

Physical Activity Frequency Patterns Influence Sleep Architecture in Young Adults

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Background: Physical activity is associated with sleep quality and changes in sleep stages. Few studies have explored specific physical activity prescription parameters for informing behavioral interventions for sleep. This secondary data analysis explores how physical activity frequency and intensity are associated with sleep architecture. **Methods:** Sixty-nine adults (mean age = 21.5 y, 63% female) wore a wrist-mounted fitness monitor to measure physical activity and sleep for 2 data collection intervals spanning a total of 8 months. Participants received triweekly electronic surveys asking to rank their levels of energy, stress, contentment, and sleep quality in the morning. Mixed effects linear models were used to determine the effects of physical activity frequency and intensity (light or moderate to vigorous) on sleep architecture, sleep quality, and mood. **Results:** Having more days with at least 10 minutes of moderate- to vigorous-intensity physical activity within a 5-day period was associated with a lower rapid eye movement/nonrapid eye movement ratio in the first 180 minutes of sleep ($\beta = -0.18$, $P = .018$). Total light-intensity physical activity was associated with the same effect ($\beta = -0.16$, $P = .048$), as well as higher morning energy levels ($\beta = 0.16$, $P = .047$). Within a day, the proportion of hours with at least 3 minutes of light-intensity physical activity was associated with greater sleep time and a lower rapid eye movement/nonrapid eye movement ratio in the first 360 minutes of sleep ($\beta = 0.10$, $P = .049$; $\beta = -0.15$, $P = .022$). The proportion of hours with at least 3 minutes of moderate- to vigorous-intensity physical activity was associated with morning contentment ($\beta = 0.13$, $P = .049$). **Conclusions:** This study suggests that the effects of physical activity on sleep are carried over across the week and identifies intraday and interday frequency to be important factors for consideration in physical activity interventions for improving sleep.

Keywords: psychology, neurophysiology, health behavior, physical activity assessment, accelerometry

Key Points

- How often a person engages in moderate-to-vigorous physical activity across the week, controlling for total time, is associated with greater nonrapid eye movement sleep at the beginning of sleep.
- Light physical activity and being active throughout the day were also associated with improved sleep metrics.

Physical activity is an essential health behavior for the maintenance and enhancement of the nervous system. Multiple mechanisms exist through which engagement in physical activity can affect brain health, namely vascular and direct signaling mechanisms that are related to changes in brain structure, neurotrophic kinetics, temperature, and cognitive performance.¹ Through such wide-ranging effects, it is no surprise that physical activity also affects sleep. Sleep is a health behavior with independent effects on neural and cardiometabolic health. Meeting 24-hour guidelines for engagement in both physical activity and sleep is associated with reductions in risk of cardiometabolic, cancerous, and neuropsychiatric disease.² However, given the current state of the physical inactivity pandemic³ and the effects of sleep deprivation among young adults,⁴ it is of public health interest to consider the

naturalistic interplay between physical activity and sleep, and how they may be interacting to impact a person's well-being.

Experimental research has demonstrated that engagement in exercise can change sleep architecture patterns to increase total sleep time (TST), sleep efficiency (SE), rapid eye movement (REM) onset latency, and decrease the amount of REM sleep compared with other sleep stages.^{5,6} Studies examining free-living conditions of sleep and physical activity have found similar effects.^{7,8} Although more evidence is needed to understand exactly how the ratio of time spent in each stage of sleep affects health, there should typically be a greater amount of REM in the latter half of the sleep bout compared with the first half.⁹ Beyond physiological measurements, appropriate sleep and physical activity are also associated with feelings of well-being, alertness, and decreased symptomatology of neuropsychiatric disorders.^{2,8,10,11} These findings highlight the benefits of understanding and promoting sustainable physical activity and sleep patterns for both objective and perceived measures of health.

Given the established benefits of physical activity and sleep, and the potential of physical activity as a tool for influencing sleep architecture, it is important to investigate how reproducible patterns of physical activity can be employed to benefit sleep. There is

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evidence that traditional physical activity and exercise prescription parameters (frequency, intensity, time, type, and volume)¹² can have unique effects on health. For example, moderate to vigorous intensities of physical activity (MVPA) have been found to improve metabolic risk profiles to a greater extent than light physical activity.¹³ Frequency is another parameter of interest. Although studies indicate minimal differences at the weekly level when comparing cardiometabolic outcomes between “weekend warrior” and “regular exerciser” archetypes,^{14,15} there may be differences at the daily level in which “active couch potatoes”—those individuals who exercise but remain sedentary for the rest of the day—may still have negative health outcomes despite having exercised compared with individuals who are regularly active.^{16,17}

