Sleep during COVID-19 Pandemic: A Longitudinal Observational Study Combining Multisensor Data with Questionnaires

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Abstract

Background: The COVID-19 pandemic led to various containment strategies, such as work-from-home policies and reduced social contact, which significantly altered people's sleep routines. While previous studies have highlighted the negative impacts of these restrictions on sleep, they often overlook a comprehensive perspective that incorporates other factors that can also influence sleep, namely seasonal variations and physical activity.

Objective: Our study aims to longitudinally examine the fine-grained changes in sleep patterns of working adults during the COVID-19 pandemic using a combination of repeated questionnaires and high-resolution passive measurements from wearable sensors. We investigate the association between sleep and 5 sets of variables capturing characteristics of individuals including (i) demographics, (ii) sleep-related habits, (iii) physical activity behaviors, and external factors including (iv) pandemic-specific constraints, and (v) seasonal variations during the study period.

Methods: We recruited working adults in Finland to participate in our one-year-long study (June 2021 - June 2022) conducted in the late stage of the COVID-19 pandemic. We collected multisensor data from fitness trackers worn by the participants as well as work and sleep-related measures through monthly questionnaires. Additionally, we used the stringency index for Finland at different points in time to estimate the degree of the pandemic-related lockdown restrictions in place during the study duration. We applied linear mixed models to study the changes in sleep patterns during the late stage of the pandemic and their association with the aforementioned five sets of variables.

Results: The sleep patterns of 27,350 nights from 111 working adults were analyzed. We observed that more stringent pandemic measures were associated with longer total sleep time (TST) (?= 0.004, 95% CI 0.002 to 0.006, P<.001) and later midpoint of sleep (MS) (?= 0.02, 95% CI 0.02 to 0.03, P<.001). Being a snoozer (i.e., snoozing the alarm when waking up from sleep) was associated with higher variability in both TST (?= 0.18, 95% CI 0.07 to 0.30, P=.002) and MS (?= 0.19, 95% CI 0.06 to 0.34, P=.008). Service staff slept more than academic staff (?= 0.36, 95% CI 0.10 to 0.61, P=.006) with also lower variability in TST (?= -0.16, 95% CI -0.27 to -0.04, P=.006). Engaging in physical activity later in the day correlated with longer sleep duration (?= 0.03, 95% CI 0.02 to 0.04, P<.001).

Conclusions: Our study provided a comprehensive view of the possible factors affecting sleep patterns during the late stage of the pandemic. Our results revealed that stringent measures implemented during the COVID-19 pandemic are associated with changes in sleep patterns. The more flexible work-life routine arising from the restriction is also linked with changes in sleep-related habits among different occupations.

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Original Manuscript

Original Paper

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We recruited working adults in Finland to participate in our one-year-long study (June 2021 - June 2022) conducted in the late stage of the COVID-19 pandemic. We collected multisensor data from fitness trackers worn by the participants as well as work and sleep-related measures through monthly questionnaires. Additionally, we used the stringency index for Finland at different points in time to estimate the degree of the pandemic-related lockdown restrictions in place during the study duration. We applied linear mixed models to study the changes in sleep patterns during the late stage of the pandemic and their association with the five sets of variables.

Results:

The sleep patterns of 27,350 nights from 112 working adults were analyzed. Stricter pandemic measures were associated with an increase in total sleep time (TST) (β= 0.003, 95% CI 0.001 to 0.005, P<.001) and a delay in the midpoint of sleep (MS) (β= 0.02, 95% CI 0.02 to 0.03, P<.001). Individuals who tend to snooze exhibited greater variability in both TST (β= 0.15, 95% CI 0.05 to 0.27, P=.006) and MS (β= 0.17, 95% CI 0.03 to 0.31, P=.01). Occupational differences in sleep pattern were found, with service staff experienced longer (β= 0.37, 95% CI 0.14 to 0.61, P=.004) and also lower variability in TST (β= -0.15, 95% CI -0.27 to -0.05, P<.001). Engaging in physical activity later in the day was linked to longer TST (β= 0.03, 95% CI 0.02 to 0.04, P<.001) and less variability in TST (β= -0.01, 95% CI -0.02 to 0.00, P=.02). Higher intradaily variability in rest-activity rhythm was associated with shorter TST (β= -0.26, 95% CI -0.29 to -0.23, P<.001), earlier MS (β= -0.29, 95% CI -0.33 to -0.26, P<.001), and reduced variability in TST (β= -0.16, 95% CI -0.23 to -0.09, P<.001).

Conclusions:

Our study offered a comprehensive view of the possible factors affecting sleep patterns during the late stage of the pandemic. As we navigate the future of work post-pandemic, it will be crucial to understand how work arrangements, lifestyle choices, and sleep quality interact to optimize well-being and performance in the workforce.

Keywords:

Introduction

Sleep is a crucial component of our daily lives, tightly interconnected with all aspects of daily routines and our overall well-being, such as mental health [1,2], physical health [3], and work performance [4,5]. The COVID-19 pandemic had a deep impact on various aspects of people's daily lives, with one particularly significant area being sleep patterns. However, the pandemic's effects on sleep were often indirect, arising from changes in daily routines and lifestyle adjustments, rather than as a direct consequence of the virus.

As a response to the pandemic, outdoor restrictions limited our exposure to natural daylight, a crucial element known to regulate our circadian rhythms and sleep patterns [6]. Similarly, mobility restrictions altered the structure of daily physical activity (PA). Additionally, workplace restrictions resulted in work-from-home policies, which led to reduced mobility and flexible working hours. While all of this led to more relaxed work schedules, it also blurred the boundaries between professional and personal life. Notably, all these factors - daylight exposure, physical activity, and work routine - all significantly affected by the pandemic, are well-established influences on sleep health [7,8].

Sleep measurements traditionally rely on self-reported methods, such as the Karolinska [9] or the Pittsburgh sleep diary [10]. While those methods are suitable for tracking day-to-day sleep over a few days or several weeks, conducting diary studies over longer time intervals is usually not favorable due to the cognitive burden on the participants. Non-intrusive measurements using smartphones and fitness trackers have recently emerged as a more viable alternative for capturing sleep over extended periods. While the consumer-grade devices remain incapable of precisely detecting sleep stages; for sleep onset, duration, and wake-up time, these devices have shown more promising results. Assessment of sleep through these devices has the advantage of measuring sleep in people's natural living environments as opposed to sleep laboratories and is not affected by memory biases, which can occur with survey responses and sleep diaries.
The evolution of mobile health (mHealth) technologies has significantly augmented traditional sleep monitoring methods, particularly through the use of wearable devices. These devices not only provide a more accessible and less invasive way to monitor sleep patterns, but also enhance our understanding of sleep-related phenomenons. For instance, wearable devices have been utilized to determine people's chronotypes and track their sleep and activity rhythms over extended periods [11,12]. They have also been employed to measure sleep alignment between coworkers [13], examine the relationship between sleep and burnout [14], and assess sleep patterns in different populations, including patients with mental disorders [15]. Several studies have confirmed the validity and reliability of those wearables, showing respectable sensitivity against the gold-standard polysomnography (PSG). For instance, a review of seven consumer sleep-tracking devices [16] demonstrated their high effectiveness in detecting sleep concerning PSG. Similarly, a study [65] evaluated six consumer wearable devices and confirmed their validity in assessing the timing and duration of sleep when compared to PSG.

Prior research has compared sleep patterns before and during the pandemic, revealing notable differences. Studies found that after the onset of the pandemic individuals tended to go to bed later [17], slept for extended durations [18], exhibited smaller variations between weekday and weekend sleep [19,20], and experienced increased sleep disturbances or diminished sleep quality [21]. Various factors are identified as contributing to these sleep routine disruptions, including a decrease in physical activity [22], social isolation [23], increased usage of electronic devices [4], and the ability to work from home [13].

