SleepSynth: Discovering Sleep Patterns with Lifestyle Modeling and Predictive Analytics

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Summary:

Poor sleep is a growing concern, linked to issues such as mental health decline and reduced cognitive function. While lifestyle factors like exercise are known to impact sleep, the influence of modern habits such as screen time and technology use remains underexplored. Our study highlights the critical impact of poor sleep on health. While the effects of traditional lifestyle factors, such as exercise, on sleep are well-documented, our research delves into the less-studied domain of modern habits, including screen time and technology use. By adopting data-driven approaches, we investigated the impact of daily habits on sleep quality, focusing on exercise routines, technology use (particularly screen time before sleep), and sleep disturbances. This research enhances our understanding of sleep patterns, paving the way for personalized recommendations to improve sleep quality and overall health.

1. Introduction:

Sleep quality is a cornerstone of overall health, influencing mental well-being, cognitive function, and physical performance. However, modern lifestyle habits, including exercise routines and technology use, significantly shape sleep outcomes. Understanding the interplay of these factors is essential for addressing the growing sleep crisis. Regular exercise is widely recognized for its positive impact on sleep duration and quality. Studies, such as Chen et al. (2021), highlight how consistent physical activity enhances sleep, though its effects vary based on timing and intensity, necessitating further investigation into these aspects, screen time before sleep poses a distinct challenge. Research by Carter et al. (2016) demonstrates that exposure to screen-based devices delays melatonin release, disrupting the sleep-wake cycle and reducing sleep quality and duration. The widespread use of portable media devices underscores the need to address this issue in sleep interventions.

Advin predictive models offer promising tools for analysing sleep patterns. For example, recent work by Gregorius Airlangga (2024) explores the application of machine learning in predicting sleep disorders using lifestyle and health data. These models reveal valuable insights but require further refinement to deliver real-time, actionable recommendations. This study is the effects of lifestyle habits—including exercise routines, screen time, and sleep disturbances—on sleep quality through data-driven approaches. By bridging gaps in existing research, we aim to develop a comprehensive understanding of sleep patterns and inform personalized strategies for improving sleep and overall health.

1.1 Data acquisition and pre-processing

To investigate the impact of lifestyle factors on sleep quality, a systematic approach was adopted to collect, pre-process, and analyse data from diverse sources. This methodology ensures a robust framework for deriving meaningful insights and developing predictive models for sleep quality assessment.

1.1.1 Data Collection

Publicly available datasets related to sleep patterns and lifestyle factors were identified and collected. These datasets provided baseline information on key variables such as sleep duration, exercise frequency, and screen time, offering a foundation for subsequent analyses. A custom survey was designed to complement the publicly available data by capturing detailed, self-reported information directly from participants. The survey focused on the following data points:

- Sleep duration and quality.
- Exercise habits, including frequency and intensity.
- Screen time, particularly before sleep.
- Additional variables such as age, gender, and lifestyle routines.

To ensure inclusivity and reach a diverse demographic, the survey was distributed online in multiple languages, including English and Korean. Participants were encouraged to share their responses anonymously to foster honesty and reliability in data collection. Special efforts were made to maximize participation, resulting in a large and diverse dataset.

1.1.2 Data Pre-processing

To prepare the collected data for analysis, a series of pre-processing steps were applied: The survey responses were reviewed to address missing or incomplete entries. Imputation techniques were applied to fill in missing data where feasible, and outliers were identified and handled using statistical methods to ensure data integrity. The publicly available data and survey responses were merged into a unified dataset. This process involved aligning variable definitions, standardizing measurement units, and ensuring consistency across datasets. Derived variables were created to enhance the dataset's analytical potential. For example, screen time before sleep was calculated as a percentage of total daily screen time. Continuous variables were categorized into bins (e.g., low, moderate, high activity levels) to improve interpretability.

The prepared dataset was analysed to identify significant relationships between lifestyle factors and sleep quality. Key analytical steps included, correlation coefficients were calculated to quantify the strength and direction of relationships between variables such as exercise frequency, screen time, and sleep quality. This analysis helped highlight the most influential lifestyle factors affecting sleep. Descriptive statistics were used to summarize the data, including mean, median, and variance for key variables. Hypothesis testing was conducted to evaluate the significance of observed patterns and relationships within the dataset.

As part of the study's objective to predict sleep quality, initial machine learning models were developed. These models aimed to leverage the processed dataset to identify patterns and predict sleep outcomes based on lifestyle inputs. Various machine learning algorithms, including regression and classification models, were evaluated for their suitability in predicting sleep quality. Efforts were made to enhance the dataset for machine learning applications, including refining feature selection and addressing class imbalances where applicable. Advanced techniques learned during the study, such as feature scaling, cross-validation, and hyper parameter tuning, were applied to improve model accuracy and reliability. This methodology is expected to uncover key lifestyle variables closely related to sleep quality, enabling the development of actionable insights. The findings could lead to personalized recommendations for improving sleep and reducing health risks associated with poor sleep habits. Additionally, this research forms the basis for creating predictive analytics tools to support better health outcomes through lifestyle adjustments.

