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The Two Fundamental Shapes of Sleep Heart Rate Dynamics and Their Connection to Mental Health in College Students

Mikaela Irene Fudolig[a, b, c] Laura S.P. Bloomfield[a, b, c, d] Matthew Price[a, e] Yoshi M. Bird[a, c] Johanna E. Hidalgo[e] Julia N. Kim[f, g] Jordan Llorin[f, g] Juniper Lovato[a, c, h] Ellen W. McGinnis[i] Ryan S. McGinnis[i] Taylor Ricketts[d, j] Kathryn Stanton[f, g] Peter Sheridan Dodds[a, c, h, k] Christopher M. Danforth[a, b, c, d]

[a]Vermont Complex Systems Center, MassMutual Center of Excellence for Complex Systems and Data Science, University of Vermont, Burlington, VT, USA; [b]Department of Mathematics and Statistics, University of Vermont, Burlington, VT, USA; [c]Computational Story Lab, MassMutual Center of Excellence for Complex Systems and Data Science, University of Vermont, Burlington, VT, USA; [d]Gund Institute for Environment, University of Vermont, Burlington, VT, USA; [e]Department of Psychological Science, University of Vermont, Burlington, VT, USA; [f]Project LEMURS, University of Vermont, Burlington, VT, USA; [g]Department of Electrical and Biomedical Engineering, University of Vermont, Burlington, VT, USA; [h]Department of Computer Science, University of Vermont, Burlington, VT, USA; [i]Wake Forest University School of Medicine, Winston-Salem, NC, USA; [j]Rubenstein School of Environment and Natural Resources, University of Vermont, Burlington, VT, USA; [k]Santa Fe Institute, Santa Fe, NM, USA

Keywords
Sleep · Heart rate · Mental health · Clustering · Wearable devices · Sleep phenotypes

Abstract
Introduction: Wearable devices are rapidly improving our ability to observe health-related processes for extended durations in an unintrusive manner. In this study, we use wearable devices to understand how the shape of the heart rate curve during sleep relates to mental health. ***Methods:*** As part of the Lived Experiences Measured Using Rings Study (LEMURS), we collected heart rate measurements using the Oura ring (Gen3) for over 25,000 sleep periods and self-reported mental health indicators from roughly 600 first-year university students in the USA during the fall semester of 2022. Using clustering techniques, we find that the sleeping heart rate curves can be broadly separated into two categories that are mainly differentiated by how far along the sleep period the lowest heart rate is reached. ***Results:*** Sleep periods characterized by reaching the lowest heart rate later during sleep are also associated with shorter deep and REM sleep and longer light sleep, but not a difference in total sleep duration. Aggregating sleep periods at the individual level, we find that consistently reaching the lowest heart rate later during sleep is a significant predictor of (1) self-reported impairment due to anxiety or depression, (2) a prior mental health diagnosis, and (3) firsthand experience in traumatic events. This association is more pronounced among females. ***Conclusion:*** Our results show that the shape of the sleeping heart rate curve, which is only weakly correlated with descriptive statistics such as the

karger@karger.com
www.karger.com/dib

Correspondence to:
Mikaela Irene Fudolig, mikaela.fudolig@uvm.edu

average or the minimum heart rate, is a viable but mostly overlooked metric that can help quantify the relationship between sleep and mental health.

Introduction

Sleep is an important component of well-being, with poor sleep leading to impaired function at the individual and societal [1–5] levels. While some aspects of sleep can be easily monitored, such as the awakening time or the time to bed, the unconscious nature of sleep requires external monitoring for proper assessment [6]. Polysomnography has been the gold standard for sleep monitoring, but it requires controlled conditions in a clinical setting, making it costly and inconvenient [7, 8]. In comparison, the growing availability of consumer-grade wearable devices allows individuals to monitor their sleep for extended periods in a nondisruptive and more affordable manner without the recall bias characteristic of self-reports [9]. Feedback from wearable devices is also available soon after data collection, which aids in delivering and assessing the effects of behavioral changes such as interventions.

Sleep has mostly been assessed in terms of sleep duration, sleep efficiency, and the time spent in different sleep stages [10, 11]. Heart rate variability (HRV) is also of interest, particularly in studies on sleep apnea [12–14], and time- and frequency-domain analysis techniques are commonly used [15, 16]. Clustering techniques have been applied on these metrics to find sleep phenotypes, sleep patterns shared by a group of individuals that may also share similar characteristics [17–20]. While most use descriptive statistics of these metrics in the clustering algorithm, more recent work used features extracted from the raw sleep-wake time series from more than 100,000 individuals to infer sleep phenotypes related to insomnia [21].

While it has long been known that heart rate generally decreases during sleep [22], the patterns of change in the sleeping heart rate are not well-studied. Unlike other sleep metrics such as sleep stages or HRV, heart rate is more reliably measured by consumer wearable devices [23–27] using photoplethysmography [28], especially when the participant is at rest [29]. Heart rate patterns during sleep may give us valuable insights that may be more consistent across brands of wearable devices compared to those obtained using other sleep metrics.

Mental health has been shown to have a bidirectional relationship with sleep [5, 30, 31], indicating that treating sleep disorders may also improve mental health [32]. Most studies on mental health and sleep focus on perceived sleep quality [33], sleep duration [34–37], HRV [16, 38], or descriptive statistics (mean or minimum) of the heart rate [39–42]. Published studies on the relationship between the shape of the heart rate curve and mental health have focused on its periodicity in the context of daily circadian rhythms [43–46] or its shape for daytime and nighttime [47] but not on how heart rate changes during the sleep period itself.

Young adulthood is a critical life stage in detecting and treating mental health conditions and has been the subject of several studies [48–51]. An ongoing study at a university in the northeast USA (the Lived Experiences Measured Using Rings Study, or LEMURS) [52–54] monitors the mental and physical well-being of a cohort of college students using surveys and the Oura ring (Gen3), a wearable sleep and activity tracker [23, 24] that provides heart rate measurements in excellent agreement with those from electrocardiography [27]. With around half of study participants diagnosed with a mental health condition or having experienced two or more traumatic events [55], this dataset provides a unique perspective on the relationship between mental health and sleep for a population at risk.

Using data from the LEMURS study, we look at different patterns of change in the heart rate over a sleep period and relate these to the reported mental health indicators of the participants. Similar to the systematic characterization of sleep phenotypes from sleep-wake measurements using wearable devices [21], we perform clustering algorithms on the heart rate time series to see if these heart rate patterns can be grouped into categories. Associations between these categories and clinically relevant information, such as mental health outcomes, are then examined.

Methods

Data

Sleep data were obtained from 603 participants in LEMURS, who, at the time of the study, were first-year students in a university in the USA [52–54]. Participants were asked to wear the Oura ring (Gen3) during sleep for 8 weeks (Oct–Dec 2022). We examine heart rate time series measured by the ring at 5-min intervals from the start of each detected primary sleep period, yielding 25,800 time series for analysis. The ring also collects sleep period start and end times, the estimated duration of each sleep stage (light, REM, and deep sleep), time spent awake during the sleep period, average and lowest heart rates, the time when the lowest heart rate is obtained, sleep latency, average respiratory rate, average respiratory rate variation, and HRV.

