

Severity of Depression and Anxiety Symptoms Manifest in Physiological and Behavioral Metrics Collected from a Consumer-Grade Wearable Ring

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Abstract

Background

Modern wearable devices generate a multitude of digital metrics, which can be used to measure human function in health and disease. This study investigated whether and how digital metrics generated from a consumer-grade smart ring were different in individuals with varying severity of depression and anxiety symptoms in a large population-based cohort.

Methods

Data were obtained from the Northern Finland Birth Cohort 1986 when participants were 33–35 years of age. Participants were asked to wear the Oura Ring for two weeks, which provided digital measures of sleep architecture, nocturnal heart rate (HR), nocturnal heart rate variability (HRV), and minute-by-minute movement intensity. Participants with at least one weekday and a weekend day with no less than 15 hours wear time were included. Depression and anxiety symptoms were assessed using the Generalized Anxiety Disorder 7-item scale (GAD-7) and the Hopkins Symptom Checklist-25 (HSCL-25). Participants were grouped into no, mild, and moderate-to-severe anxiety symptom groups based on GAD-7, and with and without depression and anxiety symptoms based on HSCL-25. Time-series data were visualized, and statistical differences between groups were assessed using one-way ANCOVA followed by Tukey's post hoc test.

Results

A total of 1,290 participants provided enough valid data and were included. The metrics generated by Oura ring were different across symptom severity groups. Participants with moderate-to-severe anxiety assessed by GAD-7 and with depression and anxiety symptoms assessed by HSCL-25 exhibited lower proportions of rapid eye movement (REM) and deep sleep, and increased light sleep compared with the group without depression and anxiety. These two groups also showed elevated HR, reduced HRV during sleep, and lower levels of moderate-to-vigorous physical activity during the day. The differences between mild anxiety group with no and moderate-to-severe anxiety groups were overall less apparent.

Conclusions

Findings suggest that severity of depression and anxiety are manifested in physical and physiological metrics generated by a consumer-grade wearable ring. These findings suggest that they may be a promising tool for large-scale monitoring and early detection of mental health risks.

1. INTRODUCTION

Mental health problems such as depression and anxiety impose a substantial burden on global health. These conditions are increasingly prevalent worldwide, but they are often underdiagnosed because of limited access to care, the effects of stigma, and a reliance on subjective self-reports[1, 2]. The timely diagnosis of depression and anxiety, along with proper treatment, can help manage health risks and reduce the burden on healthcare systems. However, traditional diagnostic and screening approaches rely on self-report questionnaires or clinical interviews, which, although valuable, are inherently subjective and prone to recall bias[3].

Depression and anxiety are associated with changes in behavioral and cognitive factors, including alterations in sleep patterns and quality, physical activity, and psychomotor function[4]. People with mental disorders often exhibit dysregulated autonomic nervous system activity, characterized by changes in the balance between sympathetic and parasympathetic nervous system functions. These changes can manifest in physiological and behavioral indicators, such as sleep, heart rate (HR), and other physical behaviors[5]. Several studies have examined how physiological and behavioral changes can be used to assess symptoms of depression and anxiety[6]. For example, the relationship between HR and heart rate variability (HRV) with symptoms of depression and/or anxiety has been well documented[7–9].

The advancement of personal digital devices, especially wearable devices, has made it possible to continuously and passively capture rich streams of physiological and behavioral metrics within a person's natural living environment. Such digital sensing signals and metrics include HR, body temperature, and physical behaviors such as active versus sedentary behavior and sleep patterns[10, 11]. The continuity of data collected via wearables is superior to that of laboratory-based measurements, which are typically obtained over brief periods only. Wearables enable earlier detection of health changes as well as screening for treatment response. In addition, they provide just-in-time support while minimizing the burden on participants[12]. Recent studies have demonstrated that wearable-collected digital metrics can be transformed into digital phenotypes and digital biomarkers[12]. The aim is to non-invasively detect, assess, and predict mental health problems, including symptoms of depression and anxiety, in terms of both severity and risk[11–13].

A wide range of consumer-grade wearable devices is available today, and they are worn at various body locations depending on their design and embedded sensing technologies[12]. Smart rings are a relatively new class of wearable devices that offer a lightweight alternative. They are often equipped with multiple sensors that enable the assessment and measurement of several physiological and behavioral metrics, such as HR, HRV, body temperature, physical activity, sedentary behavior, and sleep[14]. Their small size and comfortable fit make them particularly suitable for sleep monitoring, as bulkier devices (such as smartwatches) can be uncomfortable. Research has shown that smart rings provide sleep and HR data with greater user comfort and better long-term compliance than wrist-based wearables[15]. Because they are worn on a finger, they tend to deliver more stable signals during sleep, with fewer motion

artifacts[16]. These characteristics make smart rings suitable for continuous, longitudinal data collection in both research and daily life contexts, particularly when minimal interference with daily activities is a crucial requirement[15, 17].

Among all smart rings, the Oura Ring is one of the most frequently used in research and clinical studies. This multi-sensor, consumer-grade device is increasingly used for the continuous collection and screening of digital metrics and indicators to discover and validate digital biomarkers relevant to mental health issues and behavioral studies[14–16, 18]. For instance, reduced HRV, delayed sleep onset, fragmented sleep, and diminished activity variability, as measured by the Oura Ring, have been consistently observed in individuals with clinical depression and anxiety[19, 20]. In a pilot study using the Oura Ring, sleep HR curves and HRV changes were associated with self-reported stress and mental health indicators among young adults[21]. In another longitudinal monitoring study, the Oura Ring was used in high-burden occupational groups, such as nurses, and the results indicated strong associations between disrupted sleep cycles and worsened mental health outcomes[22]. These examples highlight the utility of Oura-measured digital metrics and indicators in both clinical contexts and daily life[18].

Despite growing evidence linking wearable-measured digital metrics to depression and anxiety, much remains unknown about whether and how such digital metrics vary in daily life among individuals with and without depression and anxiety in the general population[23]. This study investigates whether continuously and passively collected digital metrics from a consumer-grade smart ring (the Oura Ring) reflect differences in the severity of depression and anxiety symptoms in a large non-clinical population. Our goal is to assess the potential of these digital metrics for scalable mental health screening and early risk detection.

2. METHODS

2.1. Study population

Data for this study were obtained from the population-based Northern Finland Birth Cohort 1986 (NFBC1986) study[24]. NFBC1986 (N = 9,479) is a life-course cohort study involving participants born between July 1, 1985, and June 30, 1986, in Finland (N = 9,432 live-born)[25, 26]. Since birth, the cohort members have been regularly monitored prospectively using a broad set of clinical measurements, interviews, and postal questionnaires.

Figure 1 depicts the flow and overview of our study. We examined data from the most recent follow-up at ages 33 to 35 years. During the follow-up, cohort members residing in the city of Oulu or within a 250-km radius were invited to undergo a health examination and complete extensive health and behavior questionnaires. They were also invited to participate in sleep and physical behavior monitoring using a wearable device, specifically the Oura Ring (invited participants N = 5,717). As part of the 33–35-year follow-up, participants also self-reported their mental health symptoms using validated questionnaires to assess symptoms of depression and anxiety. Eligible participants for this study were cohort members who wore an Oura Ring and completed the mental health assessment questionnaires. The original NFBC1986 33–35-year follow-up study was approved by the Ethical Committee of the Northern Ostrobothnia Hospital District (108/2017), and written informed consent was obtained from all the participants[25].

