Analyzing the Interplay Between Sleep Patterns and Daily Physical Activity Using Wearable Data: Insights from Fitbit Trackers

Introduction

Increasing sedentary behavior and rising mental health concerns are significant issues in modern society, contributing to conditions like obesity, cardiovascular diseases, and sleep disorders. Wearable technology, such as Fitbit devices, have emerged as a powerful tool for health monitoring, offering detailed, real-time insights into sleep, activity, and other physiological metrics. By analyzing data from these devices, researchers can explore how sleep influences daily activity, potentially improving strategies to deal with health issues in different types of users.

Recent research has shown the effectiveness of wearable devices in providing comprehensive health insights. Veeraiah et al. (2023) analyzed Fitbit data to explore usage patterns related to exercise, sleep, and heart rate. Their study highlighted the importance of thorough data preparation, exploratory analysis, and visualization in understanding users' activity levels and health behaviors. Fuller et al. (2020) demonstrated the capability of Fitbit data to classify physical activities with high accuracy, using machine learning models to process data from 49 participants. This work supports the scalability of wearable data in population-level health research.

The interplay between sleep and physical activity has also been extensively studied. Dolezal et al. (2017) conducted a review showing that moderate-intensity aerobic exercise improves sleep quality and duration, though the effects vary based on individual factors like age and health status. Similarly, Chennaoui et al. (2015) emphasized the bidirectional nature of the sleep-exercise relationship, noting that sleep quality significantly impacts exercise performance and recovery, while physical activity enhances sleep through complex physiological pathways. Alnawwar et al. (2023) conducted a systematic review that demonstrated how physical activity improves sleep quality and reduces sleep disorders like insomnia. Their findings showed that moderate-intensity exercise consistently enhances sleep outcomes by reducing sleep latency, increasing total sleep time, and mitigating pre-sleep anxiety. Together, these studies establish the foundation of what will be discussed in this report.

This study seeks to answer the following research question: **How do sleeping patterns, including sleep length, time of sleep, and time to fall asleep, affect daily activity patterns and intensities, such as steps taken and activity duration and distance?**

To investigate this question, a publicly available dataset of Fitbit data was preprocessed as is described in the dataset section, the preprocessed data contained daily summaries of sleep and activity metrics for 17 users over a two-month period. Data preprocessing included addressing missing values, aggregating data to daily levels, and combining sleep and activity datasets for analysis. Exploratory data analysis, correlation analysis, and clustering methods as well as hypothesis testing were applied to uncover trends and behavioral profiles. Key metrics such as sleep duration, wake and sleep times, activity intensity levels, and step counts were used to explore the relationship between sleep and activity.

The study found that sleep regularity plays a key role in shaping daily physical activity patterns. Users with consistent sleep schedules exhibited balanced and predictable activity levels, often meeting health recommendations for steps and moderate activity. Conversely, irregular sleep patterns were associated with less consistent activity and higher calorie expenditure, possibly reflecting compensatory behaviors for disrupted sleep.

Cluster analysis revealed three distinct sleep profiles: *Regular Healthy Sleepers*, characterized by consistent sleep schedules and longer sleep durations; *Night Owls with Insomnia*, marked by later bedtimes, shorter sleep durations, and more time awake in bed; and *Irregular Sleepers*, exhibiting high variability in sleep and wake times. Hypothesis testing was conducted to explore whether these differing sleep behaviors led to significant differences in activity patterns. Hypothesis testing revealed no statistically significant differences in activity patterns among the clusters, indicating that the observed trends may not represent distinct activity behaviors. The lack of significance could potentially be due to the small sample size, showing the need for further analysis with a larger population to better understand and be able to generalize these relationships.

By addressing gaps in the understanding of sleep-activity dynamics, this study highlights the potential of wearable technology to understand users' habits which as a result could be used to support personalized health interventions and improve population health.

Problem Formulation

As stated, the research question is: How do sleeping patterns, including sleep length, time of sleep, and time to fall asleep, affect daily activity patterns and intensities, such as steps taken and activity duration and distance? Thus, this study investigates the relationship between sleep patterns and daily activity metrics, a topic of growing relevance due to the widespread use of wearable devices for health monitoring. Despite existing evidence of a bidirectional relationship between sleep and physical activity, most studies focus on understanding how activity affects sleep and not vice versa, thus, gaps remain in understanding how specific sleep parameters—such as sleep length, wake up and sleep hour, and time to fall asleep—impact physical activity levels and intensity in daily life. Addressing these gaps can provide insights for designing personalized health interventions and optimizing the use of wearable technology in promoting health and well-being.

This study advances the understanding of sleep-activity relationships by focusing on specific sleep metrics and leveraging data from wearable devices. It builds upon existing literature by using methods like cluster analysis to uncover behavioral profiles. The findings have practical implications for health interventions, offering insights that can inform personalized health recommendations. Additionally, this research addresses the relevance of wearable technology in tackling public health challenges, such as sedentary behavior and sleep disorders, while contributing to the growing field of data-driven health monitoring.

Dataset Description

Data Context

The dataset used in this study is sourced from Kaggle, titled "Fitbit Fitness Tracker Data" (Furberg et al., 2016), and consists of activity and sleep data collected from 35 different users. The data was gathered using Fitbit devices, which are wearable trackers designed to passively record various health metrics, including steps taken, calories burned, sleep duration in minutes, and heart rate in bpm. Fitbit trackers rely on sensors such as accelerometers and heart rate monitors, providing granular and reliable health data. For the activity measurements, the dataset includes total distances in kilometres as well as total time spent; these are also separated into the totals for each level of activity intensity: Very, Moderate, Light and Sedentary.

The dataset contains two folders, one containing data from 12/03/2016 - 12/04/2016 and the other one from 12/04/2016 - 12/05/2016, making up for 2 months of data in total. The data is collected at different levels of granularity. It includes daily, hourly and minute aggregated data allowing for a detailed analysis if desired. In total, the dataset consists of 29 csv files, each covering specific health and activity metrics with different levels of granularity. Each CSV file shares a similar structure, where each data point corresponds to a specific user (identified by their unique user ID) and a particular timestamp—either a date for daily aggregated data or a datetime for hourly or minute-level data. For each user at a given time, the dataset includes one or more measurements, such as total step count and calories burned. To answer the research question, we focused only on activities and sleep metrics and will carry out the analysis on a daily aggregation level as it is the most suitable aggregation period to detect the relationship between daily sleep and activity.