The literature on sleep and physical activity patterns has considered the effects of intensity and time of day. While there is a generally positive benefit of both light (LPA) and MVPA, intensity-specific findings are inconclusive due to variability in study design.^{5,18} There is also an interest in the effects of time of day, emerging from a concern that exercise late in the day may interfere with sleep. However, evidence supporting this concern is generally only observed when an individual exercises vigorously less than an hour before bedtime.^{5,19} To the authors’ knowledge, the analysis of physical activity frequency, how many days out of the week a person engages in an activity independent of total time in physical activity, as an exposure related to sleep architecture has not been studied in naturalistic environments. To investigate this association, we conducted a secondary data analysis from a study on physical activity, mood, and sleep architecture in university students with wearable devices.⁸ We hypothesized that given the circadian nature of sleep and physical activity patterns, a higher frequency of physical activity will be associated with a reduction in the ratio of REM to nonrapid eye movement (NREM) sleep in the first 180 minutes of the sleep bout. Furthermore, we predicted that this effect would be observed at the daily level, with a greater hourly frequency of physical activity associated with the same change in sleep architecture. Additionally, we examined the effects of these exposures on self-reported measures of well-being, including stress, contentment, energy levels, and self-reported sleep quality (SSQ).

Methods

Participants and Data Acquisition

This article presents a secondary data analysis from a study on physical activity and sleep,⁸ investigating the effects of physical activity frequency. The original study included 82 undergraduate students without neuropsychiatric disorders or taking hormone-altering medications enrolled in 2 waves of data collection. Wave 1 had 76 participants and occurred from January 2020 to March 2020. Wave 2 was a repeated measure of the first group of participants, with 6 additional participants occurring May 2020 to September 2020. Each participant received a Fitbit Inspire HR (Firmware: Fit OS 34.20001.63.5 Model FB413) and was instructed to wear it as often as possible. The Beive app and research platform²⁰ was used to collect surveys on mood every Monday, Wednesday, Friday, and Sunday mornings at 9:00 AM. Contentment, stress, and SSQ were rated on a 0 to 3 Likert scale, and perceived energy on a 0 to 4 Likert scale, with greater numbers indicating stronger feelings of that mood. The study was conducted with approval from the University of Texas at Austin Institutional Review Board (study number 2019-09-0120) and in accordance

with the Declaration of Helsinki and relevant guidelines. For a more detailed description of the study design, please refer to the article by Zapalac et al.⁸

Feature Extraction

Physical activity and sleep data were collected through the photoplethysmography and accelerometry capabilities of the Fitbit Inspire HR. Participant data were accessed through the Fitabase server, which allows researchers to see daily features of activity, such as wake time, bedtime, sleep, and minute by minute heart rate data.²¹ Data were filtered to only include observations in which the subject had worn the device for at least 18/24 hours and had at least 3 hours of sleep recorded per sleep bout, as this is the minimal sleep time required to obtain sleep stages from Fitbit. The 18-hour wear-time criterion was based on previous literature analyzing associations between physical activity, sedentary behavior, sleep, and mood,²² and it enabled the retention of more than 90% of participant data from our sample.

Proprietary algorithms enable the Fitbit Inspire HR to determine the time spent in different sleep stages, including interruptions of sleep by awakening. From this information, several sleep metrics can be calculated including: TST (the sum of all sleep stages), wake after sleep onset (WASO; awakenings while the participant is in bed), SE (the percent of TST over time in bed), minutes in light sleep, minutes in REM sleep, minutes in deep sleep, and REM onset latency (REM-L; the amount of minutes after bedtime it takes for REM to begin).²³ Naps were excluded from analysis. Validation studies have concluded that Fitbit algorithms can generate reliable measurements of TST, SE, and WASO compared to polysomnography—the laboratory gold standard in sleep architecture measurement. However, there is limited evidence for the accurate classification of light and deep sleep stages, though there is more reliable differentiation between REM and non-REM stages.²⁴ For this reason, we chose to collapse the sleep stage analysis into REM and non-REM. A systematic review of the accuracy of Fitbit devices in classifying sleep stages found accuracy values ranging from 0.81 to 0.91, with sensitivity values ranging from 0.87 to 0.99, and specificity ranging from 0.10 to 0.52.²⁴ A validation study of the Fitbit Inspire 2, a device of the same Fitbit series as the one used for this study, found the Fitbit could classify REM sleep with a sensitivity of 0.86 and specificity of 0.59.²⁵ While sleep stage classification should be interpreted with caution, the metrics show promise for showing general patterns of sleep architecture over time.