2.2. Measurements

2.2.1 Wearable data collection with Oura Ring

Participants were asked to wear the second-generation Oura Ring (made by Ōura Health, Finland). The ring is a lightweight, waterproof, multi-sensory tracker that includes photoplethysmography (PPG) sensors for HR and respiration, a temperature coefficient sensor, and a 3D accelerometer[18, 27]. The data that the ring collects are sent automatically to a cloud server. Participants were asked to wear the ring on any finger of their non-dominant hand. Ring sizes ranged from 6 to 13 (U.S. standard), and participants were asked to wear the ring continuously for 14 days, except when using a sauna. To avoid accidental resetting of the devices, which would stop data collection, the participants were not given chargers. The ring's battery typically lasts six consecutive 24-hour periods, according to the manufacturer. However, in the study, some ring batteries lasted up to 14 days. On average, data were collected for six full days per person. Participants did not receive any information or feedback from the ring about their sleep, activity, or behavior.

2.2.2 Oura-measured digital metrics

The Oura Ring measures sleep hypnograms, which estimate the time spent in light, deep, and rapid eye movement (REM) stages. Sleep stages are assessed via a five-minute hypnogram, in which each sleep stage (awake, light, deep, and REM) is classified using a sensor fusion model that incorporates PPG, movement, and temperature features. Validation studies have shown that Oura's sleep staging aligns well with polysomnography (PSG), which is the clinical gold standard for sleep assessment. For instance, one study showed that the Oura Ring detected total sleep time, sleep efficiency, and sleep onset latency, with moderate accuracy for non-REM sleep stages[17]. The Oura Ring has demonstrated a staging accuracy of approximately 78% compared with PSG, with agreement levels comparable to those of research-grade actigraphy[27].

Oura only assesses HR and RMSSD during sleeping period. Nocturnal HR is derived from pulse wave signals captured via PPG, with inter-beat intervals (IBIs) calculated after artifact removal[28]. The average HR is then computed over five-minute intervals. Nocturnal HRV is quantified using the root mean square of successive differences (RMSSD) of IBIs. This time-domain metric is sensitive to parasympathetic (vagal) activity. RMSSD is averaged over five-minute windows and serves as a validated marker of cardiac autonomic regulation. Studies have shown that HR and RMSSD values derived from the Oura Ring are strongly correlated with medical-grade electrocardiogram measurements[16, 27].

The Oura Ring estimates energy expenditure by translating accelerometer data into Metabolic Equivalent of Task (MET) values using proprietary algorithms over a 24-hour cycle. Specifically, MET minutes are calculated as the product of the activity duration and its associated MET intensity[29]. One study showed

strong agreement between Oura-derived MET values and measurements from laboratory-based calorimetry, with mean absolute percentage errors of around 20% for moderate to vigorous activity[29].

2.2.3 Mental health assessment and categorization

Depression and anxiety symptoms were assessed using two standardized instruments, namely the Generalized Anxiety Disorder 7-item scale (GAD-7) and the Hopkins Symptom Checklist–25 (HSCL-25). These scales are widely used and have been validated as reliable tools for assessing depression and anxiety in clinical and population-based research[30]. The GAD-7 consists of seven items that measure anxiety symptoms, all rated on a scale from 0 to 3, with a total possible score between 0 and 21. The instrument demonstrates high internal consistency (Cronbach's $\alpha = 0.85$) and strong criterion validity for detecting generalized anxiety disorder, with a sensitivity of 89% and specificity of 82% based on a cut-off score of 10[31]. In this study, participants were classified into anxiety severity groups based on their GAD-7 scores, as follows: 0–4, no anxiety; 5–9, mild anxiety; and ≥ 10 , moderate-to-severe anxiety.

The HSCL-25 contains 25 items that are scored on 4-point Likert scales, where 1 means “not at all” and 4 means “extremely.” The scale is divided into anxiety (10 items) and depression (15 items) subscales. Studies have confirmed the instrument's sound psychometric properties across diverse populations, demonstrating robust sensitivity and specificity in detecting common mental disorders[32, 33]. A mean HSCL-25 score of ≥ 1.75 indicates the presence of clinically relevant depression and anxiety symptoms²⁹.

2.3. Visualization and statistical analysis

We examined four Oura-measured metrics, using a time-series method, to analyze the participants' temporal physical and physiological patterns. The metrics were as follows: (1) five-minute hypnograms (sleep stages); (2) five-minute nocturnal HR; (3) five-minute nocturnal RMSSD; and (4) one-minute MET values across a 24-hour cycle (04:00 a.m. to 04:00 a.m. the following day). Although the Oura Ring provides other metrics, these four were selected because they have been validated in previous studies[34], and the literature suggests they may serve as metrics and indicators of mental health problems[35].

2.3.1 Data preparation

The original dataset included 1,610 participants with Oura Ring data on sleep and physical activity. Of these, 1,583 participants met our inclusion criteria, which required wearing the device for at least 15 hours on at least one weekday and one weekend day to ensure data quality and consistency[17, 36]. We included in our final analysis 1,290 participants whose data included valid questionnaire responses and Oura Ring metrics (see Fig. 1).

Given that each metric was distinct, separate data preparation procedures were applied to each. To ensure consistency in comparing sleep architecture, nocturnal HR, and nocturnal RMSSD across participants, we standardized the analysis by focusing on the first 6 hours of each sleep period identified by the Oura Ring. In our sample, sleep periods varied in duration from 3 to 15 hours. Most participants had at least 6 hours of sleep recorded. Hence, using only the first 6 hours allowed us to include the largest number of comparable sleep episodes without introducing bias from variable sleep lengths. We excluded records for which the total detected sleep was less than 6 hours to maintain analytical consistency. Sleep stages (awake, light, deep, and REM) were extracted from the 6-hour window. All metrics except sleep stages were numerical data. To be able to show the trajectory of sleep stages, the proportions of the various sleep stages were calculated for each group defined by the GAD-7 and HSCL-25 severity levels in each time point. For HR and RMSSD, we removed records in which more than 50% of the data were missing or zero, as these gaps were likely caused by signal loss or sensor errors.

2.3.2 Time-series plot

To examine variations in physiological and behavioral metrics among the depression and anxiety groups, we generated time-series plots of the percentages of sleep hypnogram stages, HR, RMSSD, and MET values. These measurements were then analyzed across participant groups categorized according to GAD-7 and HSCL-25 scores. Comparisons were conducted separately for weekdays and weekend days to capture potential temporal differences in physiological regulation and behavioral rhythms. We computed the mean (with 95% confidence interval) for HR, HRV, and MET values over time in each group and displayed them in plots. For HR and RMSSD, the mean (with 95% confidence interval) were also computed for the entire analytical sample and shown in the plots to enable direct comparison with the overall sample mean.

2.3.3 Statistical group comparison

Besides the signal visualizations, we used one-way ANCOVA to compare the groups based on specific dependent variables. The variables of interest included the average duration of sleep stages, average HR, RMSSD, and MET values on weekdays and weekend days. Relevant covariates were controlled to assess the main effects of group membership[37]. Covariates included sex; self-reported demographic factors (education level, employment status, marital status, and household income); lifestyle behaviors (smoking status and alcohol consumption); self-reported physician-diagnosed conditions (hypertension, congenital heart disease, and type 2 diabetes); anthropometric measurements (BMI, waist circumference); and clinically measured cardiometabolic biomarkers (fasting glucose, triglycerides, total-to-HDL cholesterol ratio, and LDL-to-HDL cholesterol ratio).

Tukey-Kramer post-hoc adjusted pairwise comparison tests were subsequently applied to evaluate the differences between groups. Statistical significance was set at $p < 0.05$, and all values are reported as means with standard deviations[38]. Analyses were performed separately for weekdays and weekend days to account for potential variations in physiological and physical patterns across the days. All statistical analyses were performed using Python (version 3.11) with the *statsmodels.stats* package[39].

