1828
AKADÉMIAI KIADÓ

Multidimensional analysis of smartphone overuse in insomnia: Integrating digital phenotyping with clinical assessment

EMMA MATSUSHITA[1†], HYUNGJU KIM[2†], MINJI KIM[3], SEOJIN YOON[3], SUJIN KIM[4], JI WON YEOM[4], SEUNG PIL PACK[5], HEON-JEONG LEE[4], TAESU CHEONG[2] and CHUL-HYUN CHO[4,6*]

[1] Keio University School of Medicine, Tokyo, Japan

[2] School of Industrial Management Engineering, Korea University, Seoul, Republic of Korea

[3] Korea University College of Medicine, Seoul, Republic of Korea

[4] Department of Psychiatry, Korea University College of Medicine, Seoul, Republic of Korea

[5] Department of Biotechnology and Bioinformatics, Korea University, Sejong, Republic of Korea

[6] Department of Biomedical Informatics, Korea University College of Medicine, Seoul, Republic of Korea

Journal of Behavioral Addictions

15 (2026) 1, 289–304

DOI:
10.1556/2006.2025.00093

FULL-LENGTH REPORT

Received: June 27, 2025 • Revised manuscript received: October 19, 2025 • Accepted: December 7, 2025
Published online: January 6, 2026

ABSTRACT

Background and aims: This study aimed to identify the differences in characteristics between high- and low-risk smartphone users among individuals with insomnia symptoms using digital phenotyping and clinical assessments. *Methods:* A total of 246 participants with insomnia symptoms (M = 31.14, SD = 10.09) were monitored for four weeks using the smartphone application and wearable devices. The participants were divided into high-(n = 141) and low-risk (n = 105) smartphone overuse groups based on a Smartphone Overuse Screening Questionnaire. Clinical scale results and wearable data were analyzed using ANCOVA and logistic regression, controlling for age, sex, and BMI. *Results:* After covariate adjustment, the high-risk group showed significantly greater biological rhythm disruption (K-BRIAN: LS-mean difference = 6.86, $p < 0.000$), more severe insomnia (ISI index: aOR: 2.63, $p = 0.0005$), and poorer sleep quality (PSQI-K: aOR: 2.41, $p = 0.0015$). Psychological distress, including depression (PHQ-9 index: aOR: 2.77, $p = 0.0001$) and anxiety (GAD-7 index: aOR: 1.59, $p = 0.0059$), was more pronounced in the high-risk group. Bedtime procrastination (BPS index: aOR: 1.96, $p = 0.0173$) and stress reactivity to insomnia (FIRST index: aOR: 1.67, $p = 0.0574$) were significantly elevated. Digital phenotyping revealed persistent differences in minimum daytime heart rate and exercise intensity patterns, while many activity-related measures lost significance after adjustment. *Discussion and conclusions:* Smartphone overuse is independently associated with severe circadian disruption, insomnia, and psychological distress. The integrated assessment approach revealed critical biomarkers and behavioral patterns. Targeted interventions focused on circadian stabilization and behavioral sleep patterns may improve sleep quality and mental health outcomes in this population. Longitudinal research is needed to establish causality.

KEYWORDS

smartphone overuse, insomnia, digital phenotyping, circadian rhythm, sleep quality, mental health

†These authors contributed equally

*Corresponding author.
E-mail: david0203@korea.ac.kr, david0203@gmail.com

INTRODUCTION

Smartphones are ubiquitous and convenient, but raising health concerns, including addiction. With most of the global population owning a smartphone, the potential negative

impacts on health have also increased (Ratan, Parrish, Zaman, Alotaibi, & Hosseinzadeh, 2021). Problematic smartphone use may be inferred when individuals exhibit preoccupation with the device, progressive increases in use consistent with tolerance, a persistent inability to cut down despite intentions to do so, or a diminished interest in other activities (H.-K. Lee, Kim, et al., 2017). Smartphone use has been linked to depression, anxiety, chronic stress, and low self-esteem (Elhai, Dvorak, Levine, & Hall, 2017). Prior research has shown that smartphone addiction correlates with higher GABA levels and a disrupted GABA–Glx balance. Here, Glx refers to the combined signal of glutamate and glutamine. This neurochemical profile has been linked to poorer mental-health outcomes (Seo et al., 2020). This trend is especially alarming among youth estimated that approximately 25% of children and adolescents engage in problematic smartphone use, leading to deteriorating mental health, such as social isolation and a decline in face-to-face communication (Sohn, Rees, Wildridge, Kalk, & Carter, 2019). Adults are also at higher risk, as emphasized in recent studies (Al-Kandari & Al-Sejari, 2021; Kusumota et al., 2022). Moreover, problematic use can exacerbate pre-existing mental health and disrupt sleep patterns (Dresp-Langley & Hutt, 2022; Gjoneska et al., 2022). Despite growing recognition of these issues, relatively few studies have examined the multifaceted effects of smartphone overuse among individuals with sleep disorders such as insomnia, including mechanisms implicating melatonin suppression via melanopsin-expressing intrinsically photosensitive retinal ganglion cells (ipRGCs) projecting to the suprachiasmatic nucleus (SCN), which delays circadian phase and sleep onset (Bozkurt, Demirdöğen, & Akıncı, 2024; Chang, Aeschbach, Duffy, & Czeisler, 2015).

Insomnia is a prevalent sleep disorder characterized by difficulty falling or staying asleep, waking up too early, and non-restorative sleep (Roth, 2007). It is often accompanied by a range of mental and physical health problems (S. Lee, Lee, & Cho, 2022; Morin & Buysse, 2024), with socioeconomic costs, such as reduced productivity, increased absenteeism, and healthcare. Recent studies showed that approximately 10% of adults suffer from chronic insomnia, and 20% experience occasional insomnia, with prevalence rising globally (Garland et al., 2018; Morin & Jarrin, 2022). While acute insomnia can resolve spontaneously, persistent cases often evolve into chronic forms that significantly impair quality of life (Benca, 2005).

Cognitive behavioral therapy for insomnia (CBT-I) is the primary treatment for insomnia targeting cognitive distortions and dysfunctional behaviors (Morin & Buysse, 2024). Cognitive distortions include catastrophic thinking about poor sleep, unrealistic sleep expectations, and excessive worry about sleep loss. Dysfunctional behaviors include irregular sleep, spending time awake in bed, and stimulatory activities before sleep (Morin & Bélanger, 2011). Smartphone overuse at bedtime is associated with insomnia symptoms likely due to circadian rhythm and delayed sleep onset (Schmid et al., 2021).

With recent advances in sensor technology and artificial intelligence improving measurement accuracy (Galatzer-Levy & Onnela, 2023), digital phenotyping has rapidly expanded in psychiatry (Chia & Zhang, 2022; Yeom et al., 2025). This approach leverages data from digital devices such as smartphones and wearables and provides objective measurements of mental health assisting traditionally subjective clinical assessments. The availability of data is estimated to lead to the expansion of digital phenotyping (De Boer et al., 2023). It could be a novel opportunity to advance our understanding of the relationship between smartphone overuse and insomnia.

This study aimed to understand the effect of smartphone overuse on insomnia by integrating digital phenotyping with clinical assessments. We analyzed the demographic, psychological, and behavioral characteristics of insomnia group based on their level of smartphone use by Smartphone Overuse Screening Questionnaire (SOS-Q) (H.-K. Lee, Kim, et al., 2017). Using a multidimensional approach, including clinical scales and data from wearable devices, this study sought to identify the key differences between high- and low-risk smartphone users and observe insights for clinical interventions. The study plan was informed by prior research on insomnia and circadian rhythm disorders, including guidance to capture habitual sleep–wake variability through multi-week monitoring (Smith et al., 2018). By analyzing the interaction between digital behavior and sleep health, we can contribute to a new approach to modern insomnia and the possibilities of sleep therapy.

METHODS

Study population

From January 2023 to July 2024, 398 participants, including patients with insomnia and non-insomnia patients, were recruited from the Korea University Anam Hospital and Datamaker Inc. (Daejeon, South Korea), a specialized data collection service company that conducted participant recruitment and data collection under the same research design and ethical protocols. Participants aged 19–65 were recruited from the local community through online community platforms and campus bulletin boards. This study was conducted on 249 participants with insomnia, defined as individuals who experienced subjective insomnia symptoms at least three times per week over the past 3 months, with an Insomnia Severity Index (ISI) score of 8 or higher (Bastien, Vallières, & Morin, 2001). Exclusion criteria for the insomnia group included intellectual disability, organic brain damage, a diagnosis of a schizophrenia spectrum disorder, current treatment for sleep disorders, and not owning a smartphone.

The participants provided informed consent at the onset of the study and completed clinical report forms covering demographic information, family medical history, and current health conditions using various scales. The participants were equipped with wearable devices (Fitbit Inspire 3, Fitbit

Inc., USA) to gather data on step count, heart rate, and sleep patterns. They were also asked to download the "SOMDAY" smartphone application (Lumanlab Inc., Seoul, South Korea) to log their daily habits. Three participants were excluded due to missing data, leaving 246 individuals for the final analysis (Fig. 1).

Measures

Clinical assessment. Demographic information, including age, sex, marital status, education, job, life pattern (e.g., morningness/eveningness and related chronotype categories), sleep environment (e.g., alone, with a partner, with children, or other), weight, and height, was collected. In addition, the participants completed a series of standardized self-reported questionnaires to assess key study variables.

To evaluate insomnia severity, the Insomnia Severity Index (ISI) (Morin, Belleville, Bélanger, & Ivers, 2011) was used as a validated measure to assess both the presence and severity of insomnia symptoms. The Smartphone Overuse Screening Questionnaire (SOS-Q) was used to classify participants into risk groups based on their smartphone usage patterns (H.-K. Lee, Kim, et al., 2017). Participants with an SOS-Q score exceeding 48 were categorized into the smartphone overuse high-risk group (SOHG) (n = 141), whereas those with a score of 48 or lower were assigned to the smartphone overuse low-risk group (SOLG) (n = 105).