For the measurement of physical activity, we used the minutes in each heart rate reserve (HRR) intensity category during the participants’ wake periods. Maximum heart rate was estimated using the 220-minus-age formula. Resting heart rate was derived from the Fitbit profile metadata from each participant. Manual inspection of the resting heart rate metadata showed it tended to match the average lowest heart rate recorded during wake time sedentary time. HRR was determined using the Karvonen method, wherein HRR is the difference between maximum and resting heart rate, and the target heart rate to be classified by intensity is the product of HRR times the desired intensity, plus the resting heart rate.²⁶ With this method, intensity is defined as the percentage of an individual’s HRR. Classification into LPA minutes versus MVPA minutes was done according to the 11th edition of the American College of Sports Medicine Guidelines for Exercise Testing and Prescription¹²: 30% to 39% HRR for LPA and $\geq 40\%$ HRR for MVPA. We chose this method to make intensity relative to the

subject, given that the most valid metric for intensity acquired from the Fitabase server was minute-by-minute heart rate.

Determining Physical Activity Frequency

We define interday MVPA frequency as the number of days a participant had at least 10 minutes of MVPA out of a period of 5 continuous days, and interday LPA frequency as the number of days a participant had at least 30 minutes of LPA out of a period of 5 continuous days. We chose these thresholds because, historically, population-based physical activity studies consider an individual to have an active MVPA day if they self-report a bout of at least 10 minutes of MVPA.²⁷ The threshold was increased to 30 minutes for LPA to increase the variance in our statistical model's features, as too many participants had achieved a day with at least 10 minutes of LPA thereby decreasing the informative value of a 10-minute LPA threshold. Thirty minutes was also the rounded mean of daily LPA in our sample. Although physical activity recommendations for adults are prescribed at the weekly level,²⁸ our participants displayed the best continuity of data (wearing the Fitbit for consecutive days) when their activity was stratified into 5-day periods. We therefore applied this filter to maximize the number of valid observations, which reduced our sample size to 69 participants after participants with poor adherence were removed. Participants were included in this sample if they provided at least one valid 5-day period of data. In addition, for the analysis of the effects of interday frequency on the REM/NREM ratio in the first 360 minutes of sleep, the sample size was further reduced to 29. It was unfortunately not common for participants to have sufficient sleep (at least 360 min) 5 nights consecutively. This 360-minute threshold was chosen to approximate the duration of 4 consecutive sleep cycles.⁹

Intraday MVPA frequency was operationalized as the proportion of hours awake with at least 3 minutes of MVPA. The same definition applies to intraday LPA frequency. Studies examining the effects of short but frequent bouts of activity on cardiovascular outcomes have found critical effects for bouts lasting 1 to 4 minutes.¹⁷ We chose 3 minutes to approximate the mean hourly activity of our sample. To maximize the validity of the measurement, a more stringent filter was applied than for the interday measurement: each observation came from a day in which the participant woke up and went to bed with the device, ensuring precision in recording wake time to sleep time within 24 hours. Forty-four participants met this criterion for the intraday analysis.

Statistical Analyses

Interday and intraday frequencies for MVPA and LPA were the exposures of interest. The statistical models accounted for total time spent in a given activity during the 5-day period (interday analysis) or during 1 day (intraday analysis). The intraday analysis also accounted for time awake. The primary outcome of interest was the REM/NREM ratio for the first 180 minutes of sleep. Other sleep architecture outcomes included TST, SE, WASO, REM-L, REM/NREM ratio for the first 360 minutes of sleep. The self-reported outcomes of morning mood were contentment, energy level, stress, and SSQ. All variables were Z-standardized to ensure valid comparisons across variables.

Linear mixed-effects models with restricted maximum likelihood estimation were used to examine the repeated-measures effects of physical activity frequency and time, stratified by intensity, on self-reported measures of mental state and sleep

architecture. Given the distribution of the data, nonparametric bootstrapping was used for the significance tests of regression coefficients. Hypothesis testing of regression coefficients involved constructing a null-hypothesis model; resampling the distribution of the null model response residuals with replacement, reconstructing a bootstrap y-response vector, and refitting the alternative hypothesis model to the bootstrap response vectors to generate 10,000 estimates of the coefficients under the null model; and using pairwise tests to compare the observed coefficients against the null bootstrap distribution.⁸ All analyses were performed using the lme4 package²⁹ in R Studio (version 4.4.1).³⁰