2. Data analysis

The data analysis results aimed to uncover significant relationships between lifestyle factors and sleep quality by leveraging the combined dataset of survey responses and publicly available data. This section presents the key findings from correlation analysis, statistical evaluation, and preliminary machine learning model performance. The results offer insights into how daily habits influence sleep patterns and pave the way for personalized interventions to improve sleep health. The survey results indicate an average sleep quality rating of 6 on a 10-point scale, reflecting moderate sleep quality among participants. The average

Body Mass Index (BMI) is 24.85, ranging from 13.9 to 41.3. Night sleep duration averages 8 hours, with a wide variation between 3.5 and 10.67 hours. A detailed summary of these findings is presented in Table 1.

Table 1 Summary Statistics of Key Variables

	Height (cm)	Weight (kg)	Sleep Quality	Stress level	Heart Rate	Daily Steps	BMI	Calculated Night Sleep Duration
count	282	282	282	282	282	282	282	282
mean	165.73	67.93	6.59	5.43	69.70	6774.70	24.64	7.24
std	7.54	12.29	1.81	1.71	3.14	1589.13	4.60	1.51
max	185.00	100.00	9.00	8.00	78.0	10000	36.5	10.67
min	150.00	43.00	3.00	3.00	65.0	3000	13.90	3.50

Furthermore, the survey highlights key trends among respondents: the most common age group is 35–44, with a higher number of males than females. Nurses constitute the largest occupational group. Most participants exercise 1–2 days per week, spend 4–6 hours daily on devices, and engage in 30–60 minutes of screen time before sleep. The typical bedtime and wake-up times are 23:00 and 7:00, respectively, with sleep onset usually taking 15–30 minutes. "No nap" is the most common response for nap duration, and most respondents rarely experience sleep disturbances or use sleep medication. The dominant language is Urdu, the most frequent blood pressure reading is 130/85, and most participants report sleeping for 6+ hours nightly as shown in the Table 2.

Table 2 Summary Statistics of Sleep Study Participants

	Age Group	Gender	Occupation	Exercise Days/Week	Device Usage (hrs/day)
count	482	482	482	482	482
unique	6	3	17	4	4
top	35-44	Male	Nurse	1-2 Days	4-6
freq	189	256	73	206	190
	Screen Time Before sleep	**Bedtime**	**Wake-up Time**	**Sleep Onset time**	**Nap Duration**
count	482	482	482	482	482
unique	5	18	20	4	5
top	30-60 min	23:00	07:00	15-30 min	No nap
freq	203	47	35	236	129
	Sleep Disturbances	**Sleep Medication**	**Language**	**Blood pressure**	**Sleep duration**
count	482	482	482	482	482
unique	5	2	6	25	3
top	Rarely	No	Urdu	130/85	6+ h
freq	61	64	48	48	68

The majority of respondents reported a sleep duration of 6+ hours, aligning with general recommendations of 7–9 hours for adults, though precise adequacy remains unclear. The average sleep quality score of 6.59 out of 10 reflects moderate sleep quality, with variability suggesting differing experiences. Most respondents rarely experience sleep disturbances and do not use sleep medication, indicating relatively mild sleep issues or a preference for non-medical solutions. The calculated average night sleep duration of 7.24 hours supports the positive trend, though a wide range (3.5 to 10.67 hours) highlights significant variability. These findings suggest generally adequate sleep quantity but moderate quality, warranting further exploration of influencing factors such as lifestyle and habits.

The distribution of sleep quality scores shows a concentration between 3 and 6, with a peak at 6, indicating moderate sleep quality among respondents. Calculated night sleep duration follows a roughly normal distribution centred around 7.5 hours, aligning with recommended sleep durations, with fewer cases of extreme short (<5 hours) or long (>9 hours) durations. Figure 1 illustrates the distribution of sleep quality scores, while Figure Y shows the histogram of calculated night sleep duration. Next, box plots will analyse sleep quality across different exercise frequencies and device usage categories, followed by a scatter plot of BMI vs. sleep quality and a bar chart for sleep disturbances.