Data Preprocessing

Activities Data

The activity data from both months was combined into a single dataset by concatenating files with identical columns. These columns included user ID, activity date, total steps, total distance, and time spent at various activity intensity levels (e.g., very active, moderate, light, and sedentary). Each data point represents a daily summary of activity metrics for a specific user. The date column was converted to a datetime format to facilitate analysis (this was done with the date time columns of all used files).

Sleep Data

The sleep data consisted of minute-level records, each with a user ID, a log identifier (logId), a timestamp, and as per the data dictionary (Fitabase, 2024) a value indicating sleep state: 1 (asleep), 2 (restless), or 3 (awake). Each data point represents a one-minute observation of the user's sleep state. Sleep logs correspond to continuous periods of sleep or attempts to sleep, either self-reported by users or automatically detected by Fitbit devices.

To create daily summaries, a "SleepDay" was assigned based on the wake-up day for each log. Total minutes asleep were calculated by summing the durations with a value of **1**, while total time in bed included all periods with values of **1, 2, or 3**. Sleep and wake-up times were extracted from the primary sleep log of each day to provide daily sleep schedules; for days with multiple logs, the log with the longest sleep duration was selected as the primary sleep log, with additional sleep logs assumed to be naps. It must be noted that sleep hour is taken as the time to go to bed, not necessarily as the time the user falls asleep.

The heart rate data, recorded at 5-second intervals, included user ID, timestamps, and heart rate values in beats per minute (bpm). Each data point represents the heart rate measurement of a user at a specific timestamp. The average resting heart rate during the longest sleep period for each user was calculated by matching the start and end times of the primary sleep logs to the heart rate data.

The processed sleep and heart rate data were merged to create a comprehensive daily sleep dataset, including metrics such as total sleep records, minutes asleep, total time in bed, sleep and wake-up times, and average resting heart rate.

Dealing with incomplete user data

A significant issue in the dataset was the presence of records where sedentary time was 1440 minutes, indicating that the Fitbit device was on but not actively used throughout the entire day. Similarly, a total distance of 0 suggests that the device was tracking at some point during the day but was never actually utilized. These records must be removed to ensure they do not skew the data analysis or compromise the accuracy of the results. It is possible that for some days a user wore the device for just a period of the day which would as well result in incomplete data but detecting these is not straightforward so we will assume the rest of the data points are accurate.

The dataset includes users with varying amounts of activity and sleep data. Initially, there were 35 unique users in the activity data and 25 unique users in the sleep data. Upon further analysis, it was determined that 10 users in the activity dataset did not have corresponding sleep data. Since the research question focuses on comparing sleep to activity, only users with both activity and sleep data were retained for analysis.

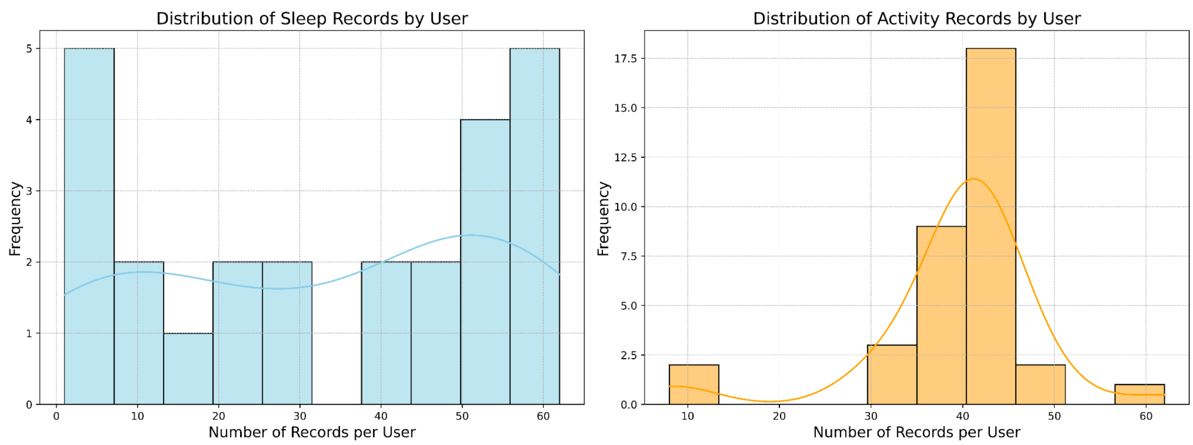


Fig. 1 - Histogram of Sleep and Activity Records per User

Before filtering out users with incomplete data, it was important to ensure that the remaining users had sufficient data points to support meaningful analysis. *Fig. 1* reveals that almost all users had incomplete data for the two months. The sleep records had a lot more gaps in the data than the activity records. To ensure each user is adequately represented while maintaining a good balance of distinct users, a minimum threshold of 20 records in at least one of activity or sleep records was set. This guarantees that each user has logged data for sleep or activity for at least one-third of the days. After filtering, the activity and sleep datasets were merged with an outer join based on user ID and date, ensuring that both datasets were aligned for comparison.

Missing Values

Following the data modifications, approximately 11% of sleep records were missing entirely, meaning all columns were absent for the same user ID and date pairs. Resting heart rate data had a notably higher proportion of missing values, around 73%, as a result, this feature had to be discarded from analysis. For activity records, about 25% of data points were missing, with all columns absent for the same user ID and date pairs.

To address the missing values in the dataset, imputation methods were applied grouped by user to maintain the individual characteristics of each user. For most variables, a KNN imputation method with 3 neighbors was used. This method has been shown to outperform simpler techniques like median or mean imputation (Suthar et al., 2012). Prior to imputation, the data was standardized to ensure that all features contributed equally to the process, and after imputation, the data was returned to its original scale.

For hour-of-day-based variables, such as sleep and wake-up times, a mean imputation method was applied using a circular mean, as described in Lee (2010). This approach accounts for the cyclical nature of time, ensuring that times like late-night and early-morning hours are treated as being close to each other rather than distant. The circular mean considers the angular relationship between times, providing a more accurate average when dealing with time data that wraps around (e.g., midnight and 1 a.m. are considered close rather than far apart).

Identifiers like user ID and date were not included in the imputation, as they serve as unique identifiers for each record. While imputation inevitably affects the data, the use of robust methods like KNN and circular means for circular data should minimize this effect by leveraging user-specific patterns, thus preserving the individual characteristics of each user. The final dataset is now ready for analysis.