Additionally, as sleep-related scales, results were collected from Dysfunctional Beliefs and Attitudes about Sleep (DBAS-16) (Morin, Vallières, & Ivers, 2007), the Korean version of Biological Rhythms Interview of Assessment in Neuropsychiatry (K-BRIAN) (Cho, Jung, Kapczinski, Rosa, & Lee, 2018), Pittsburgh Sleep Quality Index (PSQIK) (Sohn, Kim, Lee, & Cho, 2012), Berlin Questionnaire (BERLIN) (Senaratna et al., 2017), Morningness-Eveningness Questionnaire (MEQ) (Hwang et al., 2024), Bedtime Procrastination Scale (BPS) (An, ju Chung, & Suh, 2019), Ford Insomnia Response to Stress Test (FIRST) (Chang & Suh, 2018). Further, as non-sleep-related scales, International Restless Leg Scale (IRLS) (Group, 2003), The Korean version of Alcohol Use Disorders Identification Test (AUDIT-K) (Chang et al., 2016), Patient Health Questionnaire-9 (PHQ-9) (Han et al., 2008), Generalized Anxiety Disorder-7 (GAD-7) (S. H. Lee, Lee, & Cho, 2022), Korean version of Mood Disorder Questionnaire (KMDQ) (Jon et al., 2009), Body Sensation Questionnaire (BSQ) (Chambless, Caputo, Bright, & Gallagher, 1984), Korean Resilience Questionnaire-53 (KRQ-53) (Ko, Kim, Bartone, & Kang, 2018), Multidimensional Fatigue Scale (MFS) (Song et al., 2018), Spiritual Well-Being Scale (SWBS) (You & Yoo, 2016), and World Health Organization Quality of Life Brief Version (WHOQOL-BREF) (Min et al., 2002) results were collected (Supplementary Table 1).

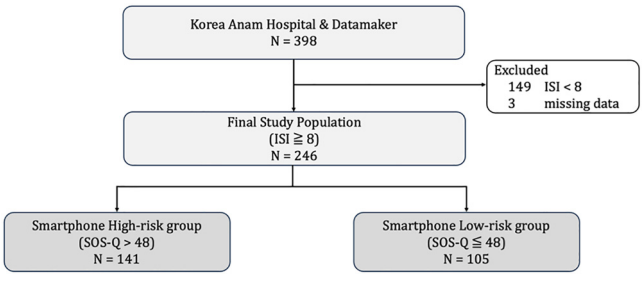

Fig. 1. Participant recruitment and data collection flowchart

Digital phenotypes (ecological momentary assessment and wearable data). *SOMDAY*, a smartphone application, was developed as a comprehensive tool to gather data on the participants' daily habits and lifestyle choices. It is compatible with both the Android (Google) and iOS (Apple) platforms, ensuring accessibility to a broad user base. Specifically designed to collect ecological momentary assessment data, the app prompts participants to log their daily habits each night at 9 PM to ensure consistent data entry, including details on alcohol intake, caffeine consumption, napping behavior, stress levels, self-reported sleep duration, and frequency of night-time awakenings.

In parallel, the Fitbit device automatically recorded various metrics such as sleep duration, number of awakenings, sleep quality, exercise time, heart rate, step count, and walking distance for four weeks (H.-A. Lee, Kim, et al., 2017). By integrating *SOMDAY* with Fitbit, the data from Fitbit was synchronized and made accessible through the *SOMDAY* app, which was then seamlessly connected to an online database for easy access by the research team for further analysis.

Datasets. Heart rate data were collected at 5-min intervals, and sleep duration was recorded daily. Because the step and walking distance data were cumulative, we applied differencing and calculated daily averages to derive features and examine circadian rhythms.

The sleep duration parameters included total sleep time, wake time, number of nighttime awakenings, and time spent in REM, light, and deep sleep. To assess sleep quality, we used total sleep and wake times. Daily maximum, minimum, and average values were calculated for the walking distance.

To analyze circadian rhythms in heart rate, we performed Cosinor analysis using a two-day time window, producing the following key parameters: mesor (midline estimating statistic of rhythm), amplitude, acrophase, and goodness of fit (Cornelissen, 2014). Mesor represents the rhythm-adjusted mean, which indicates the average value of a parameter over the analyzed period. The amplitude, defined as the difference between the mesor and peak value, quantifies the range of variation within the circadian cycle. Acrophase denotes the timing of the peak within each cycle and provides insights into circadian alignment. The goodness-of-fit measures how well the data aligns with a 24-h cosine model, reflecting the strength and clarity of the observed circadian rhythm. Additionally, we calculated the daily maximum, minimum, and average heart rates.

Steps were analyzed similarly to heart rate, with maximum, minimum, and average values computed for weekdays versus holidays (including Korean public

holidays), as well as for day (8 AM–6 PM) and night (6 PM–8 AM). Further insights into activity cycles were derived using L5 (least active 5-h period) and M10 (most active 10-h period), as well as intradaily variability (IV) and interdaily stability (IS) (Krafty et al., 2019). L5 and M10 were calculated through a moving average approach, with L5 representing the lowest activity over any 5 h, and M10, the highest activity over any 10 h. RA (relative amplitude) was caculated using L5 and M10.

Cosinor analysis features and sleep duration data were averaged over a four-week period, while maximum and minimum daily values were averaged for weekdays versus holidays and for day versus night. Similarly, L5, M10, RA, IS, and IV were separately averaged on weekdays and holidays.

Sample size, analytic hierarchy, and power. This study used rolling enrollment rather than a fixed sample size. Prior to closing recruitment, we defined a minimum sample size threshold to ensure adequate power for the primary analysis focusing on the insomnia-symptom cohort, which compared participants at high risk and low risk of problematic smartphone use.

Assuming a two-sided $\alpha = 0.05$, power = 0.80, and a mid–small standardized mean difference ($d = 0.36$) with the observed group-size ratio (low-risk:high-risk ≈ 0.75), the required total sample size was approximately $N = 247$. Recruitment continued until this threshold ($N \geq 240$–250) was achieved, resulting in a final analytic sample of $N = 246$ (high-risk = 141; low-risk = 105).

Analyses were organized into prespecified and exploratory tiers. Prespecified primary analyses assessed group differences in major clinical sleep scales (e.g., ISI, PSQI-K, K-BRIAN) using ANCOVA models adjusted for age, sex, and BMI. Prespecified secondary analyses examined associations involving digital sleep and smartphone-use parameters through linear and correlational tests. Exploratory analyses evaluated categorical or binary sleep-related outcomes (e.g., short sleep, daytime dysfunction) using logistic regression.

Sensitivity analyses included re-estimating models after covariate exclusion, applying log transformations to skewed variables, and using bootstrapped standard errors for robustness checks. Detailed assumptions, analytic structure (prespecified vs. exploratory), and power thresholds are summarized in Supplementary Table 2.

Statistical analysis. Statistical analyses were performed using JMP®, version 17 (SAS Institute Inc., Cary, NC, USA). First, an unadjusted analysis was performed, without accounting for covariates. For continuous variables such as scores, normality was tested using the Shapiro-Wilk test. If normality was rejected at the 5% level, the Wilcoxon test was used to compare values between the two groups; otherwise, a one-way analysis of variance (ANOVA) was applied. As a result, HR CR goodness of fit, mean HR day week, mean HR day holiday, max HR night week, max HR night holiday, mean HR night week, and max exercise intensity night week were conducted by ANOVA, and other continuous variables were conducted by the Wilcoxon test (Supplementary Tables 3–7). The chi-square test was used for categorical variables. If JMP Pro 17 indicated that 20% of the expected frequencies were below 5, Fisher's exact test was applied. Therefore, Marriage Status, Life Pattern, PSQIK, BPS index, IRLS index, PHQ-9 index, and GAD-7 index were conducted by Fisher's exact test (Supplementary Tables 3–6). Additionally, to account for potential confounding, we performed covariate-adjusted analyses: continuous outcomes were analyzed using analysis of covariance (ANCOVA) with age, sex, and body mass index (BMI) as fixed covariates, and categorical outcomes were analyzed using multivariable logistic regression including the same covariates. Adjusted mean differences are presented as least-squares means (LS-means) with 95% confidence intervals (CIs), and associations for categorical outcomes as adjusted odds ratios (aORs) with 95% CIs. Two-sided p values < 0.05 were considered statistically significant.

Ethics

This study was approved by the Institutional Review Board of Korea University Anam Hospital (IRB No. 2022AN0587), and written informed consent was obtained from all participants prior to data collection.

RESULTS

Based on the SOS-Q score, the study participants were classified into SOHG and SOLG. The two groups comprised 141 and 105 participants, respectively. The smartphone high-risk group was significantly younger than the low-risk group, with an average age of 28.42 years, compared to 34.80 years in the low-risk group (Hodges–Lehmann difference = 5.00 years (95% CI 3.00–7.00), $Z = 4.456$, $p < .0001$, effect size $r = 0.284$). Additionally, there were significantly more females in the high-risk group (102/141 vs 63/105, 0R = 1.74 (95% CI 1.02–2.98), $p = 0.042$, $\varphi = 0.130$). Moreover, there were significant differences between the groups in terms of marital status (df = 3, aOR = 0.35 (95% CI 0.20–0.61), $p < .0001$), employment status (68/140 vs 70/105; aOR = 0.42 (95% CI 0.24–0.74), $p = 0.003$), sleep environment (df = 6, aOR = 0.31 (95% CI 0.18–0.54), $p < .0001$), weight ($M = 60.78$ kg, SD = 12.52 kg vs. $M = 64.45$ kg, SD = 15.03 kg, Hodges–Lehmann difference = 4.00 kg (95% CI 0.00, 7.00), $Z = 2.185$, $p = 0.029$, effect size $r = 0.139$), and BMI ($M = 22.03$, SD = 3.73 vs. $M = 22.77$, SD = 3.32, Hodges–Lehmann difference = 1.00 kg/m^2 (95% CI 0.00–1.97), $Z = 2.00$, $p = 0.0456$, effect size $r = 0.127$) (Supplementary Table 3, Table 1).

Based on the ecological momentary assessment, caffeine intake, naptime, and stress did not differ significantly between the groups. However, a significant difference was observed in alcohol consumption (LS mean 19.87 (95% CI 11.01–28.72) vs 34.01 (95% CI 24.19–43.83), LS-mean difference = −14.14 (95% CI −27.34, −0.95), $p = 0.036$, partial $\eta^2 = 0.018$.; Supplementary Table 4, Table 2).