Results

Participant Data

Table 1 displays the characteristics of the participants included in the analyses. For the interday analysis, 69 participants (mean age 21.54 [3.19] y, 63% female) met the predefined threshold and provided 471 five-day observation periods with an average of 6.8 periods per participant. Of these participants, 44 (mean age 21.52 [3.17] y, 70% female) met the criteria for the intraday subanalysis and provided 949 one-day observation periods with an average of 21 days per participant. On average, our participants engaged in 91.42 (61.19) minutes of MVPA and 156.43 (88.30) minutes of LPA per 5-day period, indicating they were reasonably active, but there was wide variation in the data distribution. Participants slept an average of 403.1 (44.99) minutes per night, ranging from mild sleep deprivation to the recommended amount,³¹ with a SE of 92.19% (7.74%). Self-reported measures of mental well-being and rest from sleep are also reported in Table 1.

Interday Physical Activity Frequency

Models for interday physical activity consider the frequency, or number of days, in which a threshold of time in a physical activity intensity was met while accounting for the total time spent in that intensity. The number of days meeting a threshold of at least 10 minutes of MVPA per day was associated with a lower REM/NREM ratio in the first 180 minutes of sleep ($\beta = -0.18$, $P = .018$, 95% CI, -0.32 to -0.02 ; Figure 1). There were no statistically significant associations between interday MVPA frequency, or the total time in MVPA across 5 days, and the other measures of sleep architecture (TST, SE, WASO, REM-L, and REM/NREM in the first 360 min of sleep). No significant associations were found when analyzing interday LPA frequency (meeting a threshold of at least 30 min of LPA per day) and sleep architecture. However, the total time spent in LPA across 5 days was associated with a lower REM/NREM ratio in the first 180 minutes of sleep ($\beta = -0.16$, $P = .048$, 95% CI, -0.32 to 0.01). These findings are summarized in Table 2.

Regarding the effects of interday physical activity on mental state, there were no statistically significant effects on self-reported feelings of contentment, energy, stress, or SSQ. However, the total time spent in LPA across 5 days was positively associated with feelings of energy in the morning ($\beta = 0.16$, $P = .047$, 95% CI, -0.04 to 0.34). These findings are summarized in Table 3.

Intraday Physical Activity Frequency

Models for intraday physical activity frequency consider the proportion of hours awake meeting a given threshold for minutes

Table 1 Participant Characteristics

Characteristics	Mean (SD)	Minimum	Maximum
Age, y	21.54 (3.19)	18.19	32.53
Device wear, min	1383 (65.15)	1082	1439
5-d MVPA, min	91.42 (61.19)	0.00	337.28
Daily MVPA, min	18.28 (13.84)	0.00	67.46
Interday MVPA frequency, d	2.42 (1.52)	0.00	5.00
Intraday MVPA frequency, prop	0.19 (0.16)	0.00	0.92
5-d LPA, min	156.43 (88.30)	9.43	579.00
Daily LPA, min	31.29 (17.66)	1.89	115.80
Interday LPA frequency, d	2.05 (1.49)	0.00	5.00
Intraday LPA frequency, prop	0.44 (0.21)	0.00	1.00
TST, min	403.1 (44.99)	243.00	529.60
SE, %	92.19 (7.74)	47.00	98.40
WASO, min	60.2 (12.58)	32.00	106.20
REM-L, min	117.5 (34.96)	48.90	261.50
REM/NREM 180	0.132 (0.07)	0.00	0.41
REM/NREM 360	0.20 (0.08)	0.05	0.41
Morning contentment	1.68 (0.65)	0.00	3.00
Morning stress	1.00 (0.78)	0.00	3.00
Morning energy	1.86 (0.84)	0.00	4.00
SSQ	1.91 (0.58)	0.00	3.00

Abbreviations: LPA, light physical activity; MVPA, moderate to vigorous physical activity; REM-L, rapid eye movement sleep latency; REM/NREM 180, rapid eye movement to nonrapid eye movement sleep ration in the first 180 minutes of sleep; REM/NREM 360, rapid eye movement to non-rapid eye movement sleep ration in the first 360 minutes of sleep; SE, sleep efficiency; SSQ, self-reported sleep quality; TST, total sleep time; WASO, wake after sleep onset.