While earlier studies have focused on the immediate consequences of the lockdowns and restriction policies, less attention has been given to the long-term effects, especially in the late stages of the pandemic when restrictions began to relax. This is an important phase to study as it can provide knowledge on the residual effects of the pandemic on sleep patterns and how quickly people revert to their pre-pandemic sleep habits. The transition to work-from-home as the default working mode has resulted in a less constrained work-life routine, leading to the tendency to maintain a flexible sleep-wake schedule. Certain demographics could better leverage these transitions, such as individuals with more flexible routines like research personnel, or people who tend to snooze their alarms after waking up from sleep, which we refer to as “snoozers”. Additionally, occupation is a known factor influencing sleep patterns, with the classic example being the contrast between shift workers and non-shift workers [24,25]. However, there is less understanding of the disparities between various roles within academia, such as researchers with deadline-driven roles and administrative personnel typically following a 9-5 schedule. Therefore, a more comprehensive, longitudinal analysis of sleep patterns that includes these variables and extends into the late stages of the pandemic is important.

Objectives

Our study aims to provide a holistic view of how the pandemic has influenced sleep patterns. We evaluate the long-term relationships between sleep patterns, including average and variability in total sleep duration and sleep timing, in conjunction with individuals’ characteristics (demographics, occupation, physical activity) as well as external factors (stringency of restriction policies, seasons). Our research utilizes longitudinal data gathered from fitness trackers and questionnaires of working adults from a Finnish university. This extensive dataset allows us to examine the shifts in sleep behavior during the later stages of the COVID-19 pandemic, from June 2021 to June 2022. The study's timeframe captures a full annual seasonal cycle, crucial for analyzing sleep in Finland where its northern latitude causes significant seasonal changes and daylight variations.

Methods

We used the data from our cor:ona (comparison of rhythms: old vs. new) Study [26] to a one-year multimodal data set of working adults. The study was approved by the Aalto University Research Ethics Committee.

Participants and Procedures

The cor:ona study recruited 128 full-time employees from a university in Finland for a one-year study to examine how their daily activities changed during different stages of the COVID-19 pandemic. Throughout the study, participants wore a fitness tracker (Polar Ignite) which allowed us to unobtrusively collect various measures related to sleep and physical activity. In addition, they completed an initial baseline and an exit questionnaire, as well as a shorter version of the baseline questionnaire each month. The monthly questionnaires asked participants to provide information about their daily routines, work, and sleep quality during the past month. The detailed recruitment procedure and participants' demographic were described in a previous study [26].

Fitness Tracker Data

Sleep measures

The fitness trackers measured bedtime (the registered time pointed when a person fell asleep), waketime (the registered time pointed when a person woke up), and interruption duration (total time in seconds a person spent awake between sleep start time and end time) for each day. Here, a sleep period was defined as the most extended sleep episode for each day. Sleep patterns were measured using four metrics: (1) Total Sleep Time (TST) measured the time a person spent asleep, determined by the duration from bedtime to minus the interruption duration (2) Midsleep (MS) point, the midpoint between bedtime and waketime, was used to measure sleep timing, computed as (bedtime + TST)/2. In addition, we proposed two other metrics to measure sleep regularity: (3) TST variability was computed using the weekday (Sunday night to Thursday night) standard deviation of TST, and similarly, (4) MS variability was computed using the standard deviation of MS during weekdays. We only considered weekdays due to the expected differences between weekday and weekend sleep patterns. The Niimpy behavioral data analysis toolbox was used for sleep measurement extraction [27].

Physical activity measures

The fitness tracker recorded the number of steps taken during each hour. The hourly values were added up to provide a daily step count. To comprehensively account for daily physical activities patterns, including their timing and distribution, we introduced two additional metrics: midstep and intradaily variability (IV) [28] . These metrics are designed to capture the temporal occurrence and dispersion of physical activities throughout the day. Specifically, midstep represents the hour of the day when half the total number of steps is achieved, analogous to midsleep for physical activity. On the other hand, intradaily variability quantifies the fragmentation of activity-rest rhythm and is measured as follows::

$$IV = \frac{Var(X')}{Var(X)} = \frac{N \sum_{i=2}^{N} (X_i - X_{i-1})^2}{(N-1) \sum_{i=1}^{N} (\bar{X} - X_i)^2}$$

.

of which: $N=24$ is the total number of samples within each day, X_i is the i measurement sampled at $P=60$ minute interval, and $\bar{X}$ is the average value of all samples in a day. Low IV inidicates less fragmented activity-rest rhythm while high IV could imply daytime naps or nighttime awakenings.

External Data

Seasonal data was collected from the World Weather Online developer API [29]. Since day length varied significantly in Finland during the study (up to 13 hours), it was used as a proxy for seasonal variables. The choice of day length as a proxy was motivated by [30]. The study contrasted two geographically distinct locations with substantial differences in day length variability (Ghana and Norway). While there were no noticeable seasonal effects of day lengths on Ghanaians, Norwegians demonstrated a delay in bedtime and wake time during summer weekdays, although the sleep duration remained relatively unaffected.

We also utilized the stringency index [31], a composite index ranging from 0 to 100 to measure daily COVID-19 restriction policies. Higher values on this index reflect the implementation of more rigorous COVID-19 restriction policies, encompassing measures like school and workplace closures, the cancellation of public events, and the enforcement of stay-at-home orders. This index enables standardized comparisons of policy responses across different countries or regions or changes within the same region over time.

Questionnaire Data

Upon entering the study, participants completed a baseline questionnaire that collected basic background information, including age, gender, chronotype, occupation, and origin, among others. Chronotype was measured using the reduced Morningness-Eveningness Questionnaire (MEQ) [32], with a higher score indicating morning type and a lower score indicating evening type. For the origin-related question, participants were given three choices: Finland, Europe (except Finland), or outside of Europe. Those indicating they were from Finland were classified as Finnish, while others were described as having a “migrant background.” Concerning occupation, participants specified whether they were academic or service staff. The term “academic staff” refers to individuals engaged in academic and research activities within the organization, whereas “service staff” includes those in roles such as human resources and other administrative or support functions. A participant was determined a snoozer if they answered “yes” to the following question: “Snoozing can be considered as choosing to go back to sleep after an alarm has awakened you intending to wake up later; setting the alarm earlier than when you intend to wake up; or setting multiple alarms with the intent to not wake up on the first alarm. Do you currently consider yourself a snoozer using this definition?”, as adapted from [33].

For snoozer characteristics analysis, we employed the Patient Health Questionnaire-2 (PHQ-2) [34] and the short form of the Pittsburgh Sleep Quality Index (PSQI) [10], averaging the values collected from the monthly questionnaires. Furthermore, the short form Positive and Negative Affect Schedule (PANAS-SF) [35] was gathered in the initial baseline questionnaire.

Data exclusion and Preprocessing

Sleep data were restricted to the time range from July 1, 2021, to May 31, 2022. Due to our rolling recruitment process, which began in mid-June 2021 and concluded in June 2022, we excluded data from June of both years. This exclusion was done because we lacked complete data for these months, and including partial data could have introduced bias. A standard filter, adopted from [36], was applied to remove outliers’ TSTs (TST < 3 and TST > 13). Participants with less than 30 nights recorded due to dropout or technical issues were excluded. For gender-related analysis, non-binary participants (N=1) were excluded to preserve their privacy. To maintain the interpretability of the relationships between sleep patterns and the examined variables, we opted against normalizing the dependent and independent variables.

Statistical Analysis

We employed a logistic regression model to examine factors predicting snoozing behavior. Using snoozing behavior as the dependent variable, to replicate the findings from [33], we used the same set of independent variables: age, gender, steps count, total sleep time, BIG-5 personality, positive and negative affect, PHQ-2, PSQI, and MEQ. To further disseminate the potential confounding effects of chronotype (measured by MEQ) on the relationship between personality traits and snoozing behavior, we also performed a Baron and Kenny mediation analysis [37].