Table 1. Comparison of demographic information according to the risk of smartphone overuse in participants with insomnia symptoms

	Unadjusted analysis			Adjusted analysis		
	Mean ± SD			LS Mean (95% CI)/aOR (95% CI)		
Demographic information	Smartphone overuse high-risk group (n = 141)	Smartphone overuse low-risk group (n = 105)	p-value (two tailed)	Smartphone overuse high-risk group (n = 141)	Smartphone overuse low-risk group (n = 105)	p-value (two tailed)
Age	28.42 ± 7.90	34.80 ± 11.51	< **0.001**†††	–	–	–
Sex			**0.042**†		–	–
Female	102 (72.3%)	63 (60.0%)				
Male	39 (27.7%)	42 (40.0%)				
Marriage Status**			< **0.001**†††	aOR: 0.35 (0.20–0.61)		**<0.001**†††
Married	29 (20.6%)	52 (49.5%)				
Unmarried	111 (78.7%)	52 (49.5%)				
Separation	0 (0%)	0 (0%)				
Divorced	0 (0%)	1 (1.0%)				
Education**			**0.107**	aOR: 1.28 (0.84–1.95)		**0.248**
Uneducated	0 (0%)	0 (0%)				
Elementary school graduate	1 (0.7%)	0 (0%)				
Middle school graduate	0 (0%)	0 (0%)				
High school graduate	67 (47.5%)	36 (34.3%)				
University graduate	59 (41.8%)	51 (48.6%)				
Graduate degree or higher	13 (9.2%)	18 (17.1%)				
Employment Status**			**0.005**††	aOR: 0.42 (0.24–0.74)		**0.003**††
Employed	68 (48.2%)	70 (66.7%)				
Unemployed	72 (51.1%)	35 (33.3%)				
Life Pattern**			0.972	aOR: 1.02 (0.75–1.38)		0.912
Morning type	47 (33.3%)	36 (34.3%)				
Evening type	41 (29.1%)	28 (26.7%)				
Early morning type	11 (7.8%)	9 (8.6%)				
Flexible type	38 (27.0%)	30 (28.6%)				
Sleep Environment**			< **0.001**†††	aOR: 0.31 (0.18–0.54)		< **0.001**†††
Alone	97 (68.8%)	46 (43.8%)				
With spouse	15 (10.6%)	32 (30.5%)				
With child	3 (2.1%)	8 (7.6%)				
With family	10 (7.1%)	15 (14.3%)				
With pet	9 (6.4%)	3 (2.9%)				
Other	3 (2.1%)	1 (1.0%)				
Weight*	60.78 ± 12.52	64.45 ± 15.03	**0.029**†			
Height*	163.88 ± 16.27	165.53 ± 18.60	0.116			
BMI	22.03 ± 3.73	22.77 ± 3.32	**0.046**†	–	–	–

*Adjusted analyses performed only for variables that were not used as covariates (age, sex, BMI were used as covariates in other analyses).
$^{\dagger}p < 0.05$; $^{\dagger\dagger}p < 0.01$; $^{\dagger\dagger\dagger}p < 0.001$.
Abbreviations: BMI = Body Mass Index; LS Mean = Least squares mean; CI = Confidence interval; OR = Odds ratio.
Note: Age, sex, and BMI were used as covariates in the adjusted analyses of other tables and therefore are not adjusted here.
*ANCOVA; **Logistic Regression.

Table 2. Comparison of ecological momentary assessment according to smartphone overuse risk in participants with insomnia symptoms (adjusted analysis)

Ecological momentary assessment	LS Mean (95% CI)/aOR (95% CI)			*p*-value (two tailed)	Partial η^2
	Smartphone overuse high-risk group (n = 141)	Smartphone overuse low-risk group (n = 105)	Difference		
Caffeine intake*	20.21 (16.23–24.18)	17.44 (13.03–21.85)	2.77 (3.16–8.69)	0.359	0.003
Naptime*	5.95 (4.42–7.47)	5.71 (4.02–7.40)	0.24 (−2.03–2.51)	0.835	0.000
Stress*	21.85 (14.66–29.03)	24.74 (16.78–32.71)	−2.90 (−13.60–7.81)	0.594	0.001
Alcohol*	19.87 (11.01–28.72)	34.01 (24.19–43.83)	−14.14 (−27.34–0.95)	**0.036**†	0.018

*Adjusted for age, sex, and BMI using ANCOVA for continuous variables.
†$p < 0.05$; ††$p < 0.01$; †††$p < 0.001$.
Abbreviations: LS Mean = Least squares mean; CI = Confidence interval.
*ANCOVA; **Logistic Regression.

In sleep-related clinical assessments, the ISI score was significantly higher in the high-risk smartphone overuse group (LS Mean = 15.57 (95% CI 14.79–16.35)) compared to the low-risk group (LS Mean = 13.42 (95% CI 12.56–14.29), LS-mean difference = 2.14 (95% CI 0.98–3.09), $p = 0.0004$, partial $\eta^2 = 0.052$). Regarding the ISI classification, the proportion of participants classified as having severe insomnia was higher in the high-risk group (n = 13) than in the low-risk group (n = 5). The prevalence of mild insomnia was lower in the high-risk group (n = 60) than in the low-risk group (n = 68), whereas moderate insomnia was more frequent in the high-risk group (n = 68) than in the low-risk group (n = 32). A significant difference was observed across insomnia severity categories (df = 3, aOR = 2.63 (95% CI 1.52–4.55), $p = 0.0005$). Moreover, significant differences were found across all other sleep-related scales, including the DBAS, K-BRIAN, PSQI-K, BERLIN, MEQ, BPS, and FIRST (Supplementary Table 5, Table 3).

A significant difference was observed in non-sleep-related clinical assessments, such as PHQ-9, GAD-7, KMDQ, KRQ-53, and MFS (Supplementary Table 6, Table 4).

On comparing the data collected by SOMDAY with Fitbit, the high-risk group exhibited a lower daytime minimum heart rate on both weekdays (LS Mean 61.75 (95% CI 60.40–63.10) vs 64.17(95% CI 62.68–65.66), LS-mean difference = −2.42 (−4.42 to −0.41), $p = 0.0182$, partial $\eta^2 = 0.023$) and holiday (LS Mean 58.72 (95% CI 57.47–59.97) vs 60.83(95% CI 59.44–62.23), LS-mean difference = −2.11 (95% CI -3.98 to −0.24), $p = 0.0268$, partial $\eta^2 = 0.020$). On holidays, exercise intensity differed between groups during both daytime and nighttime (daytime: LS Mean 0.20 (95% CI 0.17–0.23) vs 0.13 (95% CI 0.10–0.17), LS-mean difference = 0.06 (95% CI 0.02–0.11), $p = 0.0052$, partial $\eta^2 = 0.032$; night time: LS Mean 0.11 (95% CI 0.09–0.23) vs 0.08 (95% CI 0.06–0.10), LS-mean difference = 0.03 (95% CI 0.00–0.06),

Table 3. Comparison of sleep-related clinical scales according to smartphone overuse risk in participants with insomnia symptoms (adjusted analysis)

Sleep-related clinical scales	LS Mean (95% CI)/aOR (95% CI)			*p*-value (two tailed)	Partial η^2
	Smartphone overuse high-risk group (n = 141)	Smartphone overuse low-risk group (n = 105)	Difference		
ISI Score*	15.57 (14.79–16.35)	13.42 (12.56–14.29)	2.14 (0.98–3.09)	**0.0004**††	0.052
ISI Index**	aOR: 2.63 (1.52–4.55)			**0.0005**†††	
DBAS-16**	92.13 (88.16–96.09)	84.51 (80.12–88.91)	7.61 (1.71–13.51)	**0.0118**†	0.026
K-BRIAN*	47.85 (45.92–49.79)	41.00 (38.85–43.15)	6.86 (3.97–9.74)	< **0.0001**†††	0.083
PSQI-K **	aOR: 2.41 (1.39–4.19)			**0.0015**††	
BERLIN*	aOR: 0.29 (0.14–0.62)			**0.0011**†††	
MEQ	20.79 (19.95–21.63)	19.56 (18.63–20.49)	1.22 (−0.03–2.48)	0.055	0.015
BPS Score	31.15 (30.43–31.86)	29.43 (28.64–30.22)	1.72 (0.65–2.78)	**0.0017**††	0.040
BPS Index**	aOR: 1.96 (1.12–3.41)			**0.0173**†	
FIRST Score*	24.55 (23.50–25.60)	22.44 (21.28–23.60)	2.11 (0.54–3.67)	**0.0085**††	0.028
FIRST Index**	aOR: 1.67 (0.99–2.83)			0.0574	

*Adjusted for age, sex, and BMI using ANCOVA for continuous variables and logistic regression for categorical variables.
†$p < 0.05$; ††$p < 0.01$; †††$p < 0.001$.
Abbreviations: ISI = Insomnia Severity Index; DBAS-16 = Dysfunctional Beliefs and Attitudes about Sleep; K-BRIAN = Korean version of Biological Rhythms Interview of Assessment in Neuropsychiatry; PSQI-K = Pittsburgh Sleep Quality Index-Korean version; MEQ = Morningness-Eveningness Questionnaire; BPS = Bedtime Procrastination Scale; FIRST = Ford Insomnia Response to Stress Test; LS Mean = Least squares mean; CI = Confidence interval; OR = Odds ratio.
*ANCOVA; **Logistic Regression.

