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RESEARCH ARTICLE

Exploring the Multidimensional Influences on Sleep and Active Heart Rate Dynamics: A Comprehensive Study

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Abstract

This study offers an in-depth examination of how various social, personal, physiological, environmental, and behavioral factors are associated with both sleep and active heart rate dynamics among college students. Utilizing data collected from 487 participants over a span of 637 days via wearable technology, this research aims to unravel the intricate relationships that influence heart rate variations. Through the application of latent growth-curve modeling, we meticulously analyzed the trajectory of heart rate changes and their associations with a broad spectrum of influencing factors. This methodological approach allowed for a nuanced understanding of the dynamic interplay between heart rate and its determinants over time. The analysis revealed a consistent increase in both sleep and active heart rates across the study period, accompanied by stable standard deviations. Peer influence significantly impacted sleep and active heart rates, especially at rest. Gender and race/ethnicity were associated with heart rate dynamics, as were conscientiousness and depression levels. Environmental factors, including days of the week, academic periods, and weather conditions, exhibited significant effects. Behavioral factors, such as physical activity and daily class attendance, played a substantial role in heart rate patterns. Our findings underscore the complex interplay of factors influencing heart rate dynamics in young adults. Tailored interventions should consider these multifaceted influences to promote optimal cardiovascular well-being.

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Introduction

Heart rate, a vital physiological marker, is integral to understanding cardiovascular health. It intersects with disciplines such as cardiology, sociology, psychology, and public health, offering crucial insights into individual well-being, identifying cardiovascular risk factors, and informing heart health strategies. Grasping the complex interactions between heart rate dynamics and various influencing factors is key to advancing our understanding in these areas.

In our previous research with the NetHealth project, we analyzed heart rate dynamics using Fitbit records, smartphone data, and survey responses from 487 undergraduate students at the University of Notre Dame over the period from August 16, 2015, to May 13, 2017[1]. Our findings indicated a gradual increase in average heart rate levels, stable standard deviations, and significant correlations between individuals' heart rates and their social networks. This study also shed light on the impact of personal factors such as gender and race/ethnicity, and psychological factors like conscientiousness, on heart rate variability. Moreover, environmental and behavioral factors, including physical activity, were seen to affect heart rate patterns.

However, our previous work did not distinguish between heart rates during sleep and wakefulness, an important aspect for a full understanding of cardiovascular dynamics. Sleep heart rate, measured during sleep, serves as a critical indicator of cardiovascular fitness and overall health, influenced by autonomic nervous system activity, cardiovascular efficiency, and metabolic rate[2][3][4]. On the other hand, active heart rate, observed during wakeful periods, reflects the heart's response to physical exertion and is crucial for assessing exercise capacity, tolerance, and physiological adaptations[5][6][7].

This study aims to fill the existing gap by exploring both sleep and active heart rates, offering a detailed model that accounts for various factors influencing cardiovascular dynamics. This comprehensive approach is invaluable for developing personalized interventions, from exercise routines to lifestyle changes, designed to optimize cardiovascular health in diverse situations and activity level..

Literature Review

This section reviews the relevant literature on the theoretical rationale for distinguishing heart rate patterns between sleep and wakefulness, while highlighting the factors associated with each. The aim is to establish a foundational understanding, identify gaps in existing research, and emphasize the importance of exploring the complex relationships between heart rate patterns and the diverse factors that influence them. By providing this analysis, the review enhances our understanding of cardiovascular dynamics and guides future research directions.

Theoretical Rationale for Distinguishing Heart Rate Patterns between Sleep and Wakefulness

The distinction between heart rate during sleep and wakefulness is grounded in key theories related to the autonomic nervous system's role in cardiovascular regulation. According to Polyvagal Theory[8], autonomic activation varies across different states of rest and activity, leading to significant differences in cardiovascular responses such as heart rate and rhythm. During sleep, the parasympathetic nervous system predominates, resulting in lower heart rates and higher heart rate variability, which are reflective of the body's restorative processes[9].

Additionally, Circadian Rhythm Theory[10] emphasizes the influence of internal circadian rhythms on physiological states, including cardiac functions. These rhythms create natural variations in heart rate, with sleep-associated patterns differing significantly from those observed during wakefulness due to the cardiovascular system's varying demands[11].

Empirical evidence supports the significance of this distinction. Specific phases of sleep, particularly those marked by reduced heart rate variability, have been linked to heightened cardiovascular risk[12]. Conversely, heart rate patterns during wakefulness reflect responses to various physical, emotional, and environmental stressors, illustrating the sympathetic nervous system's role in cardiovascular resilience[13]. By differentiating between sleep and wakefulness heart rates, this study integrates theoretical and empirical insights, providing a more nuanced understanding of how circadian rhythms and autonomic regulation influence cardiovascular health.