To denoise the heart rate time series and make them comparable for sleep periods of different durations, we use piecewise aggregate approximation (PAA) [56, 57], dividing a time series into $n = 30$ equally sized segments and taking the mean of each. With a median of 102 data points per sleep period, $n = 30$ roughly corresponds to 15 min of sleep per segment. Using $n = 30$ allows us to include even the shortest sleep period (39 data points, or roughly 3.25 h of sleep). As movement during sleep results in poorer heart rate estimates [29], the Oura ring does not provide HR measurements when there is significant movement. This creates missing values in the raw time series. Sleep periods where there is at least one segment with a missing PAA value are disregarded, reducing the number of sleep periods examined to m = 20,167 belonging to $N = 599$ individuals. The disregarded sleep periods span a similar range of sleep period lengths (online suppl. Fig. S6; for all online suppl. material, see https://doi.org/10.1159/000539487) and are from 587 individuals, indicating that disregarding time series with missing PAA values does not sufficiently discriminate against a few users or sleep period durations.

Participants completed baseline surveys (Table S1) about their demographics (e.g., gender, race), mental health diagnoses [58], impairment due to anxiety or depression, and the number of types of traumatic events experienced firsthand [55] (0, 1, or ≥2). They also completed the Perceived Stress Scale (PSS) [59] and Generalized Anxiety Disorder-7 (GAD-7) [60] questionnaires at the end of each week throughout the study period. The PSS is designed to assess stress while the GAD-7 is a tool used to screen for generalized anxiety disorder.

The students all entered the university in the same academic year, studied full-time, and were required to be within 18–24 years of age to be part of the study. 96% of the students reported birth years between 2002 and 2004.

Clustering the Time Series

We perform k-means clustering [61] on the m = 20,167 heart rate time series processed with PAA. The optimum number of clusters, k, is determined using consistency metrics. First, we use 30 randomly selected subsets of the data (10% of the total size) to train the model. For each training subset, we perform k-means with 30 different centroid initializations and assign the remaining observations to a given cluster based on the trained model. This results in 900 different k-means runs for each value of k. If the clustering is robust, the time series must be clustered similarly for different runs, resulting in the convergence of the cluster centroids across the different randomizations. Once consistent cluster centroids are found, we standardize the cluster centroids by training the k-means model on the entire dataset for 30 different initializations. We perform another round of k-means on these centroids, resulting in what we call "metaclusters." Cluster centroids assigned to the same metacluster will be assigned the same cluster label, and this cluster label will be transmitted back to the raw heart rate time series. Each raw heart rate time series will have 30 cluster labels, and the mode of these will be the final cluster label assignment for the time series. While we discuss here the results using Euclidean distance in the clustering algorithm, constrained dynamic time warping (cDTW) produced similar results (online suppl. Fig. S5).

Understanding the Clusters

We use logistic regression to gain insight into the sleep measures that differentiate the clusters. Because the clusters were obtained solely from the shapes of the heart rate curves, we do not add random effects. After performing regression models using each measure separately, we combine the sleep measures in a single model and use stepAIC of the MASS library in R to perform stepwise regression. We check for practical significance by examining the distributions and descriptive statistics of each sleep measure for the clusters found.

Relating Clusters to Mental Health

For each sleep period, we take the cluster label as the outcome variable and the survey responses of the individual as the predictors. Specifically, we look at the individual's baseline survey responses on prior mental health diagnoses, impairment due to anxiety or depression, traumatic events experienced, gender and race, and their weekly PSS and GAD-7 scores. Since the PSS and GAD-7 scores are obtained weekly while the sleep data are obtained nightly, we only include weeks where a given participant answered the weekly survey and had at least three (3) recorded sleep periods. We also require that this restriction yields at least ten (10) sleep periods for a given participant. These ensure that the weight of a given sleep period to the weekly PSS score is not artificially high and that enough data points are available for the fraction of sleep periods in a given cluster for each individual to be a reasonable measure. We note that these steps yield similar distributions of the demographic variables (online suppl. Fig. S7). This results in a dataset with 15,073 sleep periods from $N = 505$ participants. Logistic mixed-effects models, with the participant ID and the week number treated as random effects, were used in the analysis.

We then focus on predicting an individual's mental health indicators (impairment, prior mental health diagnosis, and firsthand experience of traumatic events) from their sleeping heart patterns using logistic regression. All regression models were implemented using the Python package pymer4 [62].

Results

Highly consistent cluster labels were obtained across different centroid initializations or training subsets for k = 2 clusters but not for higher values of k (Fig. 1). Using the full dataset to train the clustering model, 99.96% of the sleep periods had identical cluster assignments after performing k-means 30 times, each with different centroid initializations. Much lower values are obtained for higher values of k (online suppl. Fig. S2, S3). This separation into two groups was further confirmed with pairwise correlation maps (online suppl. Fig. S4) and high Jaccard similarity coefficients of obtained clusters under resampling, a method used to check cluster stability [63].

Cluster Characteristics

Logistic regression reveals that the two clusters are most differentiated by how far along the sleep period the lowest HR is measured. It is the most relevant predictor in the regression model, resulting in the lowest AIC and residual deviance when used as a lone predictor, and is the

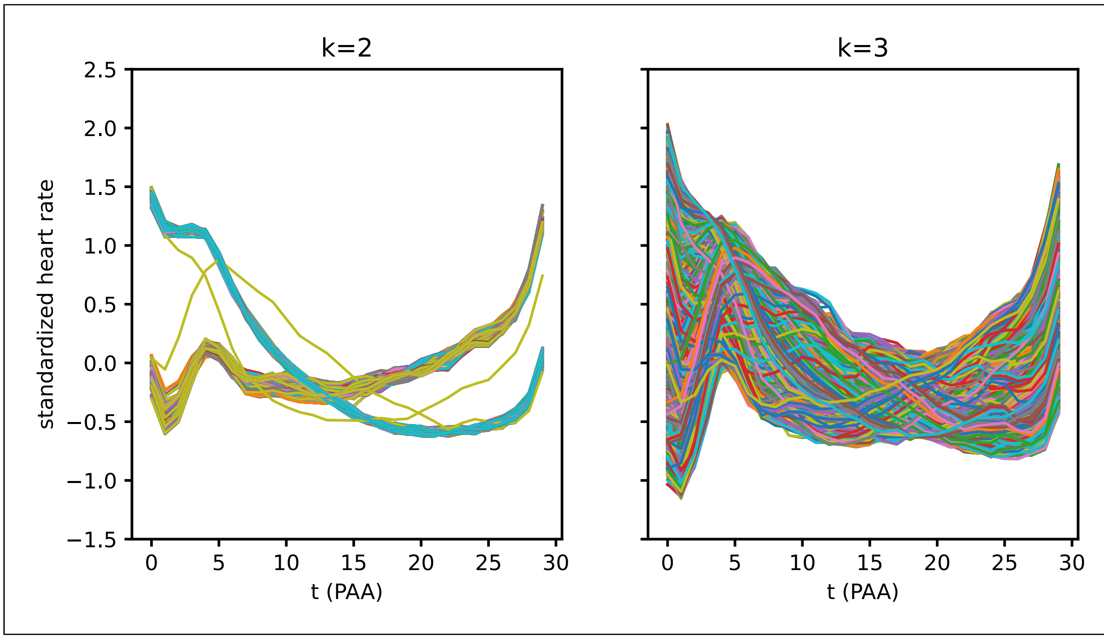

Fig. 1. Cluster consistency across different training subsets and initializations. Each curve shows a cluster centroid found for a given number of clusters k using a randomized 10% subset of the data and a randomized centroid initialization to run k-means. With 30 different randomized subsets and 30 different centroid initializations, there are 900*k curves in each plot. Highly consistent cluster centroids are found for k = 2 but are not found for k = 3 and higher (see online suppl. Fig. S1 for k > 3).