Table 4. Comparison of non-sleep related clinical scales according to smartphone overuse risk in participants with insomnia symptoms (adjusted analysis)

Sleep-related clinical scales	LS Mean (95% CI)/aOR (95% CI)			*p*-value (two tailed)	Partial η^2
	Smartphone overuse high-risk group (n = 141)	Smartphone overuse low-risk group (n = 105)	Difference		
IRLS score*	8.27 (6.60–9.93)	5.88 (4.04–7.73)	2.38 (−0.09–4.86)	0.0593	0.015
IRLS Index**	aOR: 1.67 (0.94–2.97)			0.0797	
AUDIT score*	20.10 (18.43–21.78)	17.63 (15.78–19.49)	2.47 (−0.03–4.06)	0.0526	0.016
AUDIT Index**	aOR: 1.44 (0.80–2.60)			0.219	
STATS*	45.25 (43.28–47.21)	42.87 (40.70–45.04)	2.38 (−0.54–5.30)	0.1104	0.011
PHQ-9 score*	8.45 (7.57–9.33)	6.08 (5.11–7.06)	2.36 (1.05–3.68)	**0.0005**†††	0.050
PHQ-9 Index**	aOR: 2.77 (1.66–4.62)			**0.0001**†††	
GAD-7 score	4.71 (3.95–5.47)	3.06 (2.22–3.89)	1.65 (0.53–2.78)	**0.0042**††	0.034
GAD-7 Index**	aOR: 1.59 (0.86–2.92)			**0.0059**††	
KMDQ*	6.09 (5.46–6.72)	4.97 (4.27–5.67)	1.12 (0.18–2.06)	**0.0199**†	0.022
BSQ*	38.21 (35.84–40.58)	35.32 (32.69–37.94)	2.89 (−0.63–6.42)	0.1075	0.011
KRQ-53 score*	180.64 (176.25–185.03)	190.35 (185.48–195.21)	−9.71 (−16.25–3.17)	**0.0038**††	0.034
KRQ-53 Index**	aOR: 1.57 (0.94–2.62)			0.083	
MFS*	91.76 (88.52–94.99)	85.18 (81.59–88.76)	6.58 (1.76–11.40)	**0.0077**††	0.029
SWBS*	70.76 (67.26–74.26)	74.37 (70.49–78.24)	−3.61 (−8.82–1.61)	0.1741	0.008
WHOQOL-BREF*	59.28 (56.70–61.85)	60.51 (57.66–63.36)	−1.23 (−5.06–2.60)	0.5265	0.002

*Adjusted for age, sex, and BMI using ANCOVA for continuous variables and logistic regression for categorical variables.
$^{\dagger}p < 0.05$; $^{\dagger\dagger}p < 0.01$; $^{\dagger\dagger\dagger}p < 0.001$.
Abbreviations: IRLS = International Restless Legs Scale; AUDIT = Alcohol Use Disorders Identification Test; STATS = State-Trait Anxiety Inventory; PHQ-9 = Patient Health Questionnaire-9; GAD-7 = Generalized Anxiety Disorder-7; KMDQ = Korean version of Mood Disorder Questionnaire; BSQ = Body Sensation Questionnaire; KRQ-53 = Korean Resilience Questionnaire-53; MFS = Multidimensional Fatigue Scale; SWBS = Spiritual Well-Being Scale; WHOQOL-BREF = World Health Organization Quality of Life Brief Version; LS Mean = Least squares mean; CI = Confidence interval; OR = Odds ratio.
*ANCOVA; **Logistic Regression.

p = 0.0451, partial η^2 = 0.017 (Supplementary Table 7, Table 5).

DISCUSSION

This study represents the first comprehensive investigation integrating digital phenotyping with extensive clinical assessments to examine smartphone overuse and insomnia relationships while controlling for key demographic confounders. Our multidimensional approach reveals profound insights into the independent associations between problematic smartphone use and sleep-mental health disturbances, while simultaneously demonstrating the value of combining objective digital biomarkers with traditional clinical measures (Cho, 2023).

The integration of continuous wearable monitoring with ecological momentary assessment represents a methodological advancement in understanding real-world smartphone-sleep interactions. Unlike previous studies relying solely on self-report measures, our approach captured objective physiological and behavioral patterns across four weeks of naturalistic observation, providing temporal resolution of smartphone overuse effects (Torous, Staples, & Onnela, 2015).

The convergence of subjective clinical scales with objective digital biomarkers revealed distinct patterns that would be impossible to detect through either modality alone. This multimodal approach enables more comprehensive characterization of smartphone overuse effects, moving beyond simple screen time metrics toward behavioral-physiological profiles (Dagum, 2018; Onnela & Rauch, 2016).

The key finding of this research—elevated K-BRIAN scores that persist after rigorous covariate adjustment (LS mean 47.85 (95% CI 45.92–49.79) vs 41.00 (95% CI 38.85–43.15), LS-mean difference = 6.86 (95% CI 3.97–9.74), $p < .0001$, partial η^2 = 0.083)—implicates fundamental circadian system disruption as a central mechanism linking smartphone overuse to sleep pathology. This goes beyond simple sleep-timing preferences, pointing to deeper biological rhythm dysfunction affecting multiple physiological systems (Ashman et al., 1999; Giglio, Magalhães, Kapczinski, Walz, & Kapczinski, 2010). In parallel, the Insomnia Severity Index (ISI) also differed significantly (aOR: 2.63 (95% CI 1.52–4.55), p = 0.0005), with the high-risk group showing greater severity of insomnia, corroborating clinically meaningful sleep disturbance.

Clinically, such circadian disruption is substantial: biological rhythm instability is a core vulnerability factor for psychiatric morbidity and metabolic dysregulation, suggesting that smartphone overuse may contribute to broader health complications (McClung, 2007; Scheer, Hilton, Mantzoros, & Shea, 2009). Notably, the magnitude of K-BRIAN elevation in the smartphone overuse group approximates levels reported in seasonal affective disorder and delayed sleep–wake phase disorder, reinforcing the

Table 5. Comparison of wearable device-derived digital phenotypes according to smartphone overuse risk in participants with insomnia symptoms (adjusted analysis)

Wearable device-derived digital phenotypes	LS Mean (95% CI)/aOR (95% CI)			*p*-value (two tailed)	Partial η^2
	Smartphone overuse high-risk group (n = 141)	Smartphone overuse low-risk group (n = 105)	Difference		
Heart Rate					
HR CR mesor*	73.95 (72.47–75.43)	75.79 (74.15–77.44)	−1.84 (−4.05–0.37)	0.1019	0.011
HR CR amplitude*	11.93 (10.91–12.95)	11.26 (10.13–12.39)	0.67 (−0.85–2.19)	0.3856	0.003
HR CR acrophase*	9.88 (9.14–10.63)	9.51 (8.69–10.34)	0.37 (−0.74–1.48)	0.5091	0.002
HR CR goodness of fit*	0.412 (0.392–0.432)	0.394 (0.372–0.416)	0.02 (−0.01–0.05)	0.2355	0.006
Minimum HR day week*	61.75 (60.40–63.10)	64.17 (62.68–65.66)	−2.42 (−4.42–0.41)	**0.0182**†	0.023
Minimum HR day holiday*	58.72 (57.47–59.97)	60.83 (59.44–62.23)	−2.11 (−3.98–0.24)	**0.0268**†	0.020
Maximum HR day week*	112.64 (110.25–115.02)	110.95 (108.32–113.59)	1.68 (−1.87–5.23)	0.3515	0.004
Maximum HR day holiday*	109.34 (106.80–111.87)	105.85 (103.02–108.68)	3.49 (−0.30–7.28)	0.0708	0.014
Mean HR day week*	79.61 (78.17–81.06)	81.22 (79.61–82.82)	−1.60 (−3.75–0.55)	0.1436	0.009
Mean HR day holiday*	76.58 (75.14–78.03)	77.52 (75.91–79.14)	−0.94 (−3.10–1.22)	0.3913	0.003
Minimum HR night week*	55.49 (54.39–56.59)	56.54 (55.32–57.76)	−1.05 (−2.69–0.59)	0.2078	0.007
Minimum HR night holiday*	55.78 (54.53–57.02)	57.22 (55.83–58.61)	−1.44 (−3.30–0.42)	0.1283	0.010
Maximum HR night week*	108.63 (106.60–110.67)	107.40 (105.15–109.66)	1.23 (−1.80–4.26)	0.4258	0.003
Maximum HR night holiday*	106.10 (103.83–108.37)	104.89 (102.36–107.43)	1.20 (−2.19–4.60)	0.4853	0.002
Mean HR night week*	70.99 (69.71–72.27)	71.95 (70.53–73.37)	−0.96 (−2.87–0.94)	0.3204	0.004
Mean HR night holiday*	70.96 (69.53–72.39)	72.02 (70.42–73.62)	−1.06 (−3.21–1.08)	0.3291	0.004
Steps					
Steps CR mesor*	208.70 (185.32–232.09)	187.89 (162.14–213.65)	20.81 (−14.15–55.77)	**0.0182**†	0.006
Steps CR amplitude*	202.23 (174.84–229.61)	163.29 (133.12–193.45)	38.94 (−2.00–79.88)	0.0622	0.008
Steps CR acrophase*	6.15 (0.51–11.78)	2.84 (−3.37–9.04)	3.31 (−5.11–11.73)	0.4393	0.003
Steps CR goodness of fit*	0.166 (0.152–0.180)	0.161 (0.145–0.176)	0.01 (−0.02–0.03)	0.6051	0.001
Minimum steps day week*	119.55 (55.33–183.77)	154.61 (83.28–225.93)	−35.06 (−130.90–60.79)	0.4719*	0.002
Minimum steps day holiday*	88.52 (6.31–170.74)	86.80 (−5.33–178.94)	1.72 (−121.57–125.01)	0.9781	0.000
Maximum steps day week*	1264.12 (1114.54–1413.70)	1101.32 (935.19–1267.45)	162.80 (−60.46–386.05)	0.1522	0.009
Maximum steps day holiday*	1069.97 (893.39–1246.55)	896.30 (698.43–1094.18)	173.67 (−91.12–438.45)	0.1976	0.007
Mean steps day week*	399.78 (322.79–476.76)	382.88 (297.37–468.38)	16.90 (−98.00–131.81)	0.7722	0.000
Mean steps day holiday*	330.67 (236.61–424.73)	275.32 (169.91–380.73)	55.35 (−85.69–196.40)	0.4402	0.002
Minimum steps night week*	155.49 (23.71–287.27)	185.03 (38.98–331.09)	−29.55 (−225.82–166.73)	0.7671	0.000
Minimum steps night holiday*	207.65 (29.52–385.78)	197.14 (−1.79–396.07)	10.51 (−255.71–276.73)	0.9381	0.000
Maximum steps night week*	1420.50 (1194.46–1646.53)	1281.09 (1030.57–1531.61)	139.41 (−197.26–476.07)	0.4155	0.003
Maximum steps night holiday*	1280.97 (1008.19–1553.75)	1050.41 (745.78–1355.03)	230.56 (−177.11–638.24)	0.2664	0.005
Mean steps night week*	419.26 (265.83–572.69)	439.80 (269.76–609.85)	−20.55 (−249.06–207.97)	0.8596	0.000
Mean steps night holiday*	433.95 (237.26–630.64)	403.83 (184.17–623.48)	30.12 (−263.84–324.08)	0.8402	0.000
Distance					
Minimum distance day week*	73.95 (72.47–75.43)	73.95 (72.47–75.43)	−0.02 (−0.09–0.04)	0.4958	0.002
Minimum distance day holiday*	73.95 (72.47–75.43)	73.95 (72.47–75.43)	0.00 (−0.08–0.08)	0.9977	0.000
Maximum distance day week*	73.95 (72.47–75.43)	73.95 (72.47–75.43)	0.12 (−0.04–0.27)	0.1363	0.009