2.4. Sensitivity analysis

Digital metrics measured by the Oura Ring could potentially be influenced by the presence of medical conditions and disease. To assess the robustness of our findings and minimize the potential effects of chronic health conditions on metrics generated by the Oura Ring, we conducted a sensitivity analysis. This analysis excluded participants who self-reported chronic doctor-diagnosed diseases, including hypertension, congenital heart disease, type 1 or 2 diabetes,

hypothyroidism, hyperthyroidism, sleep apnea, asthma, chronic lung disease (e.g., COPD), and fibromyalgia. These conditions are known to potentially influence physiological measures such as HR and RMSSD and behavioral metrics including sleep and MET values[40]. Following this exclusion, we redrew the associated plots to evaluate whether the observed patterns and associations remained consistent.

3. RESULTS

3.1. Eligible participants and descriptive statistics

A total of 1,290 participants were included in the final analytical sample. Their mean age was 33.8 years (SD = 0.6), and 62.7% of the participants were female. Most participants held a polytechnic or university degree (58%) and were employed (82.2%). Most were married or were cohabiting (78.7%), and over half (53.6%) reported annual household incomes ranging from €50,000 to €100,000. Current smokers accounted for 18.8% of the sample, and alcohol consumption averaged 2.9 g/day (SD = 3.5). Doctor-diagnosed hypertension was reported by 1.9% of participants, congenital heart disease by 2.1%, and type 2 diabetes by 0.8%. The mean fasting glucose level was 5.0 mmol/L (SD = 0.8), and the average BMI was 26 kg/m² (SD = 4.9). Based on the GAD-7, 120 participants were categorized as having moderate-to-severe anxiety symptoms, 423 as having mild anxiety symptoms, and 747 as having no anxiety symptoms. Based on HSCL-25, 176 participants were categorized as having moderate-to-severe depression and anxiety, 1114 participants were categorized as no depression and anxiety. The detailed characteristics of the participants are presented in Table 1.

Table 1
Characteristics of all participants who had sufficient Oura Ring data and valid GAD-7 and HSCL-25 scores.

Variables	GAD-7 groups			HSCL-25 groups		
	Whole sample ($n = 1,290$)	No anxiety ($n = 747$)	Mild anxiety ($n = 423$)	Moderate-to-severe anxiety ($n = 120$)	No depression and anxiety ($n = 1,114$)	Moderate-to-severe depression and anxiety ($n =$
Demographics						
Age, yr	33.8 (0.6)	33.8 (0.6)	33.8 (0.6)	33.9 (0.6)	33.8 (0.6)	33.8 (0.5)
Sex						
Female	809 (62.7%)	426 (57.0%)	294 (69.5%)	89 (74.2%)	677 (60.8%)	132 (75.0%)
Education						
Comprehensive school	102 (7.9%)	54 (7.2%)	37 (8.7%)	11 (9.2%)	75 (6.7%)	27 (15.3%)
Vocational/college level	440 (34.1%)	247 (33.1%)	142 (33.6%)	51 (42.5%)	368 (33.0%)	72 (40.9%)
Polytechnic/university degree	748 (58.0%)	446 (59.7%)	244 (57.7%)	58 (48.3%)	671 (60.3%)	77 (43.8%)
Employment status						
Employed	1,060 (82.2%)	642 (85.9%)	330 (78.0%)	88 (73.3%)	935 (84.4%)	121 (68.8%)
Unemployed	68 (5.3%)	26 (3.5%)	27 (6.4%)	15 (12.5%)	47 (4.2%)	21 (11.9%)
Other (e.g., student, homemaker)	162 (12.5%)	79 (10.6%)	66 (15.6%)	17 (14.2%)	126 (11.4%)	34 (19.3%)
Marital status						
Married/cohabiting	1,015 (78.7%)	586 (78.4%)	338 (79.9%)	91 (75.8%)	890 (79.9%)	125 (71.0%)
Divorced/widowed	48 (3.7%)	23 (3.1%)	18 (4.3%)	7 (5.8%)	37 (3.3%)	11 (6.3%)
Unmarried	227 (17.6%)	135 (18.1%)	66 (15.8%)	22 (18.4%)	187 (16.8%)	40 (22.7%)
Household income (€ per year)						
≤50,000	509 (39.5%)	277 (37.1%)	175 (41.4%)	57 (47.5%)	414 (37.2%)	95 (54.0%)
50,001 to 100,000	691 (53.5%)	409 (54.8%)	225 (53.2%)	57 (47.5%)	618 (55.5%)	73 (41.5%)
>100,000	90 (7.0%)	61 (8.1%)	23 (5.4%)	6 (5.0%)	82 (7.3%)	8 (4.5%)
Lifestyle factors						
Alcohol consumption, g·d ⁻¹	2.9 (3.5)	2.9 (3.5)	2.6 (3.2)	3.5 (4.4)	2.8 (3.3)	3.5 (4.3)
Smoking status						
Nonsmoker	417 (32.3%)	252 (33.8%)	127 (30%)	38 (31.7%)	363 (32.6%)	54 (30.7%)
Former smoker	631 (48.9%)	352 (47.1%)	227 (53.7%)	52 (43.3%)	550 (49.4%)	81 (46.0%)
Current smoker	242 (18.8%)	143 (19.1%)	69 (16.3%)	30 (25.0%)	201 (18.0%)	41 (23.3%)
Chronic disease						
Hypertension	25 (1.9%)	12 (1.6%)	10 (2.4%)	3 (2.5%)	20 (1.8%)	5 (2.8%)
Congenital heart disease	27 (2.1%)	15 (2.0%)	10 (2.4%)	2 (1.7%)	22 (2%)	5 (2.8%)
Type 2 diabetes	10 (0.8%)	2 (0.3%)	7 (1.7%)	1 (0.8%)	7 (0.6%)	3 (1.7%)
Cardiometabolic biomarkers						
<i>Data are mean (SD) or count (%)</i>						

Variables	GAD-7 groups				HSCL-25 groups	
	Whole sample	No anxiety	Mild anxiety	Moderate-to-severe anxiety	No depression and anxiety	Moderate-to-severe depression and anxiety
	(<i>n</i> = 1,290)	(<i>n</i> = 747)	(<i>n</i> = 423)	(<i>n</i> = 120)	(<i>n</i> = 1,114)	(<i>n</i> =)
Demographics						
Fasting glucose, mmol·L ⁻¹	5.0 (0.8)	5.1 (0.9)	5.0 (0.7)	5.0 (0.5)	5.0 (0.8)	5.0 (0.8)
Triglycerides, mmol·L ⁻¹	0.9 (0.6)	1.0 (0.6)	0.9 (0.5)	0.9 (0.5)	0.9 (0.6)	0.9 (0.5)
Total/HDL cholesterol ratio	3.3 (0.9)	3.3 (0.9)	3.2 (0.9)	3.2 (0.8)	3.3 (0.9)	3.2 (0.9)
LDL/HDL cholesterol ratio	2.0 (0.8)	2.0 (0.8)	1.9 (0.8)	1.9 (0.8)	2.0 (0.8)	1.9 (0.8)
Adiposity measures						
BMI, kg·m ⁻²	26.0 (4.9)	25.9 (4.7)	26.0 (5.2)	26.0 (5.4)	25.9 (4.8)	26.5 (5.8)
Waist circumference, cm	87.8 (12.9)	88.0 (12.4)	87.8 (13.6)	86.9 (13.6)	87.8 (12.7)	88.4 (14.4)
<i>Data are mean (SD) or count (%)</i>						

3.2 Five-minute sleep hypnogram patterns

Figure 2 shows the distribution of sleep stages across the GAD-7 and HSCL-25 symptom-severity groups. Participants with moderate-to-severe anxiety symptoms (based on GAD-7) and those with depression and anxiety symptoms (based on HSCL-25) consistently spent a lower percentage of time spent in deep sleep than participants with no or mild symptoms; this difference was particularly pronounced during the first 60 to 180 minutes (Figs. 2c, 2g, 2k, and 2o). The difference was also more pronounced on weekdays.