most highly correlated with the cluster label. We can see this clearly in the distributions of this variable for the two clusters, as well as from the shape of the cluster centroids (Fig. 2a). The time required to reach the lowest heart rate is only weakly correlated with the average heart rate (Spearman's $\rho = 0.1$ for both raw time and fraction of the sleep period) and the lowest heart rate (Spearman's $\rho = 0.03$ for raw time and $\rho = 0.05$ for fraction of the sleep period). We denote the cluster with the longer median time to reach the lowest heart rate as cluster 1, and the other cluster as cluster 2, corresponding to 64% and 36% of the sleep periods examined, respectively.

The two clusters also differ in terms of sleep stage composition. Cluster 1 is associated with shorter durations of deep (median percentage of the sleep period, 30 vs. 34%) and REM (20 vs. 22%) sleep and longer durations of light sleep (49 vs. 44%). There is no obvious difference in the distributions of the total sleep duration between the two clusters, which is confirmed by the Mann-Whitney U test ($p = 0.18$, Fig. 2f). Sleep periods in cluster 1 are also characterized by slightly longer sleep latency, earlier bedtime start and earlier bedtime end, higher average heart rate and lower average HRV. As the average HRV is highly negatively correlated with the average heart rate (online suppl. Table S3), we do not include it in the regression model (online suppl. Table S4). While the average respiratory rate variability was statistically significant in the regression model, we did not find this difference between the two clusters to be practically significant. Differences in the means and medians of the sleep metrics between the two clusters are summarized in Table 1.

Mental Health and Sleeping Heart Rate Curves

Logistic mixed-effects regression is used to reveal relationships between the cluster membership of a given sleep period and the associated individual's demographic and mental health indicators. For this analysis, cluster label is the response and participant ID is a random effect. Adding the week number as either a random or a fixed effect, or excluding it entirely, resulted in similar coefficients and *p* values for the other predictors (Table 2 vs. online suppl. Table S5). We thus omit the week number in our final models.

The following predictors were considered fixed effects (Table S1): gender (68% female, 26% male, 6% other genders), race (88% white, 12% non-white), PSS scores, GAD-7 scores, existence of a prior mental health diagnosis (45% with, 55% without), the number of traumatic event categories experienced firsthand [54] (28% with 0, 32% with 1, 40% with ≥2), and impairment due to anxiety

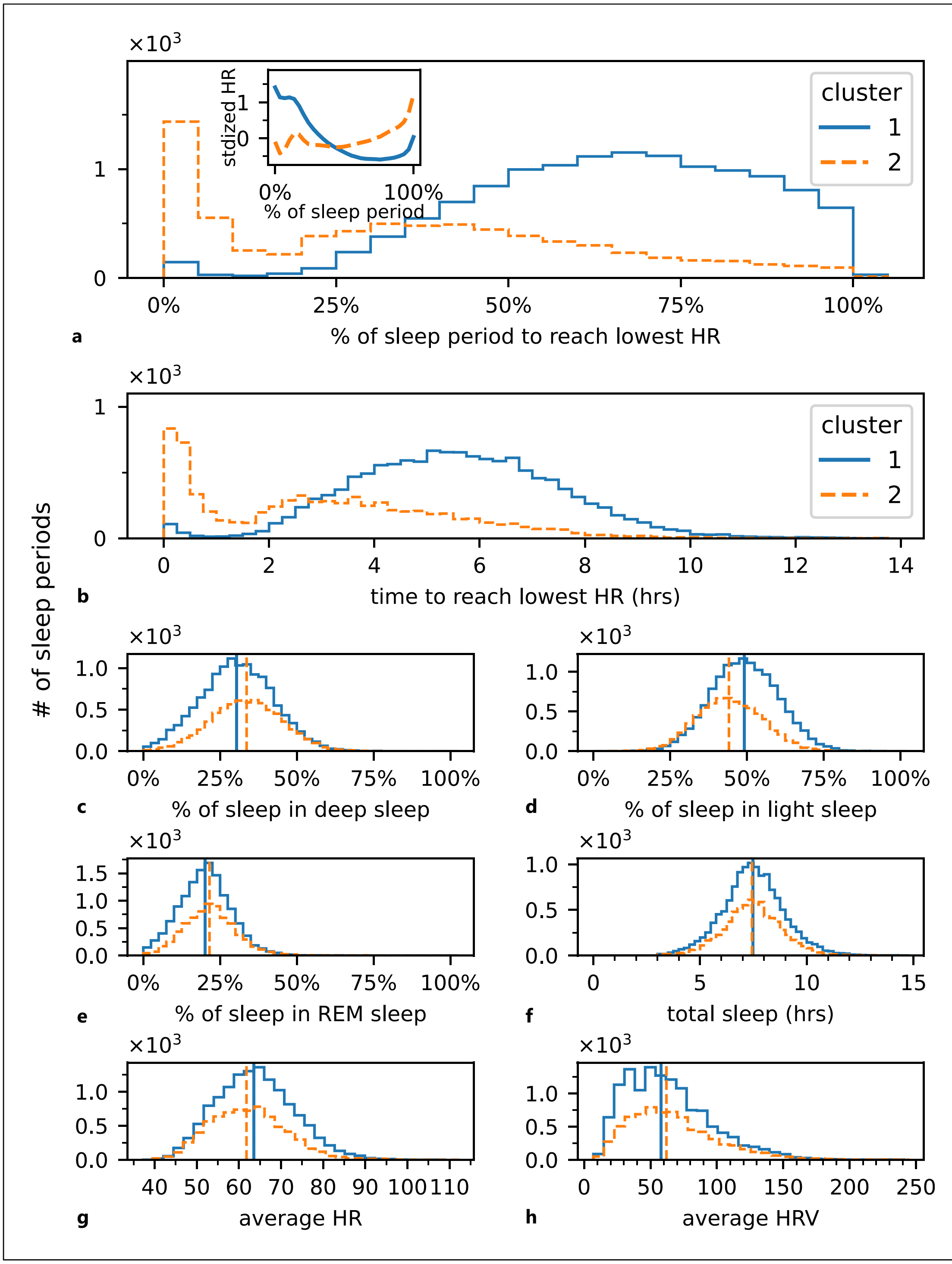

Fig. 2. Characterizing clusters of sleeping heart rate curves. The two clusters found are most clearly differentiated by the how far along the sleep period the lowest heart rate is reached (**a**) as compared to other sleep measures taken by the Oura ring. This is consistent with the centroids of the time series in each cluster (inset). Similar behavior is found for the time in hours needed to reach the lowest heart rate (**b**). The clusters also differ in their sleep stage compositions (**c–e**) but not in the total sleep duration (**f**). Smaller but statistically significant differences are also observed for the average heart rate and the average HRV (**f–h**). Vertical lines indicate the medians for each distribution.