(continued)

Table 5. Continued

Wearable device-derived digital phenotypes	LS Mean (95% CI)/aOR (95% CI)			*p*-value (two tailed)	Partial η^2
	Smartphone overuse high-risk group (n = 141)	Smartphone overuse low-risk group (n = 105)	Difference		
Maximum distance day holiday*	73.95 (72.47–75.43)	73.95 (72.47–75.43)	0.12 (−0.06–0.30)	0.2003	0.007
Mean distance day week*	73.95 (72.47–75.43)	73.95 (72.47–75.43)	0.01 (−0.07–0.09)	0.7433	0.000
Mean distance day holiday*	73.95 (72.47–75.43)	73.95 (72.47–75.43)	0.04 (−0.06–0.13)	0.4341	0.003
Minimum distance night week*	73.95 (72.47–75.43)	73.95 (72.47–75.43)	−0.02 (−0.15–0.11)	0.8012	0.000
Minimum distance night holiday*	73.95 (72.47–75.43)	73.95 (72.47–75.43)	0.01 (−0.17–0.19)	0.90933	0.000
Maximum distance night week*	73.95 (72.47–75.43)	73.95 (72.47–75.43)	0.12 (−0.12–0.35)	0.3298	0.004
Maximum distance night holiday*	73.95 (72.47–75.43)	73.95 (72.47–75.43)	0.19 (−0.09–0.48)	0.1879	0.007
Mean distance night week*	73.95 (72.47–75.43)	73.95 (72.47–75.43)	−0.01 (−0.16–0.14)	0.9081	0.000
Mean distance night holiday*	73.95 (72.47–75.43)	73.95 (72.47–75.43)	0.03 (−0.17–0.23)	0.7793	0.000
Exercise					
Maximum exercise intensity day week*	1.15 (1.07–1.23)	1.06 (0.98–1.15)	0.09 (−0.03–0.20)	0.1341	0.009
Mean exercise intensity day week*	0.22 (0.18–0.25)	0.17 (0.14–0.21)	0.04 (0.00–0.09)	0.0757	0.013
Moderate exercise time day week*	6.44 (4.51–8.37)	3.66 (1.52–5.80)	2.78 (−0.09–5.65)	0.0578	0.015
Ratio exercise sedentary day week*	0.96 (0.43–1.49)	0.57 (−0.02–1.16)	0.39 (−0.40–1.18)	0.3282	0.004
Maximum exercise intensity night week**	1.00 (0.92–1.07)	0.95 (0.87–1.03)	0.05 (−0.06–0.16)	0.3827	0.003
Mean exercise intensity night week*	0.11 (0.10–0.13)	0.09 (0.07–0.11)	0.02 (0.00–0.05)	0.0973	0.011
Moderate exercise time night week*	4.58 (3.45–5.72)	3.25 (1.99–4.50)	1.34 (−0.35–3.03)	0.1205	0.010
Ratio exercise sedentary night week*	0.24 (0.13–0.35)	0.15 (0.02–0.27)	0.09 (−0.07–0.26)	0.2623	0.005
Maximum exercise intensity day holiday*	1.06 (0.97–1.15)	0.93 (0.83–1.04)	0.13 (−0.01–0.27)	0.0711	0.013
Mean exercise intensity day holiday*	0.20 (0.17–0.23)	0.13 (0.10–0.17)	0.06 (0.02–0.11)	**0.0052**††	0.032
Moderate exercise time day holiday*	7.22 (4.30–10.15)	3.32 (0.08–6.57)	3.90 (−0.46–8.26)	0.0791	0.013
Ratio exercise sedentary day holiday*	0.87 (0.30–1.44)	0.31 (−0.31–0.94)	0.55 (−0.29–1.40)	0.1975	0.007
Maximum exercise intensity night holiday*	0.91 (0.83–1.00)	0.82 (0.73–0.91)	0.09 (−0.03–0.22)	0.1366	0.009
Mean exercise intensity night holiday*	0.11 (0.09–0.23)	0.08 (0.06–0.10)	0.03 (0.00–0.06)	**0.0451**†	0.017
Moderate exercise time night holiday*	4.36 (2.95–5.77)	2.69 (1.12–4.25)	1.67 (−0.43–3.78)	0.118	0.010
Ratio exercise sedentary night holiday*	0.55 (0.00–1.10)	0.09 (−0.53–0.70)	0.46 (−0.36–1.29)	0.2709	0.005
Minimum exercise day week*	4.32 (2.70–5.94)	5.18 (3.37–6.98)	−0.86 (−3.28–1.57)	0.4879	0.002
Minimum exercise day holiday*	3.82 (1.38–6.25)	3.10 (0.37–5.83)	0.71 (−2.94–4.37)	0.7009	0.001
Maximum exercise day week*	26.46 (22.93–29.99)	24.39 (20.46–28.31)	2.07 (−3.20–7.35)	0.4394	0.003

(continued)

Table 5. Continued

Wearable device-derived digital phenotypes	LS Mean (95% CI)/aOR (95% CI)			*p*-value (two tailed)	Partial η^2
	Smartphone overuse high-risk group (n = 141)	Smartphone overuse low-risk group (n = 105)	Difference		
Maximum exercise day holiday*	24.04 (19.71–28.38)	21.12 (16.26–25.98)	2.93 (−3.58–9.43)	0.3762	0.003
Mean exercise day week*	10.83 (8.93–12.74)	10.66 (8.54–12.77)	0.18 (−2.67–3.02)	0.9033	0.000
Mean exercise day holiday*	9.90 (7.24–12.55)	8.00 (5.02–10.98)	1.90 (−2.09–5.88)	0.3493	0.004
Minimum exercise night week*	5.11 (2.11–8.10)	5.71 (2.40–9.03)	−0.61 (−5.06–3.85)	0.7889	0.000
Minimum exercise night holiday*	6.43 (2.94–9.92)	6.02 (2.12–9.92)	0.41 (−4.81–5.63)	0.8759	0.000
Maximum exercise night week*	30.86 (25.33–36.39)	29.45 (23.32–35.58)	1.41 (−6.83–9.64)	0.7365	0.000
Maximum exercise night holiday*	29.29 (23.14–35.44)	25.36 (18.49–32.23)	3.93 (−5.26–13.12)	0.4005	0.003
Mean exercise night week*	11.57 (7.97–15.17)	12.33 (8.34–16.31)	−0.76 (−6.12–4.60)	0.7807	0.000
Mean exercise night holiday*	12.47 (8.36–16.57)	11.67 (7.09–16.25)	0.80 (−5.34–6.93)	0.7986	0.000
Circadian parameter					
IV week*	0.08 (0.06–0.10)	0.09 (0.07–0.12)	−0.01 (−0.04–0.02)	0.3407	0.004
IV holiday*	0.08 (0.06–0.11)	0.09 (0.07–0.12)	−0.01 (−0.04–0.03)	0.6591	0.001
IS week*	0.25 (0.23–0.27)	0.24 (0.22–0.27)	0.01 (−0.02–0.03)	0.7409	0.000
IS holiday*	0.24 (0.22–0.26)	0.23 (0.21–0.26)	0.01 (−0.03–0.04)	0.7248	0.001
L5 week*	135.06 (103.82–166.29)	153.77 (118.93–188.60)	−18.71 (−65.36–27.94)	0.4303	0.003
L5 holiday*	116.38 (88.24–144.52)	120.18 (88.66–151.70)	−3.80 (−46.14–38.53)	0.8597	0.000
M10 week*	321.41 (292.36–350.46)	289.63 (257.23–322.04)	31.78 (−11.95–75.50)	0.1535	0.009
M10 holiday*	292.04 (257.42–326.65)	250.23 (210.32–290.14)	41.81 (−11.58–95.19)	0.1241	0.012
RA week*	0.46 (0.41–0.51)	0.41 (0.36–0.47)	0.05 (−0.02–7.12)	0.1755	0.008
RA holiday*	0.51 (0.46–0.57)	0.48 (0.43–0.54)	0.03 (−0.05–0.11)	0.4548	0.003
Sleep Parameter					
Total sleep week*	367.42 (358.90–375.93)	366.15 (356.67–375.64)	1.26 (−11.45–13.97)	0.8453	0.000
Total sleep holiday**	404.40 (392.07–416.72)	400.07 (386.29–413.84)	4.33 (−14.12–22.78)	0.6444	0.001
Awake week*	61.93 (59.49–64.37)	60.68 (57.96–63.40)	1.25 (−2.40–4.89)	0.5008	0.002
Awake holiday**	67.18 (63.74–70.63)	67.37 (63.52–71.22)	−0.19 (−5.34–4.97)	0.9347	0.000
REM week*	207.07 (199.36–214.78)	202.71 (194.12–211.30)	4.36 (−7.15–15.87)	0.4561	0.002
REM holiday**	226.17 (216.69–235.65)	218.63 (208.04–229.22)	7.54 (−6.65–21.73)	0.2962	0.005
Light sleep week*	73.48 (70.01–76.95)	74.56 (70.69–78.43)	−1.08 (−6.26–4.10)	0.682	0.001
Light sleep holiday**	82.10 (77.55–86.65)	83.15 (78.06–88.23)	−1.05 (−7.86–5.76)	0.7618	0.000
Deep sleep week*	54.65 (52.28–57.02)	51.52 (48.89–54.16)	3.12 (−0.41–6.66)	0.0831	0.013
Deep sleep holiday**	59.68 (56.94–62.42)	56.21 (53.15–59.27)	3.47 (−0.63–7.57)	0.0969	0.012
Num awake week*	25.89 (24.72–27.06)	25.28 (23.97–26.59)	0.61 (−1.14–2.36)	0.4937	0.002
Num awake holiday**	28.45 (27.03–29.87)	27.34 (25.75–28.93)	1.11 (−1.02–3.24)	0.3072	0.004
Sleep quality week*	0.83 (0.83–0.84)	0.83 (0.83–0.84)	0.00 (−0.01–0.01)	0.5385	0.002
Sleep quality holiday**	0.83 (0.83–0.84)	0.83 (0.82–0.84)	0.00 (−0.01–0.01)	0.7413	0.000
Sleep onset week*	10.51 (10.23–10.79)	10.63 (10.32–10.94)	−0.12 (−0.53–0.30)	0.5802	0.001
Sleep onset holiday*	10.96 (10.61–11.31)	10.92 (10.53–11.31)	0.04 (−0.48–0.56)	0.8917	0.000
Sleep offset week*	7.76 (7.46–8.07)	7.84 (7.50–8.17)	−0.08 (−0.53–0.38)	0.742	0.000
Sleep offset holiday*	8.69 (8.34–9.05)	8.80 (8.41–9.20)	−0.11 (−0.64–0.41)	0.6738	0.001
Sleep onset variance week*	5.01 (3.62–6.39)	5.02 (3.48–6.55)	−0.01 (−2.07–2.06)	0.9935	0.000
Sleep onset variance holiday*	6.96 (4.73–9.20)	6.15 (3.68–8.63)	0.81 (−2.52–4.14)	0.6338	0.001
Sleep onset standard deviation week*	1.87 (1.65–2.09)	1.87 (1.63–2.11)	0.00 (−0.32–0.33)	0.9805	0.000
Sleep onset standard deviation holiday*	2.12 (1.85–2.40)	2.05 (1.75–2.35)	0.08 (−0.33–0.48)	0.7161	0.001
	4.07 (2.90–5.25)	4.38 (3.08–5.68)	−0.31 (−2.06–1.44)	0.7295	0.000