Final Dataset Description

The final dataset after preprocessing consists of data from 17 unique users, with a total of 880 records. Each record represents a single day of health and activity data for a user, including various sleep and activity metrics. These metrics include total sleep records, minutes asleep, time in bed, sleep and wake times, as well as total steps, total distance covered, and activity levels. To facilitate analysis in certain visualisations, the data from "Very Active Distance" and "Moderately Active Distance," along with their corresponding "Very Active Minutes" and "Moderately Active Minutes," were combined into a new column "Active Distance" and "Active Minutes" category. Additionally, total time in bed was discarded after it was used to calculate the time awake in bed (total time in bed minus total sleep time). The dataset also includes heart rate data, focusing on the average resting heart rate during the longest sleep period.

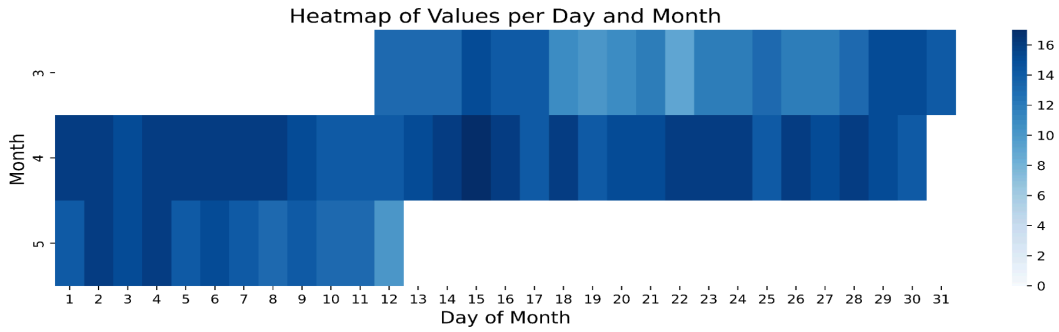


Fig. 2 - Heatmap for Records per Day

The data is aggregated on a daily level, with one record per user per day. As seen in *Fig. 2* We notice that for most of the dates we have incomplete data for all 17 users. However, all days contain records of at least 10 or more users which should suffice for analysis.

Methods

Descriptive statistics and distribution

Before proceeding with the analysis, it is essential to examine the distribution of each variable. This provides an overview of the data, helps identify any anomalies, and highlights patterns or trends that may inform the interpretation of results.

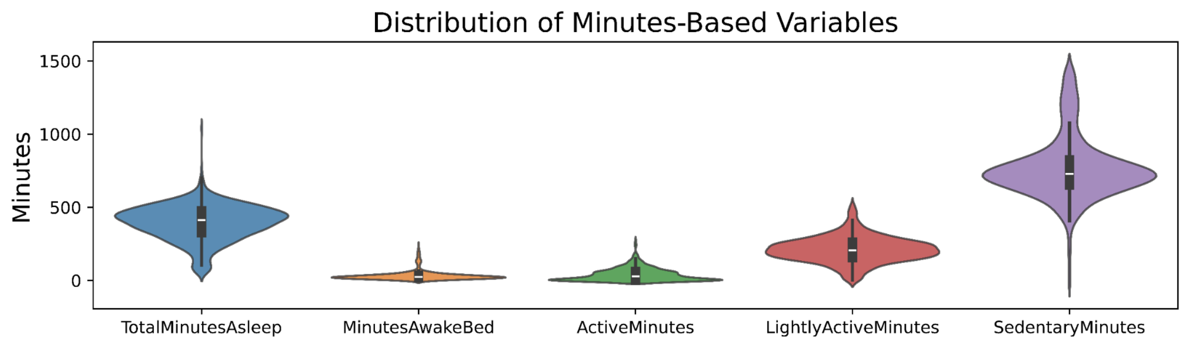


Fig. 3 - Violin Plot for Minute-Based Variables

Fig. 3 shows the distribution of the minute-based variables. We can see that total minutes asleep is and lightly active minutes are almost normally distributed with a median of 412 (~7 hours) and 206 minutes respectively. We also notice that the minutes awake in bed is right skewed with most values around 15-35 minutes but with a lot of high values some even above 200 minutes indicating sleeping problems for certain users. The sedentary minutes distribution is right skewed and is by far the one with the highest amount of minutes, indicating that most users spend most of their days not moving around, in large this is due because the sedentary minutes also includes the minutes asleep (Fitabase, 2024). The active minutes is very right skewed with a floor effect indicating, as expected, that most users have small levels of intense activity during their days with some exceptions, as the upper quartile is around 1 hour of intense active movement.

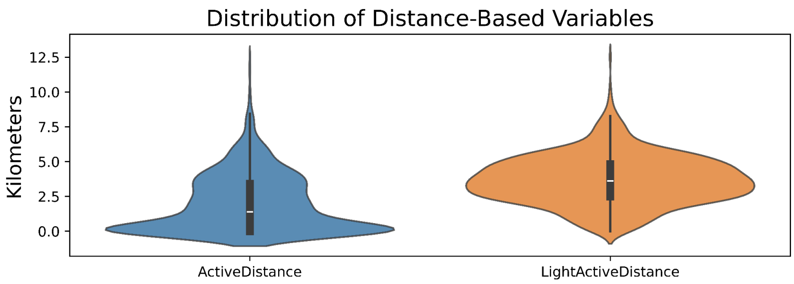


Fig. 4 - Violin Plot for Distance-Based Variables

Fig. 4 shows the distribution of distance-based features. The violin plots follow similar distributions to their minute-based counterparts (active and lightly active minutes). In fact, the Pearson correlation coefficient (Benesty et al., 2009) between active minutes and distance, and lightly active minutes and distance, is 0.89 and 0.88, respectively. Given the strong correlation and the fact that both features follow similar distributions, using minute-based features is more appropriate as time, rather than distance, provides a more consistent and direct measure of activity levels across individuals, as personal rhythms and the type of activities performed can vary significantly, making time a better indicator of activity intensity. Thus, any reference to activity intensities will now focus on the minutes instead of distance.

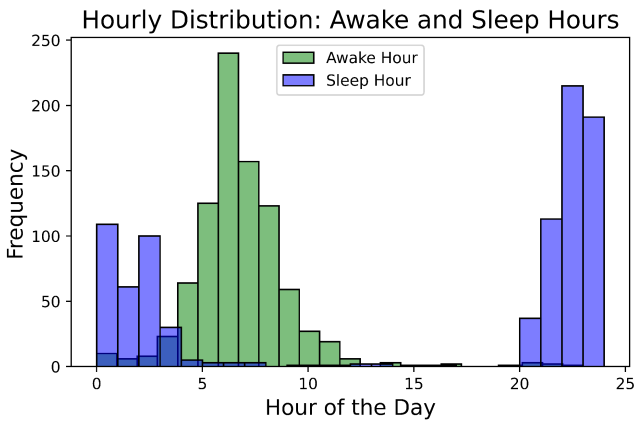


Fig. 5 - Histogram of Awake and Sleep Hours

The distribution of sleep and wake hours, as seen in *Fig. 5*, reveals the expected patterns. Wake-up times show a strong concentration in the morning, with most users waking up close to 7 a.m., and very few outliers are observed. Sleep times indicate most users going to bed between 9 p.m. and midnight, with a significant number extending past midnight until 3 a.m; as in awake time, very few outliers are observed.