Factors Associated with Sleep and Active Heart Rate

Research on heart rate patterns during both sleep and activity has revealed a broad range of influencing factors. Exploring these dynamics offers a deeper understanding of heart rate variability and its critical role in overall health and well-being. By examining how various factors affect heart rate in different states, researchers can better grasp the complexities of cardiovascular regulation and its implications for long-term health outcomes.

Social factors significantly impact heart rate dynamics. Studies reveal the influence of peer interactions, showing that individuals' heart rate patterns can mirror those of the people they interact with. Instances of heart rate synchronization have been observed in various contexts, such as intimate couples[14], romantic partners[15][16], mother-infant interactions[17], therapist-patient interactions[18][19][20], and social group activities[21][22][23]. This synchrony has also been noted between resting mothers and preschoolers[24]. Mechanisms such as social interaction[25], empathetic mirroring, shared emotional states[26][21][27], and behavioral contagion within networks[28][29][30] help explain this phenomenon. Social support also affects heart rate levels during daytime and evening work hours[31], as well as heart rate variability during rest[32], further highlighting the link between social dynamics and cardiovascular health.

Personal characteristics also influence heart rate dynamics. Females generally have higher average sleep heart rates and greater variability[33][34][35], a pattern attributed to biological and physiological factors[36][37]. Ethnicity is another influential factor: Black Americans and African immigrants tend to exhibit elevated nighttime heart rates[38], likely due to genetic and cultural influences[6][39]. Additionally, body mass index (BMI) is associated with heart rate, as individuals with higher BMI often show elevated sleep heart rates, driven by increased metabolic demands and altered autonomic nervous system activity[40][35].

Psychological factors, such as personality traits and depression levels, are closely linked to heart rate dynamics. Higher levels of conscientiousness are associated with lower average heart rates, potentially offering cardiovascular protection[41]. In contrast, depression has been found to correlate with negative heart rate patterns during the day but positive associations at night, indicating a complex mental health-heart rate relationship[42]. These findings underscore the role of psychological factors in shaping heart rate patterns and their implications for well-being.

Environmental factors also play a significant role in heart rate patterns. Studies have examined how temporal aspects like weekdays, weekends, holidays, and academic periods affect heart rates[43]. Weekdays are associated with lower sleep heart rate averages than weekends, while holidays tend to increase sleep heart rates. Summertime has been linked to lower sleep heart rates[44]. Additionally, test anxiety has been shown to raise heart rates in students[45], suggesting that cognitive engagement and changes in routine can affect cardiovascular activity.

Behavioral factors have a substantial impact on heart rate dynamics. Physical activity causes heart rate acceleration during and after exercise[46]. Higher levels of physical activity are associated with lower sleep heart rates in individuals under 50, underscoring the cardiovascular benefits of exercise[47]. Adequate sleep duration is also linked to lower sleep heart rates[35][44]. Daily routines, such as class attendance, can negatively impact physical activity[48], highlighting the influence of academic engagement on exercise and subsequent cardiovascular responses.

Existing literature illustrates the complex interactions among physiological, social, personal, psychological, environmental, and behavioral factors that affect heart rate patterns. While previous studies have expanded our understanding, there remains a gap in the long-term analysis of these factors together. Critical aspects, such as the mechanisms and interactions influencing heart rate variations during wakefulness and rest, are yet to be fully explored. This study addresses this gap by examining how various factors correlate with both sleep and active heart rate patterns over an extended period, enriching our understanding of heart rate dynamics and offering new insights into their regulation..

Materials and Methods

Data

Large-scale datasets have significantly transformed research in healthcare and public health. The NetHealth data, which includes health indicators, social interactions, psychological factors, and environmental influences, serves as a prime example of such valuable resources. This project, received approval from the Institutional Review Boards (IRB) at the University of Notre Dame. Over 600 freshmen were recruited from 2015 to 2016 for a data collection period that spanned from August 16, 2015, to May 13, 2017. Written informed consent was secured from participants aged 18 and older, and from the parents or legal guardians of those under 18. The demographics of the NetHealth participants closely reflected those of the broader 2015 freshman cohort of approximately 2000 students, covering diverse categories such as gender, race/ethnicity, and religion. A significant majority of the participants (98.55%) reported their health as ranging from fair to excellent.

Participants wore Fitbit Charge HR wristbands for continuous monitoring of heart rate, physical activity, and sleep. Fitbit Charge HR's validity in studying heart rate is supported by prior research[49][50]. Data accuracy was ensured through meticulous collection protocols, supervised by trained personnels with regular quality checks. Smartphone communications were also backed up for privacy, without content recording. Regular online surveys every three to four months gathered self-reported health behavior data, including personality and depression levels. All data were stored on a secure server.

The NetHealth data offers a unique opportunity to study individuals' heart rate patterns during wake time and rest, providing insights into cardiovascular dynamics. Analyzing continuous heart rate monitoring from wearables reveals trends over time. This longitudinal approach investigates the influence of diverse factors on heart rate dynamics, including social, personal, psychological, environmental, and behavioral factors. Linking characteristics, behaviors, and health outcomes with heart rate measurements, the NetHealth data enhances our understanding of the complex interplay of these factors on heart rate. This knowledge informs interventions and advances population health research.