In contrast, the percentage of light sleep was relatively similar across all symptom-severity groups, with only slight variations over time (Figs. 2b, 2f, 2j, and 2n). Participants with higher symptom severity of anxiety (based on GAD-7) or depression and anxiety (based on HSCL-25), had less REM sleep, particularly after the 240-minute mark (Figs. 2d, 2h, 2l, and 2p). Regarding the awake stage, individuals with higher symptom severity had more awake percentage in the early phases of sleep, especially on weekdays (Figs. 2a, 2e, 2i, and 2m).

3.3. Five-minute nocturnal heart rate patterns

Figure 3 depicts the HR patterns during the sleep period. On both weekdays and weekend days, on average, participants with moderate-to-severe anxiety symptoms consistently exhibited higher HR compared with the whole-sample. This elevated HR was evident within the first 30 minutes of sleep onset and persisted throughout the entire sleep period (Figs. 3a and 3d). Differences between participants with mild anxiety symptoms and the whole-sample were less pronounced. Participants with mild anxiety showed, on average, higher HR than the whole-sample on weekend days, but HR were generally comparable on weekdays. In contrast, on average, HR was closely aligned with the whole-sample mean on both weekdays and weekend days.

When participants were categorized based on their HSCL-25 scores, individuals with depression and anxiety symptoms showed, on average, elevated HR levels throughout the sleep duration compared to the whole-sample (Figs. 3g and 3i). The difference in HR between participants without depression and anxiety symptoms and the whole sample population were less apparent and somewhat marginal (Fig. 3h and 3j).

3.4. Five-minute nocturnal RMSSD patterns

Figure 4 illustrates the RMSSD patterns during the sleep period. On both weekdays and weekend days, on average, participants with no anxiety symptoms had higher RMSSD compared to the whole-sample RMSSD. (Fig. 4c and 4f). This higher RMSSD was evident especially after the second hour of nocturnal time. However, the difference between mild-anxiety and moderate-to-severe anxiety with whole-sample RMSSD was less apparent.

When participants were categorized based on their HSCL-25 scores, on average, those without depression and anxiety symptoms exhibited slightly higher RMSSD than the whole-sample on both weekdays and weekend days, particularly during the latter part of the nocturnal period (Fig. 4h and 4j). On weekdays, on average, individuals with depression and anxiety symptoms had lower RMSSD compared to the whole-sample (Fig. 4g).

3.5. One-Minute MET activity patterns

Figure 5 shows the 24-hour profiles of one-minute average MET values. Across all groups, the average MET level began to rise between about 6:00 a.m. and 7:00 a.m., with a peak between 10:00 a.m. and 6:00 p.m.; the level then declined after 8:00 p.m. On weekdays, participants with moderate-to-severe anxiety

symptoms had lower average MET levels throughout the active hours than people with mild or no-anxiety symptoms (Fig. 5a). Similar trends were evident for weekend days (Fig. 5b), with the no-anxiety group maintaining the highest average MET levels throughout the day, followed by the mild-anxiety group. The difference in MET levels between the moderate-to-severe anxiety group and the no-anxiety group was most pronounced around midday, between 10:00 a.m. and 4:00 p.m..

When categorized by HSCL-25 scores, groups with depression and anxiety symptoms also demonstrated notably lower average MET levels across both weekdays and weekend days, compared to the group without symptoms (Figs. 5c and 5d). These differences were most pronounced during the peak waking hours and remained evident throughout the daytime period. Overall, in both categorization systems, the no-anxiety and no-depression-and-anxiety groups (green lines) showed the highest activity profiles, whereas groups with both anxiety and depression or solely anxiety (red lines) showed below average activity levels across the entire 24-hour cycle.

3.6. Statistical analysis of differences in the patterns

Significant group differences were evident across several physiological and sleep variables, based on both the GAD-7 and the HSCL-25 categorizations. The results are summarized in Table 2. For GAD-7, participants with moderate-to-severe anxiety symptoms showed significantly lower weekday RMSSD (mean = 50.24, SD = 3.80 ms) compared to those with mild-anxiety symptoms (mean = 50.92, SD = 3.80 ms) and no-anxiety symptoms (mean = 53.83, SD = 3.75 ms; $p < 0.001$). Similar patterns were observed for deep sleep duration. There were lower values in the moderate-to-severe symptom group (mean = 91.69, SD = 45.02 min) than either the mild or no-anxiety symptom groups ($p < 0.001$). On weekend days, significant differences were again evident for deep and REM sleep, with the moderate-to-severe symptom group showing reduced values.

For HSCL-25, individuals with depression and anxiety symptoms had lower weekday mean RMSSD (Mean = 51.66, SD = 3.15 ms) compared with the no depression and anxiety symptom group (Mean = 53.16, SD = 3.93 ms; $p = 0.151$) and showed significantly less deep sleep on both weekdays and weekend days on both weekdays and weekend days ($p < 0.001$ and $p = 0.009$, respectively). Across both screening-scale categorization groups, light and REM sleep also differed, with lower values observed among higher symptom-severity groups. HR differences were significant on weekdays for both GAD-7 ($p = 0.038$) and HSCL-25 ($p = 0.027$) categorization groups. No significant group differences were observed for awake time.

The results of the sensitivity analysis, along with detailed visualizations, appear in the Supplementary material. When participants with chronic doctor-diagnosed diseases were excluded, the findings showed the same patterns as in the main results.

Table 2

Presenting the results of one-way ANCOVA and Tukey-Kramer post-hoc tests that comparing sleep stage percentages, HR, RMSSD, and MET values across different anxiety and depression symptom groups.

			GAD-7			HSCL-25					
			No anxiety	Mild anxiety	Moderate to severe anxiety	F	Overall p-value	No depression and anxiety	Depression and anxiety	F	Overall p-value
Sleep stages	Awake (Minute)	weekday	56.10 (36.42)	57.63 (38.95)	58.95 (37.99)	1.87	0.155	55.75 (37.4)	58.76 (37.4)	0.91	0.340
		weekend days	60.20 (37.53)	62.54 (42.89)	62.31 (37.34)	0.93	0.396	60.19 (39.33)	63.31 (39.36)	0.24	0.623
	Light (Minute)	weekday	247.99 (60.64) _c	246.67 (63.42) _c	262.49 (68.09) [*]	9.03	< 0.001	247.77 (61.75)	248.42 (65.94)	0.29	0.591
		weekend days	265.89 (67.78)	260.26 (67.18) _c	272.59 (58.02) ^b	3.35	0.035	262.94 (66.8)	268.07 (66.83)	1.94	0.164
	Deep (Minute)	weekday	101.41 (41.65) _c	100.87 (41.73) _c	91.69 (45.02) [*]	14.20	< 0.001	102.36 (41.54)	96.92 (45.47)	13.33	< 0.001
		weekend days	100.68 (41.44) _c	99.57 (44.08) _c	92.54 (40.08) [*]	4.74	0.009	101.12 (41.58)	96.01 (45.98)	6.80	0.009
	REM (Minute)	weekday	85.35 (36.90) _c	85.59 (37.54) _c	80.75 (40.04) [*]	6.58	< 0.001	87.43 (37.22)	84.29 (39.25)	10.51	0.001
		weekend days	98.36 (39.24) _c	98.81 (39.41) _c	91.35 (37.96) [*]	3.71	0.025	98.22 (38.94)	93.29 (40.62)	4.14	0.042
HR (beats per minute)	weekday	56.77 (3.84) [*]	56.90 (3.66) [*]	57.89 (3.66) [*]	9.50	0.038	56.93 (3.80)	57.74 (3.74)	2.06	0.027	
	weekend days	59.08 (3.37)	59.25 (3.30)	59.62 (3.51)	0.60	0.727	59.19 (3.65)	59.57 (3.70)	0.61	0.523	
RMSSD (Millisecond)	weekday	53.83 (3.75) [*]	50.92 (3.80) ^a	50.24 (3.80) ^a	3.27	< 0.001	53.16 (3.93)	51.66 (3.15)	8.14	0.151	
	weekend days	49.47 (3.81)	48.56 (3.6)	47.81 (3.82)	0.32	0.550	50.35 (3.86)	49.15 (3.86)	2.57	0.435	
MET	weekday	1.51 (0.04) [*]	1.49 (0.042) ^a	1.48 (0.039) ^a	6.67	0.001	1.49 (0.038)	1.46 (0.036)	4.91	0.004	
	weekend days	1.47 (0.04) _c	1.47 (0.035) _c	1.43 (0.038) [*]	3.24	0.039	1.46 (0.044)	1.44 (0.042)	0.41	0.109	
Values are mean (standard deviation). Differences were tested with one-way analysis of covariance (ANCOVA) and then Tukey Kramer test for pairwise comparison are reported.											
a, b, c indicate significant difference (p < 0.05) from the respective groups: a = No anxiety; b = Mild anxiety; c = Moderate to severe anxiety.											
* Indicates significant difference from all other groups.											
Abbreviations: HR: Heart Rate, MET: Metabolic Equivalent of Task, REM: Rapid Eye Movement, RMSSD: Root Mean Square of Successive Differences											