Comparing User Routines to Established Standards

To better understand the activity and sleep patterns of users in this study, it is important to compare their behavior against established health guidelines. This comparison will help identify whether users are meeting the recommended thresholds for physical activity, step counts, and sleep duration, which are critical for maintaining overall health and well-being. For the purpose of this analysis, it is assumed that all users are adults between the ages of 18 and 60.

The WHO (2020) recommends that adults should engage in at least 150-300 minutes of moderate-intensity aerobic physical activity, or 75-150 minutes of vigorous-intensity aerobic physical activity per week. Additionally, adults should limit the amount of time spent being sedentary, as replacing sedentary time with physical activity of any intensity provides health benefits. A study conducted by (Banach et al. 2023) suggests that adults should aim for at least 4,000 steps per day to significantly reduce all-cause mortality, with even fewer steps needed to reduce cardiovascular mortality. The American Academy of Sleep Medicine and Sleep Research Society (Watson et al., 2015) recommends that adults should sleep 7 or more hours per night on a regular basis to promote optimal health. Consistently sleeping less than 7 hours per night is associated with adverse health outcomes, including weight gain, diabetes, hypertension, heart disease, stroke, depression, and impaired immune function.

To evaluate how well users adhere to established health standards, the median values for key metrics were calculated to represent the community's typical behavior. The median was chosen because in the previous section we noticed distributions were skewed, thus, it is more representative as it is less influenced by extreme outliers than the mean. Additionally, the percentage of healthy users was determined by counting how many individuals surpassed the recommended threshold for each metric based on their average values. This method highlights the proportion of the community consistently meeting or exceeding health guidelines, providing insights into overall wellness

For physical activity, a combined metric ‘Activity Percentage Completion’ was created to assess adherence to the WHO's guidelines. This metric integrates moderate and vigorous activity minutes, reflecting the reality that people often engage in a mix of both intensities. For the community, it calculates the percentage of the recommended activity completed by summing the contributions from moderate activity (scaled relative to the 150-minute goal) and vigorous activity (scaled relative to the 75-minute goal). For individuals, the same method is applied using their weekly averages. This approach ensures that both types of activity are fairly considered, recognizing that a combination of moderate and vigorous activities can fully meet the guideline, even if neither alone does.

	Recommendation	Community Median	Healthy Users	% Healthy Users
Hours of Sleep per Day	7.0	7.4	10.0	59.0
Moderate Activity Minutes per Week	150.0	77.0	0.0	0.0
Vigorous Activity Minutes per Week	75.0	56.0	7.0	41.0
Activity Percentage Completion	100.0	126.0	12.0	71.0
Steps per Day	4000.0	8439.5	15.0	88.0

Table 1 - Health Metrics Adherence to Recommendations

The community adherence to established recommendations can be seen in *Table 1*. The community median for daily sleep duration was 7.4 hours, slightly exceeding the recommended 7 hours per night. This suggests that the majority of users are close to meeting the recommended amount of sleep for optimal health. However, only 59% of users consistently achieve this standard, indicating that while the community as a whole performs well, a significant proportion of individuals may experience insufficient sleep, potentially leading to health concerns associated with chronic sleep deprivation.

For physical activity, the community median for moderate-intensity activity was 77 minutes per week, just over half of the minimum 150-minute recommendation. Vigorous-intensity activity showed a similar trend, with a community median of 56 minutes per week compared to the recommended 75 minutes. As expected, relatively few users meet the guidelines when moderate or vigorous activity is considered in isolation—0% and 41%, respectively. This is because the guidelines accommodate flexibility: while either moderate or vigorous activity alone can fulfill the recommendation, most individuals engage in a combination of both. Thus, using the calculated metric 'Activity Percentage Completion' for a holistic approach, we notice that most users comply with the established physical activity standards with a community median of 126%, and 71% of users meeting the physical activity recommendations.

Daily step counts were a standout metric, with a community median of 8,439.5 steps—more than double the recommended minimum of 4,000 steps per day. This suggests that walking is a primary form of physical activity for most users. A notable 88% of users met or exceeded this guideline, indicating strong adherence to this aspect of physical activity. The high compliance rate highlights that walking is both a feasible and popular activity, making it an effective measure for promoting overall health.

Sleep Schedule Patterns

Understanding the sleeping patterns of the community is a crucial aspect of this analysis. By examining how consistent are individuals sleeping and waking up times, we can gain insights into their daily routines, identify potential disruptions, and evaluate adherence to healthy sleep schedules. A review carried out by Chaput et al. (2020) concluded that consistent sleep patterns are associated with better overall health, mood, and cognitive function, while irregular sleep schedules can lead to a range of health issues, including fatigue, poor mental health, and sleep disorders. The review also highlights that later bedtimes and wake-up times are linked to poorer mental health and cognitive function, emphasizing the importance of maintaining earlier and regular sleep schedules for optimal health outcomes.

To analyze the sleeping patterns of the community, we calculated the average sleep and wake times for each user using the circular mean, which accounts for the cyclical nature of time, as previously mentioned (Lee, 2010). This approach ensures that times close to each other, such as late-night and early-morning hours, are treated as being near one another. Along with the mean, we also calculated the circular standard deviation (Lee, 2010), which measures the variability in sleep and wake times. The circular standard deviation is calculated by first converting the sleep and wake times into radians, as time is cyclical. The sine and cosine components of these values are then averaged, and the resulting vector length is used to compute the standard deviation. A lower circular standard deviation indicates a more consistent sleep schedule, while a higher value suggests greater irregularity. The combination of the circular mean and standard deviation provides a comprehensive view of both the average sleep and wake times and the consistency of these patterns across the user base.