For this study, a subset of the NetHealth data was chosen, focusing on 487 participants with at least 80% complete daily records spanning from August 16, 2015, to May 13, 2017. This selection ensures data reliability, minimizes biases, and enhances findings' validity. This extended time frame covers an academic period of nearly two years, capturing a comprehensive view of heart rate patterns and associated factors.

Measures

This study focuses on heart rate patterns, particularly sleep and active heart rates, as dependent variables. Sleep heart rate reflects baseline cardiovascular activity during sleep[2][3][4], while active heart rate represents dynamic changes in cardiovascular responses to wakeful states and environmental influences[5][6][7]. Fitbit employs a reliable algorithm for sleep state determination using movement patterns and heart rate variability. Notably, Fitbit determines the day of a sleep episode by the rising time, irrespective of bedtime occurring before or after midnight. Consequently, mean and standard deviation of heart rate are calculated separately for wake and sleep times each day.

In addition to studying heart rate patterns, this research examines various factors linked to heart rate dynamics. Social influences like peer impact and communication patterns offer insights into social interactions' effects on heart rate responses. Peer influence is gauged by calculating the mean and standard deviation averages of sleep and active heart rates among a participant's in-study contacts, specifically, other participants in the NetHealth project. These contacts were identified through phone interactions, encompassing voice calls and text messages. The quantification of these contacts was based on the number of unique individuals. The composition of these contacts varied from day to day, underscoring the dynamic nature of social interactions throughout the study. Communication patterns are measured by daily smartphone contact count. Personal factors, including gender (woman/man), ethnicity (White/Black/Latino/Asian/Foreign), and BMI (weight/height^2), highlight potential biological, physiological, and cultural effects. Psychological aspects, such as personality and depression level, reveal links between mental well-being and heart rate dynamics. Personality is assessed using standardized factors scores for extraversion ($\alpha = 0.87$), agreeableness ($\alpha = 0.80$), conscientiousness ($\alpha = 0.83$), neuroticism ($\alpha = 0.82$), and openness ($\alpha = 0.79$)[51]. Depression is measured via the Center for Epidemiologic Studies Depression Scale (CES-D; $\alpha = 0.94$)[52]. Environmental factors encompass days of the week, academic periods, and weather conditions, revealing external contexts' impacts. Lastly, behavioral elements like physical activity level (a standardized factor score of 18 items obtained from Fitbit devices, including low range calories and minutes, fat burn calories and minutes, cardio calories and minutes, peak calories and minutes, steps, floors, sedentary minutes, lightly active minutes, fairly activity minutes, very active minutes, marginal calories, activity calories, calories BMR, and calories out; $\alpha = 0.89$), minutes in bed, and daily class count shed light on lifestyle and behavior effects on heart rate regulation.

Analytical Strategy

Using latent growth-curve models (LGCMs) in Stata V17.0, we explore temporal sleep and active heart rate patterns, integrating within-subject (Level 1) and between-subject (Level 2) variance components. These models, akin to Hierarchical Linear Models (HLMs), offer a framework to capture individual-specific initial values and linear slopes in heart rate patterns over time.

The Level 1 within-subject equation, which models how the heart rate of each subject changes across days, is represented as follows:

$$y_{id} = \eta_{0i} + \eta_{1i}(\text{ Day }) + \beta_{1d}x_{id} + \varepsilon_{id} \qquad (1)$$

Here, y_{id} is the dependent variable for subject *i* on day *d*. η_{0i} is the initial value latent factor, while η_{1i} represents the subject-specific latent factor for y_{id}'s linear slope. x_{id} is the time-varying covariate, and β_{1d} is its estimated parameter. ε_{id} is subject-specific random error.

The Level 2 between-subject equations, which model how different subjects exhibit distinct heart rate patterns, is expressed as follows:

$$\eta_{0i} = \gamma_{00} + \gamma_{01}z_i + \delta_{0i} \qquad (2)$$

$$\eta_{1i} = \gamma_{10} + \gamma_{11}z_i + \delta_{1i} \qquad (3)$$

Here, γ_{*0} is the intercept term, z_i is the time-constant variable, γ_{01} signifies the time-constant variable's effect on the intercept, γ_{11} denotes its effect on the linear slope, and δ_{*i} represents between-subject random errors.

Missing Data Treatment

In the first year, participant attrition was low, but the second year experienced more student withdrawals and less consistent use of Fitbit devices, leading to occasional missing heart rate data. Given the overall high compliance (above 80%) among the 487 participants and limited attrition, we chose not to impute missing values. Instead, we used LGCMs with a Full Information Maximum Likelihood (FIML) approach, which effectively utilizes all observed data for more accurate and robust results, especially beneficial in longitudinal studies with missing data.