4. DISCUSSION

This exploratory study provides novel evidence that digital metrics captured by a smart ring can reflect differences in the severity of depression and anxiety symptoms. The analysis of diurnal and nocturnal time-series data, including sleep stages (hypnogram), HR, HRV (indexed by RMSSD), and MET values,

showed differential patterns across groups with varying severity of anxiety and depression symptoms. Our findings show that, on average, individuals with moderate-to-severe anxiety symptoms (assessed based on GAD-7) and with depression and anxiety symptoms (assessed based on HSCL-25) had less daytime physical activity, altered sleep architecture (e.g., reduced REM and deep sleep), higher nocturnal HR, and lower HRV compared to the whole sample population. These differences were generally observed for both weekdays and weekend days. The patterns remained the same even after participants with chronic diseases were excluded. Overall, these findings highlight that mental health problems and symptoms may manifest in physical and physiological metrics that can be measured by a consumer-grade smart ring.

We observed differences in wearable-estimated sleep architecture across groups with varying levels of depression and anxiety. The largest differences were observed for light, deep, and REM sleep stages. The duration of deep and REM sleep stages was significantly reduced in the moderate-to-severe anxiety group across both weekdays and weekends. In recent years, the trend in mental health research has shifted from static self-report assessments toward continuous data-driven monitoring aided by wearable sensing and mobile technologies[41]. Several studies have demonstrated that digital metrics collected via wearable devices can serve as digital biomarkers or digital phenotypes of mental health risk[42]. These works have explored whether—and how objectively or continuously—measured sleep parameters (e.g. sleep timing, duration, quality, and circadian rhythmicity) are related to the risk of depression and anxiety[43]. This study adds to previous research by showing that consumer-grade wearable devices may be able to detect changes in sleep architectures that are linked to the severity of depression and anxiety symptoms⁴².

Among the many physiological biomarkers that can be collected in both laboratory and daily life, HR and HRV stand out as particularly promising noninvasive metrics for predicting and detecting psychological states[44]. They are relatively easy to measure, especially with the growing ubiquity of wearable technologies[45]. Most studies examining whether such metrics can be used as biomarkers of depression or anxiety have focused on 24-hour or resting HR and HRV as potential indicators of depression or anxiety symptoms[46]. Some have identified distinct 24-hour and resting HR and HRV profiles that are typically observed among people with mental disorders, whereas people without such conditions do not display the same patterns[47]. However, HR and HRV adjust constantly in response to physical and emotional demands on the body. During the day, HR and HRV can be physiologically high because of high levels of activity. During sleep, when there is minimal movement and physical demand, it is likely that HR and HRV can be measured by wearables with less artifact and noise, potentially serving as better physiological indicators. This point is especially relevant for depression and anxiety, which are often influenced by stress and emotional stimuli[48, 49].

The Oura Ring obtains HR and HRV data only during nocturnal sleep. Our study is one of the first to demonstrate that HR and HRV collected via commercial wearable devices in free-living conditions differed across individuals with varying levels of depression and anxiety symptoms. The findings showed that, on average, participants with symptoms of depression and anxiety had higher nocturnal HR and lower RMSSD. The RMSSD is widely used in mobile health tools as an indicator of stress and autonomic nervous system balance[50]. In addition, low HRV is an established marker of reduced adaptability to stress and often occurs in individuals with anxiety or depression[51]. One study found that individuals with severe depressive and anxiety symptoms had relatively low HRV, as measured by smartwatch sensors, over a 4-week period[52]. Other studies on wearable devices similarly found that anxiety disorders were associated with significantly reduced HRV outside of clinical settings[47]. Our findings add to the evidence that HR and HRV data, even when collected by consumer-wearable devices, can potentially serve as objective and non-invasive indicators of depression and anxiety[47, 53].

Individuals with higher depression and anxiety symptoms were on average less physically active during the day than people without symptoms. This pattern was particularly evident during the active hours from mid-morning to late afternoon, and these activity patterns occurred on both weekdays and weekend days. The finding suggests a possible link between overall lower movement intensity and higher depression and anxiety symptoms. Wearable motion and activity tracking has previously been used to differentiate people who experience depression or anxiety symptoms from those without such symptoms, especially in large population-based samples[54]. It is widely assumed that people with higher levels of depression and anxiety generally exhibit less physical activity and distinct movement patterns compared with people who lack such symptoms. This data can be leveraged to develop diagnostic models for identifying individuals at risk[11]. For example, studies in which wearable devices were used to track daily activity behaviors showed that machine learning can predict depression and anxiety based on physical activity, sedentary, and sleep metrics[11, 54]. Our study provides further evidence that there are noticeable differences in both the level and temporal distribution of movement intensity among individuals with depressive and anxiety symptoms, compared to people without these symptoms.

4.1. Strengths and limitations

This study has several key strengths. First, we analyzed a relatively large population-based sample of adults.[55] The sample was larger than those in previous studies on using smart rings or wearable-collected data to predict and screen for depression and anxiety.[56, 57] Second, we examined a comprehensive set of physical and physiological metrics captured continuously in daily life, not just in a laboratory. These included sleep architecture, nocturnal HR, RMSSD, and physical activity intensity measured via METs. A third strength lies in the psychological assessments, which were conducted using two validated instruments. These tools are widely recognized for their reliability, cross-cultural applicability, and clinical relevance in measuring symptoms of anxiety and depression.[31, 33] A fourth strength is the robustness of our findings, demonstrated by sensitivity analyses excluding participants with chronic health conditions. The consistency of the results after these exclusions suggests that the patterns in sleep, cardiovascular physiology, and physical activity are probably related to mental health symptoms rather than comorbid physical illnesses.

Despite these strengths, limitations must be acknowledged. A primary challenge involves the accuracy of sleep staging, particularly when distinguishing light sleep from REM sleep using consumer-grade wearables. Although recent studies support the acceptable validity of consumer-grade wearables for sleep staging[17, 58], there has been some concerns regarding the accuracy of wearable devices in sleep staging. The resolution of wearables is also limited compared to PSG [34], which is the clinical gold standard for sleep staging. Nevertheless, the ecological validity and capacity for continuous longitudinal monitoring make wearables highly practical for large-scale studies[59]. In brief, although validation studies support the general accuracy of Oura sleep

metrics[58, 60], consumer-grade devices remain an indirect proxy compared to clinical tools[60]. Another limitation is the proprietary nature of Oura's algorithms, which restricts transparency regarding how the specific metrics (e.g., METs and sleep-stage categorization) are derived. This point could affect reproducibility and hinder cross-device comparisons, especially if digital biomarkers are compared across brands or platforms.