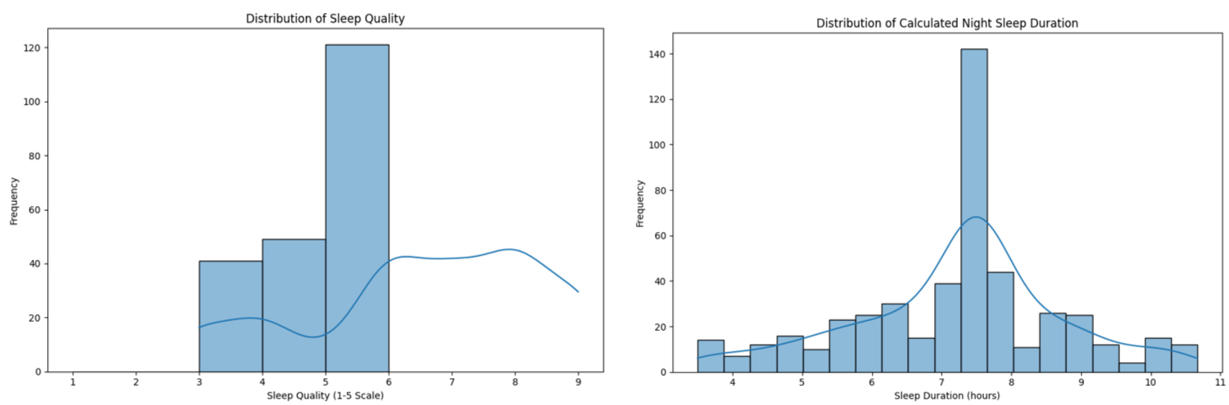


Figure 1 Sleep Quality and Duration Distribution

Analysis of the boxplots reveals that female participants exhibit a higher median sleep quality and slightly longer median sleep duration compared to male participants. Variations are observed within both groups, while the "Other" category lacks sufficient data for meaningful conclusions. Figure 3 displays the boxplots illustrating these gender-based differences in sleep quality and duration.

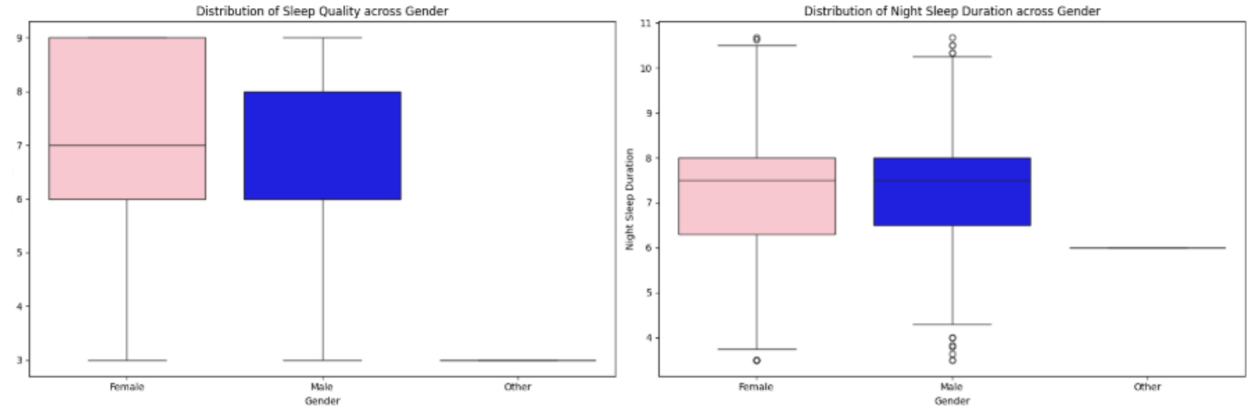


Figure 3 Gender-Based Differences in Sleep Quality and Duration

The correlation analysis reveals significant relationships among various factors influencing sleep and health. Sleep quality exhibits a strong negative correlation with stress levels (-0.51), indicating that higher stress is associated with poorer sleep. Additionally, there is a moderate positive correlation between sleep quality and age group (0.49), suggesting that older participants tend to report better sleep quality. Stress levels also show a moderate positive correlation with heart rate (0.33), implying that increased stress is linked to elevated heart rates. Exercise frequency correlates moderately with daily steps (0.48), highlighting those individuals who exercise more frequently tend to be more active overall. In contrast, variables such as BMI, calculated sleep duration, sleep onset time, and device usage demonstrate weak correlations with other factors, suggesting limited influence on sleep patterns. These findings, illustrated in Figure 2, emphasize the critical roles of stress and exercise in shaping sleep quality and health outcomes.