Results

Descriptive Statistics

Table 1 displays participant averages in the NetHealth project, disregarding the time trend. Sleep heart rate averages about 61 BPM (beats per minute) and active heart rate around 78 BPM. Sleep heart rate's standard deviation (6 BPM) is lower than active heart rate's (15 BPM). These variables show similar averages among participants' contacts.

Table 1. Summary of time-varying variables

Variables for each individual each day	Mean (SD) or *n* (%)
Daily mean sleep heart beats per minute	60.65 (9.57)
Daily standard deviation of sleep heart beats per minute	5.78 (3.62)
Daily mean active heart beats per minute	78.78 (10.43)
Daily standard deviation of active heart beats per minute	14.87 (3.90)
In-study contacts' average daily sleep mean heart beats per minute	60.84 (8.73)
In-study contacts' average daily standard deviation of sleep heart beats per minute	5.70 (3.23)
In-study contacts' average daily mean active heart beats per minute	79.27 (9.36)
In-study contacts' average daily standard deviation of active heart beats per minute	14.84 (3.79)
Daily network size	12.72 (7.33)
Daily physical activity	0.20 (0.51)
Daily minutes in bed	433.90 (133.28)
Daily number of courses taken (during regular school days)	2.52 (1.16)
Number of cases	55,744 (100.00%)
Variables for each day	
Weather indicators	
Highest temperature (°F)	58.39 (19.56)
Lowest temperature (°F)	40.22 (16.69)
Precipitation in inches	0.12 (0.40)
Snowfall in inches	0.17 (0.80)
Number of days	637 (100.00%)

Table 1 summarizes additional variables. Participants have about 13 smartphone contacts (SD = 7) and spend around 434 daily minutes (or 7.2 hours) in bed (SD = 133 minutes). They attend an average of 2.5 classes per regular school day.

Table 2 summarizes time-constant variables. Half the participants are females. Around two-thirds of the participants are white, while 13% are Latinos, 7% are Black Americans, 8% are Asians, and 5% are foreign students. The average BMI value for the participants is 23.

Table 2. Summary of time-constant variables.

Variables for each individual	Mean (SD) or *n* (%)
Female (1=yes)	247 (50.72%)
Ethnoracial category	
White (1=yes)	323 (66.32%)
Latino (1=yes)	64 (13.14%)
Black American (1=yes)	33 (6.78%)
Asian American (1=yes)	43 (8.83%)
Foreigner (1=yes)	24 (4.93%)
BMI	22.92 (3.41)
Extraversion	-0.05 (0.72)
Agreeableness	0.00 (0.59)
Conscientiousness	0.05 (0.62)
Neuroticism	-0.02 (0.64)
Openness	-0.03 (0.57)
Depression level	0.05 (0.45)
Number of individuals	487 (100.00%)

LGCM Results

Table 3 shows estimated parameters from latent growth-curve models. Models 1-4 include dependent variables: average sleep heart rate, sleep heart rate's standard deviation, average active heart rate, and active heart rate's standard deviation. Goodness of fit is indicated the Root Mean Square Error of Approximation (RMSEA) being smaller than.06 and the Comparative Fit Index (CFI) being greater than.95, both indicating a good fit.

Table 3. Results from linear growth curve models.

	Model 1	Model 2	Model 3	Model 4
	Average sleep heart rate	**SD sleep heart rate**	**Average active heart rate**	**SD active heart rate**
Day	0.011** (0.003, 0.019)	-0.001 (-0.003, 0.001)	0.011** (0.003, 0.020)	0.002 (-0.002, 0.005)
Average measure of in-study contacts	0.089*** (0.081, 0.096)	0.036*** (0.027, 0.046)	0.037*** (0.030, 0.044)	0.024*** (0.018, 0.030)
Daily network size	0.043*** (0.031, 0.054)	-0.001 (-0.007, 0.005)	0.039*** (0.029, 0.050)	-0.024*** (-0.028, -0.020)
Female (1=yes)	5.325***	0.260	5.670***	2.348***