Given the nature of our dataset, which comprised of repeated sleep measurements for each participant, we employed mixed linear-effect models [38] to analyze how sleep patterns and their regularity evolve over time. Models included TST, MS, and variability of TST and MS as dependent variables. For models including variability of TST and MS as dependent variables, the numerical independent variables were averaged across weekdays. We adopted a sequential modeling strategy in which we sequentially built three distinct models for each dependent variable. Model 1 consisted of basic characteristics such as chronotype, age, gender, origin, occupation, and parenting cohabitation status (number of children in the household). Model 2 extended Model 1 by adjusting for external factors such as the stringency of the restrictions and day length. Finally, Model 3 extended Model 2 by adding physical activity metrics using the number of step count, midstep, and IV . This approach allows for an exploration of the unique contribution of each new set of variables beyond those already accounted for in the previous model. All the models included hierarchical random effects for the study participants to account for repeated measurements The models are formulated as follows:

$$Model\,1: Y_{ij} = \beta_0 + \beta_1 x_{ij1} + \beta_2 x_{ij2} + .. + \beta_7 x_{ij7} + \beta_8 x_{ij8} + u_j + \epsilon_{ij}$$
$$Model\,2: Y_{ij} = \beta_0 + \beta_1 x_{ij1} + \beta_2 x_{ij2} + .. + \beta_9 x_{ij9} + \beta_{10} x_{ij10} + u_j + \epsilon_{ij}$$
$$Model\,3: Y_{ij} = \beta_0 + \beta_1 x_{ij1} + \beta_2 x_{ij2} + .. + \beta_{11} x_{ij11} + \beta_{12} x_{ij12} + \beta_{13} x_{ij13} + u_j + \epsilon_{ij}$$

where the independent variables are:

$$x_{ij1} = age, x_{ij2} = gender, x_{ij3} = num.of\ children, x_{ij4} = origin, x_{ij5} = occupation, x_{ij6} = Morningess - Eveningess\,Qu$$

95% confidence intervals were reported using bootstrapping. Model performances were compared using the Likelihood Ratio Test (LRT) to ensure model parsimony. All statistical analyses were performed using R software (version 3.6.1) [39]. Linear mixed models were tested using the lme4 package in R [40]. P values for linear mixed models were calculated using the lmerTest package in R [41].

Results

Data Summary

In total, 112 users and 27,350 nights were included in TST and MS analyses. The models for the variability of TST and MS used a weekday standard deviation of both measures, which contained 3,682 observations. The average age of the participants was 39.5 years (±9.9 years). 49 were academic staff while 63 were service staff. Figure 1 presents the average values of the four sleep metrics - TST, MS, and their corresponding standard deviations - for each participant included in the analysis. We illustrate the sleep patterns over time for two participants, highlighting one with low variability and the other with high variability in their sleep patterns in Figure 2.

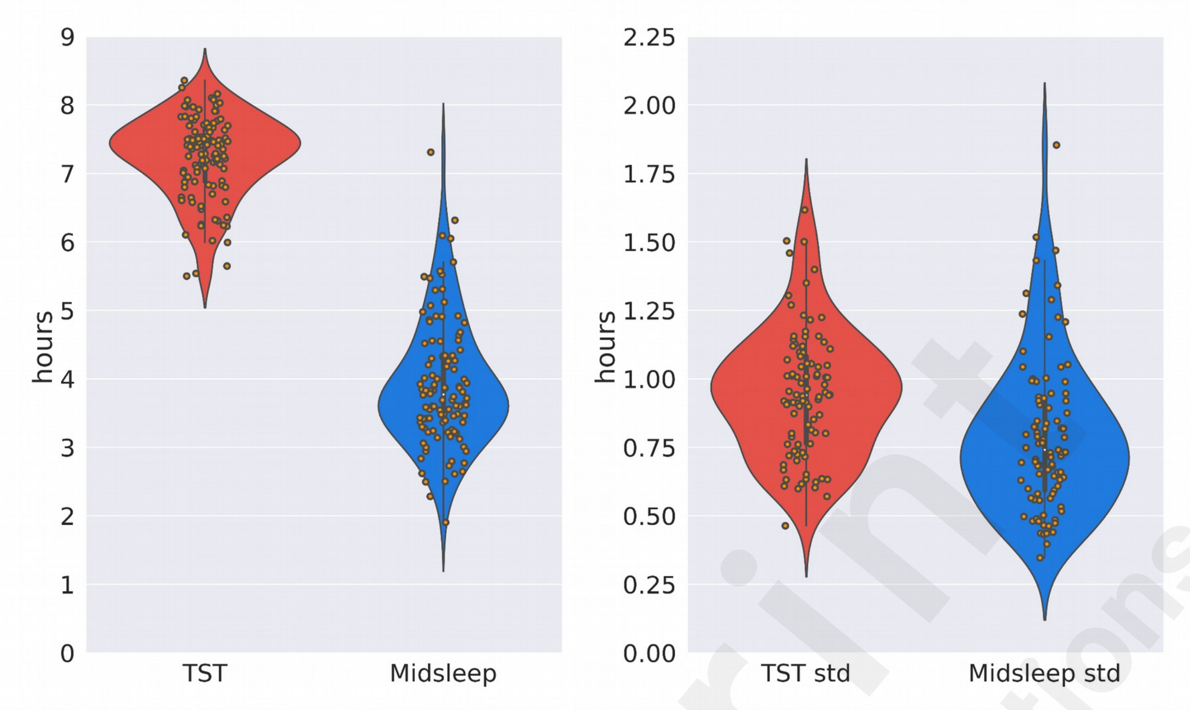

Figure 1: TST, MS, and their standard deviations of participants included in the analysis. Each dot represents the participant's mean value for the corresponding metrics.