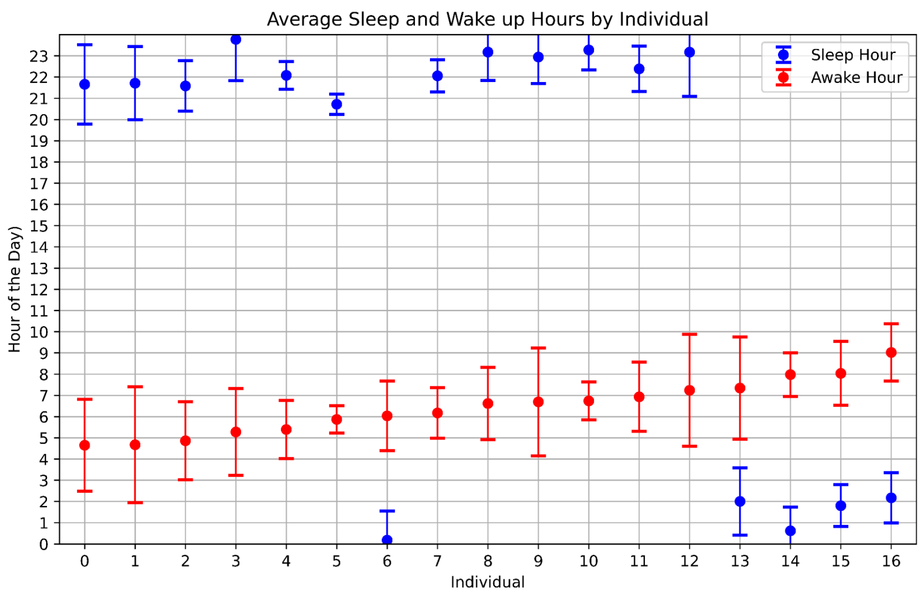


Fig. 6 - Sleep and Wake Up Times by User

Fig. 6 depicts the average sleep and wake-up times of all users, along with the variability of these patterns, represented by error bars indicating circular standard deviation. The results highlight a diverse range of sleeping habits, with notable trends and outliers. The visualization is ordered by average wake up time.

Most individuals tend to go to bed between 8 PM and midnight, showing a relatively consistent bedtime schedule. However, a few individuals, particularly those labeled as 13–16, sleep significantly later, with bedtimes between midnight and 3 AM. The variability in sleep times, as indicated by the error bars, is generally small for most individuals, reflecting regular bedtime habits. Nevertheless, a few outliers display higher variability, indicating irregular sleep schedules or inconsistencies in their routines.

Wake-up times cluster primarily between 5 AM and 8 AM for the majority of individuals, but some individuals wake up as early as 4am. None of the users wake up what would normally be considered late. Variability in wake times is often higher than for sleep times, suggesting that individuals are less consistent in their waking routines. For certain participants, such as individuals 1, 9, 12, and 13, significant variability in wake-up times suggests irregular or disrupted morning schedules.

We can observe that individuals who sleep later tend to wake up later, while earlier sleepers wake earlier. We also notice that individuals with high variability in sleep time also tend to have a high variability in wake up time, in fact, the pearson coefficient (Benesty et al., 2009) between their standard deviations is 0.81 with a significant p-value of less than 0.01.

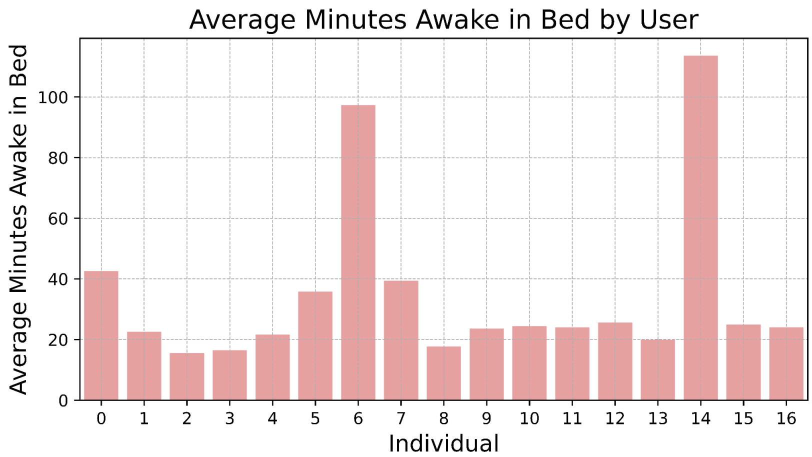


Fig. 7 - Average Time Awake in Bed by User

Another important aspect of the analysis is the time users spend awake in bed before falling asleep, as this can help identify potential sleep disorders, such as insomnia. *Fig. 7* highlights this data, showing that individuals 6 and 14 spend an average of about two hours in bed without sleeping, a possible indicator of insomnia or disrupted sleep schedules. Interestingly, these same individuals were observed in *Fig. 6* to have significantly later bedtimes, further suggesting issues with their sleep patterns. In contrast, the rest of the users display relatively normal time-to-sleep durations.

Overall Sleep and activity relationship comparisons

To further understand the interplay between sleep and activity metrics, we conducted a correlation analysis of the user summary data. The purpose of this analysis was to explore the relationships between various sleep and activity variables, particularly focusing on how sleep metrics relate to physical activity metrics. Given that this study includes only 17 users, the results should be interpreted with caution as they may not be fully generalizable to larger populations.

The calculations of the circular standard deviation for sleep and wake times, as well as the averages and standard deviations for other variables like total sleep time, steps, and activity minutes, were aggregated for each user. The resulting correlations were visualized in a heatmap (*Fig. 8*), which provides insights into the interactions between sleep habits and physical activity patterns.