	(3.932, 6.717)	(-0.013, 0.533)	(4.116, 7.225)	(1.952, 2.745)
Female × Day	0.001 (-0.001, 0.003)	0.000 (-0.000, 0.001)	-0.002 (-0.005, 0.000)	-0.001** (-0.002, -0.000)
Latino (1=yes)	0.831 (-1.134, 2.797)	-0.557** (-0.956, -0.158)	1.032 (-1.153, 3.218)	-0.014 (-0.570, 0.543)
Latino × Day	-0.000 (-0.004, 0.003)	0.000 (-0.001, 0.001)	0.001 (-0.002, 0.005)	-0.001 (-0.002, 0.001)
African American (1=yes)	4.745** (1.885, 7.605)	0.439 (-0.164, 1.041)	2.736 (-0.414, 5.886)	0.145 (-0.685, 0.975)
African American × Day	-0.003 (-0.008, 0.002)	-0.001 (-0.003, 0.000)	0.000 (-0.005, 0.005)	-0.000 (-0.002, 0.002)
Asians American (1=yes)	-0.236 (-2.594, 2.122)	0.052 (-0.423, 0.527)	1.745 (-0.885, 4.376)	-0.244 (-0.917, 0.429)
Asians American × Day	0.000 (-0.003, 0.004)	0.000 (-0.001, 0.001)	-0.001 (-0.005, 0.003)	0.001 (-0.001, 0.002)
Foreigner (1=yes)	-0.095 (-3.279, 3.090)	0.516 (-0.179, 1.210)	-0.995 (-4.532, 2.542)	-0.598 (-1.527, 0.331)
Foreigner × Day	-0.000 (-0.006, 0.005)	-0.001 (-0.002, 0.001)	0.003 (-0.003, 0.009)	0.001 (-0.001, 0.004)
BMI	0.351*** (0.153, 0.550)	-0.021 (-0.061, 0.020)	0.147 (-0.074, 0.367)	-0.172*** (-0.230, -0.115)
BMI × Day	-0.000** (-0.001, -0.000)	0.000 (-0.000, 0.000)	-0.001** (-0.001, -0.000)	0.000 (-0.000, 0.000)
Extraversion	-0.125 (-1.087, 0.837)	-0.006 (-0.199, 0.187)	-0.280 (-1.352, 0.791)	-0.126 (-0.400, 0.147)

Extraversion × Day	0.000 (-0.001, 0.002)	-0.000 (-0.001, 0.000)	-0.000 (-0.002, 0.002)	0.000 (-0.000, 0.001)
Agreeableness	-0.922 (-2.123, 0.280)	-0.075 (-0.313, 0.163)	-0.837 (-2.173, 0.498)	0.041 (-0.299, 0.382)
Agreeableness × Day	-0.002 (-0.004, 0.000)	-0.000 (-0.001, 0.000)	-0.002* (-0.004, -0.000)	0.000 (-0.000, 0.001)
Conscientiousness	-1.592** (-2.729, -0.454)	0.043 (-0.183, 0.269)	-1.518* (-2.785, -0.250)	0.284 (-0.041, 0.610)
Conscientiousness × Day	0.001 (-0.001, 0.003)	0.000 (-0.000, 0.001)	0.000 (-0.002, 0.002)	0.000 (-0.000, 0.001)
Neuroticism	-0.129 (-1.345, 1.088)	0.145 (-0.097, 0.388)	0.031 (-1.322, 1.385)	0.137 (-0.214, 0.488)
Neuroticism × Day	-0.002 (-0.003, 0.000)	-0.000 (-0.001, 0.000)	-0.001 (-0.003, 0.001)	0.000 (-0.000, 0.001)
Openness	0.058 (-1.145, 1.260)	0.234 (-0.001, 0.470)	-0.432 (-1.772, 0.909)	-0.143 (-0.486, 0.200)
Openness × Day	-0.000 (-0.002, 0.002)	-0.000 (-0.001, 0.000)	0.000 (-0.002, 0.003)	-0.001 (-0.001, 0.000)
Depression	1.144 (-0.533, 2.820)	0.051 (-0.350, 0.451)	0.703 (-1.138, 2.544)	0.619* (0.115, 1.122)
Depression × Day	-0.002 (-0.005, 0.001)	0.000 (-0.001, 0.001)	-0.001 (-0.004, 0.002)	-0.001 (-0.002, 0.000)
Monday to Thursday(1=yes)	-1.434*** (-1.639, -1.230)	0.032 (-0.080, 0.143)	-0.741*** (-0.932, -0.550)	0.064 (-0.013, 0.141)
Friday(1=yes)	-0.254* [illegible]	-0.023 [illegible]	0.372*** [illegible]	-0.642*** [illegible]

