

Tracking Long-Term Sleep and Activity Differences across Chronotypes: A Case Study in Finland Using Oura Rings

Chandreyee Roy *, Kunal Bhattacharya and Kimmo Kaski

Department of Computer Science, Aalto University School of Science, 02150 Espoo, Finland

* Correspondence: chandreyee.roy@aalto.fi

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Abstract: Non-invasive mobile wearables like fitness trackers, smartwatches, and smart rings allow for an easy and relatively less expensive approach to studying patterns of everyday human sleep and activity patterns compared to traditional longitudinal methods. We used smart rings manufactured by Oura to obtain granular data from 19 healthy participants over the time span of one year (October 2023–September 2024), to investigate longitudinal sleep and activity patterns of three chronotype groups among them: morning type (MT), neither type (NT), and evening type (ET). We find that while ET individuals do not seem to lead as healthy patterns as MT or NT individuals in terms of overall sleep and activity, they seem to have significantly improved their habits over the duration of the study. The activity in all chronotype groups varies throughout the year with the ET individuals showing an increasing trend. Furthermore, we show that the Daylight Saving Time changes in autumn affect the sleep quality of the MT individuals. Finally, using a mixed-effects regression model, we show that the perceived stress of an individual is significantly associated with their time spent in bed during nighttime sleep, monthly survey response time, chronotype and age, while accounting for individual variability.

Keywords: wearables; chronotype; circadian rhythms; daylight saving time; human behaviour

1. Introduction

In the past few years, there has been a rapid growth of wearable mobile devices such as fitness trackers and smart watches that are being used by millions of people around the world [1,2]. This phenomenon started with just simple trackers that were able to track the steps and basic activity of the user, but by now they have been developed to measure and collect data of the user's sleep, heart rate, heart rate variability, calories burned, daily activity, menstrual cycles, among others [3]. The added advantage of this personal data is that it can be synchronized to their respective applications on users' smartphones to provide them with in-depth analysis of their own health and progress reports. There are several motivations for the widespread adoption of these devices [4]. One of them is that users are driven by the need to improve their physical fitness and these devices can serve as aid by providing instant feedback along with features such as reminders to move, to achieve daily step goals and details of the workout [5]. Additionally, they have already proven quite useful in tracking the early onset of infectious diseases [6–9].

Several users are also motivated by the need to improve their sleep due to the ability of these devices to gauge an individual's sleep quality throughout the night [10,11]. Sleep has often been considered one of the pillars of health, along with nutrition and exercise, due to its profound impact on all aspects of our daily functioning [12]. Several studies have shown that neglecting sleep can lead to a cascading number of negative health outcomes [13,14], and therefore prioritizing it is emphasized to improve one's quality of life. Since sleep plays such an important role in human physiological processes, cognition, and overall wellbeing [15], its monitoring and assessment have taken precedence among those who want to lead a healthy life.

Traditionally, an individual's sleep and health have been assessed using polysomnography (PSG) [16] and actigraphy [17], but they have mainly been used for research purposes only. The advent of advanced fitness trackers

from all price brackets have allowed humans to conveniently assess their sleep and daily activities on a regular basis. These devices encompass a wide range of gadgets, such as watches, rings, and activity bands, among others that are worn close to or on the body [18, 19]. These devices typically have sensors that can collect their users' physiological data, which are then processed and interpreted using algorithms and machine learning methods by health applications that can nowadays be downloaded easily on smartphones. This method of monitoring one's health is now very popular among the general population [20].

Conventional methods for detecting sleep and activity generally involve sleep laboratories [21, 22] and the use of a myriad of wires, electrodes, and overnight stays by subjects, which does not simulate a natural environment for studying sleep for extended periods of time. These wearables have provided a way in which we can now capture sleep patterns in the real world without being too intrusive [23–25]. Today, the most popular method is to use wristwatches that detect movement using accelerometers and rings that can measure heart rate variability and body temperatures [26]. The wearables offer an unparalleled insight into one's sleep cycles, sleep quality, and even circadian rhythm [27].

In the current study, we have used Oura rings [28] to investigate behavioural health patterns among volunteers for a period of one year. Some of the sleep and activity metrics of the Oura rings have been previously validated against gold standard methods and therefore considered as a suitable consumer grade device for the present study [29–31]. Our main objective is to investigate seasonal and weekly differences in sleep and activity patterns of a group of volunteers from a long-term perspective. We focus on the circadian rhythms of volunteers, as it plays a pivotal role in their sleep-wake cycles, eating patterns, hormone cycles, and other physiological processes [32]. Disruptions in individuals' circadian rhythms due to lifestyle, travel, and work shifts can have a major impact on their health and well-being [33]. We have identified each individual's chronotype [34] his or her sleeping or waking time preferences using the Horne and Ostberg morningness eveningness questionnaire [35]. Consequently, if a person is unable to get up in the morning but gets most of the daily tasks done during the latter part of the day, then his or her chronotype would resemble that of an "owl" and is more commonly known as the evening type (ET) [36]. On the other hand, if one prefers getting up early in the morning and starts to feel groggy in the evening, then the chronotype would resemble that of a "lark" (also known as the morning type (MT)). Most people in a large population fall within the spectrum of these two categories of larks and owls. Those individuals in the middle of the spectrum constitute the majority of the people and are known as "third birds" of neither types (NT) [37].

While the proverb "early to bed, early to rise makes a man healthy, wealthy, and wise" suggests that larks lead better lives than owls, there are some studies showing that owls can also lead healthy lives if they follow their own sleeping patterns [38]. This is because alignment of one's body clock with their inherent chronotypes, results in most productivity in their daily lives. Unfortunately, misalignment of one's chronotype is quite common [39] even though it is considered an issue that leads to irregular sleep patterns, unhealthy eating habits, and general poor health. Most of the time people are simply unaware of this misalignment or are unable to follow their inherent circadian rhythms due to non-flexible work or school schedules [40]. This is predominately seen to affect ET individuals [41, 42] due to the global bias towards morning friendly schedules, and therefore it is the most vulnerable group among the chronotypes. In the present study, our aim is to use behavioural data of individuals related to their sleep and activity patterns collected from Oura rings to identify the long-term differences between chronotypes. Specifically, we are interested to understand whether long-term use of these devices can capture the behavioural changes or adjustments and whether it can help in mitigating the adverse effects commonly associated with ET individuals, who are often misaligned with societal schedules.

The present study was conducted among participants living in the Helsinki capital region, Finland, which is situated at northern latitude (60.2° N). The contrast in sunlight hours at this latitude, along with the weather conditions, provides an interesting backdrop for studying the behaviour of chronotypes throughout the year. In the present study we find that while ET individuals have poorer sleep quality in general, they can potentially improve with time. We also find that the Daylight saving times (DST) in autumn may affect the chronotypes differently. In addition, the time spent in bed for night sleep was significantly associated with less reported stress. The association between age and reported stress levels differed significantly across the chronotype groups.

2. Materials and Methods

2.1. Study Design

Participants were recruited through public advertisements provided online on the university website, online marketplace and through the student chat groups. Data collection period lasted from the 1st October 2023 till 30th September 2024. Data were collected in the form of digital surveys carried out from January 2024 till the end of the study (a total of nine questionnaires) along with the digital health data from Oura rings that participants wore

throughout the study period. Sizing kits were provided to obtain the correct sized ring for each of the participants. Health data collected from the rings were stored in the company's cloud through which the researcher accessed the data using APIs. Each participant was associated with a unique identifier before storing in secure Aalto servers and any personal direct identifiers were removed from the data after the data collection period was over. At the end of the study, the participants were provided a 20€ gift card from the Aalto University shop as compensation for participating in the study.