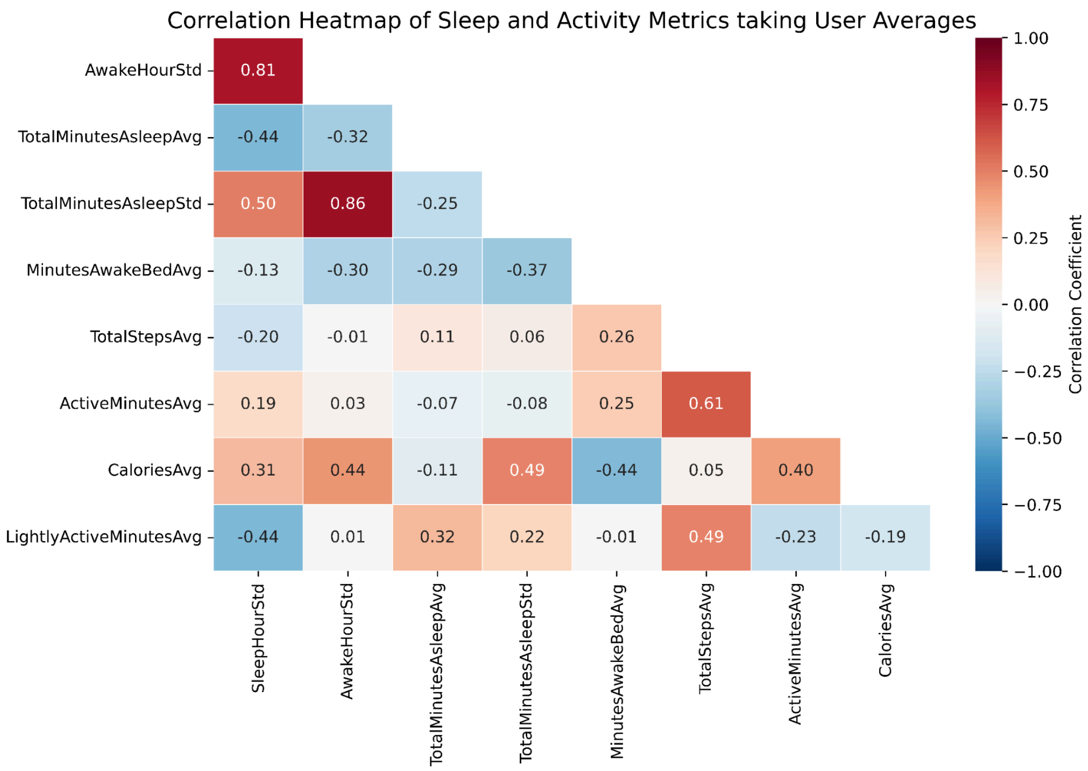


Fig. 8 - Correlation Matrix between Activity and Sleep Metrics aggregated by User

The heatmap shown in *Fig. 8* reveals several interesting correlations between sleep and activity metrics. A key finding is the negative correlation between Sleep Hour Standard Deviation and Light Active Minutes Average (-0.44), suggesting that irregular sleep may lead to lower light activity levels. Disrupted sleep can affect energy and motivation, potentially resulting in less physical activity. This is supported by the positive correlation between Sleep Hour Standard Deviation and Calories Average (0.31), which indicates that irregular sleep patterns may increase calorie expenditure, possibly due to metabolic adjustments.

Looking at Minutes Awake in Bed Average, there's a negative correlation with Calories Average (-0.44), suggesting that people who spend more time awake in bed, perhaps due to poor sleep quality, may burn fewer calories. However, the positive correlation between Minutes Awake in Bed Average and Active Minutes Average (0.25) complicates this, implying that longer awake times may lead to more activity, but the overall effect on physical activity could be influenced by other factors.

A positive correlation between Total Minutes Asleep Average and Light Active Minutes Average (0.32) suggests that more sleep is linked to more light activity. However, the relationship with higher-intensity activity, like Active Minutes Average, is weak (0.19), indicating that sleep mainly influences less intense physical activities. Lastly, Total Minutes Asleep Standard Deviation's moderate positive correlation with Calories Average (0.49) supports the idea that irregular sleep is associated with higher calorie expenditure, possibly due to the body's response to inconsistent sleep schedules.

The main takeaway from the analysis is that irregular sleep patterns seem to be linked to both lower light activity and higher calorie expenditure, while more sleep is associated with increased light activity. However, it's important to note that these are correlations, not causations, and we cannot draw definitive conclusions about cause-and-effect relationships. As previously stated, with only 17 users in the sample, these findings are not very generalizable, and the small sample size limits the ability to make strong conclusions.

Cluster Analysis

This section focuses on applying cluster analysis to uncover behavioral profiles based on users' sleep patterns, with the aim of identifying distinct sleeper types. By clustering only on sleep variables, we can more effectively isolate sleep behavior from activity patterns, which is crucial for understanding how sleep influences daily activity. The clustering will help classify users into different sleeper types, which can then be used to investigate the relationship between sleep and physical activity levels. After clustering, hypothesis testing will be conducted to assess if there are significant differences in activity metrics (such as steps, active minutes, and calories) between the identified sleeper types. The clustering will include sleep variables, such as total sleep time, sleep duration consistency, and average sleep and awake times. To account for the cyclical nature of time, both sleep and awake times will be transformed using cosine and sine functions. This transformation is necessary because it accurately captures the circular nature of time: the cosine function represents the horizontal position of the time relative to midnight, while the sine function captures the vertical position, reflecting how far the time is from the peak of the 24-hour cycle (e.g., noon or midnight) (Lee, 2010). This approach ensures a more precise representation of time in the clustering process.

The K-means clustering (MacQueen, 1967) will be used to group users based on their sleep and activity patterns. K-means is a widely used algorithm that assigns data points to clusters based on their similarity, minimizing the variance within each cluster. To enhance the performance of K-means, especially with high-dimensional data, Principal Component Analysis (PCA) (Hotelling, 1933) will be applied as a preprocessing step. PCA reduces the dimensionality of the data by transforming it into a smaller set of uncorrelated components that capture the most variance. This not only reduces computational complexity but also helps mitigate issues like the curse of dimensionality and noise, improving the quality of the clusters. Ding and He (2004) demonstrated that combining PCA with K-means can improve clustering outcomes by focusing on the most informative components of the data, thus enhancing both efficiency and interpretability.

For PCA, the variables were scaled beforehand to ensure that all features contributed equally to the analysis, as differences in scale could otherwise disproportionately influence the principal components. In cluster analysis, it is common to retain about 80% of the variability when performing PCA. In this case, we used 3 principal components, which accounted for approximately 77% of the total variability in the data.

Fig. 9 - Metrics to Choose Optimal K

To choose the appropriate value of k for clustering, we use two evaluation metrics: the Silhouette Score and the Calinski-Harabasz Index. The Silhouette Score (Rousseeuw, 1987) measures how well-separated and defined the clusters are, with higher values indicating better-defined clusters. The Calinski-Harabasz Index (Calinski and Harabasz, 1974) evaluates the ratio of between-cluster dispersion to within-cluster dispersion, where higher values indicate more distinct and well-separated clusters. As seen in *Fig. 9,* taking both metrics into account and considering the small sample size, k=3 or k=4 seem as the most appropriate choices. For simplicity we take k=3 as it will provide a balance between capturing meaningful patterns in the data while avoiding excessive complexity, making it a more suitable option for this analysis.