Table 1. Descriptive statistics of the sleep measures for each cluster

Sleep measure/cluster	Mean		SD		Median		IQR	
	1	2	1	2	1	2	1	2
Lowest HR time offset (% of sleep period)	64.9	35.1	20.3	26.6	66.0	33.6	29.9	45.4
% of sleep period in deep sleep	30.5	33.7	11.8	11.5	30.4	33.6	16.0	15.7
% of sleep period in REM sleep	20.1	21.8	8.3	8.6	20.2	21.6	10.8	11.0
% of sleep period in light sleep	49.4	44.5	10.8	10.6	49.1	44.1	14.9	14.8
Total sleep duration, h	7.49	7.46	1.44	1.37	7.48	7.43	1.77	1.71
Sleep efficiency, %	87.8	88.5	5.5	5.2	89.0	89.0	7.0	6.0
Sleep latency, min	12.9	9.0	12.6	6.6	9.0	7.0	11.5	8.0
Bedtime start, h (from 12 mn)	0.46	0.63	1.67	1.61	0.38	0.54	1.99	1.97
Bedtime end, h (from 12 mn)	9.01	9.06	1.76	1.67	8.92	8.98	2.21	2.12
Bedtime duration, h	8.54	8.44	1.60	1.54	8.52	8.43	1.92	1.88
Average respiratory rate, breaths/min	15.6	15.5	1.7	1.6	15.5	15.4	2.4	2.1
Average respiratory rate variability, breaths/min	3.35	3.36	0.68	0.70	3.25	3.25	0.875	0.875
Average heart rate, beats/min	63.9	62.2	9.2	9.1	63.6	61.8	12.6	12.4
Average HRV, ms	63.3	67.2	32.1	33.6	58.0	62.0	43.0	42.0

Table 2. Results of logistic mixed-effects regression models for predicting the cluster membership of a sleep period using variables related to the individual, with the participant ID as a random effect

Fixed effects	Model with lone predictors				Final model			
	odds ratio	2.5% CI	97.5% CI	*p* value	odds ratio	2.5% CI	97.5% CI	*p* value
Gender (male)	1.207	0.940	1.552	0.141	1.324	1.031	1.701	**0.028**
Gender (nonbinary)	1.345	0.857	2.111	0.198	1.205	0.771	1.883	0.413
Race (non-white)	0.942	0.680	1.304	0.718				
Impairment due to anxiety/depression	1.538	1.226	1.929	<**0.001**	1.477	1.163	1.875	**0.001**
Prior mental health diagnosis	1.435	1.156	1.782	**0.001**				
Traumatic events experienced (≥2)	1.453	1.167	1.809	<**0.001**	1.329	1.061	1.664	**0.013**
	Coeff	2.5% CI	97.5% CI	*p* value				
Week number	0.013	–0.005	0.031	0.15				
PSS	–0.003	–0.011	0.005	0.493				
GAD	–0.004	–0.016	0.008	0.52				

For the dependent variable, cluster 1 is coded as 1 and cluster 2 is coded as 0.

or depression (35% with, 65% without). We note that 96% of those with a prior mental health diagnosis reported anxiety or depression.

While prior mental health diagnosis and impairment are highly correlated (Spearman's $\rho = 0.8$) and should not be used in the same model, we can test which of these two predictors produces a better fit. Similarly, PSS and GAD-7 scores are highly correlated (Spearman's $\rho = 0.7$) so we only use one in any given model to determine the effect of stress or anxiety levels.

Having a prior mental health diagnosis, impairment, or firsthand experience in 2 or more traumatic events are highly significant ($p \leq 0.001$) as lone predictors of the sleep period cluster. Gender is not statistically significant at $\alpha = 0.05$ when used as a lone predictor or used together with traumatic events experienced but is statistically significant when used together with impairment or prior mental health diagnoses (Table 2). PSS scores, GAD-7 scores, and race are not statistically significant at $\alpha = 0.05$, regardless of whether they are used as lone predictors or used in conjunction with others. Interaction effects between gender and impairment, as well as gender and traumatic events experienced, were not statistically significant when the main effects are also included.

For the final model (Table 2), we use impairment, traumatic events experienced, and gender as fixed effects. Impairment was highly associated with being in cluster 1, which is characterized by reaching the lowest HR later during sleep, as is having experienced 2 or more traumatic events. Being male is also associated with higher odds of being in cluster 1.

As a post hoc analysis (online suppl. Table S6), we also ran the regression models separately for males, females, and those who do not identify as either gender, which we denote here as "non-binary." Impairment is associated with increased odds of being in cluster 1 in sleep periods among females, while the number of traumatic events (whether <2 or ≥ 2) is associated with increased odds of being in cluster 1 in sleep periods among females and nonbinary individuals. Both variables are not statistically significant for males. In addition, if we restrict the data to sleep periods of those with or without impairment, we find that the odds of being in cluster 1 among those without impairment are higher for males than for females. No gender effect is seen among those with impairment. On the other hand, gender is only a significant predictor for those with two or more traumatic events, with nonbinary individuals having sleep periods of higher odds of being in cluster 1, but not for those who experienced fewer than two.

With both the normalized and raw time to reach the lowest heart rate being main differentiators of the two clusters (Fig. 2a, b), we look at whether these variables are also associated with demographic information. Using linear mixed-effects regression with the participant ID as a random effect (online suppl. Table S7), we see that impairment continues to be a significant predictor for both the normalized time ($p = 0.010$) and raw time ($p = 0.015$). However, while gender ($p = 0.001$) and traumatic events ($p = 0.021$) are also significant predictors for normalized time, similar to what we observed for the cluster prediction, they are not significant in predicting raw time ($p > 0.05$). This indicates that while different genders with similar mental health information may reach the lowest HR at similar times, the difference in the shape of the heart rate curve can be attributed to the shorter sleep duration among males (online suppl. Fig. S9; online suppl. Table S9). On the other hand, the relationship between mental health and the time to reach the lowest heart rate is robust.

Predicting an Individual's Mental Health Indicator from Sleep Period Cluster Data

With the main predictors not related to any of the weekly measures, we can aggregate our data at the individual level and predict mental health indicators from how often their sleep periods belong in a given cluster. Using logistic regression (Table 3), we find that having a higher fraction of sleep periods in cluster 1 is associated with higher odds of having impairment, a prior mental health diagnosis, or experience in 2 or more traumatic events. It is a statistically significant predictor of being female (vs. non-female). Still, this fraction is not significant in differentiating males and non-males or nonbinary individuals and those who are either male or female.

As gender is common demographic information to ask in health-related apps, we check whether this aids in predicting mental health indicators when used together with the fraction of sleep periods in cluster 1. This fraction and gender are statistically significant in predicting impairment and prior mental health diagnoses. However, in predicting experience in 2 or more traumatic events, gender is not statistically significant (see Table S8 for the detailed regression results).

We also perform a post hoc analysis to dig deeper into the effect of gender (Table 4). The fraction of sleep periods belonging to cluster 1 is a statistically significant predictor for impairment only for females; for traumatic events, it is statistically significant only for females and nonbinary individuals. In these cases, having more sleep periods in cluster 1 results in higher odds of having an impairment or experience in two or more traumatic events. This mirrors our earlier post hoc analysis in predicting the sleep period cluster based on the individual's characteristics. One can get an intuition of the regression results from the composition of our data as given in Table 5 and online supplementary Figures S8, S9, and S10.