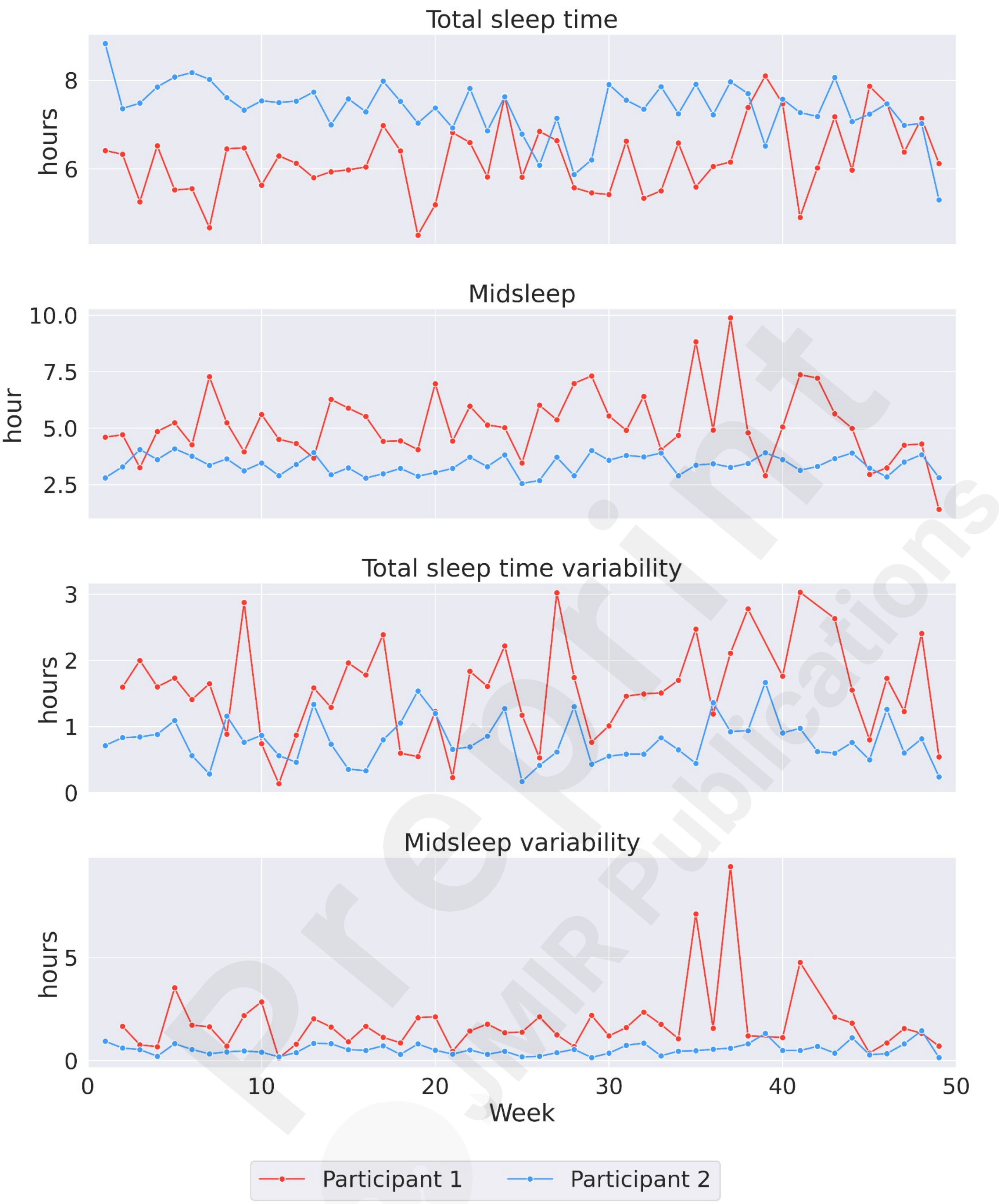

Figure 2: Sleep data over time from two participants. Participant 1 (red line) demonstrates shorter, later, and more variable sleep compared to Participant 2 (blue line).

Total sleep time

	Model 1			Model 2			Model 3		
lictors	*Est*	*CI*	*p*	*Est*	*CI*	*p*	*Est*	*CI*	*p*
	-0.02	-0.03 to -	*.002***	-0.02	-0.03 to -0.01	*.002***	-0.02	-0.03 to -0.01	*.008***

		0.01							
der (male)	-0.34	-0.55 to -0.14	*<.001****	-0.34	-0.55 to -0.14	*<.001****	-0.34	-0.55 to -0.13	*<.001****
children	0.04	-0.07 to 0.15	.51	0.04	-0.07 to 0.15	.51	0.03	-0.07 to 0.14	.56
n (migrant ground))	0.01	-0.27 to 0.27	.97	0.01	-0.27 to 0.27	.97	0.01	-0.24 to 0.24	.93
upation vice)	0.36	0.11 to 0.60	*.01**	0.36	0.11 to 0.60	*.01**	0.37	0.14 to 0.61	*.004***
Q	-0.01	-0.04 to 0.02	.59	-0.01	-0.04 to 0.02	.60	0.30	-0.20 to 0.22	.79
ozer (Yes)	-0.2	-0.44 to 0.05	.11	-0.2	-0.44 to 0.05	.11	-0.18	-0.44 to 0.05	.14
day (Yes)	0.10	0.07 to 0.13	*<.001****	0.10	0.07 to 0.13	*<.001****	0.08	0.06 to 0.11	*<.001****
gency index				0.005	0.003 to 0.007	*<.001****	0.003	0.001 to 0.005	*<.001****
length				-0.01	-0.01 to -0.01	*<.001****	-0.01	-0.012 to -0.006	*<.001****
s (x1000)							-0.01	-0.01 to 0.01	<.001***
teps							0.03	0.02 to 0.04	*<.001****
							-0.26	-0.29 to -0.23	*<.001****
dom Effects									
	1.13			1.13			1.1		
	0.19			0.19			0.19		
ginal R^2 / ditional R^2	0.055 / 0.234			0.057 / 0.235			0.069 / 0.245		
	81208.16			81154.98			80783.26		

Table 1: Estimates of fixed effects from linear mixed effects model predicting TST. Model 1: demographic and occupational variables; Model 2: Model 1+ restriction and seasonal factors; Model 3: Model 2 + physical activity (PA) influences.

We begin by investigating the factors that influence TST, using the three linear mixed models mentioned earlier. Table 1 presents the results of the three models predicting TST. For improved interpretability, the rate of change in TST was measured as the estimate of the predictors multiplied by 60 minutes. In the full model (Model 3), an increase in age by one year was linked to a 1.2

minutes decrease in TST (95% CI -1.8 to -0.6, *P*=. 008). Considering the gender effect, males were found to sleep 20.4 minutes less than females (95% CI -33.0 to -7.8, *P*<.001). When comparing between occupations, we found that service staff sleep 22.2 minutes more than academic staff (95% CI 8.4 to 36.6, *P*=.004). After adjusting for day length and stringency index, an hour increase in day length was associated with a 0.60 minutes decrease in TST (95% CI -0.72 to -0.36, *P*<.001). However, a one-point increase in the stringency index offset this change by 0.18 minutes (95% CI 0.06 to 0.30, *P*<.001). The full model, which took into account physical activity, showed that a one-unit increase in IV corresponded to an 15.6 minutes decrease in TST (95% CI -17.5.5 to -13.8.2, *P*<.001). Moreover, an hour increase in midstep was associated with a 1.8 minute increase in TST (95% CI 1.2 to 2.4, *P*<.001).

The marginal R^2 values represented the proportion of variance explained by the fixed effects, and the conditional R^2 values illustrated the proportion of variance accounted for by both fixed and random effects. The growth in both R^2 values signified that the more complex models, particularly Model 3, explained more variance in the dependent variable. The Likelihood Ratio Test (LRT) between Model 1 and Model 2 revealed that Model 2 was a significantly better fit (χ^2=57.17, *df*=2, *P*<0.001). Furthermore, the LRT between Model 2 and Model 3 demonstrated that Model 3 was a significantly improved fit (χ^2=377.72, *df*=3, *P*<0.001). The performance of the full model (Model 3) was additionally supported by the Akaike Information Criterion (AIC), which was the lowest for Model 3 (AIC=80783.26), demonstrating that it provided the most optimal fit for the data.

Midsleep

	Model 1			**Model 2**			**Model 3**		
tors	*Est*	*CI*	*p*	*Est*	*CI*	*p*	*Est*	*CI*	*p*
	-0.01	-0.02 to 0.01	.38	-0.01	-0.02 to 0.01	.46	-0.006	-0.02 to 0.01	.56
er (male)	0.13	-0.16 to 0.41	.39	0.12	-0.17 to 0.40	.43	0.11	-0.19 to 0.38	.49
ildren	-0.1*	-0.33 to -0.02	*.02**	-0.18	-0.33 to -0.02	*.02**	-0.14	-0.30 to 0.02	.08
(migrant round)	0.19	-0.18 to 0.55	.32	0.18	-0.20 to 0.53	.34	0.09	-0.29 to 0.02	.63
ation ce)	-0.17	-0.51 to 0.17	.33	-0.18	-0.52 to 0.15	.29	-0.21	-0.55 to 0.14	.23
	-0.14	-0.18 to -0.09	*<.001****	-0.14	-0.18 to -0.09	*<.001****	-0.14	-0.18 to -0.09	*<.001****
er (Yes)	0.27	-0.06 to 0.61	.09	0.29	-0.04 to 0.63	.08	0.32	-0.05 to 0.66	.08
lay (Yes)	0.21	0.18 to 0.24	*<.001****	0.21	0.18 to 0.24	*<.001****	0.19	0.16 to 0.21	*<.001****

ency index				0.02	0.02 to 0.03	*<.001****	0.02	0.02 to 0.03	*<.001****
ngth				0.00	0.00 to 0.01	*.048**	0.01	0.00 to 0.01	*.002***
(x1000)							-0.01	-0.02 to -0.01	*<.001****
eps							0.00	-0.00 to 0.01	.43
							-0.29	-0.33 to -0.26	*<.001****
om Effects									
	1.38			1.36			1.36		
	0.26			0.26			0.27		
nal R^2 / tional R^2	0.168 / 0.389			0.178 / 0.400			0.179 / 0.400		
	86990.188			86573.060			86315.145		

Table 2: Estimates of fixed effects from linear mixed effects models predicting MS. Model 1: demographic and occupational variables; Model 2: Model 1+ restriction and seasonal factors; Model 3: Model 2 + physical activity (PA) influences.