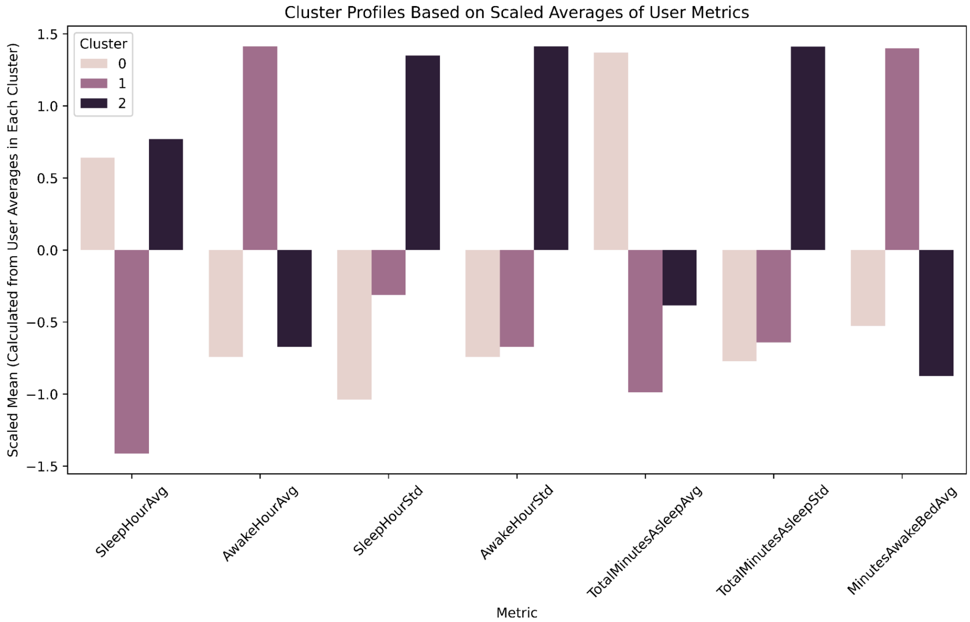
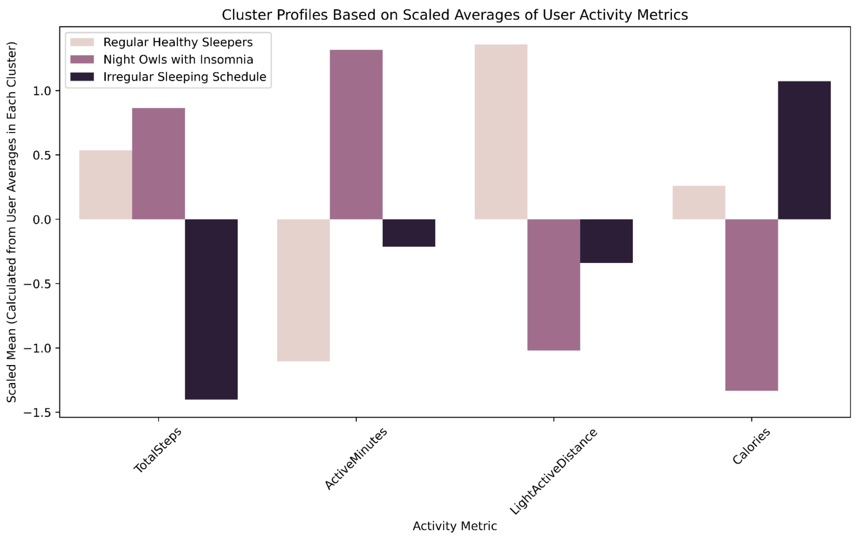


Fig. 10 - Identifying Cluster Profiles through Mean of Sleep Metrics

The three defined clusters are made up of 6, 3, and 8 users respectively. To visualize the different metrics in a single plot, given their varying units, the averages of the averages for each user in the cluster were scaled, allowing for consistent comparison across the profiles. Based on the cluster analysis, three distinct sleep profiles were identified, as visualized in *Fig. 10*. Cluster 0, termed *Regular Healthy Sleepers*, represents users with consistent sleep and wake times (average sleep time of 10 PM and wake time of 6 AM, not visible in the scaled plot), low variability in sleep-related metrics, and the highest average sleep duration of approximately 7.5 hours, aligning with WHO recommendations for healthy sleep. Cluster 1, described as *Night Owls with Insomnia* , consists of users who sleep the latest (indicated by the lowest scaled values in sleep time, as after midnight is represented as a lower value), wake up the latest, and experience the shortest sleep durations. They also spend the most time awake in bed, potentially reflecting difficulty falling or staying asleep. Finally, Cluster 2, labeled *Irregular Sleepers*, includes users with the most variability in their sleep and wake times as well as total sleep duration, indicating a lack of consistent sleep patterns. These



profiles highlight the diversity in sleeping behaviors and set the stage for further analysis of how these patterns relate to physical activity metrics.

Fig. 11 - Comparing Activity Metrics by Cluster Profiles

Now we will analyze how the clusters' behavior is for physical activity during the day. Once again, for visualization purposes the averages of the averages for each user in the cluster were scaled. Based on the activity metrics shown in *Fig. 11*, three distinct patterns emerge across the clusters. *Regular Healthy Sleepers* display moderate levels of activity across all metrics. Their total steps and active minutes are near the average, with a slight positive trend in light active distance and calories burned. This suggests a balanced level of physical activity, consistent with their stable sleep patterns. *Night Owls with Insomnia* stand out with significantly higher total steps and active minutes compared to the Regular Healthy Sleepers. These users are notably more engaged in physical activity, as seen in their higher total steps and active minutes scores. However, their light active distance and calories burned are lower, potentially indicating more intense but less frequent activity. Their sleep disturbances may lead them to expend more energy during the day in an attempt to counteract poor sleep quality. *Irregular Sleepers* display the most pronounced variation in activity. While their total steps and active minutes are lower compared to the *Night Owls with Insomnia*, their calories burned and light active distance are higher, suggesting that although they may not engage in consistent, structured physical activity, their erratic sleep patterns might lead to bursts of energy expenditure throughout the day. This irregularity in both sleep and activity metrics reflects a less predictable relationship between sleep quality and activity levels in this group.

While these differences suggest interesting trends, it is difficult to determine whether they are statistically significant based on the current data. To further investigate the significance of these relationships, hypothesis testing will be conducted to assess whether the observed differences in activity metrics across clusters are statistically significant.