Discussion

Using wearable and self-reported health data from first-year university students, we study how heart rate changes over a sleep period and how these relate to

Table 3. Results of logistic regression models predicting the response variable from the fraction of sleep periods an individual has in cluster 1

Response	Coeff	2.5% CI	97.5% CI	p value
With impairment	1.408	0.582	2.235	<**0.001**
With mental health diagnosis	1.177	0.404	1.949	**0.003**
With ≥2 traumatic events	1.308	0.513	2.103	**0.001**
Gender (0 if male, 1 otherwise)	−0.705	−1.583	0.172	0.115
Gender (0 if female, 1 otherwise)	0.840	0.018	1.663	**0.045**
Gender (0 if nonbinary, 1 otherwise)	−0.832	−2.440	0.776	0.31

Table 4. Post hoc analysis for predicting the response variable using the fraction of sleep periods in cluster 1 for a given individual in a subset of the data defined by gender

Subset	Response	Coeff	2.5% CI	97.5% CI	p value
Female only	With impairment	1.556	0.605	2.506	**0.001**
Female only	With ≥2 traumatic events	1.166	0.247	2.085	**0.013**
Male only	With impairment	0.733	−1.553	3.017	0.530
Male only	With ≥2 traumatic events	1.236	−0.604	3.076	0.188
Nonbinary only	With impairment	2.803	−0.371	5.977	0.083
Nonbinary only	With ≥2 traumatic events	3.835	0.154	7.517	**0.041**

Table 5. Impairment, trauma, and cluster consistency by gender

Gender	Impairment	Individuals		Nights		frac_1		Trauma	Individuals		Nights		frac_1	
		size	pct (%)	size	pct (%)	mean (SD)	median (IQR)		size	pct (%)	size	pct (%)	mean (SD)	median (IQR)
Female (68%)	0	212	61.6	6,584	62.9	0.59 (0.24)	0.62 (0.37)	<2	204	59.3	6,443	61.5	0.60 (0.25)	0.62 (0.40)
	1	132	38.4	3,885	37.1	0.68 (0.24)	0.72 (0.36)	≥2	140	40.7	4,026	38.5	0.66 (0.23)	0.69 (0.30)
Male (26%)	0	106	82.2	3,027	84.1	0.66 (0.20)	0.68 (0.25)	<2	83	64.3	2,359	65.5	0.65 (0.21)	0.67 (0.29)
	1	23	17.8	574	16.0	0.69 (0.24)	0.72 (0.33)	≥2	46	35.7	1,242	34.5	0.70 (0.18)	0.71 (0.22)
Nonbinary (6%)	0	11	34.4	388	38.7	0.57 (0.29)	0.66 (0.44)	<2	18	56.3	584	58.2	0.60 (0.24)	0.65 (0.35)
	1	21	65.6	615	61.3	0.74 (0.21)	0.76 (0.28)	≥2	14	43.8	419	41.8	0.79 (0.23)	0.88 (0.25)

frac_1 is the fraction of sleep periods in cluster 1.

mental health. We find two broad categories of sleeping heart rate curves mainly differentiated by when the lowest heart rate is attained. Sleep periods where the lowest heart rate is reached later are also characterized by shorter deep and REM sleep and longer light sleep, but not significantly different sleep duration. While studies tend to aggregate heart rate measurements into a single statistic (e.g., mean, minimum), these are only weakly correlated with the pattern of change in the sleeping heart rate, indicating that the shape of the sleeping heart rate curve contains new information outside of these aggregate values.

To our knowledge, the only other study on the shapes of sleeping heart rate curves was performed by Oura [64]. They found four shapes, contrasting with the two broad categories for which we found strong support. While the methodology and analysis in this study were not released, we were able to reproduce these four shapes by setting k = 4 in the k-means algorithm and taking the cluster centroids (online suppl. Fig. S3). However, for our dataset, setting k = 4 results in less consistent cluster labels with different training subsets or initializations, unlike the case of k = 2. Our analysis points to a spectrum of shapes, including the four shapes that Oura found that can be broadly categorized into two groups. It is worth noting that Oura's analysis reflects several orders of magnitude more individuals, with far broader demographic variation.

We also find that these sleeping heart rate patterns are related to mental health indicators, particularly traumatic events experienced and impairment due to anxiety or depression, with the latter being highly correlated with having a prior mental health diagnosis. Individuals who self-report impairment or who have experienced two or more traumatic events [55] are more likely to attain the lowest heart rate later in sleep. The fraction of sleep periods of a participant in a given pattern is a significant predictor for impairment and the number of traumatic events experienced. Finding differential sleep patterns by mental health status is consistent with previous works [65–67]. With the majority of the mental health diagnoses in our sample being anxiety or depression, our findings also point to links between these disorders and how heart rate changes during sleep.

While several studies show that concurrent stress and anxiety levels affect sleep [40, 68–70], we find that weekly stress and anxiety scores are not statistically significant in predicting the sleeping heart rate curve pattern. This may be due to a difference in temporal resolution: sleep periods are monitored nightly, while the stress and anxiety levels are only obtained from a weekly self-report [53]. We are implementing more frequent surveys in future studies to ascertain whether daily fluctuations in stress or anxiety relate to how heart rate changes during sleep. Another possible explanation is that the heart rate signatures may have been formed after impairment or trauma and may have stabilized since. These signatures may not be as sensitive to weekly or daily fluctuations in stress or anxiety. More studies will have to be done to test this hypothesis.

We also observe differences across genders in how sleeping heart rate patterns relate to mental health indicators. Impairment and traumatic events experienced are both related to the sleeping heart rate clusters for females, but not for males. For nonbinary individuals, the sleeping heart rate patterns differ by experienced trauma only. Further, males, whether or not they have impairment or traumatic experiences, have higher odds of reaching the lowest heart rate later in sleep. Gender differences in sleep have been observed in prior studies [71–74], although there are conflicting results [75] possibly due to different study designs. We also note that our sample is highly homogeneous in age, which is not the case in most research on gender differences in sleep. In summary, our results show that not only do we find different patterns in how the heart rate changes during sleep, but that these patterns are related to mental health, indicating that the shape of the heart rate curve is a viable but underexplored sleep metric.

We are interested in studying university students [76] as they are a population at risk [77] for which mental health interventions are highly relevant and more easily implementable [52–54]. However, this sample limits the generalizability of our results in terms of demographics, sleep disorder prevalence [78], and life stressors [79]. We hope to address these limitations by expanding our recruitment to include a more diverse set of individuals in future work.

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Statement of Ethics

Participants were required to complete a comprehension assessment with completely correct answers before being able to provide written informed consent through REDCap, a HIPAA-compliant online application. This study protocol was reviewed and approved by the University of Vermont Institutional Review Board (protocol number 00002126).

Conflict of Interest Statement

All authors declare no financial or nonfinancial competing interests.

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Author Contributions

M.I.F., L.S.P.B., M.P., J.u.L., E.M., R.M., T.R., P.S.D., and C.D. designed the study. M.I.F., M.P., L.S.P.B., and E.M. performed the analysis. Y.M.B., J.E.H., J.K., J.o.L., and K.S. performed the data collection and cleaning. M.I.F. wrote the manuscript with inputs from all the authors. All authors approved the final version of the manuscript.