Using the same approach, we provided three linear mixed models to assess the associations between the same set of predictors and MS. The results are presented in Table 2. Using the same approach as above to improve interpretability, the rate of change in MS is measured as the estimate of the predictors multiplied by 60 (minutes). Across the three models, chronotype (MEQ) and sleep on a free day consistently emerged as significant factors. In the full model (Model 3), a point increase in the MEQ corresponded with an 8.4 minutes decrease in MS (95% CI -10.8 to -5.4, P<.001). Sleep on a free day tended to occur 11.4 minutes later (95% CI 9.6to 12.6, P<.001), compared to a workday. When adjustments were made for the season and restriction policies, we found that MS was delayed by 0.6 minutes (95% CI 0.6 to 1.2, P<.001) following an hour's increase in day length. A point increase in the stringency index also resulted in a 1.2 minutes increase in MS (95% CI 1.2 to 1.8, P<.001). In the full model, which included physical activity variables, a unit increase in IV was associated with a 17.4minutes earlier MS (95% CI -19.8 to -15.6, P<.001). Similarly, an increase in step count was linked to 0.6 minutes earlier MS (95% CI -1.2 to 0.0, P=.04).

While the more complex models did not significantly surpass the baseline model in terms of R^2, the LRT between Model 1 and Model 2 revealed that Model 2 was a better fit (χ^2=443.70, df=2, P<0.001). Additionally, the LRT between Model 2 and Model 3 demonstrated that Model 3 was a significantly improved fit (χ^2=291.63, df=3, P<0.001). The AIC value for Model 3 was also the lowest (AIC=86315.145), indicating that it provided the best fit for the data.

Total sleep time variability

	Model 1			Model 2			Model 3		
tors	*Est*	*CI*	*p*	*Est*	*CI*	*p*	*Est*	*CI*	*p*
	0.01	0.00 to 0.01	*.01**	0.01	0.00 to 0.01	*.01**	0.01	0.00 to 0.01	*.01**
r (Male)	0.11	0.01 to 0.21	*.038***	0.11	0.01 to 0.21	*.03***	0.10	0.00 to 0.21	.06
ildren	-0.05	-0.11 to 0.00	.056	-0.05	-0.11 to 0.00	.052	-0.06	-0.11 to -0.00	*.01***
(migrant round)	-0.03	-0.15 to 0.10	.56	-0.03	-0.15 to 0.09	.54	-0.03	-0.15 to 0.08	.56
ation e)	-0.17	-0.28 to -0.05	*.004***	-0.17	-0.28 to -0.05	*.004***	-0.15	-0.27 to -0.05	*<.001****
	0	-0.01 to 0.02	.55	0	-0.01 to 0.02	.57	0	-0.01 to 0.02	.60
er (Yes)	0.18	0.07 to 0.30	*.002***	0.18	0.07 to 0.30	*.002***	0.15	0.05 to 0.27	*.006***
ngth				0	-0.00 to 0.01	.16	0	-0.00 to 0.01	.08
ency index				0	-0.00 to 0.00	.10	0	-0.00 to 0.01	.17
(x1000)							-0.01	-0.01 to 0.00	.007**
ps							-0.01	-0.02 to -0.00	*.02**
							-0.16	-0.23 to -0.09	*.001****
om Effects									
	0.14			0.14			0.14		
nal R^2 / tional R^2	0.059 / 0.195			0.060 / 0.194			0.068 / 0.200		
	5458.745			5457.957			5436.793		

Table 3: Estimates of fixed effects from linear mixed effects model predicting TST variability. Model 1: demographic and occupational variables; Model 2: Model 1+ restriction and seasonal factors; Model 3: Model 2 + physical activity (PA) influences.

Table 3 presents the factors predicting the variability in TST. Across the three models, age, the number of children, occupation, and snoozing behavior emerged as significant factors. In the final model (Model 3), every additional year of age corresponded to a 0.01 unit increase in TST variability (95% CI 0.00 to 0.01, *P*=.01). Notably, participants with snoozing habits exhibited higher TST variability, increasing by 0.15 units (95% CI 0.05 to 0.27, *P*=.006). Each additional child slightly was associated with 0.06 unit reduced the variability in TST (95% CI -0.11 to -0.00, *P*=.032). Service staff also demonstrated lower TST variability of 0.15 unit (95% CI -0.27 to -0.05, *P*=<.001) in comparison to academic staff. When accounting for physical activity, a decrease of one hour in midsteps correlated with a 0.01 unit increase in TST variability (95% CI -0.02 to -0.00, *P*=.028) while a unit increase in IV was associated with 0.16 unit decrease in TST variablity (95% CI -0.23 to -0.09, *P*=.028). The LRT indicated that Model 2 did not provide an improvement over the baseline (χ^2=4.78, df=2, *P*=0.09), however, Model 3 demonstrated a better performance than the baseline model (χ^2=31.95, df=5, *P*<.001). Despite this improved performance, the improvement in Model 3 was marginal as the R-squared value did not show a significant increase.

Midsleep variability

	Model 1			Model 2			Model 3		
tors	*Est*	*CI*	*p*	*Est*	*CI*	*p*	*Est*	*CI*	*p*
	0.00	-0.00 to 0.01	.41	0.00	-0.00 to 0.01	.41	0.00	-0.00 to 0.01	.55
er (Male)	0.10	-0.03 to 0.23	.12	0.10	-0.03 to 0.23	.12	0.09	-0.04 to 0.22	.17
ildren	-0.09	-0.16 to -0.02	.01*	-0.09 *	-0.16 to -0.02	*.01**	-0.10	-0.16 to -0.03	*.004***
(migrant round)	-0.05	-0.19 to 0.11	.49	-0.05	-0.19 to 0.11	.49	-0.05	-0.20 to 0.09	.45
ation ce)	-0.12	-0.26 to 0.02	.11	-0.12	-0.25 to 0.02	.11	-0.11	-0.25 to 0.02	.10
	0.00	-0.02 to 0.02	.96	0.00	-0.02 to 0.02	.98	0.00	-0.02 to 0.02	.94
er (Yes)	0.20	0.06 to 0.35	*.006***	0.20	0.06 to 0.35	*.006***	0.17	0.03 to 0.31	*.01**
ngth				0.00	-0.00 to 0.01	.34	0.00	-0.00 to 0.01	.26
ency index				0.00	-0.00 to 0.00	0.94	0.00	-0.00 to 0.00	.89
(x1000)							0.00	-0.01 to 0.01	.41
ps							-0.02	-0.03 to -0.00	*.008***
							-0.09	-0.21 to -0.02	09
om Effects									
	0.59			0.59			0.59		
	0.09			0.09			0.09		
nal R^2 / ional R^2	0.034 / 0.120			0.034 / 0.120			0.038 / 0.122		
	8679.371			8682.369			8679.197		

Table 4: Estimates of fixed effects from linear mixed effects model predicting MS variability. Model

1: demographic and occupational variables; Model 2: Model 1+ restriction and seasonal factors; Model 3: Model 2 + physical activity (PA) influences.

Table 4 presents the factors predicting the variability of MS. Across the three models, the number of children, snoozing behavior, midsteps, and IV emerged as significant factors. For each additional child, the variability of MS was reduced by 0.10 units (95% CI -0.16 to -0.03, *P*=0.004). In all models, being a snoozer correlated with an increase in MS variability. Specifically, snoozers experienced a 0170 unit increase (95% CI 0.03 to 0.31, *P*=0.01) in MS variability compared to non-snoozers. To better understand the characteristics of snoozers, we ran an analysis based on Mattingly's study [33]. Interestingly, our results revealed that age and chronotype were significant factors in predicting a snoozer. The full results are shown in Appendix 2.