2.2. Data

We collected daily aggregated data from a total of nineteen volunteers (nine females and ten males between the ages of 24 and 74). All participants were healthy with no known diagnosed diseases. Around 42% of the participants reported not having any habit of consuming alcohol, while the rest reported having ≥ 1 dose (equivalent to 0.33 L bottle or can of beer/ 4 cL strong alcohol) per week, 47% reported having 1–4 doses, and 11% reported having more than 7 doses of alcohol per week. Most of the participants worked five days per week with 89% having reported desk jobs. Finally, only 16% of the participants reported workout duration for ≤ 1 h per week with the rest being moderate to fairly active individuals. The demographics of the participants along with their age and bmi are presented in the first column of Table 1.

Table 1. Demographics of the participants in the study. The study included 19 participants with 47% being females. We divided the participants into 3 sub groups : Morning types (MT), Neither types (NT) and Evening types (ET) based on the Morningness—Eveningness questionnaires [35]. The NTs had lower bmi compared to the other groups. N stands for the number of participants, SD is for Standard Deviation, IQR for Inter Quartile Range and BMI stands for Body Mass Index.

	All	Morning Type (MT)	Neither Type (NT)	Evening Type (ET)
N	19	7	8	4
Female Percentage	47%	57%	38%	50%
Mean age (SD)	37.9 (11.8)	35 (6.75)	42.8 (15.9)	33.3 (6.23)
Median age (IQR)	34 (30.5–40)	34 (28.8–41.2)	37 (29.4–56.1)	34 (30.8–36.3)
Mean BMI (SD)	24.8 (3.44)	25.8 (4.5)	23.1 (2.5)	26.5 (1.4)
Median BMI (IQR)	24.4 (23.1–26.5)	24.61 (21.7–29.9)	23.01 (20.9–25.2)	27 (24.4–28.7)

From Oura rings, we collected daily bedtimes and awake times of the participants, along with night sleep metrics such as the duration of sleep stages and sleep scores. The ring specifies the durations of the different sleep stages within a sleep event: deep, light, rapid eye movement (REM), and awake; and it also provides a hypnogram that classifies the sleep stages every five minutes. An example of the sleep stages within one night sleep event is shown in Figure 1. It also assigns a sleep score to each sleep event taking into account several sleep-related metrics. In addition, the ring automatically detects activities such as walking, running, and cycling and the number of steps taken per day by the individual. It assigns an activity score based on several activity-related metrics. Each of the metrics for both the sleep score and the activity score have different weights, and since we have not found any public description of the algorithms for their scoring methods, we consider the score data provided by the ring for the purpose of this paper (see Figure A5 for correlation with other variables). All the variables used in the present study along with their explicit definitions have been provided in the Table 2.

Along with objective data collected from the rings, the participants were required to answer the standard morningness-eveningness questionnaire (MEQ) [35] developed by Horne and Ostberg to get their chronotype and resulted in seven MTs having MEQ scores between 59–86, eight NTs with scores between 42–58, and four ETs having scores between 16–31. The demographic information of each of these groups are provided in Table 1. A total of nine surveys were conducted during the study period spanning from “January 2024” to “September 2024” and sent at the end of each month ensuring a minimum of two weeks gap between two consecutive questionnaires to obtain subjective perspective of the participants on their stress levels. Participants received one questionnaire over a period of nine months, ensuring temporal spacing between responses to reduce recall bias and participant fatigue. For the present paper, we tracked the stress of the participants through the question “Stress refers to a situation in which a person feels tense, restless, nervous or anxious or has difficulty sleeping when things are constantly bothering his mind. Think about the last 2 weeks. Have you felt this kind of stress during that time?” with the options being “Not at all”, “Just a little”, “Somewhat”, “Quite a lot”, and “Very much” which were converted to continuous numerical scale for modelling purposes with 1 being not stressed at all and 5 being very stressed. In

Table 2 we have summarised all the variables and their definitions discussed in this section along with variables that have indirectly contributed to the study through the sleep and activity scores.

Table 2. Definitions of variables used in the present study. The variables that are bolded have been used directly in the present study. The sleep score and the activity score are assigned by Oura company utilising a variety of sleep and activity metrics. The variables that contribute to the sleep scores and the activity scores have been marked with ζ and Λ , respectively. The variables marked by ϕ are calculated specifically for the study and those by τ is a response variable obtained from the participants every month through questionnaires.

Variable	Definition
Bedtime start	Start (date and time) of night sleep event
Bedtime end	End (date and time) of night sleep event
Light sleep duration	Duration of light sleep within a sleep event in seconds
Time in bed duration	Duration of time spent in bed within a sleep event in seconds
Sleep score	Daily sleep score (an integer between 1 and 100)
Total sleep duration ζ	Total sleep duration within a sleep event in seconds that includes light, REM and deep sleep duration.
Total Sleep Efficiency ζ	Percentage of time spent asleep while in bed.
Restfulness ζ	A score (1–100) based on body movement during sleep events with low scores indicating a more restless sleep affecting overall sleep quality.
REM sleep duration ζ	Duration of Rapid Eye Movement (REM) phase within a sleep event in seconds
Deep sleep duration ζ	Duration of deep sleep phase within a sleep event in seconds
Sleep latency ζ	Time taken to fall asleep after going to bed in seconds
Timing ζ	A score (1–100) defined to indicate how optimal one's bedtime and wake up time are taking chronotype into account.
Activity score	Daily activity score (an integer between 1 and 100)
Stay Active Λ	A score (1–100) based activity in the last 24 h with lower scores indicating a more sedentary day.
Move every hour Λ	A score (1–100) based on how long a person has remained passive (for example sitting, etc.) in the last 24 h.
Meet daily goals Λ	A score (1–100) based on how well an individual has reached their daily goal activities in last 7 days.
Training frequency Λ	A score (1–100) based on how often an individual has been participating in medium and high activity exercise in the last 7 days.
Training volume Λ	A score (1–100) based on how much time an individual has spent in exercising (medium and high activity periods) in the last 7 days.
Recovery time Λ	A score (1–100) based on rest days in the last 7 days. Higher numbers indicate optimal number of rest days taken helping in recovery.
Steps	Total number of steps taken in a day
Mid sleep time (MST) ϕ	Mid point time of a night sleep event in hours.
Sleep diversity index (SDI) ϕ	Percentage of total sleep time spent moving between different stages of sleep (i.e., deep, light, REM and awake stages) as shown in Figure 1 (See Section 2.4.1)
Perceived Stress τ	Response to the question “Stress refers to a situation in which a person feels tense, restless, nervous or anxious or has difficulty sleeping when things are constantly bothering his mind. Think about the last 2 weeks. Have you felt this kind of stress during that time?” with answer options: (1) “Not at all”, (2) “Just a little”, (3) “Somewhat”, (4) “Quite a lot”, and (5) “Very much”.

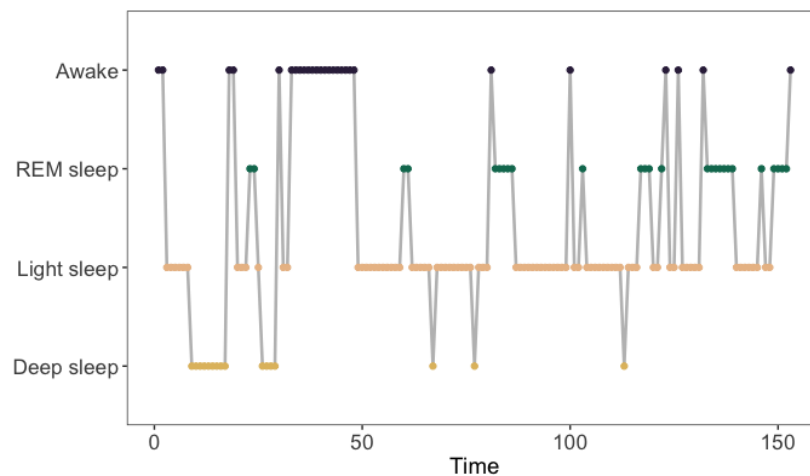


Figure 1. Example of a sleep hypnogram provided by Oura ring. The different stages of sleep recorded during night time sleep is displayed. Each time point in the x-axis represents an interval of five minutes. The four stages of sleep are shown in the y-axis.