Data Availability Statement

The data to replicate most of the results are available through this public repository: https://doi.org/10.6084/m9.figshare.25877302. Due to the small size of minorities from which the identity of a participant may be inferred, information on the race of the participants will be shared on reasonable request to the corresponding author. We note that race was not found to be relevant in our results.

References

1 Magnavita N, Garbarino S. Sleep, health and wellness at work: a scoping review. Int J Environ Res Public Health. 2017;14(11):1347. https://doi.org/10.3390/ijerph14111347
2 Hafner M, Stepanek M, Taylor J, Troxel WM. Why Sleep Matters-The Economic Costs of Insufficient Sleep: A Cross-Country Comparative Analysis. Rand Health Q. 2017; 6(4):11.
3 Hillman D, Mitchell S, Streatfeild J, Burns C, Bruck D, Pezzullo L. The economic cost of inadequate sleep. Sleep. 2018;41(8):2. https://doi.org/10.1093/sleep/zsy083
4 Chaput JP, Carrier J, Bastien C, Gari´epy G, Janssen I. Economic burden of insufficient sleep duration in Canadian adults. Sleep Health. 2022;8(3):298–302. https://doi.org/10.1016/j.sleh.2022.02.001.
5 Palagini L, Hertenstein E, Riemann D, Nissen C. Sleep, insomnia and mental health. J Sleep Res. 2022;31(4):e13628. https://doi.org/10.1111/jsr.13628
6 Ravichandran R, Sien S-W, Patel SN, Kientz JA, Pina LR. Making sense of sleep sensors: how sleep sensing technologies support and undermine sleep health. Proceedings of the 2017 CHI conference on human factors in computing systems. New York: CHI '17 (Association for Computing Machinery; 2017. p. 6864–75.
7 Kelly JM, Strecker RE, Bianchi MT. Recent developments in home sleep-monitoring devices. ISRN Neurol. 2012;2012:e768794. https://doi.org/10.5402/2012/768794
8 Guillodo E, Lemey C, Simonnet M, Walter M, Baca-García E, Masetti V, Moga S, Larsen M, HUGOPSY Network, Ropars J, Berrouiguet S. Clinical applications of mobile health wearable–based sleep monitoring: systematic review. JMIR Mhealth Uhealth. 2020;8(4): e10733. https://doi.org/10.2196/10733
9 Lauderdale DS, Knutson KL, Yan LL, Liu K, Rathouz PJ. Sleep duration: how well do self-reports reflect objective measures? The CARDIA Sleep Study. Epidemiology. 2008; 19(6):838–45. https://doi.org/10.1097/EDE.0b013e318187a7b0
10 Shrivastava D, Jung S, Saadat M, Sirohi R, Crewson K. How to interpret the results of a sleep study. J Community Hosp Intern Med Perspect. 2014;4(5):24983. https://doi.org/10.3402/jchimp.v4.24983
11 Kaplan KA, Hirshman J, Hernandez B, Stefanick ML, Hoffman AR, Redline S, et al. When a gold standard isn't so golden: lack of prediction of subjective sleep quality from sleep polysomnography. Biol Psychol. 2017;123:37–46. https://doi.org/10.1016/j.biopsycho.2016.11.010
12 Guilleminault C, Winkle R, Connolly S, Melvin K, Tilkian A. Cyclical variation of the heart rate in sleep apnoea syndrome: mechanisms, and usefulness of 24 h electrocardiography as a screenting technique. Lancet. 1984;323(8369): 126–31. https://doi.org/10.1016/s0140-6736(84)90062-x
13 Sequeira VCC, Bandeira PM, Azevedo JCM. Heart rate variability in adults with obstructive sleep apnea: a systematic review. Sleep Sci. 2019;12(3):214–21. https://doi.org/10.5935/1984-0063.20190082
14 Ucak S, Dissanayake HU, Sutherland K, de Chazal P, Cistulli PA. Heart rate variability and obstructive sleep apnea: current perspectives and novel technologies. J Sleep Res. 2021;30(4):e13274. https://doi.org/10.1111/jsr.13274
15 Penzel T, Kantelhardt JW, Bartsch RP, Riedl M, Kraemer JF, Wessel N, et al. Modulations of heart rate, ECG, and cardio-respiratory coupling observed in polysomnography. Front Physiol. 2016;7:460. https://doi.org/10.3389/fphys.2016.00460
16 Correia ATL, Lipinska G, Rauch HGL, Forshaw PE, Roden LC, Rae DE. Associations between sleep-related heart rate variability and both sleep and symptoms of depression and anxiety: a systematic review. Sleep Med. 2023;101:106–17. https://doi.org/10.1016/j.sleep.2022.10.018
17 Miller CB, Bartlett DJ, Mullins AE, Dodds KL, Gordon CJ, Kyle SD, et al. Clusters of insomnia disorder: an exploratory cluster analysis of objective sleep parameters reveals differences in neurocognitive functioning, quantitative EEG, and heart rate variability. Sleep. 2016;39(11):1993–2004. https://doi.org/10.5665/sleep.6230
18 Chiu VW, Ree M, Janca A, Iyyalol R, Dragovic M, Waters F. Sleep profiles and CBT-I response in schizophrenia and related psychoses. Psychiatry Res. 2018;268: 279–87. https://doi.org/10.1016/j.psychres.2018.07.027
19 Zinchuk AV, Jeon S, Koo BB, Yan X, Bravata DM, Qin L, et al. Polysomnographic phenotypes and their cardiovascular implications in obstructive sleep apnoea. Thorax. 2018;73(5):472–80. https://doi.org/10.1136/thoraxjnl-2017-210431
20 Kramer Fiala Machado A, Wendt A, Menezes AMB, Gonçalves H, Wehrmeister FC. Sleep clusters and modifiable risk behaviors for noncommunicable diseases in young adults: data from a birth cohort in Brazil. Sleep Health. 2023;9(3):346–53. https://doi.org/10.1016/j.sleh.2023.01.004
21 Katori M, Shi S, Ode KL, Tomita Y, Ueda HR. The 103,200-arm acceleration dataset in the UK Biobank revealed a landscape of human sleep phenotypes. Proc Natl Acad Sci U S A. 2022;119(12):e2116729119. https://doi.org/10.1073/pnas.2116729119
22 Snyder F, Allan Hobson J, Morrison DF, Goldfrank F. Changes in respiration, heart rate, and systolic blood pressure in human sleep. J Appl Physiol. 1964;19:417–22. https://doi.org/10.1152/jappl.1964.19.3.417
23 de Zambotti M, Rosas L, Colrain IM, Baker FC. The sleep of the ring: comparison of the OURA sleep tracker against polysomnography. Behav Sleep Med. 2019;17(2):124–36. https://doi.org/10.1080/15402002.2017.1300587
24 Altini M, Kinnunen H. The promise of sleep: a multi-sensor approach for accurate sleep stage detection using the Oura ring. Sensors. 2021;21(13):4302. https://doi.org/10.3390/s21134302
25 Bellenger CR, Miller DJ, Halson SL, Roach GD, Sargent C. Wrist-based photoplethysmography assessment of heart rate and heart rate variability: validation of WHOOP. Sensors. 2021;21(10):3571. https://doi.org/10.3390/s21103571
26 Imtiaz SA. A systematic review of sensing technologies for wearable sleep staging. Sensors. 2021;21(5):1562. https://doi.org/10.3390/s21051562
27 Cao R, Azimi I, Sarhaddi F, Niela-Vilen H, Axelin A, Liljeberg P, et al. Accuracy assessment of Oura Ring nocturnal heart rate and heart rate variability in comparison with electrocardiography in time and frequency domains: comprehensive analysis. J Med Internet Res. 2022;24(1):e27487. https://doi.org/10.2196/27487