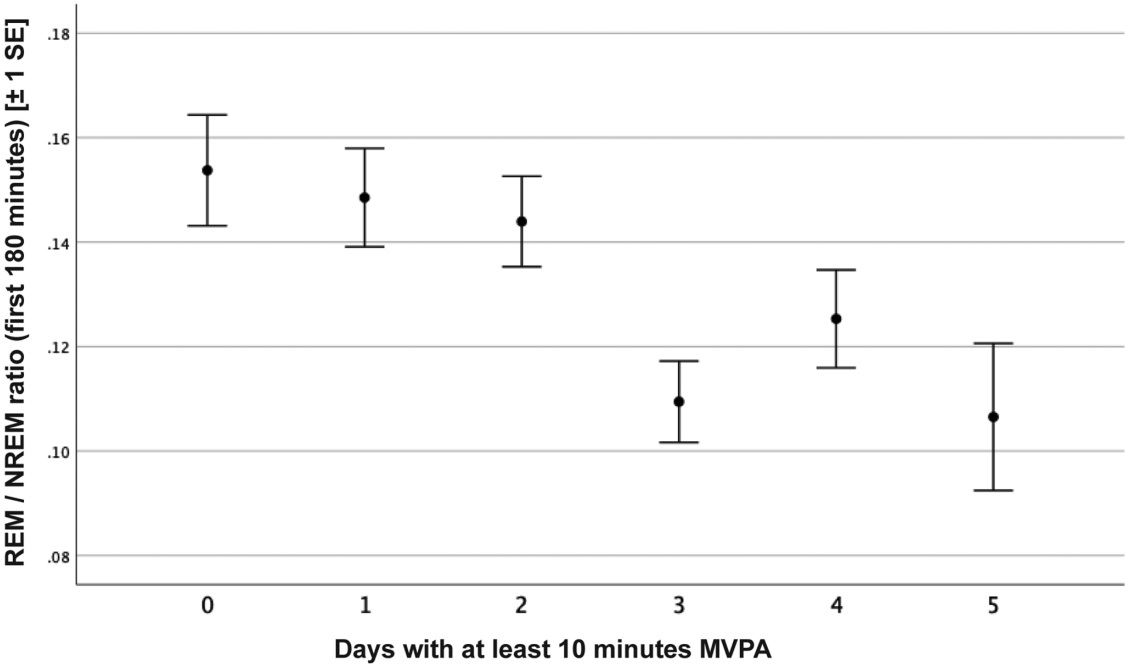


Figure 1 — A standard error plot showing the negative association between REM/NREM ratio in the first 180 minutes of sleep and the number of days spent with at least 10 minutes of MVPA across a 5-day period. MVPA indicates moderate to vigorous physical activity; REM, rapid eye movement; NREM, nonrapid eye movement.

Table 2 Multivariate Modeling of Associations Between Interday Physical Activity Frequency and Sleep Architecture

Independent variable	TST		SE		WASO		REM-L		REM/NREM 180		REM/NREM 360	
	β	<i>P</i>	β	<i>P</i>	β	<i>P</i>	β	<i>P</i>	β	<i>P</i>	β	<i>P</i>
Model 1: Interday LPA and sleep												
Interday LPA frequency	0.04	.522	0.01	.546	−0.03	.658	0.08	.319	0.07	.386	−0.11	.426
Total LPA	−0.03	.635	−0.03	.199	0.07	.187	0.07	.385	−0.16	.048*	−0.008	.955
Model 2: Interday MVPA and sleep												
Interday MVPA frequency	0.06	.344	−0.04	.117	0.04	.476	0.13	.075	−0.18	.018*	−0.16	.157
Total MVPA	−0.07	.266	−0.01	.814	0.01	.875	0.024	.776	0.09	.255	0.02	.856

Abbreviations: LPA, light physical activity; MVPA, moderate to vigorous physical activity; REM-L, rapid eye movement sleep latency; REM/NREM 180, rapid eye movement to nonrapid eye movement sleep ratio in the first 180 minutes of sleep; REM/NREM 360, rapid eye movement to nonrapid eye movement sleep ratio in the first 360 minutes of sleep; SE, sleep efficiency; TST, total sleep time; WASO, wake after sleep onset. Note: Model 1 shows a multivariate mixed effects model with interday LPA frequency and total LPA as independent variables related to sleep architecture outcomes. Between-participant differences were controlled by setting the participant as a random effect variable. Model 2 shows the same, with interday MVPA frequency and total MVPA as independent variables.

Bold indicates significance, $\alpha < .05$.