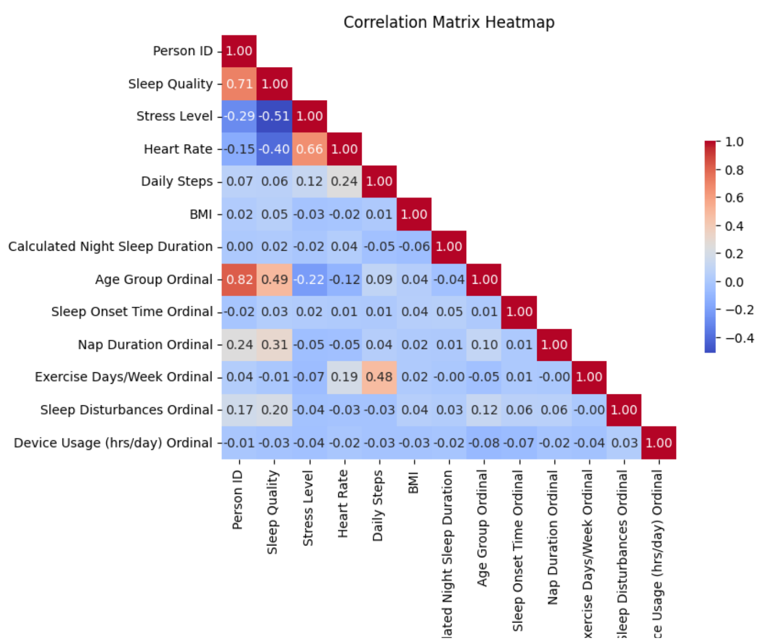


Figure 2 Correlation Analysis Results

The analysis of sleep quality across different exercise frequencies shows varied distributions, with no clear pattern linking exercise frequency to sleep quality. Sleep quality scores are generally concentrated around 6-8 across all categories. Similarly, sleep quality across device usage categories shows no significant trends, with scores consistently clustered between 6-8 hours across all usage levels. These results suggest minimal impact of exercise frequency or device usage on sleep quality. Figure 4 illustrates these distributions.

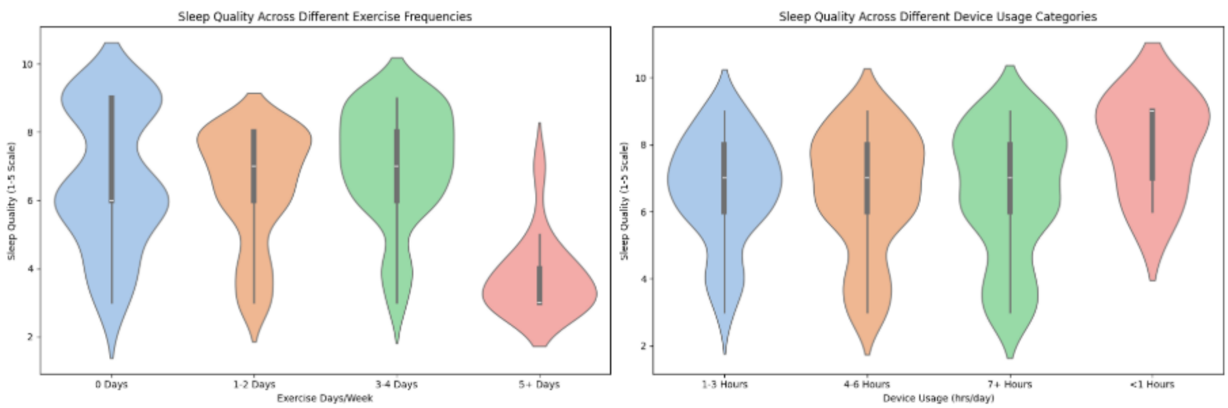


Figure 4 Analysis of Sleep Quality Across Exercise Frequency and Device Usage Categories

The analysis of sleep duration across exercise frequency and device usage shows some variation but no strong, consistent patterns. Higher exercise frequencies (3-4 Days, 5+ Days) tend to be associated with longer sleep durations, though not uniformly as shown in the Figure 5. In contrast, lower exercise frequencies (0 Days, 1-2 Days) and higher device usage (4-6 Hours, 7+ Hours) are linked to shorter sleep durations. This suggests that reduced physical activity and increased screen time may contribute to shorter sleep, likely due to factors like lower physical fatigue, stress, or blue light exposure. These findings