2.3. Data Preprocessing

For the sleep data, the nights spent in Finland by the participants were considered for analysis. In addition, sleep data of nights during public national holidays of the country was removed from this analysis. This was done to eliminate irregular sleep schedules that may happen due to vacations and holiday celebrations. We opted for night-time sleep events (i.e., sleep that starts from 20:00 h or later) that lasted at least 4 h and were labelled by Oura as a “long sleep”. If a long sleep event occurred during the day, then they were not considered for this analysis. This resulted in a total of 5637 nights for all 19 participants in the study with the mean number of nights per participant being 296.7 and 70.6 as the standard deviation. For the activity data, we removed only Finnish public holidays from our analysis and were left with the total of 6182 days with the mean number of days per participant being 325.3 and 62.8 being the standard deviation. We calculated averages of sleep metrics over nights for participants within each chronotype group and aggregated daily activity for each day within each group, rather than between individuals, due to the low number of participants. We also conducted between-individual averages and found similar patterns in the activity and sleep. To assess the effects of sleep and activity on the stress of participants we took the averages of activity and sleep metrics fourteen days before the participant answered the stress-related question. For this purpose, in the statistical analysis, we included night sleep and the steps taken during the holidays as well.

2.4. Methods

2.4.1. Sleep Diversity Index

The sleep diversity index (SDI) uses Shannon entropy to capture the diversity of sleep stages, thus quantifying sleep disruptions within a sleep event. It is defined as the percentage of total sleep time that was spent moving between different stages of sleep [43]. A previous study has shown that SDI is positively correlated with the sleep fragmentation index and negatively correlated with efficiency. It is calculated from an individual sleep hypnogram as shown in Figure 1. The Oura ring can detect four stages of sleep (deep, light, REM and awake) and in each of the sleep sessions of an individual. Each data point constitutes five minutes of sleep time.

We consider a sampling frequency of 40 min that allows for a maximum of 8 data points within each “analysis window” and calculate the Shannon entropy in them as described in Ref. [43] using the following equations:

$$H' = - \sum_{i=1}^S \frac{n_i}{n} \log_2 \frac{n_i}{n} \quad (1)$$

where n_i represents the number of times a sleep stage occurs within a sampling window and n is the total number of sleep stages. S is the total number of samples in each sleep session. If n_i out of n for all i , is in the awake stage, then $H' = \max(H')$. The sleep diversity index is then calculated by the following formula:

$$SDI = \frac{\sum_{(j > H'_{max}/2)}^{H'_{max}} H'_j}{\sum_{j=1}^N H'_j} \times 100 \quad (2)$$

where H_j is the entropy of the sample j . Higher values of SDI mean more fluctuations within a sleep session.

2.4.2. Model

Since we have repeated measures of each individual, we have used the random intercept linear mixed effects (LME) model [44] in R using the packages “lme4” and “lmeR” to model longitudinal stress [45]. The participants answered the questions on vastly different days. Therefore, we considered the averages of the time spent in bed on weekdays and weekends separately, fourteen days before the date each of them answered the surveys. This method ensured that the latest objective measurements of sleep were considered as predictors of perceived stress. Additionally, if we did not find data for the fourteen days before the survey answer date, we replaced it by averaging the metric over the entire month. For each individual, we analysed data across nine time points using the random intercept model. The survey answer time, chronotype, and time in bed were included as fixed covariates, while random effects were incorporated to allow each individual to have their own intercept. We have used the following sequence of models to find whether different factors and their possible correlations had significant effect on longitudinal stress:

$$\text{Null model: } y_{it} = \beta_0 + u_{0i} + \epsilon_{it}, \quad (3)$$

$$\text{Intermediate model 1: } y_{it} = \beta_0 + \beta_1 Z_1(\text{Time}) + \beta_2 Z_2(\text{Time}) + u_{0i} + \epsilon_{it}, \quad (4)$$

$$\begin{aligned} \text{Intermediate model 2: } y_{it} = & \beta_0 + \beta_1 Z_1(\text{Time}) + \beta_2 Z_2(\text{Time}) + \beta_3 \text{Type} \\ & + \beta_4 TIB_{wd} + \beta_5 TIB_{we} + u_{0i} + \epsilon_{it}, \end{aligned} \quad (5)$$

$$\begin{aligned} \text{Final model: } y_{it} = & \beta_0 + \beta_1 Z_1(\text{Time}) + \beta_2 Z_2(\text{Time}) + \beta_3 \text{Type} \\ & + \beta_4 TIB_{wd} + \beta_5 TIB_{we} + \beta_6 \text{Age} + \beta_7 (\text{Age} \times \text{Type}) + u_{0i} + \epsilon_{it}, \end{aligned} \quad (6)$$

where y_{it} is the perceived stress for each individual i at time point $t \in \{1, 9\}$ modelled as a dependent variables on a continuous scale. Type represents the chronotype of the individual, which is a categorical variable (MT, NT, and ET), and $TIB_{wd/we}$ stands for the time spent in bed on a weekday or a weekend day, respectively, detected by the ring during a sleep event. $Z_1(\text{Time})$ and $Z_2(\text{Time})$ are transformations of Time and Time^2 in an orthogonal way to reduce collinearity and represent independent linear and quadratic trends, respectively. In the Final model, $(\text{Age} \times \text{Type})$ represents the interaction term between the age of the individuals and the chronotype groups. u_{0i} is the random intercept for each individual and ϵ_{it} is the residual error term. β_0 is the overall mean stress level, β_1 and β_2 capture the linear and non-linear time effects, β_3 models the group effect of chronotypes, β_4 and β_5 capture the effects of time spent in bed during weekdays and weekends, and finally, β_6 and β_7 models the effects of age and the chronotype and age interactions, respectively.

Ethics Approval Statement

This study design was reviewed and approved by the Aalto University Research Ethics Committee (approval id: D/134/03.04/2023). All participants were provided with a detailed information sheet about the study, along with the privacy notice, and written informed consent was obtained via consent forms at the beginning of the study.

3. Results

3.1. Differences in Sleeping Patterns among Chronotypes

In the present study we first observe the known differences in the sleeping patterns of the participants' chronotypes. The MST for all chronotypes on free days is depicted in Figure 2a. It is well known that humans tend to follow their own circadian rhythms on free days due to experiencing less effect of work or study-related schedules [37] (See also the weekly variation of the MSTs in Figure A1a in the Appendix A). A similar pattern is also observed for work days, but is not shown in the present manuscript. The MSTs for ET individuals are observed to be significantly later in the study period compared to MT or NT. A seasonal variation is also observed for all chronotypes with individuals having late MSTs during winter and summer holidays, as can be seen from the seasonal indices shown in Figure A2 in the Appendix A.

In Figure 2b we have shown the average monthly sleep scores for the different chronotypes. Although we observed the worst sleep scores for ETs compared to other chronotypes, they were found to make significant progress in their sleep scores during the course of the study. Some of the sleep metrics used to measure sleep scores are plotted in Figure A3 in the Appendix A.