Table 3 Multivariate Modeling of Associations Between Interday Physical Activity Frequency and Morning Subjective Mental State

Independent variable	Content		Energy		Stress		SSQ	
	β	<i>P</i>	β	<i>P</i>	β	<i>P</i>	β	<i>P</i>
Model 3: Interday LPA and mental state								
Interday LPA frequency	−0.04	.547	−0.10	.194	−0.05	.507	−0.09	.282
Total LPA	0.11	.117	0.16	.047*	−0.09	.264	0.05	.535
Model 4: Interday MVPA and mental state								
Interday MVPA frequency	0.02	.81	−0.10	.183	−0.12	.081	0.04	.589
Total MVPA	0.08	.318	0.15	.056	0.021	.808	0.08	.371

Abbreviations: LPA, light physical activity; MVPA, moderate to vigorous physical activity; SSQ, self-reported sleep quality. Note: Model 3 shows a multivariate mixed effects model with interday LPA frequency and total LPA as independent variables related to subjective mental state outcomes. Between-participant differences were controlled by setting the participant as a random effect variable. Model 4 shows the same, with interday MVPA frequency and total MVPA as independent variables.

Bold indicates significance, $\alpha < .05$.

Table 4 Multivariate Modeling of Associations Between Intraday Physical Activity Frequency and Sleep Architecture

Independent variable	TST		SE		WASO		REM-L		REM/NREM 180		REM/NREM 360	
	β	<i>P</i>	β	<i>P</i>	β	<i>P</i>	β	<i>P</i>	β	<i>P</i>	β	<i>P</i>
Model 5: Intraday LPA and sleep												
Intraday LPA frequency	0.10	.049*	−0.05	.325	0.10	.052	−0.03	.731	−0.07	.257	−0.15	.022*
Daily LPA	−0.04	.450	0.06	.200	−0.07	.130	0.07	.391	0.07	.199	0.10	.083
Hours awake	−0.38	.001*	0.03	.407	−0.26	.001*	−0.19	.001*	0.16	.001*	0.21	.001*
Model 6: Intraday MVPA and sleep												
Intraday MVPA frequency	0.061	.235	0.01	.893	0.05	.326	−0.001	.981	0.06	.380	0.08	.224
Daily MVPA	−0.002	.953	0.02	.766	−0.04	.480	0.08	.254	−0.07	.238	−0.05	.348
Hours awake	−0.39	.001*	0.04	.266	−0.27	.001*	−0.18	.001*	0.19	.001*	0.25	.001*

Abbreviations: LPA, light physical activity; MVPA, moderate to vigorous physical activity; REM-L, rapid eye movement sleep latency; REM/NREM 180, rapid eye movement to nonrapid eye movement sleep ratio in the first 180 minutes of sleep; REM/NREM 360, rapid eye movement to nonrapid eye movement sleep ratio in the first 360 minutes of sleep; SE, sleep efficiency; TST, total sleep time; WASO, wake after sleep onset. Note: Model 5 shows a multivariate mixed effects model with intraday LPA frequency and daily LPA as independent variables related to sleep architecture outcomes while considering the time the participant was awake. Between-participant differences were controlled by setting the participant as a random effect variable. Model 6 shows the same, with intraday MVPA and daily MVPA as independent variables.

Bold indicates significance, $\alpha < .05$.

Table 5 Multivariate Modeling of Associations Between Intraday Physical Activity Frequency and Morning Subjective Mental State

Independent variable	Content		Energy		Stress		SSQ	
	β	<i>P</i>	β	<i>P</i>	β	<i>P</i>	β	<i>P</i>
Model 7: Intraday LPA and mental state								
Intraday LPA frequency	−0.02	.731	−0.004	.953	−0.09	.133	−0.05	.479
Daily LPA	0.06	.304	0.02	.712	0.03	.620	0.10	.166
Hours awake	−0.08	.042*	−0.08	.087	0.01	.742	−0.14	.003*
Model 8: Intraday MVPA and mental state								
Intraday MVPA Frequency	0.13	.049*	0.04	.650	−0.01	.90	0.05	.554
Daily MVPA	−0.08	.174	0.002	.982	−0.02	.658	0.03	.722
Hours awake	−0.06	.118	−0.07	.094	0.03	.420	−0.13	.005*

Abbreviations: LPA, light physical activity; MVPA, moderate to vigorous physical activity; SSQ, self-reported sleep quality. Note: Model 7 shows a multivariate mixed effects model with intraday LPA frequency and daily LPA as independent variables related to subjective mental state outcomes while considering the time the participant was awake. Between-participant differences were controlled by setting the participant as a random effect variable. Model 8 shows the same, with intraday MVPA and daily MVPA as independent variables.

