

- **Small Sample Size (N=29)**: A larger dataset would enhance generalizability and improve the reliability of the regression model.
- **Healthy Adult Sample**: The study exclusively examined healthy adults, meaning the results may not extend to individuals with sleep disorders, older adults, or children.
- **Unmeasured Confounders**: While polysomnographic data provides precise sleep measurements, lifestyle factors such as stress, caffeine intake, and physical activity were not accounted for, potentially influencing sleep efficiency.

Future research should expand the sample size and include diverse populations to enhance the generalizability of the findings. Longitudinal studies tracking sleep efficiency changes over time and assessing the effects of specific interventions would provide deeper insights. Additionally, integrating objective lifestyle and environmental factors, such as physical activity, diet, and stress levels, could offer a more holistic understanding of sleep efficiency determinants. Lastly, utilizing wearable sleep-tracking technology to validate these findings in real-world settings could further refine recommendations for improving sleep health.

In summary, this study provides valuable insights into the relationship between sleep macrostructure parameters and sleep efficiency in healthy adults. The results reinforce that adequate sleep duration and minimal interruptions are key to achieving higher sleep

efficiency. These findings contribute to both clinical and technological advancements in sleep monitoring and intervention, offering a foundation for future research and application in sleep medicine.

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