When accounting for physical activity variables in the full model, midsteps also gained significance. For each hour increase in midsteps, MS variability decreased by 0.02 units (95% CI -0.04 to -0.00, *P*=0.008). However, the more complex models did not provide a significant improvement over the baseline model, as validated by LRT (Model 2: χ^2=1.00, df=2, *P*=0.60 and Model 3: χ^2=10.17, df=5, *P*=0.07).

Discussion

Principal Findings

In this study, we used a year-long longitudinal wearable data from 112 working adults and discovered various significant relationship between the over-time change in sleep and multiple factors (restriction policies, seasons, physical activity, sociodemographics). While more stringent restrictions were associated with increased TST and delayed MS, seasonal factors also played a significant role: increased day length was linked to reduced TST and delayed MS. Changes in work arrangements, particularly the shift to remote work, had a direct impact on individuals with different occupations and sleep structures. Academic personnel, who had more flexible schedules, slept less and exhibited higher variability in TST compared to service personnel, whose work schedules are more structured. Additionally, individuals identified as 'snoozers' maintained a more flexible sleep schedule with greater variability in both TST and MS compared to non-snoozers. Furthermore, activity pattern was another important factor: exercising later in the day was associated with longer TST and less variability in both TST and MS. To highlight the relevance of our results in the context of sleep during the pandemic, in the below section, we detail the findings of the current study and compare them to previous studies.

Demographic factors

Past research indicated various epidemiological factors affecting sleep patterns, most notably age, gender, and chronotype. In line with previous studies, we also find an association between age and sleep in which older people tend to sleep less [42,43]. However, we discover a correlation between older age and higher TST variability, contradicting prior results [44]. The variance in the observed correlations may be attributed to the current study's use of objective sleep measures, whereas [44] relied on self-reported data. On the other hand, no significant association between MS variability and age is found. Regarding gender differences, we show that males exhibit less consistent and overall shorter TST. While the shorter TST among males is well documented [45,46], the evidence for gender disparity in TST variability is inconsistent. For example, an actigraphy study on a middle-aged cohort showed that females demonstrated greater TST variability than males [47]. In contrast, a survey-based study conducted on university students [48] revealed no difference in TST variability across genders. We also observe that parental duties significantly influence sleep patterns. Parents typically exhibited earlier sleep times, as well as more consistent TST and MS than non-parents. The underlying reasons for these observations remain uncertain, but one hypothesis is that parents' sleep/wake schedules are more stable compared to non-parents, as they need to align their sleep patterns with those of their children. While the specific relationship between parenting and sleep pattern variability has not been extensively studied in previous research, the general concept that living with others (cohabitation) can impact sleep patterns by reducing variability in sleep timing and duration has been explored in other studies [49,50]. This context aims to highlight that factors related to shared living arrangements, such as parenting, can contribute to sleep pattern regularity.

Snoozing behavior

We reveal a higher variability in TST and MS among individuals who identify as 'snoozers'. Interestingly, our findings also suggest that younger individuals and those with an evening chronotype are more likely to identify as 'snoozers', which suggests a potential interplay between age, chronotype, and the habit of snoozing. The inherent sleep-wake patterns of an individual's chronotype might impact their desire to snooze their alarms. Morning types, who naturally wake up earlier, may not find the need to snooze as they align better with societal schedules, compared to evening types.

On the clinical side, snoozing can be associated with prolonged sleep inertia [51] — a state of reduced alertness upon waking. If morning types (high MEQ scores), are less prone to snooze, they might avoid significant sleep inertia, thereby experiencing enhanced alertness and performance. In contrast, evening types might face negative effects due to increased sleep inertia, posing additional challenges, such as catching up with work demands.

Occupational factors

We show that academic staff maintain a shorter as well as more variable TST compared to service staff. Moreover, academic staff also exhibit more variable MS compared to service staff. The flexibility, deadline-driven nature of academic schedules may be the main driver behind the irregular sleep pattern. As academics often need to adjust their schedules to meet project deadlines or prepare for lectures, the dynamic nature of their workload can disrupt regular sleep schedules. Moreover, academic work often requires intellectual and creative work which do not conform to a typical 9-5 workday, which further contributes to irregular sleep patterns.

Nonetheless, it is noteworthy that increased variability in sleep patterns might impact overall health and well-being. For example, studies utilizing actigraphy have found that higher TST variability is linked to an increase in depressive symptoms [52,53]. The implications of these findings become even more relevant in the context of the COVID-19 pandemic. The shift to remote working and learning may introduce even greater flexibility for academic personnel. This flexibility could give them more control over their schedules, but it could also mix work and personal life, leading to longer work hours and more irregular sleep schedules.

Restriction policies

The influence of lockdown measures during the pandemic on sleep patterns is well documented, with increased TST and later MS observed during lockdown periods [17,20,21]. Our findings provide further reinforce earlier evidences at a more granular scale. In a more detailed analysis using the SI to measure the severity of the lockdowns, Ong et al. [54] showed that a higher SI was correlated with later and more variable MS. Contrary to Ong's findings, our study did not find a correlation between the SI and the variability of MS. However, it's worth noting that there are methodological differences in our approaches. While [54] conducted their correlation measurements on a monthly basis, our analysis was more granular and performed on a weekly level, which could explain the different conclusions.

Even though not closely examined in this study, we postulate that the side effects of the restriction policies might play a significant role in sleep. The stress induced by prolonged periods of staying at home could have negatively affected sleep, increasing the prevalence of insomnia [54]. Furthermore, loneliness due to self-isolation could futher worsen sleep quality [55] . Despite the adverse effects, restriction policies also have their positive aspects. The shift to remote work continues, as post-pandemic workplace policies now encourage hybird and remote work [56], thus allowing more flexibility in how individuals schedule their day, and potentially better and longer sleep.

Seasonality

Seasonal factors such as day length have been shown to influence sleep patterns, particularly sleep duration and timing [58,59]. Longer daylight hours during the summer might encourage longer waking periods, while shorter days in the winter might disrupt melatonin production and lead to extended sleep duration. Additionally, these seasonal shifts align with changes in social schedules, like holidays, potentially further affecting regular sleep routines. In southern Finland (the location of our study) where the variance in day length can vary up to 13 hours between summer and winter, these influences could be more noticeable. It is possible that limited exposure to natural daylight induced by reduced mobility during the pandemic could potentially adjust the effect of day length on sleep.

Physical activity

The connection between physical activity (PA) and sleep has been the subject of numerous studies [60–62]. Although consistent PA is typically recommended for promoting good sleep, it's important to understand that PA is a complex behavior with multiple elements such as duration, timing, and intensity, each potentially influencing sleep [60]. Therefore, we propose that investigations examining the interplay between sleep and PA need to take into account the multifaceted nature of PA.

When considering the timing of PA and its effect on sleep, we find that doing PA later in the day is linked with longer TST and reduced variability in both TST and MS. This aligns with previous research, such as a review by Youngstedt et. al [62], which suggests that engaging in exercise later in the day can be beneficial for sleep. Similarly, a survey study showed that engaging in light- to moderate-intensity workouts early in the evening might impart beneficial effects on sleep [63]. The impact of PA's intensity on sleep could potentially modify the effects of its timing. Sleep hygiene guidelines have suggested that vigorous exercise late in the night might lead to heightened arousal, subsequently impairing sleep quality [64]. However, recent research seems to challenge this convention. For instance, a study conducted under controlled laboratory conditions by Myllymaki et al. [65] found that exercise performed four hours before bedtime did not disturb sleep. Further, a review by Stutz et al. [66] suggested that evening exercise does not adversely impact sleep; however, exercising less than an hour before bedtime could potentially disrupt sleep.