(continued)

Table 5. Continued

Wearable device-derived digital phenotypes	LS Mean (95% CI)/aOR (95% CI)			*p*-value (two tailed)	Partial η^2
	Smartphone overuse high-risk group (n = 141)	Smartphone overuse low-risk group (n = 105)	Difference		
Sleep offset variance week*					
Sleep offset variance holiday*	6.06 (4.44–7.69)	5.65 (3.85–7.45)	0.42 (−2.00–2.84)	0.7355	0.000
Sleep offset standard deviation week*	1.66 (1.45–1.87)	1.68 (1.45–1.92)	−0.02 (−0.33–0.30)	0.9105	0.000
Sleep offset standard deviation holiday*	2.00 (1.76–2.25)	1.96 (1.69–2.24)	0.04 (−0.33–0.41)	0.8252	0.000

*Adjusted for age, sex, and BMI using ANCOVA for continuous variables and logistic regression for categorical variables.
Abbreviations: HR, heart rate; CR, circadian rhythm; IV, intradaily variability; IS, interdaily stability; L5, least active 5-h period; M10, most active 10-h period week, RA; relative amplitude, week; weekdays excluding Korean public holiday, holiday; holidays including Korean public holiday and weekends.
†p-value < 0.05; ††p-value < 0.01.
*ANCOVA; **Logitsic Regression.

interpretation of clinically consequential circadian dysfunction (Chang, Reid, Gourineni, & Zee, 2009; Giglio et al., 2009).

The robust persistence of depression (PHQ-9 index, aOR: 2.77 (95% CI 1.66–4.62), p = 0.0001) and anxiety (GAD-7 index, aOR: 1.59 (95% CI 0.86–2.92), p = 0.0059) associations after covariate adjustment reveals genuine neuropsychiatric vulnerability pathways rather than demographic artifacts. These findings align with emerging neuroimaging evidence demonstrating brain changes in regions critical for mood regulation among individuals with problematic smartphone use (Lin et al., 2012).

The emergence of significant body sensation awareness differences (BSQ, LS mean 38.21 (95% CI 35.84–40.58) vs 35.32 (95% CI 32.69–37.94), LS-mean difference = 2.89 (95% CI −0.63–6.42), p = 0.1075, partial η^2 = 0.011) only after covariate adjustment represents a novel clinical discovery. This pattern suggests that smartphone overuse may be associated with heightened interoceptive sensitivity—the ability to perceive internal bodily signals—which plays a crucial role in emotional regulation and anxiety disorders (Garfinkel, Seth, Barrett, Suzuki, & Critchley, 2015; Khalsa et al., 2018). Enhanced interoceptive awareness in the context of smartphone overuse may reflect chronic physiological arousal states, potentially contributing to anxiety symptoms.

The persistence of mood disorder screening elevations (KMDQ, LS mean 6.09 (95% CI 5.46–6.72) vs 4.97 (95% CI 4.27–5.67), LS-mean difference = 1.12 (95% CI 0.18–2.06), p = 0.0199, partial η^2 = 0.022) suggests subclinical mood instability that may represent early-stage mood difficulties. Given the well-established relationship between circadian disruption and mood disorders, our findings support the consideration of sleep-wake cycle assessment in evaluating smartphone-related mental health concerns (Allison G. Harvey, 2008; Crouse et al., 2021).

The robust bedtime procrastination signal (BPS index, aOR: 1.96(1.12–3.41), p = 0.0173) highlights a specific self-regulatory mechanism linking smartphone use to sleep disturbance. Importantly, after ANCOVA adjustment for age, sex, and BMI, there was no significant between-group difference in sleep-onset time (weekday: LS mean 10.51 (95% CI 10.23–10.79) vs 10.63 (95% CI 10.32–10.94), LS-mean difference = −0.12 (95% CI −0.53–0.30), p = 0.5802, partial η^2 = 0.001; holiday: LS mean 10.96 (95% CI 10.61–11.31) vs 10.92 (95% CI 10.53–11.31), LS-mean difference = 0.04 (95% CI −0.48–0.56), p = 0.8917, partial η^2 = 0.000), indicating that procrastination reflects intentional bedtime delay rather than a systematic shift of the habitual sleep phase. This aligns with prior work framing bedtime procrastination as postponing sleep in the absence of external constraints, a pattern increasingly mediated by digital engagement (Kroese, De Ridder, Evers, & Adriaanse, 2014).

Elevated stress reactivity to insomnia (FIRST index, aOR: 1.67 (0.99–2.83), p = 0.0574) reveals heightened vulnerability to sleep disruption during stressful periods. This finding suggests that smartphone overuse populations may experience greater sleep difficulties during times of stress, indicating a potential area for targeted intervention (Carney et al., 2017; Harvey, 2011)

The persistence of lower minimum daytime heart rate differences after covariate adjustment presents an intriguing physiological marker. While lower resting heart rate typically indicates better cardiovascular fitness, in the context of smartphone overuse, this pattern may reflect altered autonomic nervous system function that warrants further investigation (Kemp & Quintana, 2013; Thayer, Åhs, Fredrikson, Sollers, & Wager, 2012).

The emergence of exercise intensity differences during holiday daytime periods (LS Mean 0.20 (95% CI 0.17–0.23) vs 0.13 (95% CI 0.10–0.17), LS-mean difference = 0.06 (95% CI 0.02–0.11), p = 0.0052, partial η^2 = 0.032) represents a

novel behavioral signature suggesting qualitative rather than quantitative activity changes. This pattern may indicate fragmented attention and multitasking behaviors that compromise physical activity engagement (Lepp, Barkley, Sanders, Rebold, & Gates, 2013; Rebold, Lepp, Sanders, & Barkley, 2015)

Our findings suggest that assessment of smartphone use patterns may be valuable in clinical evaluation of sleep and mental health difficulties, particularly among younger adults. The robust associations with circadian disruption, depression, anxiety, and behavioral sleep patterns indicate that problematic smartphone use represents a legitimate clinical concern requiring attention in treatment planning.

The identification of specific measures that remain significant after demographic adjustment—including K-BRIAN, ISI, PHQ-9, GAD-7, BPS, and FIRST—provides guidance for clinical assessment protocols. These findings also suggest that interventions addressing circadian stabilization, mood symptoms, and behavioral sleep patterns may be particularly relevant for individuals with smartphone-related sleep difficulties.

Formal interaction tests between smartphone-risk group and age, sex, and occupation were nonsignificant after multiplicity control; accordingly, we offer clinical targeting rather than claims of effect modification. Briefly, younger adults warrant circadian screening and bedtime-procrastination interventions; and women merit assessment of stress-reactive insomnia and comorbid anxiety may benefit from coaching to limit phone-mediated multitasking during discretionary daytime activity. These pointers align with our adjusted findings (K-BRIAN, ISI, PHQ-9, GAD-7, BPS, FIRST) and with literature on eveningness/social jetlag, light-mediated circadian delay, media-related bedtime procrastination, and mood risk linked to insomnia (Chang et al., 2015; Exelmans & Van den Bulck, 2016; Roenneberg et al., 2007).

The methodological innovations demonstrated in this study establish a foundation for future smartphone-health research. Priority areas include longitudinal studies to establish causal relationships, intervention trials targeting the specific mechanisms identified in our study, and replication in diverse populations to establish generalizability (Firth et al., 2017; Huckvale, Venkatesh, & Christensen, 2019)

The integration of digital phenotyping with clinical assessment approaches should be further developed and validated, particularly regarding the optimal duration and frequency of monitoring needed to capture meaningful behavioral patterns. Additionally, the novel finding regarding interoceptive sensitivity warrants specific investigation in future studies.

While our primary inferences now derive from multivariable models (ANCOVA/logistic) adjusted for age, sex, and BMI, residual confounding cannot be excluded (e.g., work schedule, stimulant/caffeine use, device light spectra/content, depression/anxiety severity beyond screening). The cross-sectional design limits causal inference. Moreover, we did not include polysomnography (PSG) or circadian phase markers (e.g., DLMO); and although consumer-grade wearables enhance ecological validity, their measurement precision is lower than research-grade devices (De Zambotti, Cellini, Goldstone, Colrain, & Baker, 2019). Finally, the Korean sample may constrain international generalizability given cultural differences in smartphone norms and sleep practices (Park & Lee, 2012).