	(-0.491, -0.017)	(-0.153, 0.107)	(0.150, 0.595)	(-0.732, -0.553)
Saturday(1=yes)	0.710*** (0.481, 0.938)	-0.057 (-0.182, 0.068)	0.888*** (0.675, 1.102)	-0.622*** (-0.707, -0.537)
Home football game day (1=yes)	0.806*** (0.391, 1.221)	-0.221 (-0.448, 0.007)	2.051*** (1.659, 2.442)	-2.118*** (-2.271, -1.965)
Midterm break (1=yes)	0.653*** (0.353, 0.954)	0.744*** (0.580, 0.908)	-1.708*** (-1.985, -1.430)	-0.497*** (-0.612, -0.381)
Winter break(1=yes)	-0.369* (-0.681, -0.056)	0.298*** (0.127, 0.468)	-1.633*** (-1.918, -1.349)	-0.114 (-0.231, 0.002)
Summer break(1=yes)	-0.484*** (-0.747, -0.222)	0.915*** (0.774, 1.057)	-3.772*** (-4.018, -3.526)	0.077 (-0.025, 0.179)
Thanksgiving holidays (1=yes)	-0.513* (-0.992, -0.034)	0.379** (0.118, 0.640)	-1.579*** (-2.024, -1.135)	-0.148 (-0.330, 0.034)
Easter holidays (1=yes)	-1.025*** (-1.549, -0.501)	0.012 (-0.274, 0.297)	-1.445*** (-1.942, -0.949)	0.297** (0.097, 0.497)
Orientation week (1=yes)	-0.821** (-1.389, -0.253)	0.615*** (0.305, 0.925)	-2.438*** (-2.966, -1.910)	-1.449*** (-1.671, -1.226)
Final exam week (1=yes)	-0.717*** (-1.051, -0.383)	0.087 (-0.096, 0.270)	0.320* (0.010, 0.630)	-0.592*** (-0.715, -0.470)
Highest temperature (°F)	-0.009* (-0.016, -0.001)	-0.001 (-0.005, 0.003)	-0.001 (-0.009, 0.006)	-0.013*** (-0.015, -0.010)
Lowest temperature (°F)	-0.016*** (-0.025, -0.007)	0.001 (-0.004, 0.006)	-0.010* (-0.018, -0.002)	-0.003 (-0.006, 0.001)
Precipitation in inches	0.275*** (0.119, 0.430)	0.045 (-0.040, 0.130)	0.114 (-0.035, 0.263)	0.033 (-0.029, 0.096)

Snowfall in inches	-0.096** (-0.167, -0.025)	-0.014 (-0.053, 0.024)	-0.006 (-0.073, 0.061)	-0.059*** (-0.086, -0.032)
Physical activity	1.983*** (1.840, 2.126)	1.095*** (1.018, 1.173)	8.194*** (8.063, 8.324)	4.982*** (4.929, 5.034)
Minutes in bed	0.001* (0.000, 0.001)	0.006*** (0.006, 0.006)	0.001*** (0.000, 0.001)	-0.002*** (-0.002, -0.002)
Number of classes	-0.309*** (-0.367, -0.251)	0.013 (-0.019, 0.045)	-0.230*** (-0.284, -0.175)	-0.011 (-0.033, 0.011)
Intercept	45.870*** (41.160, 50.590)	2.784*** (1.796, 3.772)	69.770*** (64.540, 75.000)	18.070*** (16.710, 19.430)
Number of cases	49,079	49,060	55,744	50,584
Number of individuals	483	483	487	484
Goodness-of-fit				
AIC	320852.60	260492.60	364853.10	233658.60
BIC	321292.70	260932.60	365299.50	234100.20
Wald chi-square/df	4180.73/45	2424.08/45	22515.15/45	37560.62/45
Log-likelihood	-160376.30	-130196.28	-182376.55	-116779.30

*Note: *p < 0.05, **p < 0.01, ***p < 0.001*

Regarding the time trend, we find that the participants' average levels of sleep heart rate and active heart rate increase over time. Both are expected to rise by 7 BPM at the end of the 637 days. However, there is no evidence that the standard deviations of these two indicators change during the study period.

Peer influence affects participants' sleep and active heart rates, as seen in positive associations with their in-study contacts' averages. The magnitudes of the parameters suggest that the peer influence on the sleep heart rate is stronger than that on the active heart rate. Daily smartphone contacts positively impact average sleep and active heart rates and negatively affect active heart rate's standard deviation.

Among personal factors, females generally exhibit higher average sleep and active heart rates than males. The standard deviation of active heart rate in females decreases slightly by 0.6 BPM over 637 days. Latinos show lower standard deviation of sleep heart rate compared to average white participants. African Americans display higher average sleep heart rate. High BMI correlates with higher average sleep heart rate and lower standard deviation of active heart rate.

For psychological factors, a higher level of conscientiousness is negatively associated with the average level of a participant's sleep heart rate and active heart rate. The level of depression is positively associated with the standard deviation of a participant's active heart rate.

Environmental factors display intricate effects on our variables. Compared to Sundays, weekdays show lower sleep and active heart rates from Monday to Thursday. Fridays demonstrate lower sleep and higher active heart rates but lower standard deviation in active heart rate. Saturdays indicate higher sleep and active heart rates with lower standard deviation in active heart rate. Compared to regular school days, home football game days associate with higher sleep and active heart rates but lower active heart rate standard deviation. Midterm breaks are linked to higher sleep and active heart rates and lower active heart rate standard deviation. Winter breaks, summer breaks, Thanksgiving holidays show lower sleep and active heart rates but higher standard deviation in sleep heart rate. Easter holidays correlate with lower sleep and active heart rates and higher active heart rate standard deviation. Orientation weeks result in lower sleep and active heart rates, higher sleep heart rate standard deviation, and lower active heart rate standard deviation. Final exam weeks display lower sleep, higher active heart rates, and lower active heart rate standard deviation. Snowy days correspond to lower sleep and active heart rates and lower active heart rate standard deviation. Rainy days show higher sleep heart rates.