5. CONCLUSION

This study provides novel evidence that depression and/or anxiety severity are reflected in passive physiological and behavioral metrics captured by a consumer-grade wearable device. Group of participants with different levels of depression and anxiety symptoms exhibited differences in sleep architecture, HR, HRV, and movement intensities. Our results reveal that groups with higher levels of depression and anxiety symptoms exhibited reduced deep and REM sleep, elevated nocturnal HR, lower RMSSD, and decreased daytime MET values. Overall, our findings support the use of consumer-grade wearable devices as tools for screening and detecting depression and anxiety in daily life settings, potentially complementing existing clinical tools and methods for mental health disorders. These findings provide further support for the growing body of research on integrating wearable digital devices into broader mental health assessments, where passive data streams and digital metrics can enhance symptom tracking, enable early detection, and inform personalized care strategies.

Declarations

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Competing interests

The authors declare that there is no conflict of interest

Data availability

NFBC data is available from the University of Oulu, Infrastructure for Population Studies. Permission to use the data can be applied for research purposes via electronic material request portal. In the use of data, we follow the EU 395 general data protection regulation (679/2016) and Finnish Data Protection Act. The use of personal data is based on cohort participant's written informed consent at his/her latest follow up study, which may cause limitations to its use. Please, contact NFBC project center [NFBCprojectcenter\(at\)oulu.fi](mailto:NFBCprojectcenter(at)oulu.fi) and visit the cohort website for more information.

Author contributions

AS and SA: Conceptualization and study design, Data analysis and interpretation, Methodology development or software/tool creation, Drafting and revising the manuscript (first two co-authors with same contribution)

LN: Revising the manuscript

NK: Revising the manuscript

MN: Data acquisition or provision, Drafting and revising the manuscript

VF: Conceptualization and study design, Drafting and revising the manuscript, Supervision

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Figures

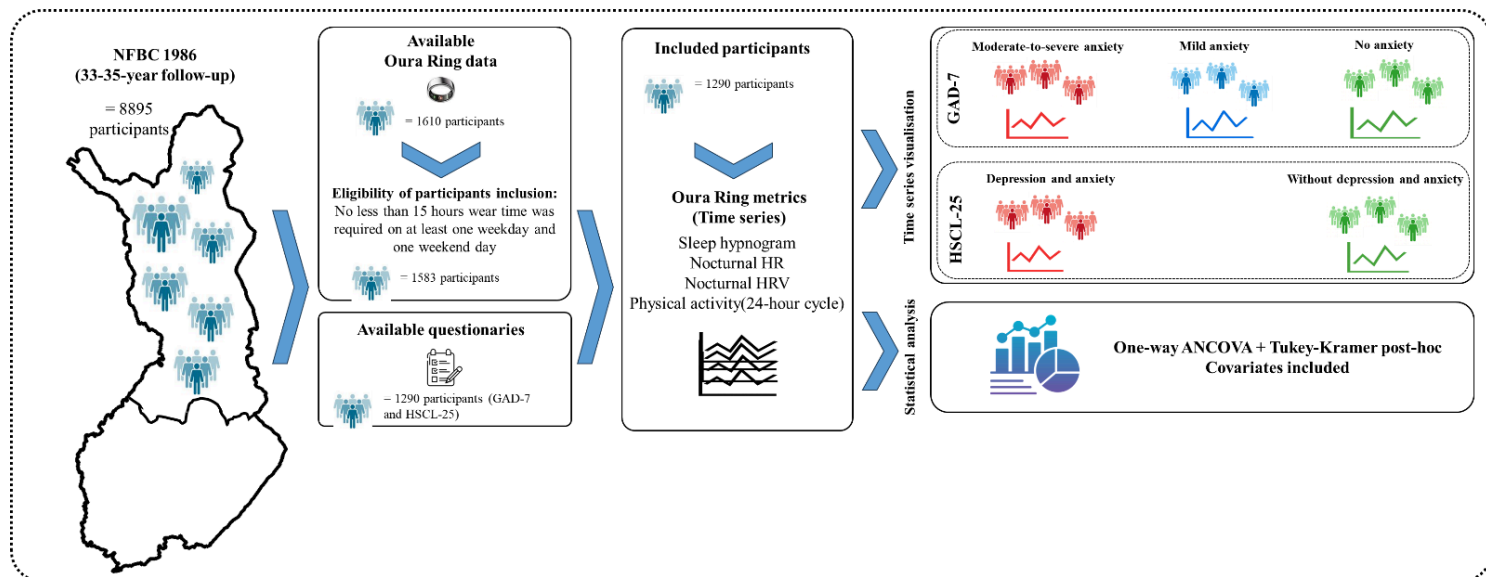


Figure 1

Overview of the study design, eligible participants selection, and analysis performed.