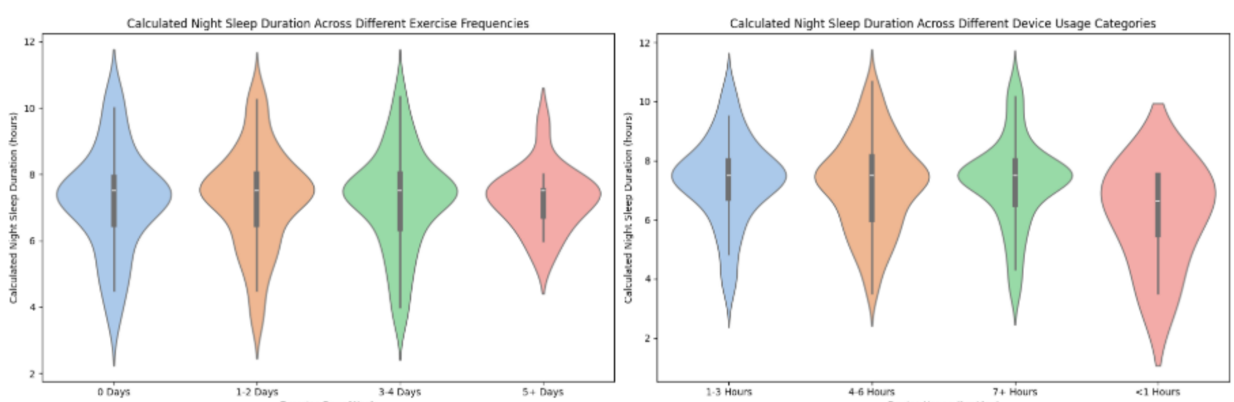


Figure 5 General Trends and Impact on Sleep Duration

highlight the complex relationship between lifestyle factors and sleep duration, warranting further investigation.

The Figure 6 shows sleep disturbance responses (Never, Rarely, Sometimes, Frequently, Often) across exercise frequencies (0 Days, 1-2 Days, 3-4 Days, 5+ Days). Individuals with no exercise (0 Days) report more disturbances, especially in the 'Sometimes' and 'Rarely' categories. As exercise frequency increases, sleep disturbances decrease, particularly for 'Sometimes' and 'Rarely'. Those exercising '5+ Days' report fewer disturbances. The 'Never' response remains consistent across all categories, indicating some individuals experience no disturbances regardless of exercise habits.

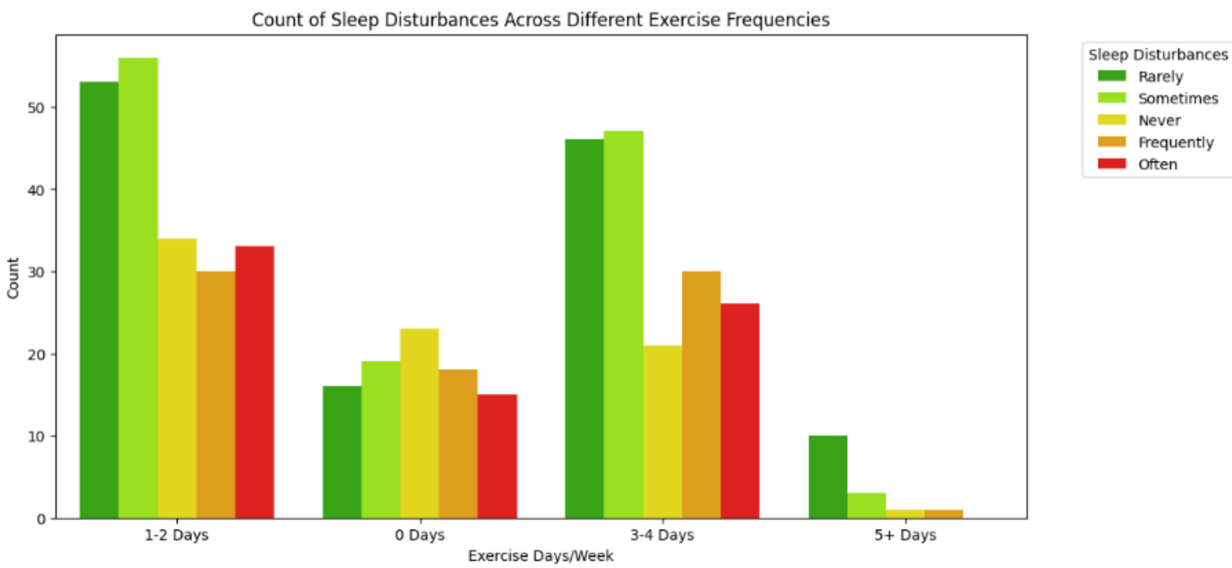


Figure 6 Sleep Disturbances Across Different Exercise Frequencies

The Figure 8 illustrate the distribution of sleep disturbances across different exercise categories. In the '0 Days' exercise category, the largest proportion reports 'Never' experiencing disturbances (25.3%), followed by 'Sometimes' (20.9%), and 'Frequently' (19.8%). In the '1-2 Days' category, 'Rarely' (25.7%) and 'Sometimes' (27.2%) are the most common responses, with 'Never' at 16.5%. In the '3-4 Days' category, 'Rarely' (27.1%) and 'Sometimes' (27.6%) dominate, while 'Never' accounts for 12.4%. In the '5+ Days' category, the majority report 'Rarely' (66.7%) experiencing disturbances, with smaller proportions for other categories. This suggests that regular exercise is associated with fewer sleep disturbances.

The scatter plots show no clear correlation between BMI and sleep quality or sleep duration, indicating other factors may influence these outcomes. However, the box plot reveals higher sleep disturbances in the "Obese III" category, with a wider range and higher median compared to other BMI categories. This suggests BMI may play a role in sleep disturbances, particularly in higher BMI ranges, though further analysis is needed to confirm these patterns.