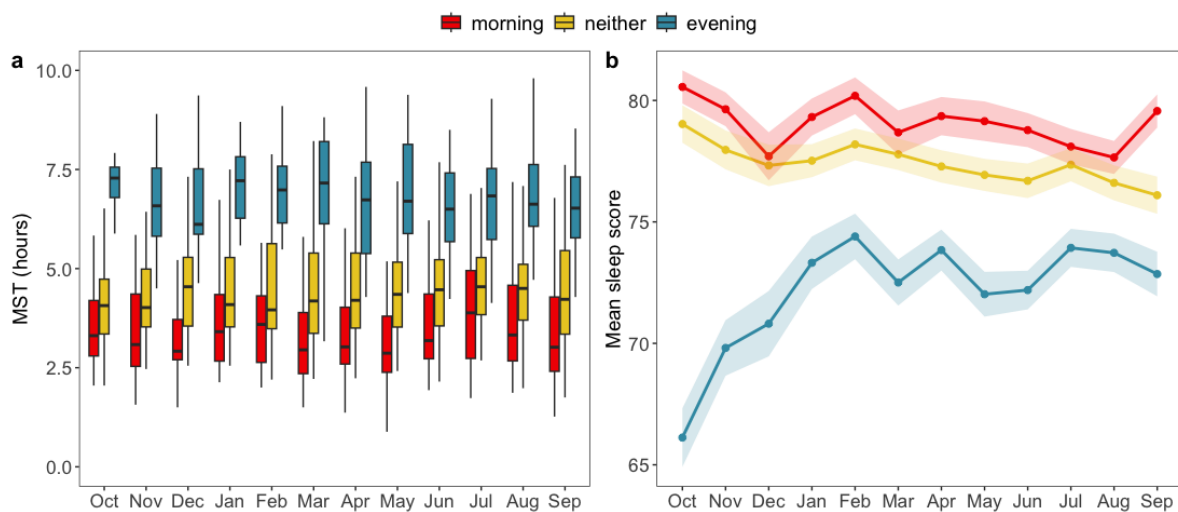


Figure 2. Mid sleep time (MST) and sleep scores of the chronotypes. (a) Evening-types (ET) in blue have later MSTs while morning-types (MT) in red have earlier MSTs when compared with neither-types (NT) in yellow. We observe seasonal changes in all chronotypes for winter and summer holidays, showing later MSTs as can be seen from Figure A2 in the Appendix A. (b) The sleep scores of the Oura ring takes into account several different sleep metrics for scoring as displayed here. ETs are observed to have poorer sleep scores when compared to other chronotypes, but their scores improve considerably with time. The shaded region around the line plots show the 95% confidence interval of the data.

In Figure 3a we have plotted the monthly variation of the SDI. A higher value of SDI suggests more disruptive sleep (i.e., a worse sleep quality) and we observe that NTs have better quality sleep throughout the year compared to both ETs and MTs. Additionally, ETs have better SDI values towards the latter part of the study. In the weekly variation in Figure 3b we observe that sleep quality for ETs and NTs is more disruptive toward the end of the week, while MTs are able to maintain their sleep quality. Since each data point in the hypnogram is five minutes, we considered a sampling frequency of 40 min for the SDI calculation, which ensures a maximum of eight data points within each sampling. We also carried out the same analysis using a smaller sampling frequency of 20 min and is shown in Figure A4 in the Appendix A. In the latter case, we observe similar trends but higher fluctuations in the values.

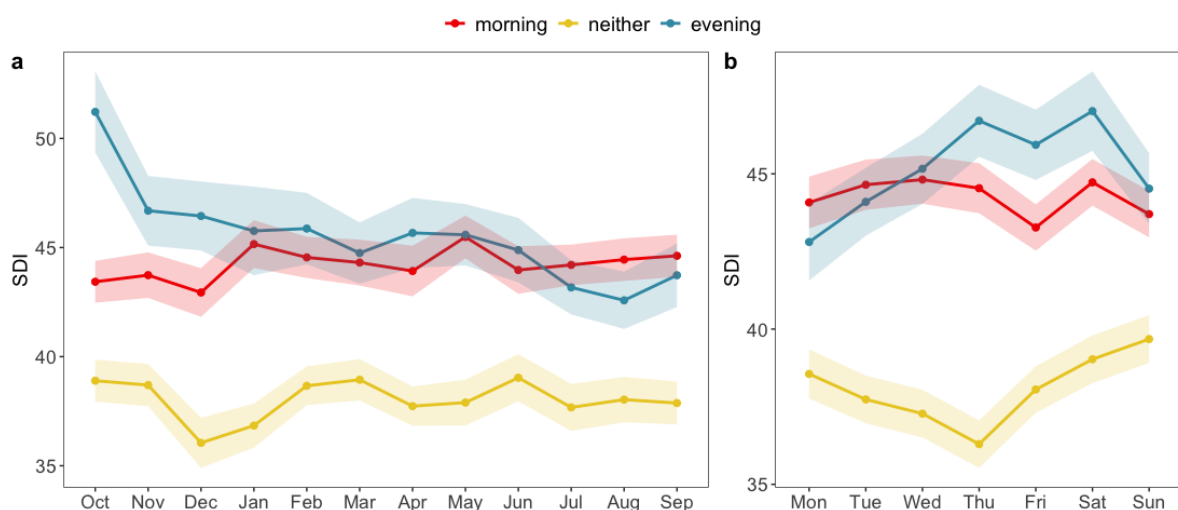


Figure 3. Sleep diversity index (SDI). The SDI is calculated using Shannon entropy from Equations (1) and (2) utilising sleep hypnograms (see Figure 1) such that the number ranges from 1 to 100. Higher values indicate a more fragmented sleep during the night time. We find that NTs display lowermost values throughout the (a) year, as well as (b) on a weekly basis indicating better sleep quality than both MTs and ETs. The shaded regions represent 95% confidence interval. The ETs had poorer values of SDI at the start of the study, but improved with time. We also observe that the ETs regularly have poorer quality sleep towards the later part of the week.

We have also investigated the differences in sleep scores, sleep latency, SDI, and total sleep duration during daylight saving time (DST) changes both in the autumn (29 October 2023) and spring (31 March 2024). Since the changes occurred on Saturday-Sunday night we present the average of nights from Monday to Saturday before and after change in the DST as shown in Figure 4 (Note that if any of the volunteers were found travelling outside of Europe around this time, then they were not included in the DST calculations). Even though the number of participants are small, we find that during autumn the latency for NT individuals seem to decrease significantly and the sleep scores and total sleep duration of MT individuals seem to decrease significantly as well. In the spring we did not find any significant changes in the sleep metrics.