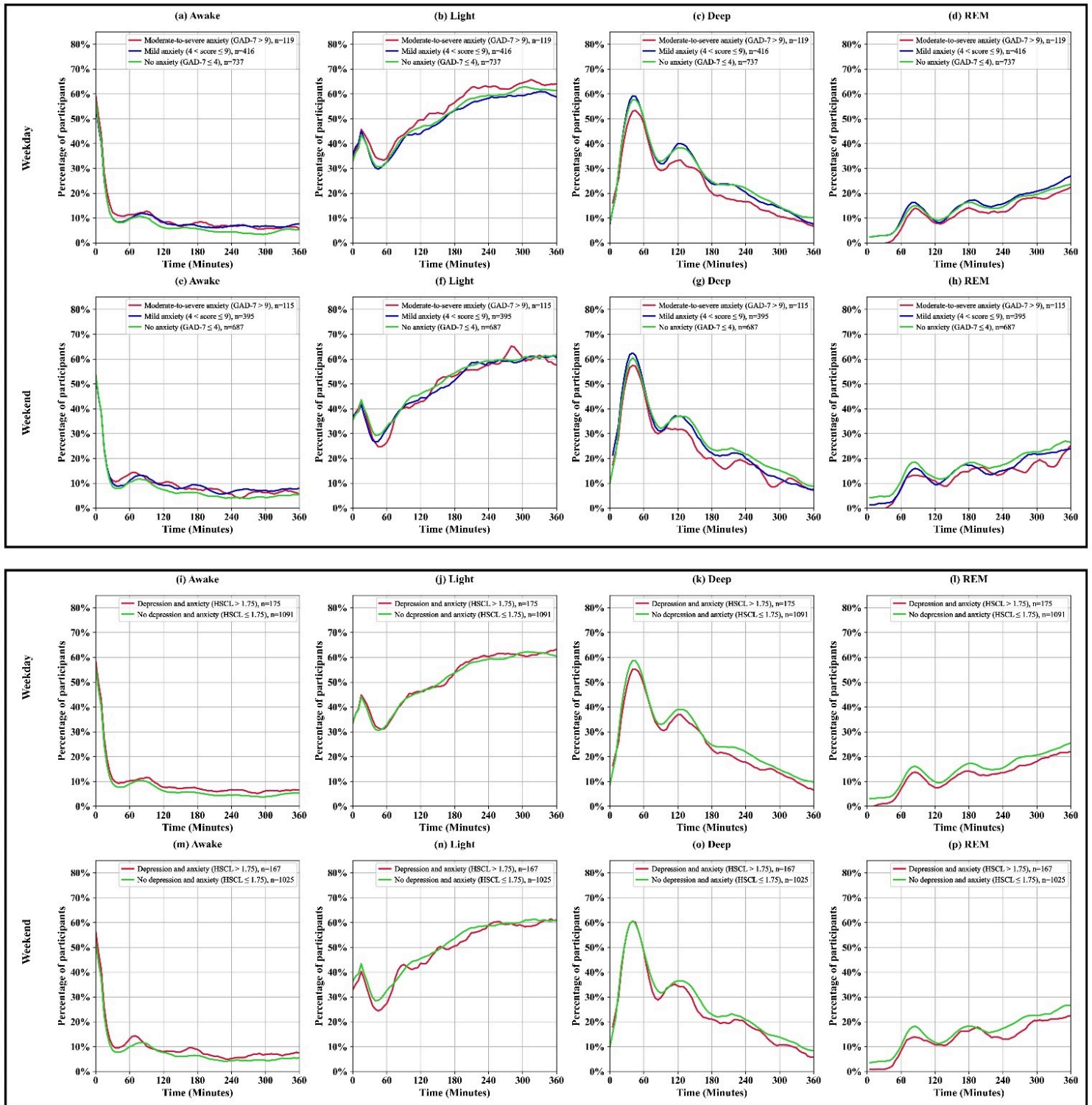


Figure 2

Percentage of participants in each sleep stage (Awake, Light, Deep, and REM) over time during detected sleep period on weekdays and weekend days, stratified by anxiety and depression symptom levels. Panels (a–h) represent comparisons based on anxiety severity measured using the GAD-7 score, categorized as no anxiety, mild anxiety, and moderate-to-severe anxiety. Panels (i–p) represent comparisons based on the presence or absence of depression and anxiety symptoms measured by the HSCL-25. The top rows (a–d, i–l) show sleep stage percentages for weekdays, and the bottom rows (e–h, m–p) show percentages for weekend days. The y-axis indicates the percentage of participants, and the x-axis represents time (minutes) over the sleep period. The number of participants in each group is indicated by n in the panel legends.

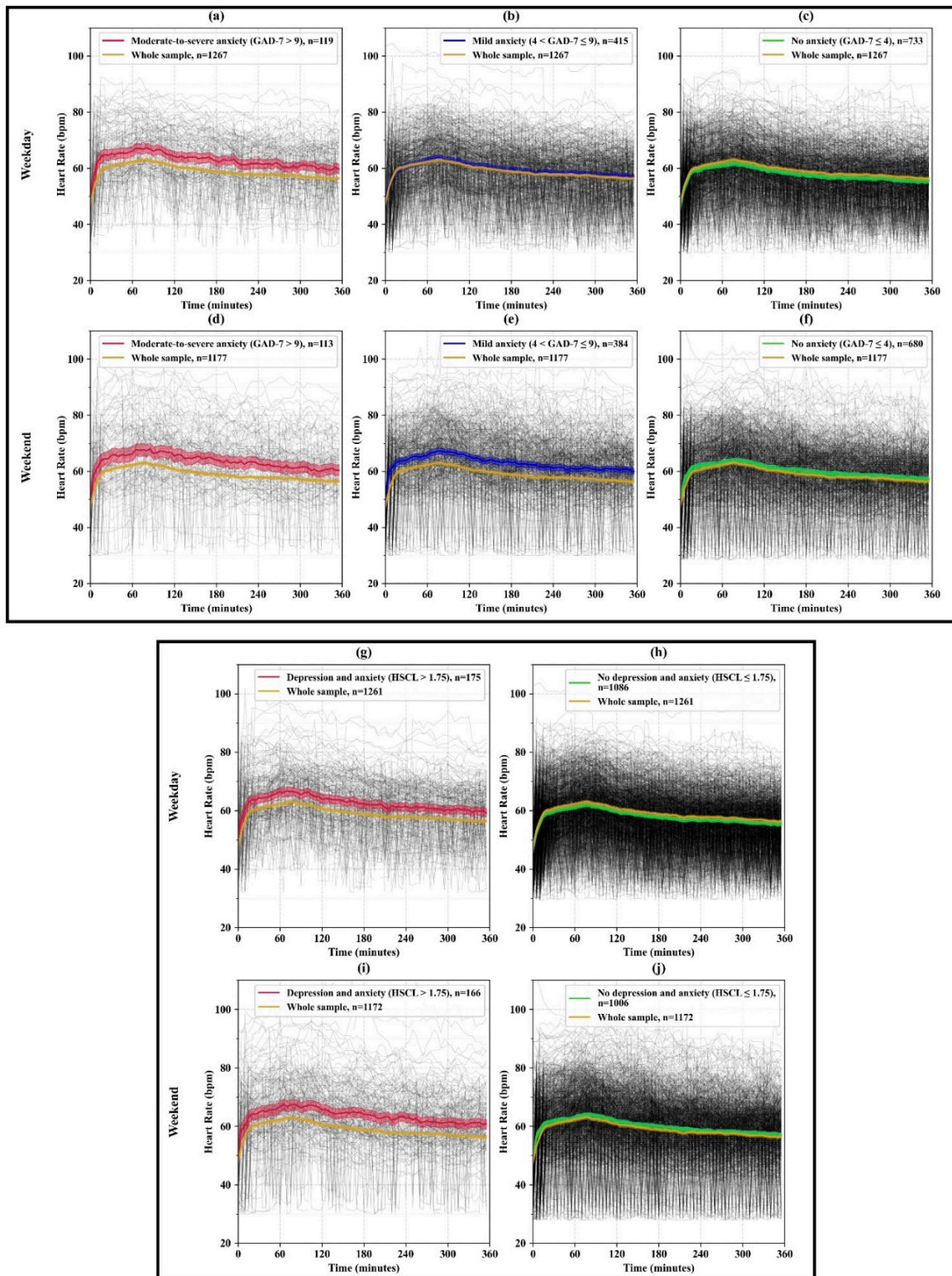


Figure 3

Mean HR (beats/minute) during detected sleep period on weekdays and weekend days. Panels (a–f) show the results based on anxiety severity measured by the GAD-7 scores, categorized as no anxiety, mild anxiety, and moderate-to-severe anxiety. Panels (g–j) show the results based on the no depression and anxiety and depression and anxiety symptoms measured by the HSCL-25. The number of participants in each group is indicated by n in the panel legends. The gray lines represent individual HR trajectories, while the coloured lines indicate the mean HR for each group. The y-axis shows HR (bpm), and the x-axis represents time (minutes) over the sleep period.