Figure 8 Distribution of Sleep Disturbances Across Exercise Categories

3. Hypothesis testing

Based on the observed correlations from the data analysis and visualizations, several hypotheses have been identified that warrant further investigation. These hypotheses aim to explore the relationships between various factors such as sleep disturbances, age, sleep onset time, exercise, and nap duration with sleep quality and duration. To test these hypotheses, we will employ statistical methods using the Scipy library, including t-tests, chi-square tests, or correlation analysis, depending on the nature of the

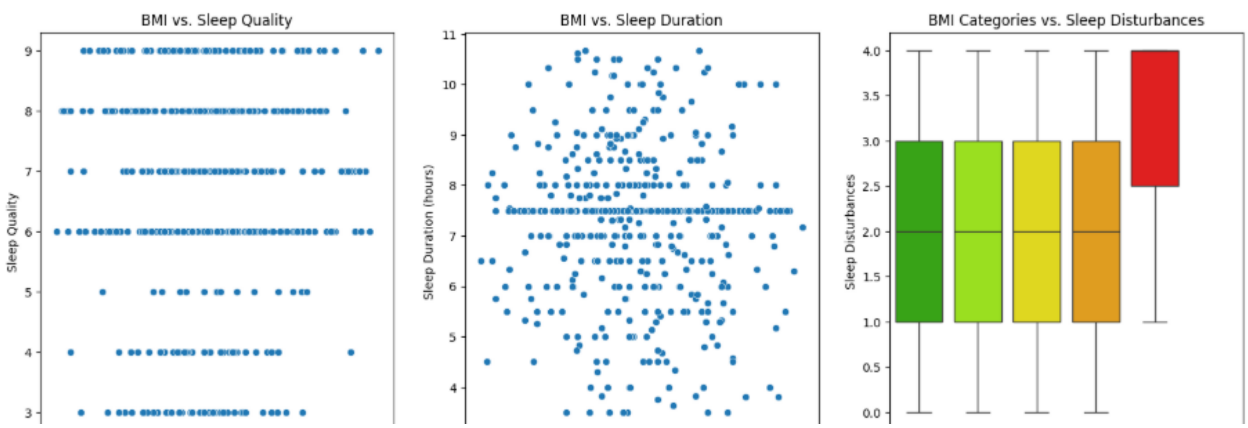
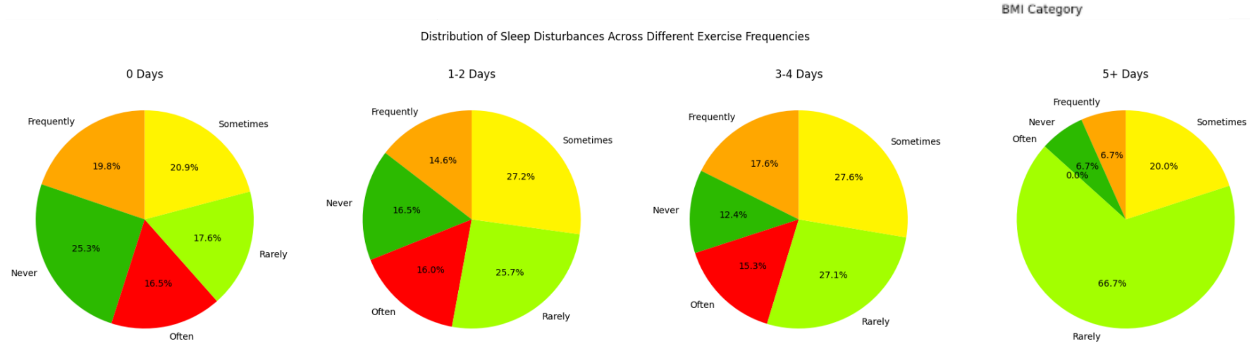


Figure 7 BMI and Sleep Patterns Analysis



data. The goal is to determine whether these relationships are statistically significant and provide insights into the factors influencing sleep patterns.

3.1 Hypothesis 1: Increased Sleep Disturbances Negatively Impact Sleep Quality

Null Hypothesis (H_0): Sleep disturbances have no impact on sleep quality. **Alternative Hypothesis (H_1):** Sleep disturbances negatively impact sleep quality. The Spearman correlation coefficient is 0.177, indicating a weak positive correlation between sleep disturbances and sleep quality, which contradicts the hypothesis. The p-value of 0.99995 is very high, suggesting the correlation is likely due to random variation and is not statistically significant. Therefore, we cannot reject the null hypothesis.