28 Castaneda D, Esparza A, Ghamari M, Soltanpur C, Nazeran H. A review on wearable photoplethysmography sensors and their potential future applications in health care. Int J Biosens Bioelectron. 2018;4:195–202. https://doi.org/10.15406/ijbsbe.2018.04.00125
29 Bent B, Goldstein BA, Kibbe WA, Dunn JP. Investigating sources of inaccuracy in wearable optical heart rate sensors. NPJ Digit Med. 2020;3:18–9. https://doi.org/10.1038/s41746-020-0226-6
30 Robotham D. Sleep as a public health concern: insomnia and mental health. J Public Ment Health. 2011;10(4):234–7. https://doi.org/10.1108/17465721111188250
31 Sun X, Liu B, Liu S, Wu DJH, Wang J, Qian Y, et al. Sleep disturbance and psychiatric disorders: a bidirectional Mendelian randomisation study. Epidemiol Psychiatr Sci. 2022;31:e26. https://doi.org/10.1017/S2045796021000810
32 Freeman D, Sheaves B, Waite F, Harvey AG, Harrison PJ. Sleep disturbance and psychiatric disorders. Lancet Psychiatr. 2020;7:628–37. https://doi.org/10.1016/S2215-0366(20)30136-X
33 Ramsawh HJ, Stein MB, Belik S-L, Jacobi F, Sareen J. Relationship of anxiety disorders, sleep quality, and functional impairment in a community sample. J Psychiatr Res. 2009;43(10):926–33. https://doi.org/10.1016/j.jpsychires.2009.01.009
34 Rosa RR, Bonnet MH, Kramer M. The relationship of sleep and anxiety in anxious subjects. Biol Psychol. 1983;16(1–2):119–26. https://doi.org/10.1016/0301-0511(83)90058-3
35 Fuller KH, Waters WF, Binks PG, Anderson T. Generalized anxiety and sleep architecture: a polysomnographic investigation. Sleep. 1997;20(5):370–6. https://doi.org/10.1093/sleep/20.5.370
36 Van Mill JG, Hoogendijk WJG, Vogelzangs N, Van Dyck R, Penninx BWJH. Insomnia and sleep duration in a large cohort of patients with major depressive disorder and anxiety disorders. J Clin Psychiatry. 2010;71(3):239–46. https://doi.org/10.4088/JCP.09m05218gry
37 Baglioni C, Nanovska S, Regen W, Spiegelhalder K, Feige B, Nissen C, et al. Sleep and mental disorders: a meta-analysis of polysomnographic research. Psychol Bull. 2016;142(9):969–90. https://doi.org/10.1037/bul0000053
38 Valenza G, Citi L, Lanata A, Gentili C, Barbieri R, Scilingo EP. Applications of heartbeat complexity analysis to depression and bipolar disorder. In: Barbieri R, Scilingo EP, Valenza G, editors. Complexity and nonlinearity in cardiovascular signals. Cham: Springer International Publishing; 2017. p. 345–74.
39 Koskima¨ki H, Kinnunen H, Ro¨nk¨a S, Smarr B. Following the heart: what does variation of resting heart rate tell about us as individuals and as a population. Adjunct proceedings of the 2019 ACM international joint conference on pervasive and ubiquitous computing and proceedings of the 2019 ACM international symposium on wearable computers. New York, 2019: UbiComp/ISWC '19 Adjunct (Association for Computing Machinery. p. 1178–81.
40 Azza Y, Grueschow M, Karlen W, Seifritz E, Kleim B. How stress affects sleep and mental health: nocturnal heart rate increases during prolonged stress and interacts with childhood trauma exposure to predict anxiety. Sleep. 2020;43(6):zsz310. https://doi.org/10.1093/sleep/zsz310
41 Woodward SH, Jamison AL, Gala S, Lawlor C, Villasenor D, Tamayo G, et al. Heart rate during sleep in PTSD patients: moderation by contact with a service dog. Biol Psychol. 2023;180:108586. https://doi.org/10.1016/j.biopsycho.2023.108586
42 Siddi S, Bailon R, Giné-Vázquez I, Matcham F, Lamers F, Kontaxis S. PAB members, et al. The usability of daytime and night-time heart rate dynamics as digital biomarkers of depression severity. Psychol Med. 2023;53(8):3249–60. https://doi.org/10.1017/S0033291723001034
43 Taillard J, Lemoine P, Boule P, Drogue M, Mouret J. Sleep and heart rate circadian rhythm in depression: the necessity to separate. Chronobiol Int. 1993;10(1):63–72. https://doi.org/10.3109/07420529309064483
44 Stampfer HG. The relationship between psychiatric illness and the circadian pattern of heart rate. Aust N Z J Psychiatry. 1998;32(2):187–98. https://doi.org/10.3109/00048679809062728
45 Hickie IB, Naismith SL, Robillard R, Scott EM, Hermens DF. Manipulating the sleep-wake cycle and circadian rhythms to improve clinical management of major depression. BMC Med. 2013;11:79. https://doi.org/10.1186/1741-7015-11-79
46 Lutin E, Schiweck C, Cornelis J, De Raedt W, Reif A, Vrieze E, et al. The cumulative effect of chronic stress and depressive symptoms affects heart rate in a working population. Front Psychiatry. 2022;13:1022298. https://doi.org/10.3389/fpsyt.2022.1022298
47 Karimi F, Amoozgar Z, Reiazi R, Hosseinzadeh M, Rawassizadeh R. Longitudinal analysis of heart rate and physical activity collected from smartwatches. CCF Trans Pervasive Comp Interact. 2024;6(1):18–35. https://doi.org/10.1007/s42486-024-00147-y
48 Adlaf EM, Gliksman L, Demers A, Newton-Taylor B. The prevalence of elevated psychological distress among Canadian undergraduates: findings from the 1998 Canadian campus survey. J Am Coll Health. 2001;50(2):67–72. https://doi.org/10.1080/07448480109596009
49 Becker SP, Jarrett MA, Luebbe AM, Garner AA, Burns GL, Kofler MJ. Sleep in a large, multi-university sample of college students: sleep problem prevalence, sex differences, and mental health correlates. Sleep Health. 2018;4(2):174–81. https://doi.org/10.1016/j.sleh.2018.01.001
50 Adams KL, Saunders KE, Keown-Stoneman CDG, Duffy AC. Mental health trajectories in undergraduate students over the first year of university: a longitudinal cohort study. BMJ Open. 2021;11(12):e047393. https://doi.org/10.1136/bmjopen-2020-047393
51 Copeland WE, McGinnis E, Bai Y, Adams Z, Nardone H, Devadanam V, et al. Impact of COVID-19 pandemic on college student mental health and wellness. J Am Acad Child Adolesc Psychiatry. 2021;60(1):134–41.e2. https://doi.org/10.1016/j.jaac.2020.08.466
52 Price M, Hidalgo JE, Bird YM, Bloomfield LSP, Buck C, Cerutti J, et al. A large clinical trial to improve well-being during the transition to college using wearables: the Lived Experiences Measured Using Rings Study. Contemp Clin Trials. 2023;133:107338. https://doi.org/10.1016/j.cct.2023.107338
53 Bloomfield L, Fudolig MI, Kim J, Llorin J, Lovato JL, et al. Predicting stress in first-year college students using sleep data from wearable devices. PLOS Digital Health. 2024;3(4). 10.1371/journal.pdig.0000473.
54 Bloomfield L, Fudolig M, Dodds P, Kim J, Llorin J, Lovato J, et al. Events and behaviors associated with symptoms of generalized anxiety disorder in first-year college students. PsyArXiv. 2023:278ey.
55 Gray MJ, Litz BT, Hsu JL, Lombardo TW. Psychometric properties of the life events checklist. Assessment. 2004;11(4):330–41. https://doi.org/10.1177/1073191104269954
56 Keogh E, Chakrabarti K, Pazzani M, Mehrotra S. Locally adaptive dimensionality reduction for indexing large time series databases. *Proceedings of the 2001 ACM SIGMOD international Conference on Management of data*, SIGMOD '01. New York: Association for Computing Machinery; 2001. p. 151–62.
57 Lin J, Keogh E, Wei L, Lonardi S. Experiencing SAX: a novel symbolic representation of time series. Data Min Knowl Discov. 2007;15(2):107–44. https://doi.org/10.1007/s10618-007-0064-z
58 Maier M, Carlotto H, Saperstein S, Sanchez F, Balogun S, Merritt S. Improving the accuracy and transparency of underwriting with artificial intelligence to transform the life-insurance industry. AI Mag. 2020;41(3):78–93. https://doi.org/10.1609/aimag.v41i3.5320
59 Cohen S, Kamarck T, Mermelstein R. A global measure of perceived stress. J Health Soc Behav. 1983;24(4):385–96. https://doi.org/10.2307/2136404
60 Spitzer RL, Kroenke K, Williams JBW, Löwe B. A brief measure for assessing generalized anxiety disorder: the GAD-7. Arch Intern Med. 2006;166(10):1092–7. https://doi.org/10.1001/archinte.166.10.1092
61 MacQueen J. Some methods for classification and analysis of multivariate observations. In Proceedings of the fifth berkeley symposium on mathematical statistics and probability Statistics University of California Press; 1967. Vol. 5.1. p. 281–98.
62 Jolly E. Pymer4: connecting R and Python for linear mixed modeling. J Open Source Softw. 2018;3(31):862. https://doi.org/10.21105/joss.00862