In addition to the volume and timing of PA, we have identified that the fragmentation of activity rhythms, measured by intradaily variability (IV), was a significant predictor of sleep patterns. Our finding of a negative association between IV and total sleep time (TST) reinforces previous research [67], suggesting that greater fragmentation in daily PA is linked to shorter sleep duration. Additionally, the novel associations between IV and midsleep (MS) as well as the variability of TST contribute new insights to the study of activity rhythms and sleep patterns.

By leveraging longitudinal data from fitness trackers, our study highlights the potential of mHealth to provide deeper insights into behavioral health patterns, particularly in how lifestyle changes during the pandemic have influenced sleep patterns. This integration of mHealth approaches in sleep research demonstrates an example of how technological advancements can enhance understanding and interventions in public health.

Limitations

This work encounters several inevitable limitations. First, our study is limited by the absence of baseline data from the pre-pandemic period, preventing us from comparing sleep patterns and quality before and during the later stages of the pandemic against the baseline. Second, our study was conducted among the university staff, resulting in a non-representative sample that may introduce bias and a limited sample size. The relatively small sample size may have contributed to the wide confidence intervals observed. This suggests that the precision of our estimates could be improved, and our findings should be interpreted with caution, particularly when generalizing to a broader population. Third, while we tried to control for all the known factors affecting sleep, potentially unaddressed confounding variables can still exist. Fourth, we use consumer-grade wearables for data collection, which, despite their accessibility, may not match the accuracy and reliability of professional-grade equipment. Fifth, recall bias in self-reported measures is an inherent challenge. Nevertheless, we mitigate this issue by using validated questionnaires and conducting monthly data collection to reduce recall intervals. Finally, the study is also geographically limited, which restricts the generalizability of our findings to other cultural or social contexts.

Future directions

One possible future research directions would be to further investigate the relationship between snoozing behavior and certain demographic, such as age, to identify potential causative factors. For example, one could consider a case-control study design to compare individuals who frequently snooze against those who rarely or never do, across a range of age groups. This approach would allow for a detailed examination of how snoozing behavior varies with age, while controlling for potential confounding variables.

Conclusions

Through a holistic approach, our study provided insights into the changes in sleep patterns and physical activity levels among working adults during the late stage of the COVID-19 pandemic. The flexible working hours during the pandemic have resulted in a corresponding flexibility in sleep patterns among certain occupations and sleep traits, particularly among individuals who self-identified as snoozers. Our findings highlight the significant role that lifestyle habits play in sleep health, especially during unprecedented times like a global pandemic. Moving forward, it is crucial to further investigate the alterations in sleep patterns among diverse populations. Such research will aid in designing workplace policies in the post-pandemic era, taking into account the potential benefits and drawbacks of remote work. One notable advantage to be considered is the increased amount of sleep that workers may experience, which has the potential to enhance overall efficiency and productivity. As we navigate the future of work, understanding the interplay between work arrangements, lifestyle choices, and sleep quality will be essential for promoting optimal well-being and performance in the workforce.

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Conflicts of Interest

The authors declare no conflicts of interest.

Abbreviations

TST: Total sleep time
MS: Midsleep point
PA: Physical activity
LRT: Likelihood Ratio Test
AIC: Akaike Information Criterion
PSG: polysomnography

Multimedia Appendix 1

Staff	Academic		Service	
	TST	MS	TST	MS
July	7.02 (+-1.25)	4.50 (+-1.63)	7.52 (+-1.13)	4.16 (+-1.49)
August	7.13 (+-1.24)	4.16 (+-1.50)	7.42 (+-1.11)	3.72 (+-1.15)
September	7.15 (+-1.15)	4.06 (+-1.76)	7.43 (+-1.09)	3.49 (+-1.47)
October	7.09 (+-1.26)	4.09 (+-1.80)	7.45 (+-1.13)	3.62 (+-1.35)
November	7.13 (+-1.23)	3.91 (+-1.41)	7.36 (+-1.06)	3.51 (+-1.20)
December	7.22 (+-1.33)	4.28 (+-1.77)	7.49 (+-1.21)	3.85 (+-1.41)
January	7.17 (+-1.34)	4.30 (+-1.62)	7.53 (+-1.12)	3.84 (+-1.32)
February	7.14 (+-1.21)	4.04 (+-1.56)	7.44 (+-1.10)	3.66 (+-1.55)
March	7.04 (+-1.27)	3.87 (+-1.53)	7.36 (+-1.07)	3.42 (+-1.33)
April	6.99 (+-1.24)	3.90 (+-1.30)	7.38 (+-1.12)	3.63 (+-1.64)
May	7.01 (+-1.23)	4.12 (+-1.59)	7.25 (+-1.10)	3.63 (+-1.36)

Table S1: Sleep patterns characteristic of academic and service occupation

Multimedia Appendix 2

Snoozer	Odds ratio	z	P-value	95% CI
Age	0.92	-2.26	*.02*	0.86 to 0.99
Gender (male)	0.45	-1.13	.25	0.11 to 1.78
Avg. steps (x1000)	1.06	0.57	.57	0.87 to 1.28
Avg. total sleep time	0.44	-1.56	.11	0.16 to 1.23
Extraversion	1.01	0.08	.92	0.82 to 1.24
Agreeableness	1.13	0.98	.32	0.89 to 1.44

Conscientiousness	0.90	-0.82	.41	0.70 to 1.16
Negative Emotionality	0.98	-0.14	.88	0.79 to 1.22
Open Mindedness	0.94	-0.42	.67	0.71 to 1.24
Positive Affect	1.06	0.58	.56	0.87 to 1.30
Negative Affect	1.07	0.58	.56	0.86 to 1.32
PHQ-2	1.09	0.20	.84	0.49 to 2.44
PSQI	1.00	-0.002	.99	0.73 to 1.37
MEQ	0.71	-3.02	*.002*	0.57 to 0.89

Table S1: Summary of logistic regression model predicting snoozing behavior

We perform a Baron and Kenny 4-step mediation analysis [68] to discern the mediation role of chronotype on the relationship between personality and snoozing behavior. We modeled logistic regression with five personality traits as IVs, snoozing behavior as the DV, and chronotype (MEQ) as the mediator (M). At step 1, only Conscientiousness significantly predicted snoozing behavior negatively (Odds ratio = 0.79, p-value = 0.01). At step 2, a linear regression model showed that Conscientiousness was positively associated with MEQ (beta = 0.41, p < 0.001). At step 3, the logistic regression model showed that MEQ significantly predicted snoozing behavior negatively (Odds ratio = 0.79, p-value = 0.01). In a final logistic model including both MEQ and Conscientiousness, MEQ was a significant predictor of snoozing (Odds ratio = 0.86, p-value = 0.01), while Conscientiousness was not (p-value = 0.12), suggesting MEQ fully mediated this relationship. The detailed results of all steps are displayed in Table S2.

Path	**Chronotype as a mediator**			
	Step 1 (odds ratio)	Step 2 (beta)	Step 3 (odds ratio)	Step 4 (beta)
C -> Sz	0.79*			-0.15

N -> Sz	1.07			0.07
O -> Sz	0.92			-0.08
A -> Sz	1.01			0.04
E -> Sz	0.96			-0.06
C -> Ch		0.41***		
N -> Ch		-0.04		
O -> Ch		0.08		
A -> Ch		-0.01		
E -> Ch		-0.02		
Ch-> Sz			0.77 *	

Table S2: Mediation analysis using Baron & Kenny's method to investigate chronotype as a mediator between snoozing behavior and personality traits. Step 1 = IV -> DV; Step 2 = IV -> M; Step 3 = M -> DV; Step 4 = (IV + M) ->DV.

IV = independent variable; DV = dependent variable; M = mediator.
Sz = Snoozer; Ch = Chronotype (MEQ); C = Conscientiousness; N = Neuroticisim; O = Openness; A = Agreeableness; E = Extraversion.

*p<0.05. ** p<0.01. *** p<0.001.