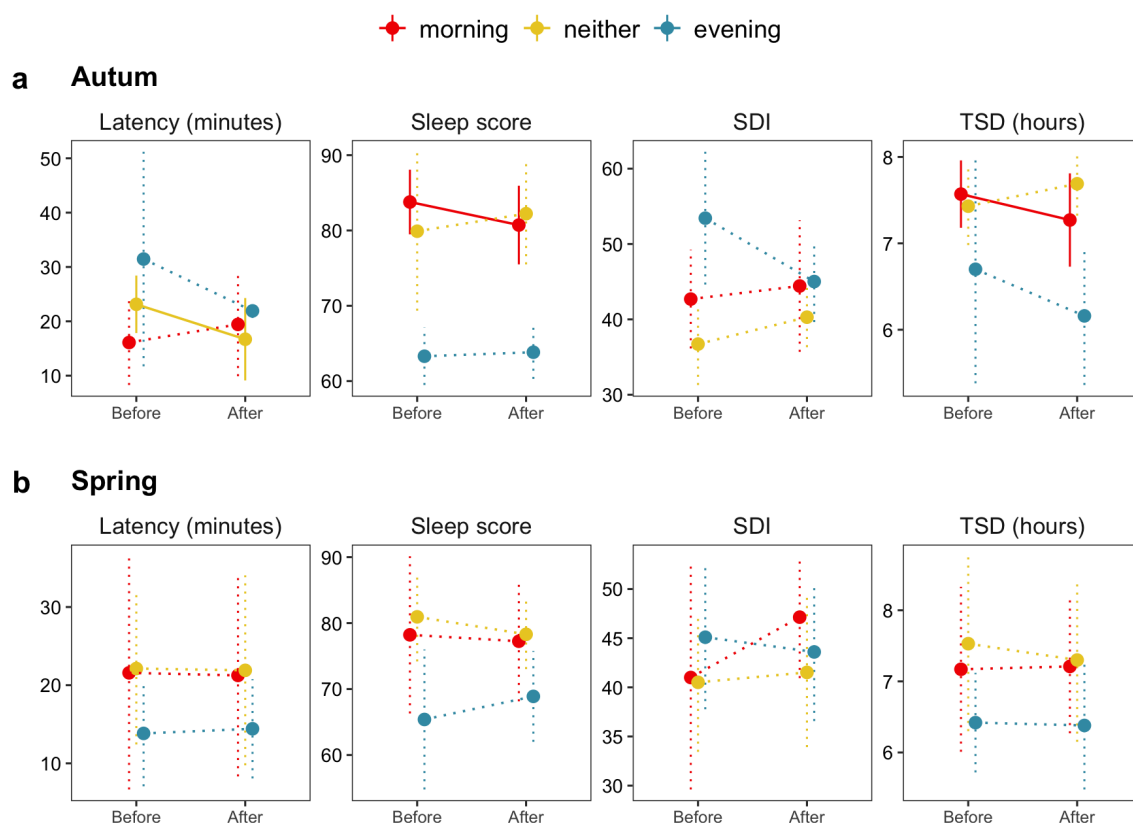


Figure 4. Daylight saving time. Differences in the mean sleep metrics (sleep score, latency, Sleep Diversity Index (SDI), and Total sleep duration (TSD)) measured by the Oura rings among the chronotypes six days before and six days after the time is changed in the autumn and spring. The most significant changes ($p < 0.05$) are shown as solid lines and the non significant changes are displayed as dotted lines. Despite small number of participants, we find significant decrease in the sleep scores and TSD among MT individuals, as well as a significantly reduced latency among NT individuals round the autumn DST change. We did not find any significant differences round the spring DST change. The corresponding table containing paired t-statistics comparing the before and after changes have been reported in Table A1 in the Appendix A.

3.2. Activity Differences among the Chronotypes

The monthly variation in the activity scores recorded by the Oura ring for each day is plotted in Figure 5a. We find that while ETs scored low values at the beginning of the study, they increased with time while the other chronotypes maintained steady scores. We observe mainly two peaks for NTs and MTs during February-March and during the month of May. A significant jump in sleep scores was observed in January for ETs. The weekly variation is shown in the inset of the figure and we observe that ETs and MTs have better scores on weekends than on weekdays. The total number of steps taken by participants each day and its monthly variation is plotted in Figure 5b. The weekly variation of the steps are shown in the inset and all chronotypes are observed to have low steps on the weekends compared to the weekdays. NTs have maintained the highest step counts throughout the duration of the study and MTs and ETs have increased the average monthly step counts over time. Here we also observe peaks in the average steps for NTs and MTs and an overall increasing trend for ETs till May. The summer months of June and July are observed to be a period of low activity for the volunteers in the study.

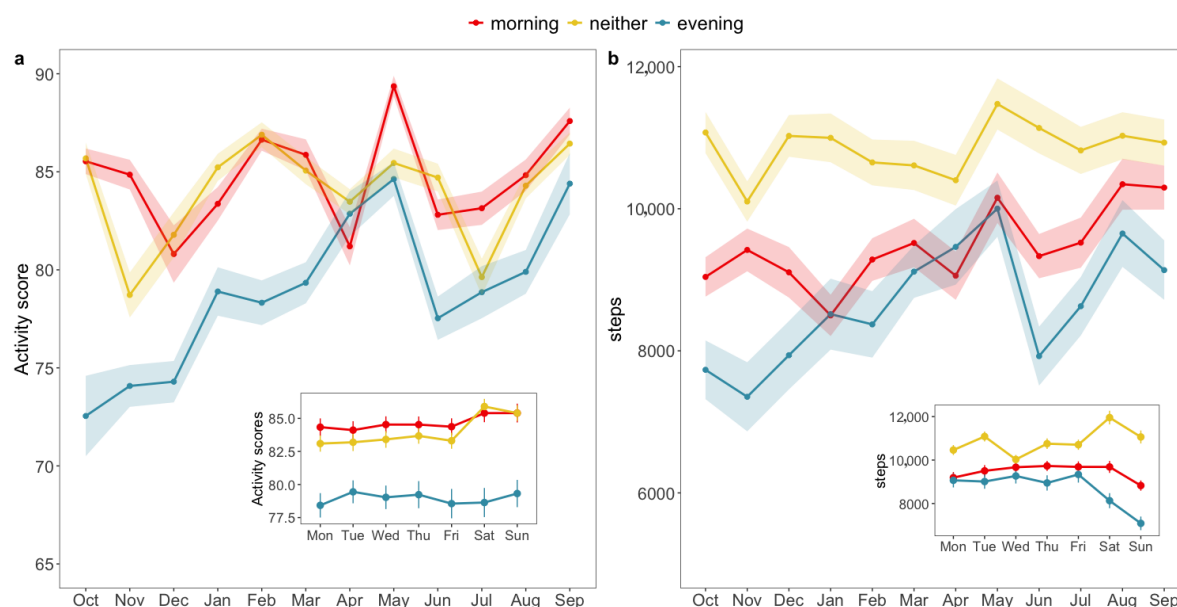


Figure 5. Activity scores and steps. The monthly variation of the activity scores throughout the study period is shown in (a) along with the weekly variation in the inset of the figure. The ETs have low scores in the beginning but their scores are observed to have increased with time. Peaks in activity scores of the MTs and ETs coincide with the annual summer and winter activity schedules of Finland. A similar trend is observed in the average monthly steps taken by the participants as shown in (b). NTs have maintained higher number steps when compared with other chronotypes and MTs and ETs are observed to have improved their average of steps by the end of the study.

3.3. Subjective Stress from Questionnaires

We conducted a total of nine monthly questionnaires from January 2024 till September 2024 and tracked the subjective perception of stress. The coefficients of the models discussed in the Methods section with comparison statistics are listed in Table 3. Based on likelihood ratio tests, the final model has the best fit and also the lowest AIC. Adding the gender, BMI or step counts did not improve the model and therefore has not been included in the present paper. We find that the survey response time, which was broadly speaking answered on a monthly basis, has a significant non-linear effect on stress. The random intercepts account for the individual variability in the stress. Spending more time in bed during the weekdays is associated with lower reported stress levels. In Intermediate model 2, we find that the NTs have significantly lower stress than the reference group (MT), but the ETs do not differ significantly from them. However, in the Final model, when the interaction term of chronotype with age was added, we observed a significant interaction effect indicating that the association between age and stress differed significantly across chronotype groups. Older individuals in the NT and ET groups reported lower stress compared to older individuals in the MT group after adjusting for non linear effects of time, time in bed, and individual level random effects.

Table 3. Summary of the coefficients of the Linear Mixed Effects models for predicting stress. The Time variable here refers to the nine time points when the questionnaires were answered by the participants. $Z_1(Time)$ and $Z_2(Time)$ capture the non-linear trends of stress with time and has a significant effect. The superscript ^a indicates that the reference group for chronotype is the MT group. SD, SE and ICC in the table refer to Standard deviation, Standard error and Interclass correlation coefficient. The significance levels are as follows: $p < 0.01$ (**), $p < 0.05$ (*). The models utilise individual variation in the form of random intercepts of stress. The correlations between the fixed effects is displayed in Table A2 in the Appendix A. More time spent in bed on the weekdays cause less stress among the individuals. Through the Final model we observe that, both older ET and NT individuals reported lower stress compared to older MT individuals.

	Null Model	Intermediate Model 1	Intermediate Model 2	Final Model
Random effects	Variance (SD)			
Participant intercept	0.38 (0.61)	0.39 (0.63)	0.37 (0.61)	0.16 (0.40)
Residual	0.64 (0.8)	0.56 (0.75)	0.54 (0.74)	0.54 (0.74)

Table 3. Cont.