Kruskal Wallis Test on Activity Metrics by Cluster

Ideally, to test if the activity metrics mean is different across clusters, we would use ANOVA (Fisher, 1970). However, the small sample sizes make it difficult to reliably test if the assumptions of ANOVA are met. ANOVA assumes normality, homogeneity of variance, and independence. Small sample sizes make it harder to test these assumptions properly, as fewer observations can lead to an inaccurate assessment of normality and variance equality. Violations of these assumptions can lead to incorrect conclusions, such as Type I or Type II errors. Given these limitations, we use the Kruskal-Wallis test (Kruskal & Wallis, 1952), a non-parametric alternative to ANOVA, which does not assume normality or equal variances. The Kruskal-Wallis test assesses whether there are significant differences in the distribution of the data across groups by comparing ranks rather than the actual values. Unlike ANOVA, which compares group means, the Kruskal-Wallis test compares the rank sums of the data from different groups. To apply this test, continuous data must first be converted into ranks; all values across groups are sorted, and then ranks are assigned, with the smallest value getting a rank of 1 and so on. This process allows the Kruskal-Wallis test to handle continuous data that does not meet the assumptions of ANOVA, making it a more robust option when sample sizes are small. However, small sample sizes can still reduce the power of the Kruskal-Wallis test, making it more difficult to detect significant differences when they exist.

The null hypothesis for the Kruskal-Wallis test in this context is that the different sleep profiles have the same central tendency in their activity metrics, meaning they come from the same population. The alternative hypothesis is that at least one sleep profile exhibits a different central tendency in activity metrics, suggesting that it comes from a different population.

	Statistic	p-value
TotalSteps	0.81	0.67
ActiveMinutes	0.79	0.67
LightActiveDistance	2.27	0.32
Calories	3.46	0.18

Table 2 - Kruskal-Wallis Test Results for Activity Metrics Across Clusters

As shown in *Table 2* the results of the Kruskal-Wallis tests for all activity metrics have a *p-value* > 0.05, thus, we fail to reject the null hypothesis for all metrics, implying that there is no substantial evidence to suggest that the activity patterns differ between the different sleeper types. While the statistical tests found no differences, it is important to note that the small sample sizes within each group may limit the statistical power of the tests, making it more challenging to detect meaningful differences. This limitation suggests that, although no differences were found, there may still be subtle effects that were not detected due to the low power of the tests associated with small sample sizes.

Results

This study investigated the relationship between sleep patterns and daily physical activity using data from Fitbit trackers. It is important to remember that the findings presented here are derived from a small sample of 17 users with varying levels of data completeness. The absence of demographic or contextual information about the users limits the generalizability of these results, which should primarily be interpreted within the scope of this study's participants. Additionally, while some patterns and correlations were observed, they may not hold statistical significance due to the limited sample size, and thus conclusions should be approached with caution.

The results suggest a relationship between sleep regularity and physical activity, with users who maintained consistent sleep schedules generally exhibiting more predictable and balanced activity patterns. These individuals, who demonstrated stable sleep and wake times, tended to meet the recommended daily step counts and engage in moderate levels of physical activity. This aligns with existing literature, such as the findings by Chennaoui et al. (2015) and Dolezal et al. (2017), which highlight the bidirectional effects of sleep and physical activity.

On the other hand, users with irregular sleep patterns, such as those with significant variability in sleep times or extended time awake in bed, exhibited less consistent activity behaviors. This variability was often accompanied by higher calorie expenditure, which may indicate compensatory mechanisms for poor sleep quality, such as increased physical activity or altered metabolism. These findings are consistent with the literature suggesting that disrupted sleep can lead to behavioral adjustments, although the exact nature of these compensations remains unclear due to potential for confounding factors.

The cluster analysis revealed differences in activity levels and sleep behavior across users with different sleep patterns. For example, users with regular sleep schedules exhibited more moderate levels of activity, while those with irregular sleep or delayed bedtimes demonstrated more intense but less consistent activity patterns. While these differences were not statistically significant, the observed trends suggest that the timing and consistency of sleep may influence how active a person is during the day. This adds to the body of research that emphasizes the role of sleep in shaping physical activity patterns and suggests that interventions focused on improving sleep consistency may help support more balanced activity behaviors.

Conclusion & Discussion

Limitations & Shortcomings

Several limitations affected the study's outcomes and potential impact. The small sample size of 17 users limited the ability to draw generalizable conclusions. If a larger, more diverse dataset had been used, it would allow for more robust statistical analysis, possibly uncovering stronger relationships and validating the trends observed in this study. Additionally, missing data for sleep and activity metrics, which, despite using advanced techniques, introduces the possibility of bias. Avoiding missing data would enhance the reliability of results and allow for a fuller exploration of relationships between variables, while also allowing to analyze other factors like resting heart rate, which were excluded from some analyses due to insufficient data.

The short data collection period of two months further restricted the study's scope. A longer observation period would enable the identification of seasonal or long-term trends in sleep and activity behaviors. Furthermore, the dataset lacked demographic details, such as age, gender, and occupation, which are critical for contextualizing sleep and activity patterns. Incorporating this information could lead to more nuanced analyses and enable targeted interventions based on individual characteristics.

Future Steps

Future research should address these limitations by incorporating larger, more diverse datasets and extending the observation period. This would improve the generalizability of findings and allow for the exploration of temporal trends. Demographic data should also be integrated to examine how age, gender, and lifestyle factors influence sleep-activity relationships. Expanding the scope of metrics to include variables such as diet, mental health, and stress levels would provide a more comprehensive understanding of the factors influencing sleep and activity.

Building on the cluster analysis, future studies could use larger populations to test whether the identified sleep profiles correlate with distinct activity behaviors across different contexts. For example, it would be valuable to explore how a recommendation system, tailored to each sleep profile, could guide individuals toward healthier behaviors. By providing personalized suggestions based on users' specific sleep and activity patterns, wearables like Fitbit could be used to track progress and assess how well these tailored recommendations improve long-term health outcomes. Additionally, incorporating surveys to track users' health status, such as mental well-being, stress levels, and overall satisfaction with the recommendations, could provide a more holistic understanding of the effectiveness of such systems. This type of research could demonstrate the potential of wearables and data-driven health recommendations in enhancing health behaviors, improving long-term health outcomes, and promoting overall well-being.

Summary

In summary, while the findings support the existing literature on the relationship between sleep and physical activity, the limitations in data quality prevent these results from being broadly generalized. Nevertheless, the study provides useful insights into how sleep regularity may affect activity levels and highlights the importance of further research in this area. The observed trends suggest that detecting sleep habits could be a key factor in promoting better physical activity and overall health through the use of wearable devices like Fitbit, but larger, more diverse studies are needed to validate these findings.

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