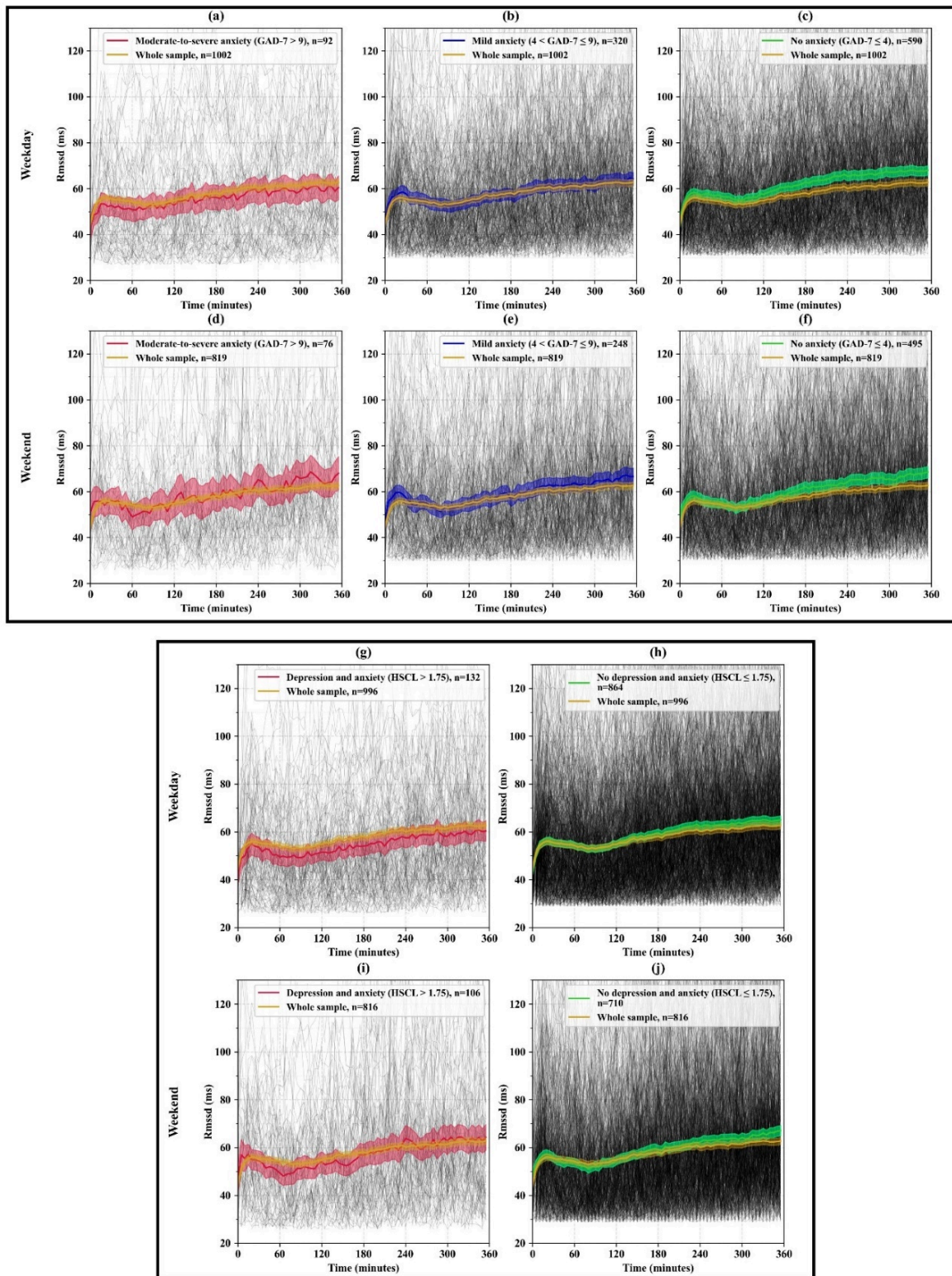


Figure 4

Mean RMSSD (milliseconds) during detected sleep period on weekdays and weekend days. Panels (a–f) show the results based on anxiety severity measured by the GAD-7 scores, categorized as no anxiety, mild anxiety, and moderate-to-severe anxiety. Panels (g–j) show the results based on the no depression and anxiety and depression and anxiety symptom measured by the HSCL-25. The number of participants in each group is indicated by n in the panel legends. The gray lines represent individual RMSSD trajectories, while the colored lines indicate the mean RMSSD for each group. The y-axis shows RMSSD (ms), and the x-axis represents time (minutes) over the sleep period.

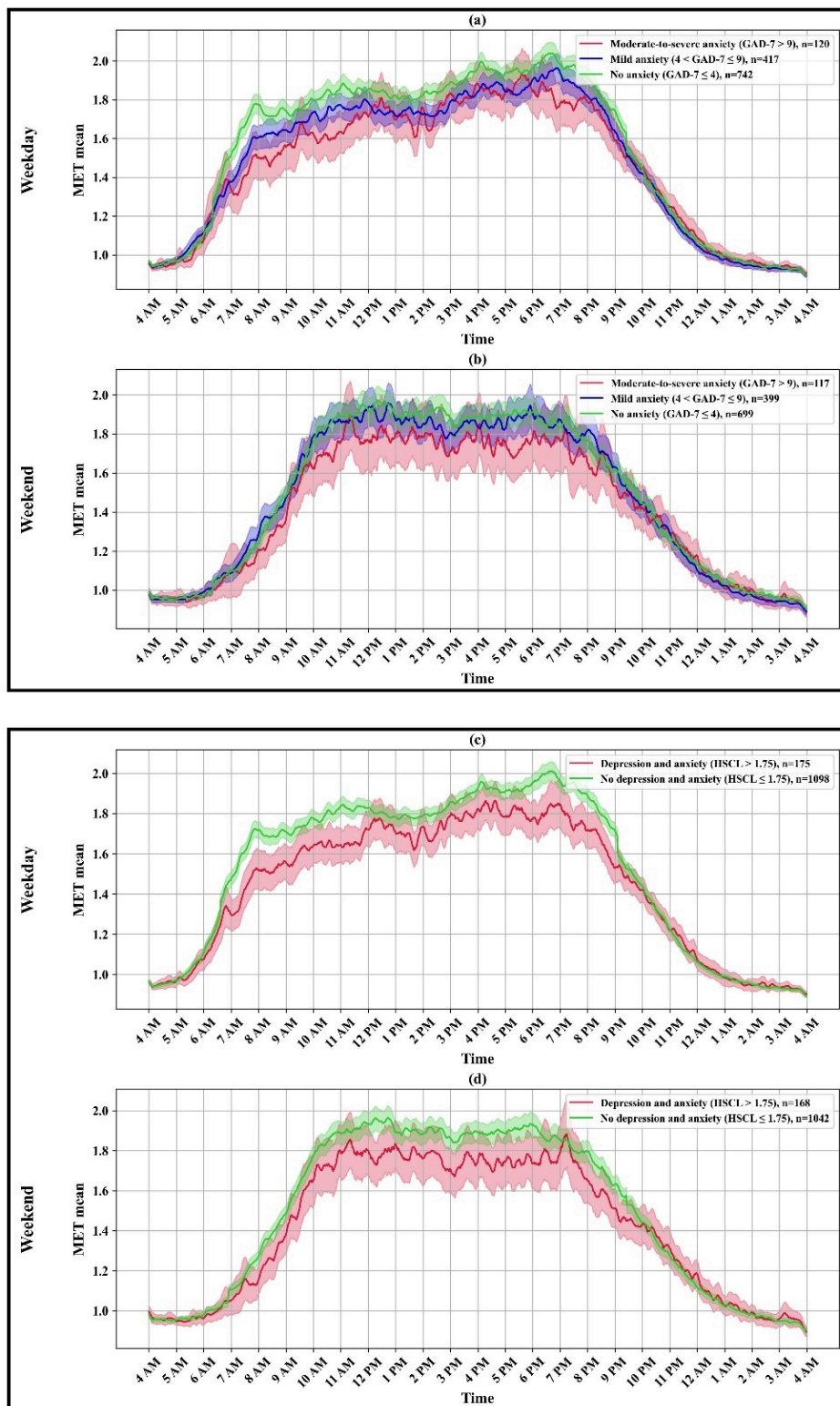


Figure 5

Mean MET values across 24 hours on weekdays and weekend days. Panels (a–b) show the results based on anxiety severity measured by the GAD-7 scores, categorized as no anxiety, mild anxiety, and moderate-to-severe anxiety. Panels (c–d) show the results based on the presence or absence of depression and anxiety symptom measured by the HSCL-25. The number of participants in each group is indicated by n in the panel legends. The coloured lines represent the mean MET values for each group, and the shaded areas indicate the 95% confidence intervals. The y-axis shows the mean MET values, and the x-axis represents time of day (hours).

Supplementary Files

This is a list of supplementary files associated with this preprint. Click to download.

- [Supplementarymaterial.docx](#)