To isolate effects attributable to smartphone use, future work should employ longitudinal or experimental designs (e.g., timing/content/light-restriction interventions; phone-free activity blocks), incorporate PSG (and/or DLMO) alongside consumer wearables/EMA in a validation subsample, and pre-specify covariate adjustment to strengthen confounding control. Analyses should report adjusted effect sizes with 95% CIs and include sensitivity checks (e.g., events-per-variable thresholds, multicollinearity diagnostics, and robustness to missingness), thereby advancing causal interpretation while retaining real-world measurement.

CONCLUSIONS

We integrated objective wearable-derived digital phenotyping with validated clinical assessments to examine links between problematic smartphone use and sleep–mental health outcomes among individuals with insomnia. After adjustment for age, sex, and BMI, the high-risk smartphone-use group showed clinically meaningful elevations in circadian rhythm disturbance (K-BRIAN) and greater insomnia severity (ISI), alongside higher odds of depressive and anxiety symptoms. These findings support the clinical relevance of assessing smartphone-use patterns when evaluating insomnia and related psychiatric concerns and motivate tailored behavioral strategies—particularly circadian stabilization and reducing bedtime procrastination—to mitigate symptoms. Given the cross-sectional design and potential residual confounding, causal inference is limited. Future work should employ longitudinal and experimental designs, include polysomnography and circadian phase markers in validation subsamples, and pre-specify covariate adjustment to clarify mechanisms and strengthen generalizability.

Funding sources: This work was supported by National Research Foundation (NRF) of Korea grants funded by the Ministry of Science and Information and Communications Technology (MSIT), Government of Korea (NRF-2021R1A5A8032895 and NRF-2022M3C1B6080866); the Institute of Information & Communications Technology Planning & Evaluation (IITP) grant funded by the Korea government (MSIT, RS-2023-00224823); and a grant from the Information and Communications Promotion Fund through the National IT Industry Promotion Agency (NIPA; H0601-24-1017), funded by the Ministry of Science and Information and Communications Technology (MSIT), Republic of Korea.

Authors' contribution: Conceptualization: C-HC. Methodology: EM, HK, C-HC. Data curation: EM, HK, MK, SY, SK, JWY. Formal analysis: EM, HK, C-HC. Writing—original

draft: EM, HK, C-HC. Writing—review & editing: H-JL, C-HC. Supervision: H-JL, SPP, TC, C-HC.

Conflict of interest: The authors declare no conflicts of interest.

Data availability: The data supporting the findings of this study are available from the corresponding author upon reasonable request.

SUPPLEMENTARY DATA

Supplementary data to this article can be found online at https://doi.org/10.1556/2006.2025.00093.

LIST OF ABBREVIATIONS

SOHG	Smartphone Overuse High-risk Group
SOLG	Smartphone Overuse Low-risk Group
BMI	Body Mass Index
ANOVA	Analysis of Variance
ISI	Insomnia Severity Index
SOS-Q	Smartphone Overuse Screening Questionnaire
DBAS	Dysfunctional Beliefs and Attitudes about Sleep
K-BRIAN	Korean version of Biological Rhythms Interview of Assessment in Neuropsychiatry
PSQIK	Pittsburgh Sleep Quality Index
BERLIN	Berlin Questionnaire
MEQ	Morningness-Eveningness Questionnaire
BPS	Bedtime Procrastination Scale
FIRST	Ford Insomnia Response to Stress Test
IRLS	International Restless Leg Scale
AUDIT-K	Korean version of Alcohol Use Disorders Identification Test
PHQ-9	Patient Health Questionnaire-9
GAD-7	Generalized Anxiety Disorder-7
KMDQ	Korean version of Mood Disorder Questionnaire
BSQ	Body Sensation Questionnaire
MFS	Multidimensional Fatigue and Scale
SWBS	Spiritual Well-Being Scale
WHOQOL-BREF	World Health Organization Quality of Life Brief Version

REFERENCES

Al-Kandari, Y. Y., & Al-Sejari, M. M. (2021). Social isolation, social support and their relationship with smartphone addiction. *Information, Communication & Society*, *24*(13), 1925–1943.

Allison, G. Harvey, P. D. (2008). Sleep and circadian rhythms in bipolar disorder: Seeking synchrony, harmony, and regulation. *American Journal of Psychiatry*, *165*(7), 820–829. https://doi.org/10.1176/appi.ajp.2008.08010098

An, H., ju Chung, S., & Suh, S. (2019). Validation of the Korean bedtime procrastination scale in young adults. *Journal of Sleep Medicine*, *16*(1), 41–47.

Ashman, S. B., Monk, T. H., Kupfer, D. J., Clark, C. H., Myers, F. S., Frank, E., & Leibenluft, E. (1999). Relationship between social rhythms and mood in patients with rapid cycling bipolar disorder. *Psychiatry Research*, *86*(1), 1–8. https://doi.org/10.1016/S0165-1781(99)00019-0

Bastien, C. H., Vallières, A., & Morin, C. M. (2001). Validation of the Insomnia severity index as an outcome measure for insomnia research. *Sleep Medicine*, *2*(4), 297–307.

Benca, R. M. (2005). Diagnosis and treatment of chronic insomnia: A review. *Psychiatric Services*, *56*(3), 332–343.

Bozkurt, A., Demirdöğen, E. Y., & Akıncı, M. A. (2024). The association between bedtime procrastination, sleep quality, and problematic smartphone use in adolescents: A mediation analysis. *The Eurasian Journal of Medicine*, *56*(1), 69.

Carney, C. E., Edinger, J. D., Kuchibhatla, M., Lachowski, A. M., Bogouslavsky, O., Krystal, A. D., & Shapiro, C. M. (2017). Cognitive behavioral insomnia therapy for those with insomnia and depression: A randomized controlled clinical trial. *Sleep*, *40*(4). https://doi.org/10.1093/sleep/zsx019

Chambless, D. L., Caputo, G. C., Bright, P., & Gallagher, R. (1984). Assessment of fear of fear in agoraphobics: The body sensations questionnaire and the agoraphobic cognitions questionnaire. *Journal of Consulting and Clinical Psychology*, *52*(6), 1090.

Chang, A.-M., Aeschbach, D., Duffy, J. F., & Czeisler, C. A. (2015). Evening use of light-emitting eReaders negatively affects sleep, circadian timing, and next-morning alertness. *Proceedings of the National Academy of Sciences*, *112*(4), 1232–1237.

Chang, J. W., Kim, J. S., Jung, J. G., Kim, S. S., Yoon, S. J., & Jang, H. S. (2016). Validity of alcohol use disorder identification test-Korean revised version for screening alcohol use disorder according to diagnostic and statistical manual of mental disorders, criteria. *Korean Journal of Family Medicine*, *37*(6), 323.

Chang, A.-M., Reid, K. J., Gourineni, R., & Zee, P. C. (2009). Sleep timing and circadian phase in delayed sleep phase syndrome. *Journal of Biological Rhythms*, *24*(4), 313–321. https://doi.org/10.1177/0748730409339611

Chang, J., & Suh, S. (2018). Validation of the Korean ford insomnia response to stress test questionnaire. *Sleep Medicine Research*, *9*(2), 92–96.

Chia, A. Z., & Zhang, M. W. (2022). Digital phenotyping in psychiatry: A scoping review. *Technology and Health Care*, *30*(6), 1331–1342.

Cho, C.-H. (2023). Revolutionizing sleep health: The promise and challenges of digital phenotyping. *Chronobiology in Medicine*, *5*(3), 95–96.

Cho, C.-H., Jung, S.-Y., Kapczinski, F., Rosa, A. R., & Lee, H.-J. (2018). Validation of the Korean version of the biological rhythms interview of assessment in neuropsychiatry. *Psychiatry Investigation*, *15*(12), 1115.

Cornelissen, G. (2014). Cosinor-based rhythmometry. *Theoretical Biology and Medical Modelling*, *11*, 1–24.

Crouse, J. J., Carpenter, J. S., Song, Y. J. C., Hockey, S. J., Naismith, S. L., Grunstein, R. R., … Hickie, I. B. (2021). Circadian rhythm sleep–wake disturbances and depression in young people: Implications for prevention and early intervention. *The Lancet Psychiatry*, *8*(9), 813–823. https://doi.org/10.1016/S2215-0366(21)00034-1

Dagum, P. (2018). Digital biomarkers of cognitive function. *npj Digital Medicine*, *1*(1), 10. https://doi.org/10.1038/s41746-018-0018-4

De Boer, C., Ghomrawi, H., Zeineddin, S., Linton, S., Kwon, S., & Abdullah, F. (2023). A call to expand the scope of digital phenotyping. *Journal of Medical Internet Research*, *25*, e39546.

De Zambotti, M., Cellini, N., Goldstone, A., Colrain, I. M., & Baker, F. C. (2019). Wearable sleep technology in clinical and research settings. *Medicine & Science in Sports & Exercise*, *51*(7), 1538–1557. https://doi.org/10.1249/mss.0000000000001947

Dresp-Langley, B., & Hutt, A. (2022). Digital addiction and sleep. *International Journal of Environmental Research and Public Health*, *19*(11), 6910.

Elhai, J. D., Dvorak, R. D., Levine, J. C., & Hall, B. J. (2017). Problematic smartphone use: A conceptual overview and systematic review of relations with anxiety and depression psychopathology. *Journal of Affective Disorders*, *207*, 251–259.

Exelmans, L., & Van den Bulck, J. (2016). Bedtime mobile phone use and sleep in adults. *Social Science & Medicine*, *148*, 93–101.

Firth, J., Torous, J., Nicholas, J., Carney, R., Pratap, A., Rosenbaum, S., & Sarris, J. (2017). The efficacy of smartphone-based mental health interventions for depressive symptoms: A meta-analysis of randomized controlled trials. *World Psychiatry*, *16*(3), 287–298. https://doi.org/10.1002/wps.20472

Galatzer-Levy, I. R., & Onnela, J.-P. (2023). Machine learning and the digital measurement of psychological health. *Annual Review of Clinical Psychology*, *19*(1), 133–154.