Chi-Squared Test:

Table 3 Contingency Table for Sleep Disturbances and Sleep Quality:

Sleep Quality	3.0	4.0	5.0	6.0	7.0	8.0	9.0
Sleep Disturbances							
Frequently	2	2	0	25	26	13	11
Never	5	6	6	20	10	20	12
Often	1	0	1	19	11	24	18
Rarely	17	27	7	19	19	22	14
Sometimes	16	14	2	22	25	30	16

The Chi-squared statistic is 86.14, with a p-value of 6.21e-09, which is extremely low. This provides strong evidence to reject the null hypothesis of independence, indicating a significant association between sleep disturbances and sleep quality.

3.2 Hypothesis 2 - Older People Have Shorter Night Sleep

Null Hypothesis (H_0): Age group has no impact on sleep duration.

Alternative Hypothesis (H_1): Age group has a negative correlation with sleep duration.

The Pearson correlation coefficient for age group and calculated night sleep duration is -0.044, suggesting a very weak negative correlation. This indicates a slight tendency for sleep duration to decrease with age, but the relationship is minimal. The p-value of 0.1766 is greater than the typical significance level of 0.05, meaning we cannot reject the null hypothesis. Thus, there is insufficient evidence to suggest that age significantly impacts sleep duration. Additionally, the Kendall's Tau correlation coefficient is -0.032, showing a similarly weak negative correlation, and the p-value of 0.2005 further supports the conclusion that the correlation is not statistically significant. Therefore, we cannot conclude that age group is a meaningful predictor of sleep duration. Other factors likely influence sleep duration more than age alone.

3.3 Hypothesis 3 - The Longer It Takes to Fall Asleep, the Worse Sleep Quality Becomes

Null Hypothesis (H_0): The increase in sleep onset time has no impact on sleep quality.

Alternative Hypothesis (H_1): The increase in sleep onset time leads to a decline in sleep quality.

The Spearman correlation coefficient is 0.034, indicating a very weak positive correlation, suggesting that longer times to fall asleep are slightly associated with higher sleep quality ratings, which is counterintuitive. The p-value of 0.7723, being much greater than 0.05, shows that the correlation is not statistically significant, and we cannot reject the null hypothesis.

Chi-Squared Test:

Table 4 : Contingency Table for Sleep Onset Time and Sleep Quality with Chi-Squared Test Results.

Sleep Quality	3.0	4.0	5.0	6.0	7.0	8.0	9.0
Sleep Onset Time							
15-30 Minutes	22	27	8	46	50	46	37
30-60 Minutes	12	4	1	18	24	29	15
<15 Minutes	5	16	6	33	10	27	18
>60 Minutes	2	2	1	8	7	7	1

Additionally, the Chi-squared test shows a statistic of approximately 31.23 with a p-value of 0.0270, indicating a statistically significant association between sleep onset time and sleep quality. This suggests that while a relationship exists, it is not very strong, and other factors may also contribute to sleep quality. Based on this, we reject the null hypothesis for the Chi-squared test, but the relationship is modest.

3.4 Hypothesis 4a - Weekly Exercise Frequency Improves Sleep Quality

Based on the Spearman correlation test, the correlation coefficient is approximately 0.044, indicating a very weak positive relationship between weekly exercise frequency and sleep quality. The p-value of 0.1665 is higher than the conventional alpha level of 0.05, suggesting that the observed correlation is not statistically significant. Therefore, we cannot conclude that increased exercise frequency improves sleep quality.

However, the Chi-squared test results indicate a statistically significant relationship between exercise frequency and sleep quality. The calculated Chi-square statistic is approximately 177.98, and the p-value is extremely low (2.41e-28), significantly less than the 0.05 alpha level. This indicates a strong association between exercise frequency and sleep quality, suggesting that exercise frequency does impact sleep quality in a meaningful way.

Table 5 Contingency Table for Weekly Exercise Frequency and Sleep Quality with Chi-Squared Test Results.

Sleep Quality	3.0	4.0	5.0	6.0	7.0	8.0	9.0
Exercise Days/Week							
0 Days	6	11	5	31	6	0	32
1-2 Days	20	20	8	42	45	71	0
3-4 Days	7	13	2	32	39	38	39
5+ Days	8	5	1	0	1	0	0

3.5 Hypothesis 4b - Weekly Exercise Frequency Improves Sleep Duration

The Spearman correlation test shows a very weak positive correlation coefficient of approximately 0.0102 between weekly exercise frequency and night sleep duration. The p-value of 0.4117 is much higher than the standard significance level of 0.05, indicating that the observed relationship is not statistically significant. Therefore, the data suggests that weekly exercise frequency does not have a meaningful impact on sleep duration, and other factors may be more influential in determining sleep duration.

ANOVA Test - Sleep Duration and Exercise Frequency

The F-statistic of 0.0633 indicates minimal variation between the group means for sleep duration across exercise frequency groups. With a p-value of 0.9792, which is much greater than 0.05, we find no statistically significant differences in sleep duration among the groups. This suggests that exercise frequency does not significantly impact sleep duration in this dataset. Further investigation into other potential factors may be needed.