	Null Model	Intermediate Model 1	Intermediate Model 2	Final Model
Fixed effects	Coefficients (SE)			
$Z_1(\text{Time})$		−2.40 (0.76) **	−2.24 (0.75) **	−2.29 (0.75) **
$Z_2(\text{Time})$		2.33 (0.76) **	2.25 (0.75) **	2.19 (0.75) **
Neither type ^a			−0.80 (0.35) *	−0.80 (0.27) *
Evening type ^a			−0.23 (0.43)	−1.05 (0.39) *
Time in bed (Weekday)			−0.21 (0.10) *	−0.29 (0.10) **
Time in bed (Weekend)			0.10 (0.09)	0.09 (0.08)
Age				0.53 (0.33)
Neither type ^a × age				−0.88 (0.36) *
Evening type ^a × age				−2.01 (0.59) **
Model fit statistics				
AIC	410.92	396.36	394.33	383.50
BIC	420.07	411.61	421.77	420.10
Log Likelihood	−202.46	−193.18	−188.16	−179.75
ICC (adjusted)	0.37	0.41	0.41	0.228
ICC (unadjusted)	0.37	0.38	0.33	0.149

4. Discussion

In this study, we have used Oura rings to track nineteen individuals for one year and observed monthly and weekly variations in their sleep and activity patterns. Through our results of sleep and activity data, we have found some distinct seasonal patterns across all chronotypes. Consistent with past literature on seasonality [46,47] as well as weekly effects [48] in chronotype groups, we find that ETs have greater variation in their sleep and activity compared to MTs and they consistently sleep later than MTs and NTs. It is a fairly well established result that the way ETs sleep late is more related to biological rhythmic cycles than to a voluntary lifestyle choice [49,50]. In our study, having healthy participants with no known disease diagnosed, ETs were found to have sleep and activity metrics that are not as high as the MTs and NTs, which aligns well with previous studies [48]. However, during the duration of the study, the ETs have made significant improvements in their sleeping and activity habits. While they continued sleeping at later hours, their sleep scores increased considerably in the middle of the study along with the total duration of sleep. We conducted a final questionnaire at the end of the study period regarding the individual experiences, answered by fourteen out of the nineteen participants. When asked whether they were able to “follow their natural circadian rhythms” by adjusting their schedules and activities to match their inherent rhythms, all of them answered either “sometimes” or “often”. This sentiment is also observed from the data. We observe that their sleep quality has also improved with time.

We find similar increase in the activities of ETs and a noticeable jump in January may indicate the impacts of New Year resolutions for ETs. Interestingly, the double peaks in the activity scores are indicative of various sports activities that are played around this time in Finland. Finland has a short skiing holiday in February or March and people also participate in several outdoor activities during the end of spring. Similar trends are also observed in the average monthly steps taken by the participants. A noticeable fall of activity scores and steps during the summer holiday months (June and July) for all chronotype groups could be an indication of a popular aspect of Finnish culture in which individuals visit their summer cottages with their families. In addition, we find that a longer time spent in bed for night sleep cause less stress among participants and that age is significantly associated with chronotype groups. Although our model shows a non-linear relationship of stress with time, it should be noted that there may be several factors that directly or indirectly affect the feeling of stress. While we believe our longitudinal survey approach gives us some insight on subjective stress, it is a rather multifaceted issue and influenced by environmental as well as psychological factors, among others. For this reason, it may be difficult to capture the confounding factors causing stress with just one question. In the future, we plan to use standardised stress related questionnaires and more streamlined sampling approaches for both objective and subjective measurements of stress.

We have also studied how the chronotypes are affected by the DST changes, especially in the context of Finland, since the sunlight hours change drastically around this time of the year. In the spring the clock is turned forward by one hour and in autumn the clock is turned back by one hour. This change is known to cause disruption to individuals’ sleep habits [51–53]. In our study, we find that while MTs and ETs experience opposite effects of

change due to DST, and the most significant changes are observed to occur round the autumn DST change. During this change, NTs show significantly lower sleep latency. The MTs also show significantly decreased sleep scores and total sleep duration. For the spring-time DST change we do not observe any major changes in any of the sleep metrics measured. The DST change is currently adopted in several countries around the world and past research has suggested that these changes may affect sleep quality, especially among individuals that do not or are not able to follow proper sleep hygiene regularly [53]. In our current study, we also find lower sleep quality for MT individuals; however, we cannot conclude whether ETs are adversely affected by this change or not. For future studies on this matter, we plan to use more health metrics collected by the rings and other devices to provide a more comprehensive picture of the potential disruptions in sleep around DST.

While our study identifies several key differences across the chronotype groups, along with seasonal and weekly changes among the participants, however, their limited number restricts the generalizability of the study. Moreover, the specific geographical location where the study was conducted, may cause seasonal changes specific to the region. Nonetheless, our study showcases valuable outcomes with respect to the use of wearables for longitudinal tracking of chronotypes in naturalistic settings. In the future we will focus on larger group of participants for generalizability purposes.

5. Conclusions

Smart wearables and fitness trackers have already been proven to be versatile tools to study well-being related attributes of individuals in a non-invasive manner [6–9]. The Oura rings used in the present study enabled us to collect objective physiological data from participants in realistic settings, thereby providing a unique long-term perspective to investigate the chronotypes of individuals. One of the strengths of the present study is the finding that even though ETs among chronotypes seem to be most susceptible to health related issues due to misalignment of circadian rhythms, wearables could serve as the means towards healthier habits. Our findings suggest that these non-invasive devices with associated applications could be used to find ways to enhance health habits and maintain them.

Author Contributions

C.R.: conceptualization, methodology, data curation, writing—original draft preparation, reviewing and editing, visualization, investigation; K.B.: writing—reviewing and editing; K.K.: writing—reviewing and editing, supervision. All authors have read and agreed to the published version of the manuscript.

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Institutional Review Board Statement

This study design was reviewed and approved by the Aalto University Research Ethics Committee (approval id: D/134/03.04/2023).

Informed Consent Statement

Informed consent was obtained from all subjects involved in the study.

Data Availability Statement

The dataset contains personal and sensitive data from human participants and, therefore, cannot be publicly shared due to privacy/ethical restrictions. Anonymized and aggregated data to reproduce the results from the paper can be provided upon reasonable request from the authors.

Conflicts of Interest

The authors declare no conflict of interest.

Use of AI and AI-Assisted Technologies

During the preparation of this work, the authors used AI assisted writing tools solely to correct grammatical errors in the text. After using this tool, the authors reviewed and edited the content as needed and take full responsibility for the content of the published article.

Appendix A

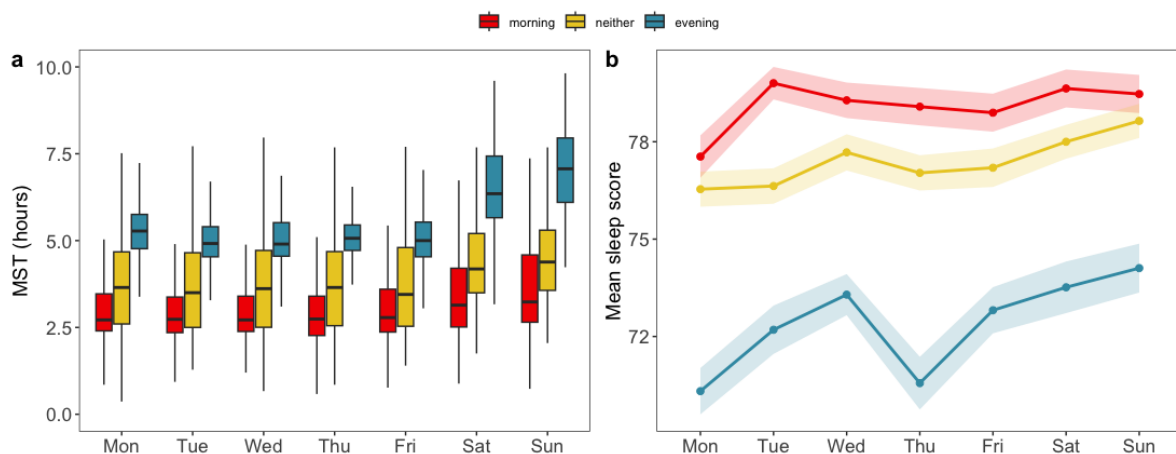


Figure A1. Mid sleep times on weekly basis. The MSTs of all chronotypes follow different patterns on weekdays and weekends. **(a)** On weekends the MST of all chronotypes are later than on weekdays. **(b)** The sleep scores also show an increasing trend towards the weekends.