In relation to behavioral factors, physical activity level is positively linked to all four dependent variables. Daily time spent in bed relates positively to average levels of sleep and active heart rate, as well as standard deviation of sleep heart rate, while negatively correlating with standard deviation of active heart rate. More daily classes are associated with lower average levels of sleep and active heart rate.

Discussion

This study provides notable contributions to literature. Firstly, it comprehensively investigates diverse categories' impact on sleep and active heart rate patterns, revealing a nuanced interplay between these determinants and heart rate dynamics. Secondly, a longitudinal design with a sizable sample size uncovers heart rate changes over 637 days, highlighting contextual factors' extended-period sensitivity. Thirdly, advanced latent growth-curve models enhance methodological rigor, accounting for within- and between-subject variations in individual and group-level heart rate dynamics. Lastly, the study scrutinizes specific events like home football games and breaks, revealing their effects on heart rate patterns and emphasizing contextual factors' physiological impact. Overall, through its multidimensional approach, longitudinal designs, advanced statistical techniques, and event exploration, this research offers a comprehensive analysis of factors influencing heart rate patterns, enhancing understanding and informing targeted interventions for cardiovascular health.

More specifically, this study elaborates on our previous research[1], broadening the scope of our earlier observation of an increasing average heart rate over time. We now apply this observation to both sleep and active heart rates, maintaining consistent standard deviations. Such a progression indicates a prevalent trend in heart rate dynamics among participants, suggesting nuanced variations in heart rate patterns across different states of activity and rest.

Regarding social factors, we reaffirm earlier findings on social influences, noting that an individual's heart rates (average and standard deviation) mirror those of their friends. This pattern is evident in both sleep and active heart rates, highlighting the strong social influence on heart rate responses. For social network size, we confirm our previous study's findings of a positive relationship between network size and average active heart rate, coupled with a negative impact on heart rate variability. However, in the case of sleep heart rate, our current study reveals a new aspect: while there is a positive correlation with the average sleep heart rate, this relationship does not hold for its variability. This suggests that social interactions have varying impacts on heart rate, depending on whether the individual is in an active or sleep state.

Among personal factors, gender differences are pronounced in our findings. We observe that female students have higher initial average heart rates compared to males, a consistent finding in both our past and current studies. In active states, females not only exhibit a higher average heart rate but also greater variability. However, for sleep heart rates, females show a higher average but similar variability to males, indicating that gender predominantly affects the baseline heart rate in restful conditions. Racial disparities are also evident. African American students, who had higher average heart rates in our earlier study, particularly exhibit this trend in sleep heart rates in our current study, but not in active heart rates, compared to white students. This finding suggests more pronounced racial differences in baseline heart rate during periods of inactivity. Regarding BMI, our current findings reveal a nuanced picture compared to our previous study. Initially, students with higher BMI had similar average starting heart rates but lower variability. However, now we find that they have a higher average starting point for sleep heart rate, coupled with lower variability in active heart rate. This indicates a more substantial effect of higher BMI on sleep heart rate and a lesser impact on the variability of heart rate during active states.

In terms of psychological factors, our earlier investigation indicated that students with higher levels of agreeableness experienced a declining average heart rate, and this study reveals that this trend was attributed to the active heart rate, indicating a potential connection between this personality trait and physiological responses under active conditions. In our prior study, students with higher levels of conscientiousness were found to have a lower initial average heart rate but increased variability. However, the current study refines this, showing that high conscientiousness is associated with lower starting points for both average sleep and active heart rates. Contrary to our earlier findings, the variability in heart rate for this group is not markedly different, implying that conscientiousness influences baseline heart rate more consistently across different states, but has a less pronounced effect on heart rate variability. Furthermore, while our earlier study did not find significant differences in the starting average heart rate and its variability among students with higher depression levels, our current research reveals a new aspect. We observe a higher starting variability in active heart rate among these students, suggesting a relationship between elevated depression levels and greater variability in physiological responses during active states.

Turning to environmental factors, our earlier study found that students exhibited a lower average heart rate and a higher standard deviation of heart rate from Monday to Thursday compared to Sunday. This study confirms a lower average sleep and active heart rate during these weekdays, with no significant difference in their standard deviations. On Fridays, our prior study identified higher average heart rate and lower standard deviation, whereas this study reveals a lower average sleep heart rate, similar standard deviation of sleep heart rate, higher average active heart rate, and lower standard deviation of active heart rate. Saturdays showed a higher average heart rate and a lower standard deviation in our previous research, and this study confirms higher average sleep and active heart rates, but a lower standard deviation only in active heart rate. These findings illustrate how daily and weekly routines distinctly influence both sleep and active heart rates, as well as their variability.