63 Hennig C. Cluster-wise assessment of cluster stability. Comput Stat Data Anal. 2007;52(1):258–71. https://doi.org/10.1016/j.csda.2006.11.025
64 Oura Team. Sleeping heart rate: look for these 3 patterns; 2023. https://ouraring.com/blog/sleeping-heart-rate.
65 Miano S, Parisi P, Villa MP. The sleep phenotypes of attention deficit hyperactivity disorder: the role of arousal during sleep and implications for treatment. Med Hypotheses. 2012;79(2):147–53. https://doi.org/10.1016/j.mehy.2012.04.020
66 Winsper C, Tang NKY, Marwaha S, Lereya ST, Gibbs M, Thompson A, et al. The sleep phenotype of Borderline Personality Disorder: a systematic review and meta-analysis. Neurosci Biobehav Rev. 2017;73:48–67. https://doi.org/10.1016/j.neubiorev.2016.12.008
67 Miano S, Amato N, Foderaro G, Pezzoli V, Ramelli GP, Toffolet L, et al. Sleep phenotypes in attention deficit hyperactivity disorder. Sleep Med. 2019;60:123–31. https://doi.org/10.1016/j.sleep.2018.08.026
68 Hall M, Vasko R, Buysse D, Ombao H, Chen Q, Cashmere JD, et al. Acute stress affects heart rate variability during sleep. Psychosom Med. 2004;66(1):56–62. https://doi.org/10.1097/01.psy.0000106884.58744.09
69 Akerstedt T, Kecklund G, Axelsson J. Impaired sleep after bedtime stress and worries. Biol Psychol. 2007;76(3):170–3. https://doi.org/10.1016/j.biopsycho.2007.07.010
70 Drake CL, Pillai V, Roth T. Stress and sleep reactivity: a prospective investigation of the stress-diathesis model of insomnia. Sleep. 2014;37(8):1295–304. https://doi.org/10.5665/sleep.3916
71 Lindberg E, Janson C, Gislason T, Björnsson E, Hetta J, Boman G. Sleep disturbances in a young adult population: can gender differences Be explained by differences in psychological status? Sleep. 1997;20(6):381–7. https://doi.org/10.1093/sleep/20.6.381
72 Tsai L-L, Li S-P. Sleep patterns in college students: gender and grade differences. J Psychosom Res. 2004;56(2):231–7. https://doi.org/10.1016/S0022-3999(03)00507-5
73 Goel N, Kim H, Lao RP. Gender differences in polysomnographic sleep in young healthy sleepers. Chronobiol Int. 2005;22(5):905–15. https://doi.org/10.1080/07420520500263235
74 Mong JA, Cusmano DM. Sex differences in sleep: impact of biological sex and sex steroids. Philos Trans R Soc Lond B Biol Sci. 2016;371(1688):20150110. https://doi.org/10.1098/rstb.2015.0110
75 Voderholzer U, Al-Shajlawi A, Weske G, Feige B, Riemann D. Are there gender differences in objective and subjective sleep measures? A study of insomniacs and healthy controls. Depress Anxiety. 2003;17(3):162–72. https://doi.org/10.1002/da.10101
76 Creswell JD, Tumminia MJ, Price S, Sefidgar Y, Cohen S, Ren Y, et al. Nightly sleep duration predicts grade point average in the first year of college. Proceedings of the National Academy of Sciences. 2023;120:e2209123120. https://doi.org/10.1073/pnas.2209123120
77 Liyanage S, Saqib K, Khan AF, Thobani TR, Tang W-C, Chiarot CB, et al. Prevalence of anxiety in university students during the COVID-19 pandemic: a systematic review. Int J Environ Res Public Health. 2021;19(1):62. https://doi.org/10.3390/ijerph19010062
78 Senaratna CV, Perret JL, Lodge CJ, Lowe AJ, Campbell BE, Matheson MC, et al. Prevalence of obstructive sleep apnea in the general population: a systematic review. Sleep Med Rev. 2017;34:70–81. https://doi.org/10.1016/j.smrv.2016.07.002
79 Gebreab SZ, Vandeleur CL, Rudaz D, Strippoli M-PF, Gholam-Rezaee M, Castelao E, et al. Psychosocial stress over the lifespan, psychological factors, and cardiometabolic risk in the community. Psychosom Med. 2018;80(7):628–39. https://doi.org/10.1097/PSY.0000000000000621