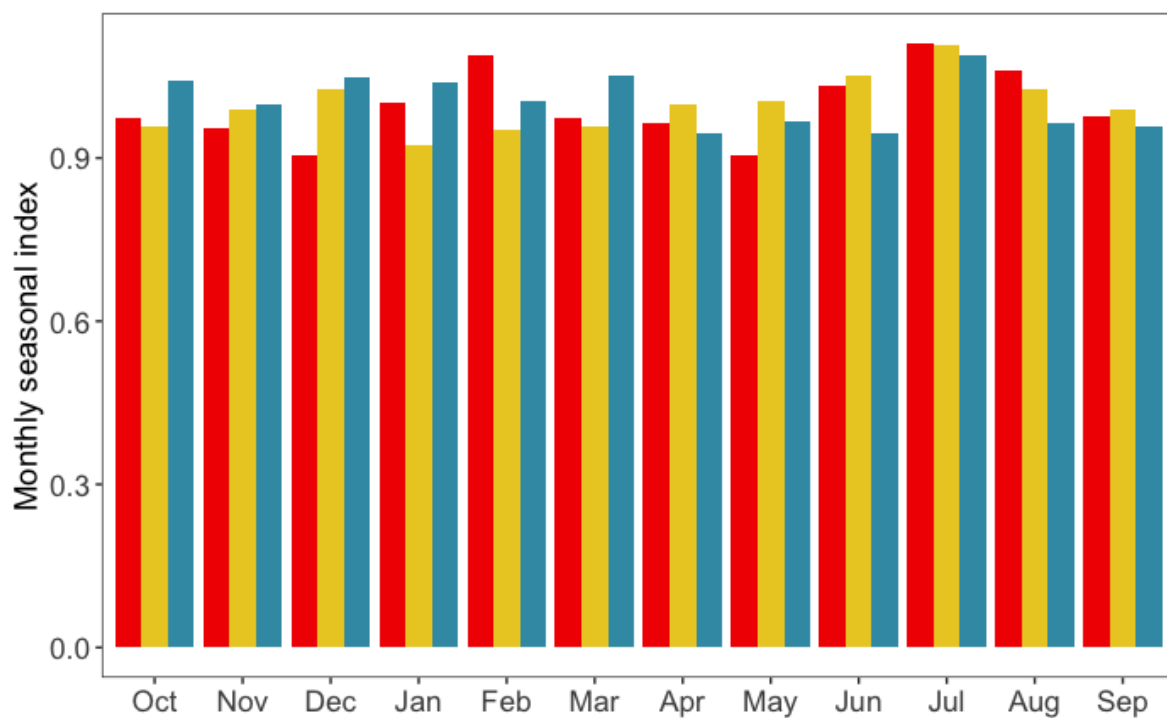


Figure A2. Monthly seasonal indices of the MSTs across chronotypes. A bar chart showing the seasonal indices for each month to show how much the values deviate from the overall average values in each group. The seasonal indices are calculated as monthly mean/overall group mean. A clear peak can be seen during summer time indicating that all the participants slept at later hours around that time. The colour coding is same as all other figures in the paper.

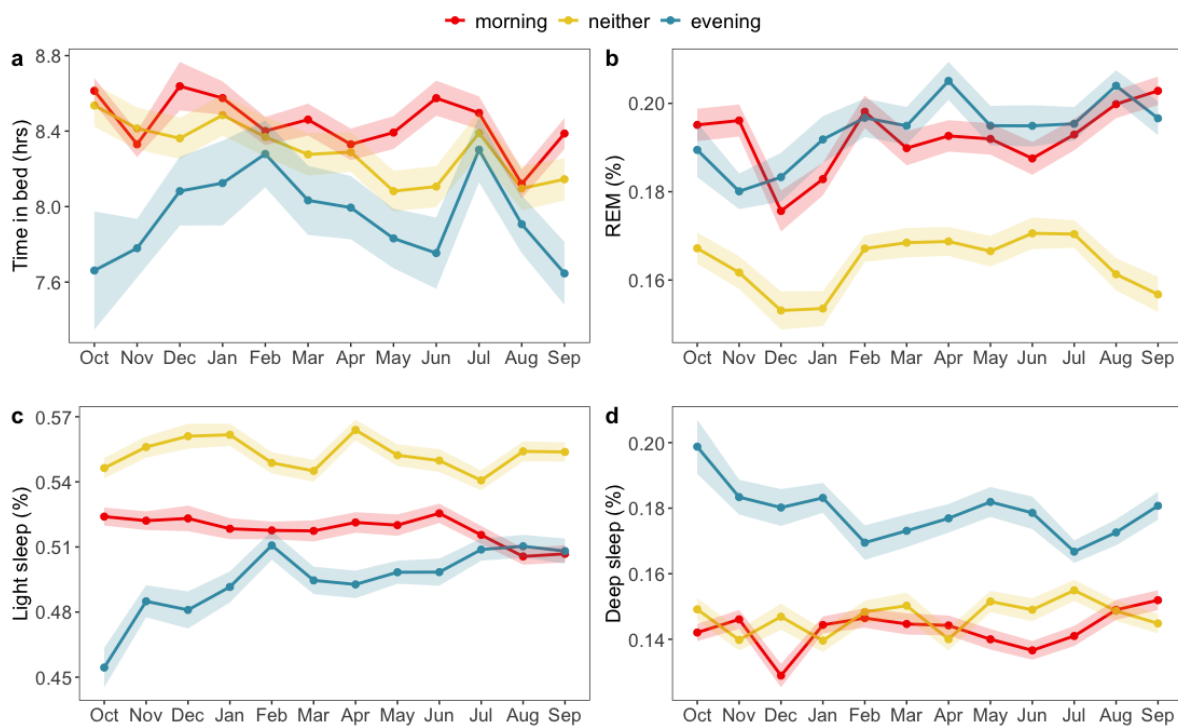


Figure A3. Some of the sleep metrics that are detected by Oura rings and used to calculate the sleep scores. In (a) we have shown the time spent in bed during night sleep events. We observe double peaks during winter and summer holiday times with a decreasing trend during the spring time. In (b–d) the percentage of night sleep time spent in REM, light and deep sleep stages out of the total sleep duration respectively are displayed.

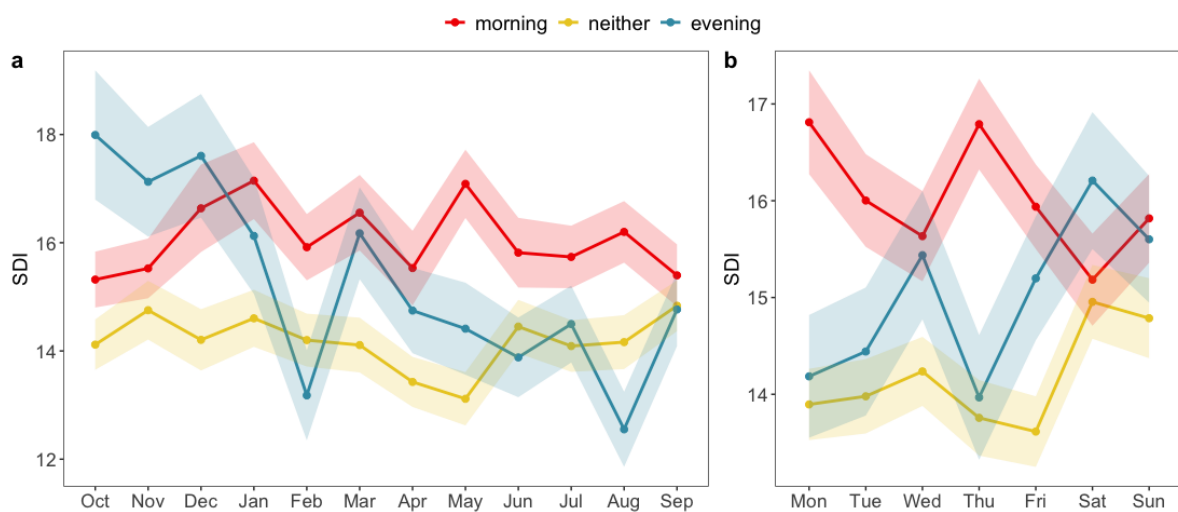


Figure A4. SDI for 20 min sampling frequency. The SDIs calculated from a shorter epoch has more variation but overall shows similar trends as the 40 min epoch. (a) The ET had an improving sleep quality over the months and the MT and ET had stable values. (b) On a weekly basis, the ETs and the MTs observe higher SDI towards end of the week, while MTs remain stable overall.