Concerning special time periods, on home football game days, our earlier study reported a higher average heart rate but a lower standard deviation compared to regular school days. This study supports a higher average sleep and active heart rate but a lower standard deviation only in active heart rate. Midterm breaks, previously associated with lower average heart rate and standard deviation, exhibit complex effects in this study. It reveals higher levels of both average and standard deviation of sleep heart rate and lower levels for both in active heart rate during specific times. Winter break, summer break, Thanksgiving holidays, Easter holidays, and orientation week, previously linked to a lower average heart rate, show consistent patterns in both sleep and active heart rates. However, for standard deviations, winter break, summer break, and Thanksgiving holidays, which previously showed no difference, now indicate a higher standard deviation of sleep heart rate. Easter holidays, previously linked to higher standard deviation, show this effect in active heart rate. Orientation week, previously associated with lower standard deviation, now reveals higher sleep and lower active heart rate standard deviations. During the final exam week, our previous study indicated a consistent average heart rate but lower standard deviation, whereas this study demonstrates a lower average sleep heart rate, higher average active heart rate, and a lower standard deviation of active heart rate. These findings highlight the dynamic nature of heart rate responses to different academic and social events, with distinct patterns emerging in sleep and active states.

Concerning weather conditions, our prior study found no association between daily highest temperature and average heart rate but a negative association with its standard deviation. This study reveals a negative association with average sleep heart rate and the standard deviation of active heart rate. The previous association of daily lowest temperature with a positive association with average heart rate and a negative association with its standard deviation is confirmed, showing a negative association with both average sleep and active heart rates but no association with their standard deviation. Rainy days, previously associated with higher average heart rate, now apply to sleep heart rate only. Regarding snowfall, initially reported as unrelated to average and standard deviation of heart rate, this study finds a negative association with average sleep heart rate and the standard deviation of active heart rate. These findings illustrate a complex interaction between weather conditions and heart rate, highlighting the sensitivity of the cardiovascular system to different weather conditions.

Finally, among behavioral factors, our prior study identified a positive association between physical activity level and both average and standard deviation of heart rate. This study confirms this association for both sleep and active heart rates, suggesting that increased physical activity elevates heart rate levels and induces greater variability, indicative of a responsive cardiovascular system. Minutes spent in bed were previously linked to a negative association with average heart rate and its standard deviation. However, this study reveals a positive association with average sleep heart rate, standard deviation of sleep heart rate, average active heart rate, and a negative association with the standard deviation of active heart rate. This suggests that longer sleep duration is linked to higher average heart rates during rest and activity but might lead to more consistent heart rates during active states. The daily number of classes was initially associated with a negative correlation with average heart rate, and this study confirms a negative association with both average sleep and active heart rates, possibly influenced by the sedentary behavior during classes, as suggested by Dittmer and Grebe[53]. These findings underscore the significant impact of lifestyle and daily behaviors on heart rate dynamics.

It is essential to highlight that while our study explores various factors significantly associated with sleep and active heart rates, their magnitudes vary considerably. For instance, the effects on sleep heart rate span from -1.592 for conscientiousness (suggesting a substantial impact) to 0.001 for minutes in bed (exerting a more modest effect), and 5.325 for female gender, indicating a notable increase. This nuanced perspective in our study sheds light on the potential impact of different factors on cardiovascular health.

Limitations

This study offers valuable insights, but certain limitations should be recognized. Firstly, the data's single-campus source might raise concerns about generalizability, although participant characteristics align with the 2015 cohort. Acknowledging potential selection bias, especially among actively engaged participants, is essential. Secondly, reliance on self-reported measures, especially for psychological variables, introduces potential response bias and recall errors. This may affect data accuracy and reliability. Thirdly, heart rate is influenced by multifaceted factors, some not explored here, like genetics, medications, substance use (e.g., alcohol, marijuana), pollutants, hormones, health conditions, personalized exercise plans, and stress management. Lastly, the study identifies associations, not causation, and relies on statistical analysis. Despite these limitations, this research enriches understanding of sleep and active heart rate dynamics, urging consideration of these aspects in future research for comprehensive cardiovascular insights.

Implications for Future Research

This study illuminates influences on sleep and active heart rate dynamics, inspiring future research directions. Exploring mediating mechanisms like autonomic nervous system activity or hormonal regulation could enhance understanding of how factors impact heart rate patterns. Additionally, comprehending cumulative effects and their interplay would deepen insights into cardiovascular health. Larger-scale longitudinal studies across diverse populations could enhance generalizability. Integrating objective measures like wearable devices would provide real-time data and reduce reliance on self-reports. Further exploration of interactions among factors across diverse socioeconomic, racial, and gender categories represents a potential avenue for subsequent studies. By focusing on these aspects, future research can advance knowledge and guide interventions for cardiovascular health promotion.

Conclusion

In conclusion, this study uncovers the complex factors affecting sleep and active heart rate, including social, personal, psychological, environmental, and behavioral elements. It highlights how peer influence, gender, ethnicity, personality traits, mental health, daily routines, physical activity, and academic life contribute to heart health. These insights can inform targeted healthcare interventions, research directions, and policy-making, fostering personalized strategies to improve cardiovascular outcomes. Future research should further investigate these mechanisms and their long-term effects on heart health, enhancing the precision of interventions in this vital area.

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