Bold indicates significance, $\alpha < .05$.

in each physical activity intensity, the total time spent in that physical activity intensity across the day, and the number of hours awake. The proportion of hours within 1 day with at least 3 minutes of LPA was associated with more TST ($\beta = 0.10$, $P = .049$, 95% CI, 0.005 to 0.19), and a lower REM/NREM ratio in the first 360 minutes of sleep ($\beta = -0.15$, $P = .022$, 95% CI, -0.26 to -0.04). In both the LPA and MVPA model, hours awake before a bout of sleep was associated with less TST, less WASO, less REM-L, and greater REM/NREM ratio in the first 180 and 360 minutes of sleep. No statistically significant effects were found for intraday MVPA frequency or total MVPA. These findings are summarized in Table 4.

There were no statistically significant effects of intraday LPA frequency or total LPA on any self-reported measures. However, in the intraday LPA model (Table 5, model 7), time awake before a bout of sleep was associated with less feelings of contentment ($\beta = -0.08$, $P = .042$) and SSQ ($\beta = -0.14$, $P = .003$) the following morning. In the intraday MVPA model, intraday MVPA frequency was associated with greater feelings of contentment ($\beta = 0.13$, $P = .049$, 95% CI, 0.0002 to 0.26). These findings are summarized in Table 5.

Discussion

The purpose of this secondary data analysis was to examine the effects of intraday and interday physical activity frequency on sleep architecture and morning mental state. Our findings show the frequency of MVPA across the week may beneficially influence sleep architecture by increasing the amount of NREM sleep during the first 180 minutes of sleep. General engagement in LPA, regardless of distribution across the week, may have comparable effects and may also increase feelings of energy in the morning. However, the associations of LPA with REM/NREM and morning energy should be interpreted with caution given these results had P values of less than .05 but also CIs including zero. Within 1 day, a higher frequency of LPA per hour may increase TST that night and increase the amount of NREM sleep during the first 360 minutes of sleep. The intraday MVPA frequency was also associated with greater feelings of contentment the following morning.

Overall, the results of this study point to the importance of considering frequency as an additional parameter in the prescription

and analysis of physical activity behaviors for promoting sleep. Both frequency and total time of activity were related to beneficial outcomes, implying the possibility of utilizing a “staircase approach”³² to the promotion of physical activity for better sleep. In other words, people could be encouraged to be as active as they are able to, and when they are ready, they can craft a specific routine to increase the frequency of MVPA.³³ Interestingly, the effects of frequency on sleep we found in this study are different than the effects found on cardiometabolic risk, in which there appears to be no difference among activity distributions as long as the total volume of the activity is the same.¹⁵ However, given that sleep is circadian by nature, it makes sense that it is sensitive to daily rhythms and that repeated engagement in physical activity can enhance sleep health.⁵

The findings related to sleep architecture imply physical activity could be acting as a normalizer of the sleep cycle, encouraging more REM later in the night rather than at the start of sleep, where NREM is expected.⁹ This complements the findings of the primary study of these data, in which sedentary behavior was linked to a greater REM/NREM ratio at the beginning of the night.⁸ The protection of this increased NREM period in the first half of the night is important given the role of deep and light sleep in memory consolidation and cellular maintenance.^{34,35} Furthermore, an increased REM/NREM ratio at the beginning of the night is related to depressive disorders and comorbidity of sleep abnormalities.^{36,37} The findings on reduced REM/NREM ratio at the beginning of sleep are in line with laboratory research examining the effects of acute bouts of exercise on subsequent sleep.^{5,38,39}

The findings on physical activity frequency and mental state may also spur further research on activity frequency and self-reported well-being. While most findings were not statistically significant, we did see an association of intraday MVPA frequency and contentment, as well as some evidence for the association of total interday LPA and feeling energized. Physical activity has been long known to improve mental health, particularly depressive symptoms.⁴⁰ Studies analyzing the effects of exercise interventions on mood typically find benefits from bouts of exercise of at least moderate intensity with a duration of at least 10 minutes, which has some similarities with our findings given the threshold used in this study for MVPA frequency.⁴¹ Our previous study on this data set (Zapalac et al,⁸ *Scientific Reports*)

found beneficial associations of mood with total light activity, indicating overall engagement with activity of this intensity may be more important than its temporal distribution.⁸ Other research in this field has also touted physical activity as a useful stress-buffering intervention, though we did not see a statistically significant effect of frequency in this sample.⁴²