3.6 Hypothesis 5 - Nap Duration and Night Sleep Duration

The Spearman correlation test shows a very weak positive correlation (0.033) between nap duration and night sleep duration, with a high p-value of 0.829, indicating no statistically significant relationship. This suggests that nap duration does not have a notable impact on night sleep duration. Further studies with larger sample sizes may be needed to explore this relationship more thoroughly.

4. Modelling

In this modeling section, we focus on the variables identified as significant predictors of sleep patterns in our hypothesis testing, specifically Nap Duration, Exercise Days/Week, Sleep Disturbances, and Age Group. These variables, which showed notable correlations with sleep duration and quality, are used in various machine learning models to predict night sleep duration and sleep quality. The following subsections present the performance of each model, offering an analysis and comparison of their effectiveness in these prediction tasks.

4.1 Predicting night sleep duration

The task of predicting night sleep duration was approached using multiple regression models. Model performance was assessed based on Mean Squared Error (MSE) and R-squared (R^2) scores.

Model	Mean Squared Error	R^2 Score
Linear Regression	2.34	-0.064
Decision Tree Regressor	3.75	-0.70
K-Nearest Neighbours	2.77	-0.25
Support Vector Machine	2.31	-0.053

The performance of the models was evaluated using Mean Squared Error (MSE) and R^2 score. Linear Regression performed the best, with an MSE of 2.34 and an R^2 score of -0.064, indicating reasonable predictive accuracy, though it failed to explain much of the variability in sleep duration. The Decision Tree

Regression performed poorly, with an MSE of 3.75 and an R^2 score of -0.70, suggesting overfitting and larger prediction errors. K-Nearest Neighbors (KNN) and Support Vector Machine (SVM) showed similar results, with MSE values of 2.77 and 2.31, respectively, and negative R^2 scores, indicating that they too struggled to explain the variability in sleep duration. Overall, while Linear Regression performed the best, all models had limitations in explaining the data.

4.2 Predicting sleep quality

To predict sleep quality, classification models such as Multiclass Logistic Regression, Decision Tree Classifier, Random Forest, KNN, and SVM were assessed using accuracy and weighted average F1-score as metrics.

Model	Accuracy	Weighted Avg F1-Score
Multiclass Logistic Regression	0.21	0.16
Decision Tree Classifier	0.60	0.61
Random Forest	0.63	0.63
K-Nearest Neighbours	0.47	0.48
SVM	0.23	0.16

The comparison of classification models for predicting sleep quality highlights distinct performance differences. Multiclass Logistic Regression exhibited the lowest accuracy and F1-score, indicating poor overall performance, particularly across all classes. While SVM outperformed logistic regression with slightly better accuracy, it faced challenges in effectively predicting minority classes. K-Nearest Neighbors achieved moderate accuracy, performing better than logistic regression but not as well as the tree-based models. Decision Tree demonstrated higher accuracy and F1-scores, showcasing a significant improvement over logistic regression. Among all models, Random Forest emerged as the most effective, achieving the highest accuracy and F1-score, and delivering the best performance in class predictions.

5. Summary of Model Performance

Among regression models, Linear Regression demonstrated the lowest error but still fell short with a negative R^2 score, indicating limited suitability for predicting night sleep duration. Support Vector Machine showed slightly higher error but displayed potential with modest performance, warranting further tuning. For classification, Random Forest outperformed other models with the highest accuracy and effective class prediction capabilities. However, challenges with minority class predictions remain across all models. Future improvements could include balancing the dataset, refining features, and optimizing hyper parameters to enhance model performance. While some models performed relatively better, all require further refinement and data for improved outcomes.

6. Conclusion

This study explored various regression and classification models to predict night sleep duration and sleep quality based on significant predictors such as Nap Duration, Exercise Days/Week, Sleep Disturbances, and Age Group. Among regression models, Linear Regression demonstrated the lowest error, making it the most effective model for predicting sleep duration, despite its negative R^2 score indicating limited explanatory power. Classification models highlighted the Random Forest as the most robust predictor of sleep quality, achieving the highest accuracy and F1-score, though challenges with minority class predictions persist across all models. Overall, the findings suggest that while some models perform relatively better, further optimization is required to enhance their predictive power. Improvements could include data balancing, feature engineering, and hyper parameter tuning. These steps would address current limitations, refine model performance, and provide more actionable insights into sleep behaviour.

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Member	ID No	Role
Suleman Khan	02423029	Data preparation, cleaning, analysis, modelling
Muhammad Farooq	02323027	Visualization, evaluations, final report writing
Adnan Mumtaz	02421070	Hypothesis testing, presentation preparation and final presentation

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