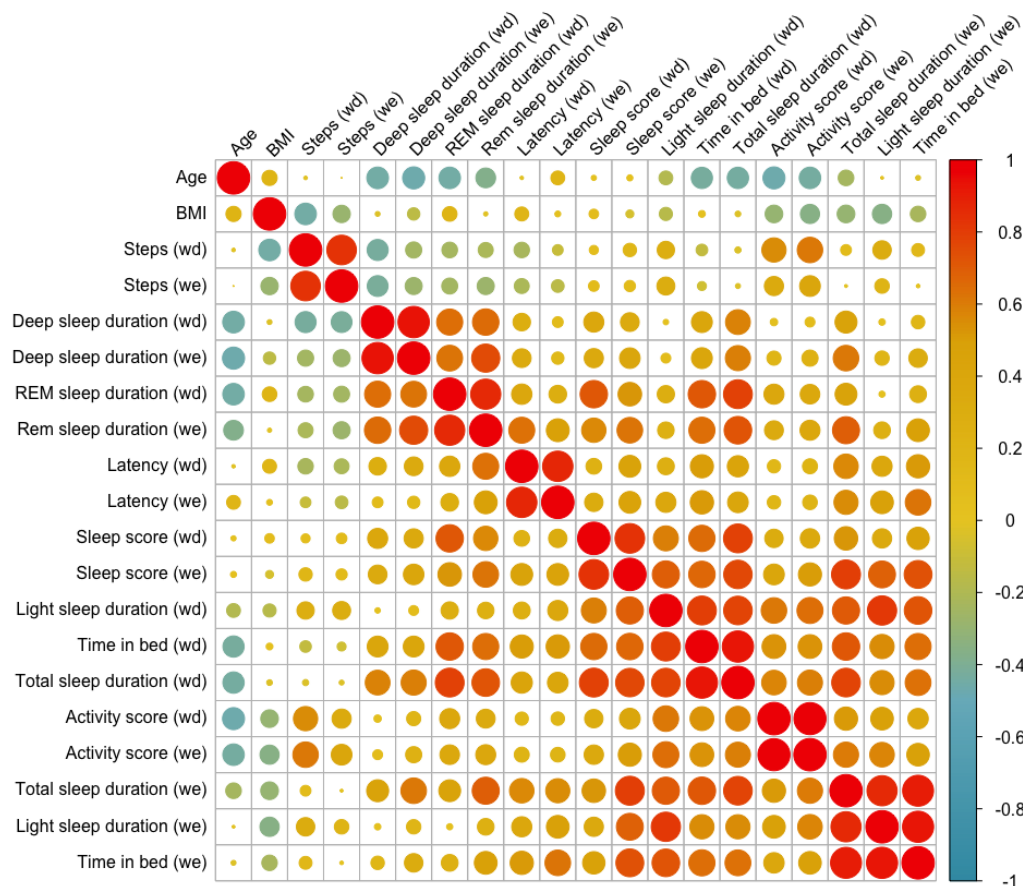


Figure A5. Correlation plots of the variables from used in the study along with the age and body mass index (BMI) of the volunteers. The sleep metrics are mostly correlated with each other and so we chose only one variable (time in bed) as a covariate for the model.

Table A1. Mean and standard deviations of the sleep metrics before and after DST change. The table shows mean values along with the standard deviations of six days before and after the DST change in both Autumn and Spring. We find significant changes in the case of autumn DST change when the clock is moved backward by one hour. Despite small number of participants we observe significant decrease during Autumn DST change for the morning type individuals' (6 participants) sleep scores and total sleep durations. Neither type individuals (5 participants) have significant decrease in their latency. No significant changes were observed for evening type individuals.

	Autumn				Spring			
	Before	After	t (df)	p Value	Before	After	t (df)	p Value
Latency (minutes)								
morning	16.10 ± 7.82	19.43 ± 9.53	−1.70 (5)	0.149	21.58 ± 14.92	21.25 ± 12.92	0.09 (5)	0.930
neither	23.13 ± 5.29	16.70 ± 7.58	2.90 (4)	0.044	22.13 ± 9.71	21.90 ± 12.15	0.11 (6)	0.920
evening	31.46 ± 19.74	21.92 ± 1.30	0.73 (1)	0.598	13.83 ± 6.77	14.42 ± 6.35	−0.71 (2)	0.551
Sleep score								
morning	83.78 ± 4.29	80.72 ± 5.22	4.03 (5)	0.010	78.22 ± 11.92	77.25 ± 9.11	0.31 (5)	0.770
neither	79.90 ± 10.55	82.23 ± 6.73	−1.01 (4)	0.370	80.95 ± 6.76	78.30 ± 5.27	1.15 (6)	0.295
evening	63.30 ± 3.82	63.83 ± 3.54	−2.67 (1)	0.228	65.39 ± 10.61	68.89 ± 6.89	−1.62 (2)	0.248
Sleep diversity index								
morning	42.69 ± 6.55	44.43 ± 8.74	−0.46 (5)	0.665	41.00 ± 11.39	47.14 ± 6.20	−1.28 (5)	0.256
neither	36.72 ± 5.43	40.29 ± 3.98	−1.36 (4)	0.245	40.51 ± 7.07	41.52 ± 7.60	−0.37 (6)	0.723
evening	53.43 ± 8.81	45.02 ± 5.38	3.47 (1)	0.178	45.10 ± 7.33	43.60 ± 7.03	0.35 (2)	0.757
Total sleep duration (hours)								
morning	7.57 ± 0.39	7.27 ± 0.54	3.62 (5)	0.015	7.17 ± 1.16	7.21 ± 0.94	−0.09 (5)	0.931
neither	7.43 ± 0.45	7.69 ± 0.37	−1.05 (4)	0.351	7.53 ± 1.23	7.30 ± 1.15	1.03 (6)	0.345
evening	6.70 ± 1.32	6.16 ± 0.80	1.50 (1)	0.375	6.42 ± 0.70	6.38 ± 0.90	0.07 (2)	0.952

Table A2. Correlations between the covariates used in the Final model. The superscript ^a indicates that the reference group for chronotype is the MT group.

	$Z_1(\text{Time})$	$Z_2(\text{Time})$	Neither Type	Evening Type	Time in Bed (wd)	Time in Bed (we)	Age	Neither Type ^a × Age
$Z_1(\text{Time})$								
$Z_2(\text{Time})$	0.00							
Neither type	−0.02	0.0						
Evening type	0.01	0.07	0.39					
Time in bed (wd)	−0.07	0.07	0.08	0.24				
Time in bed (we)	0.09	−0.06	−0.15	−0.07	−0.3			
Age	−0.01	0.0	−0.30	−0.22	−0.05	−0.05		
Neither type ^a × age	0.01	0.02	0.20	0.23	0.17	0.07	−0.92	
Evening type ^a × age	0.02	0.02	0.20	0.57	0.14	−0.15	−0.56	0.52

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