While the biological mechanisms, psychological consequences, and implications for sleep quality of decreased REM/NREM ratio at the beginning of sleep require more research, the primary study of these data⁸ found that these changes were associated with positive effects on both mood and sleep quality. Specifically, we observed that longer REM latency was associated with decreased stress and increased energy the morning after sleep. Furthermore, a higher REM/NREM ratio in the first 180 minutes of sleep was associated with lower morning energy and worse SSQ. Thus, our findings suggest that the decrease in the REM/NREM ratio early in the night that is associated with physical activity is associated with more energy in the morning after sleep as well as increased perceived restfulness of sleep. Intriguingly, these findings parallel polysomnography studies of depressed patients which show the opposite pattern of a disinhibition of REM sleep, including a shorter REM latency, prolonged REM sleep early in the night, and increased REM density.³⁶

Potential physiological mechanisms that may explain these changes include increased circulation of catecholamines related to physical activity³⁹ and thermoregulatory responses by the nervous system in response to activity-induced increases in core body temperature.¹⁰ Physical activity also increases the circulation of myokines—messenger molecules secreted by skeletal muscle when contracting in an exercise intensity-dependent manner, such as lactate, and irisin, that have downstream effects resulting in increased production of brain-derived neurotrophic factor.⁴³ Brain-derived neurotrophic factor is generally related with structural and functional health of the central nervous system, may be associated with increased deep sleep, and is a key protective mechanism against the cerebrotrophic effects of depression, stress, and aging.⁴⁴ More research is needed to trace these mechanisms at the cellular level in response to personal physical activity patterns, but we speculate that increases in physical activity frequency may be providing a “reset” of these mechanisms every day that activity is performed thereby enacting more consistent effects on sleep architecture compared to a bout of activity of equal duration that is concentrated into a single day. It should be noted that many variables outside of physical activity may influence sleep quality in the context of our college student population, such as caffeine use and academic workload.⁴⁵ The statistical modeling technique used in this study evaluates within-subject effects and accounts for between-subject variability such that an individual’s unique exposures to confounders are statistically controlled.⁴⁶ It would be interesting for future work to assess the interaction effects of physical activity frequency with known sleep disruptors encountered in daily living.

A limitation of this study is the reliance on age-predicted maximum heart rate and HRR data as a means of classifying physical activity intensity. Ideally, maximum heart rate is assessed objectively during a graded exercise test; however, that option was not available for this secondary data analysis. There are ongoing debates about methods for the prediction of age related maximum heart rate.⁴⁷ Some formulas are purported to be more accurate than others, yet replication of accuracy may be inconsistent due to natural participant and sample size variability.⁴⁸ The 220-minus-age formula was used to match the context of the original study and

align the findings for the ready implementation of interventions evaluating the effectiveness of using Fitbit-derived activity data for the promotion of better sleep. Although newer methods exist the 220-minus-age formula remains a method that holds good predictive quality for the general adult population.^{49,50} Additionally, we were not able to differentiate between the types of activity performed. This results in bias against finding benefits brought on by resistance training, given the lower reliability of wrist-mounted wearables for tracking this form of physical activity.⁵¹ Despite these limitations, the categorization of physical activity used in this study incidentally improves the ecological validity of the analysis for the preparation of Fitbit-based interventions. At the time of writing, the Fitbit app uses 220-minus-age and HRR methods for calculating target heart rate “zones” that users could strive to reach during a workout.⁵² The values of LPA and MVPA that were used to answer our research question were calculated in the same way the Fitbit app would do so for a person exercising to improve their sleep architecture.

The present study was exploratory in nature; larger sample sizes with improved device-wear adherence and greater heterogeneity of participant activity levels could also explore the effects of different frequency thresholds to assess the combined effects of frequency, time, and intensity parameters. The decision to use of 10-minute and 30-minute thresholds for MVPA and LPA respectively was informed by standard population-level physical activity questionnaires,²⁷ previous guidelines,⁵³ and inspection of the mean physical activity distribution of our participants. Future research should test these findings experimentally and promote continuous wearing of the device for an assessment that is better aligned to the current weekly physical activity guidelines for adults.

Conclusions

Our results show higher frequencies of interday and intraday physical activity may promote improvements in mood and sleep architecture. Most importantly, a greater number of days with engagement in at least 10 minutes of MVPA was associated with a lower REM/NREM ratio at the beginning of sleep across a 5-day observation period. To the authors’ knowledge, this is the first investigation to explicitly examine frequency as a physical activity parameter related to sleep architecture using objective measures in free-living conditions. Future research should replicate these findings in diverse populations with larger sample sizes, and design interventions promoting physical activity frequency.

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