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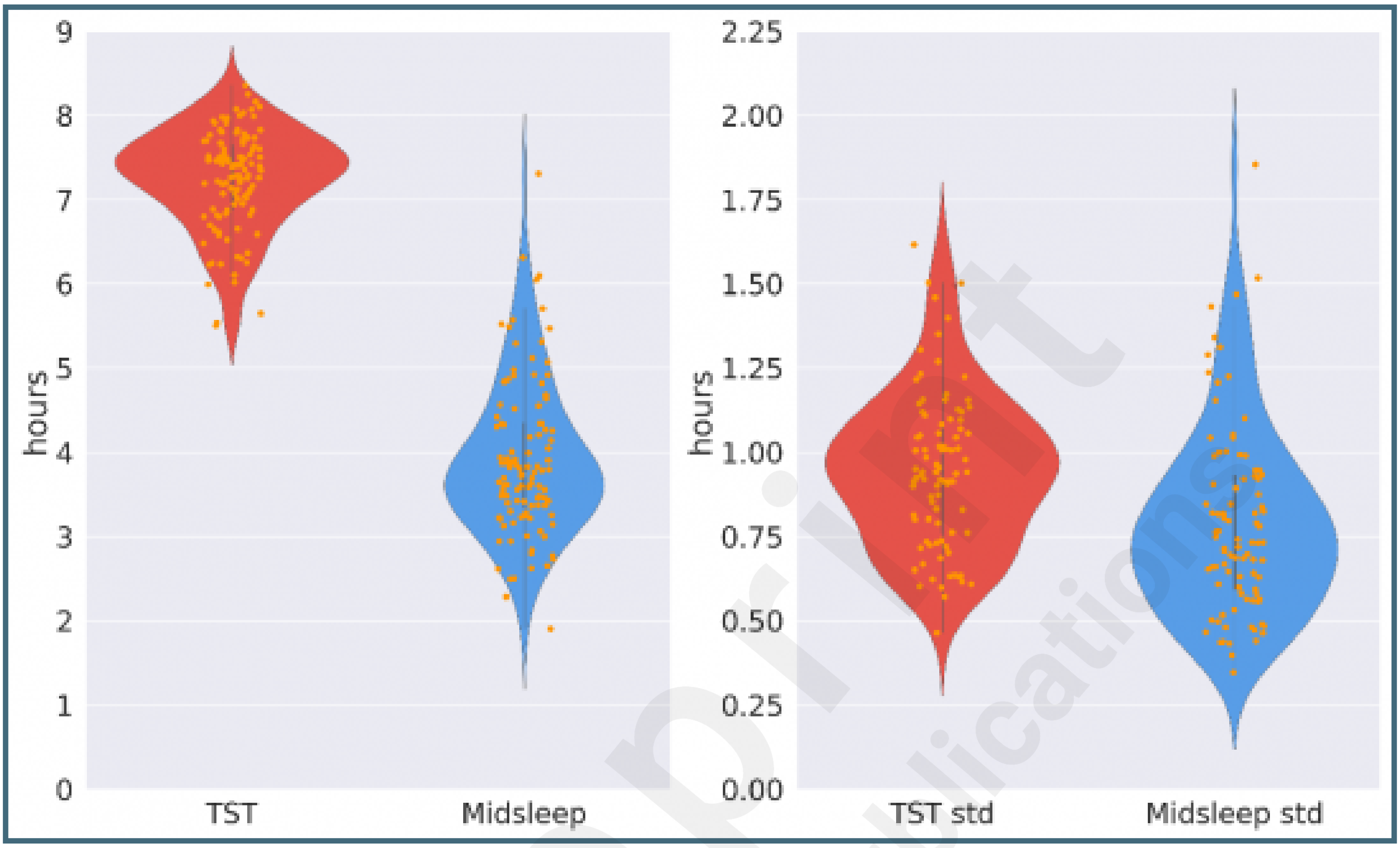
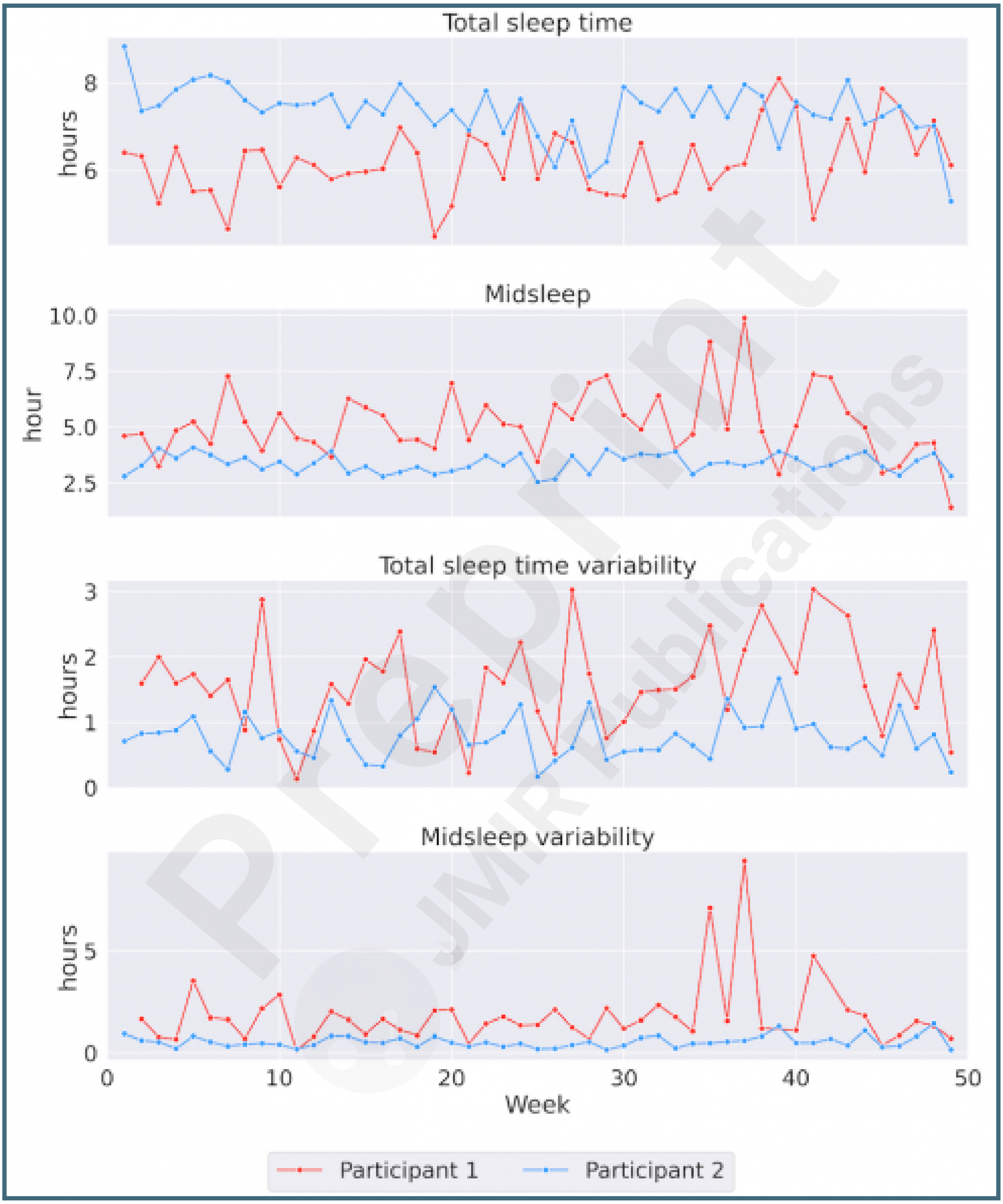
Supplementary Files

Figures

TST, MS, and their standard deviations of participants included in the analysis. Each dot represents the participant's mean value for the corresponding metrics.



Sleep data over time from two participants. Participant 1 (red line) demonstrates shorter, later, and more variable sleep compared to Participant 2 (blue line).



Multimedia Appendixes

Supplementary tables for additional analyses.
URL: http://asset.jmir.pub/assets/f40a84220fc91a841365ae4ce849cc44.docx