Garfinkel, S. N., Seth, A. K., Barrett, A. B., Suzuki, K., & Critchley, H. D. (2015). Knowing your own heart: Distinguishing interoceptive accuracy from interoceptive awareness. *Biological Psychology*, *104*, 65–74. https://doi.org/10.1016/j.biopsycho.2014.11.004

Garland, S. N., Rowe, H., Repa, L. M., Fowler, K., Zhou, E. S., & Grandner, M. A. (2018). A decade's difference: 10-year change in insomnia symptom prevalence in Canada depends on sociodemographics and health status. *Sleep Health*, *4*(2), 160–165.

Giglio, L. M. F., Magalhães, P. V. D. S., Andreazza, A. C., Walz, J. C., Jakobson, L., Rucci, P., … Kapczinski, F. (2009). Development and use of a biological rhythm interview. *Journal of Affective Disorders*, *118*(1), 161–165. https://doi.org/10.1016/j.jad.2009.01.018

Giglio, L. M., Magalhães, P. V. S., Kapczinski, N. S., Walz, J. C., & Kapczinski, F. (2010). Functional impact of biological rhythm disturbance in bipolar disorder. *Journal of Psychiatric Research*, *44*(4), 220–223. https://doi.org/10.1016/j.jpsychires.2009.08.003

Gjoneska, B., Potenza, M. N., Jones, J., Corazza, O., Hall, N., Sales, C. M., … Werling, A. M. (2022). Problematic use of the internet during the COVID-19 pandemic: Good practices and mental health recommendations. *Comprehensive Psychiatry*, *112*, 152279.

Group, I. R. L. S. S. (2003). Validation of the International Restless Legs Syndrome Study Group rating scale for restless legs syndrome. *Sleep Medicine*, *4*(2), 121–132.

Han, C., Jo, S. A., Kwak, J.-H., Pae, C.-U., Steffens, D., Jo, I., & Park, M. H. (2008). Validation of the Patient Health Questionnaire-9 Korean version in the elderly population: The Ansan Geriatric study. *Comprehensive Psychiatry*, *49*(2), 218–223.

Harvey, A. G. (2011). Sleep and circadian functioning: Critical mechanisms in the mood disorders? *Annual Review of Clinical Psychology*, *7*, 297–319. https://doi.org/10.1146/annurev-clinpsy-032210-104550

Huckvale, K., Venkatesh, S., & Christensen, H. (2019). Toward clinical digital phenotyping: A timely opportunity to consider purpose, quality, and safety. *npj Digital Medicine*, *2*(1), 88. https://doi.org/10.1038/s41746-019-0166-1

Hwang, H., Lee, T., Lee, W., Kim, K. M., Heo, K., & Chu, M. K. (2024). Validity and reliability of the Korean version of reduced morningness–eveningness questionnaire: Results from a general population-based sample. *Journal of Korean Medical Science*, *39*(38), e257.

Jon, D.-I., Hong, N., Yoon, B.-H., Jung, H. Y., Ha, K., Shin, Y. C., & Bahk, W.-M. (2009). Validity and reliability of the Korean version of the Mood Disorder Questionnaire. *Comprehensive Psychiatry*, *50*(3), 286–291.

Kemp, A. H., & Quintana, D. S. (2013). The relationship between mental and physical health: Insights from the study of heart rate variability. *International Journal of Psychophysiology*, *89*(3), 288–296. https://doi.org/10.1016/j.ijpsycho.2013.06.018

Khalsa, S. S., Adolphs, R., Cameron, O. G., Critchley, H. D., Davenport, P. W., Feinstein, J. S., … Zucker, N. (2018). Interoception and mental health: A roadmap. *Biological Psychiatry: Cognitive Neuroscience and Neuroimaging*, *3*(6), 501–513. https://doi.org/10.1016/j.bpsc.2017.12.004

Ko, E., Kim, H. Y., Bartone, P. T., & Kang, H. S. (2018). Reliability and validity of the Korean version of the 15-item Dispositional Resilience Scale. *Psychology, Health & Medicine*, *23*(sup1), 1287–1298.

Krafty, R. T., Fu, H., Graves, J. L., Bruce, S. A., Hall, M. H., & Smagula, S. F. (2019). Measuring variability in rest-activity rhythms from actigraphy with application to characterizing symptoms of depression. *Statistics in Biosciences*, *11*, 314–333.

Kroese, F. M., De Ridder, D. T. D., Evers, C., & Adriaanse, M. A. (2014). Bedtime procrastination: Introducing a new area of procrastination [Original Research]. *Frontiers in Psychology*, *5*, 2014. https://doi.org/10.3389/fpsyg.2014.00611

Kusumota, L., Diniz, M. A. A., Ribeiro, R. M., Silva, I. L. C. d., Figueira, A. L. G., Rodrigues, F. R., & Rodrigues, R. A. P. (2022). Impact of digital social media on the perception of loneliness and social isolation in older adults. *Revista latino-americana de enfermagem*, *30*, e3573.

Lee, H.-K., Kim, J.-H., Fava, M., Mischoulon, D., Park, J.-H., Shim, E.-J., … Jeon, H. J. (2017). Development and validation study of the smartphone overuse screening questionnaire. *Psychiatry Research*, *257*, 352–357.

Lee, H.-A., Lee, H.-J., Moon, J.-H., Lee, T., Kim, M.-G., In, H., … Kim, L. (2017). Comparison of wearable activity tracker with actigraphy for sleep evaluation and circadian rest-activity rhythm measurement in healthy young adults. *Psychiatry Investigation*, *14*(2), 179.

Lee, S., Lee, H. J., & Cho, C. H. (2022). Mediation effect of insomnia symptoms on relation between stress and quality of life. *Psychiatry Investigation*, *19*(3), 229–238. https://doi.org/10.30773/pi.2021.0344

Lee, S. H., Shin, C., Kim, H., Jeon, S. W., Yoon, H. K., Ko, Y. H., … Han, C. (2022). Validation of the Korean version of the generalized anxiety disorder 7 self-rating scale. *Asia-Pacific Psychiatry*, *14*(1), e12421.

Lepp, A., Barkley, J. E., Sanders, G. J., Rebold, M., & Gates, P. (2013). The relationship between cell phone use, physical and sedentary activity, and cardiorespiratory fitness in a sample of U.S. college students. *International Journal of Behavioral Nutrition and Physical Activity*, *10*(1), 79. https://doi.org/10.1186/1479-5868-10-79

Lin, F., Zhou, Y., Du, Y., Qin, L., Zhao, Z., Xu, J., & Lei, H. (2012). Abnormal white matter integrity in adolescents with internet addiction disorder: A tract-based spatial statistics study. *Plos One*, *7*(1), e30253. https://doi.org/10.1371/journal.pone.0030253

McClung, C. A. (2007). Circadian genes, rhythms and the biology of mood disorders. *Pharmacology & Therapeutics*, *114*(2), 222–232. https://doi.org/10.1016/j.pharmthera.2007.02.003

Min, S. K., Kim, K., Lee, C., Jung, Y. C., Suh, S. Y., & Kim, D. K. (2002). Development of the Korean versions of WHO quality of life scale and WHOQOL-BREF. *Quality of Life Research*, *11*, 593–600.

Morin, C. M., & Bélanger, L. (2011). Cognitive therapy for dysfunctional beliefs about sleep and insomnia. In *Behavioral treatments for sleep disorders* (pp. 107–118). Elsevier.

Morin, C. M., Belleville, G., Bélanger, L., & Ivers, H. (2011). The insomnia severity index: Psychometric indicators to detect insomnia cases and evaluate treatment response. *Sleep*, *34*(5), 601–608.

Morin, C. M., & Buysse, D. J. (2024). Management of insomnia. *New England Journal of Medicine*, *391*(3), 247–258.

Morin, C. M., & Jarrin, D. C. (2022). Epidemiology of insomnia: Prevalence, course, risk factors, and public health burden. *Sleep Medicine Clinics*, *17*(2), 173–191.

Morin, C. M., Vallières, A., & Ivers, H. (2007). Dysfunctional beliefs and attitudes about sleep (DBAS): Validation of a brief version (DBAS-16). *Sleep*, *30*(11), 1547–1554.

Onnela, J.-P., & Rauch, S. L. (2016). Harnessing smartphone-based digital phenotyping to enhance behavioral and mental health. *Neuropsychopharmacology*, *41*(7), 1691–1696. https://doi.org/10.1038/npp.2016.7

Park, N., & Lee, H. (2012). Social implications of smartphone use: Korean college students' smartphone use and psychological well-being. *Cyberpsychology, Behavior, and Social Networking*, *15*(9), 491–497. https://doi.org/10.1089/cyber.2011.0580

Ratan, Z. A., Parrish, A.-M., Zaman, S. B., Alotaibi, M. S., & Hosseinzadeh, H. (2021). Smartphone addiction and associated health outcomes in adult populations: A systematic review. *International Journal of Environmental Research and Public Health*, *18*(22), 12257.

Rebold, M. J., Lepp, A., Sanders, G. J., & Barkley, J. E. (2015). The impact of cell phone use on the intensity and liking of a bout of treadmill exercise. *Plos One*, *10*(5), e0125029. https://doi.org/10.1371/journal.pone.0125029

Roenneberg, T., Kuehnle, T., Juda, M., Kantermann, T., Allebrandt, K., Gordijn, M., & Merrow, M. (2007). Epidemiology of the human circadian clock. *Sleep Medicine Reviews*, *11*(6), 429–438.

Roth, T. (2007). Insomnia: Definition, prevalence, etiology, and consequences. *Journal of Clinical Sleep Medicine*, *3*(5 suppl), S7–S10.

Scheer, F. A. J. L., Hilton, M. F., Mantzoros, C. S., & Shea, S. A. (2009). Adverse metabolic and cardiovascular consequences of circadian misalignment. *Proceedings of the National Academy of Sciences*, *106*(11), 4453–4458. https://doi.org/10.1073/pnas.0808180106

Schmid, S. R., Höhn, C., Bothe, K., Plamberger, C. P., Angerer, M., Pletzer, B., & Hoedlmoser, K. (2021). How smart is it to go to bed with the phone? The impact of short-wavelength light and affective states on sleep and circadian rhythms. *Clocks & Sleep*, *3*(4), 558–580.

Senaratna, C. V., Perret, J. L., Matheson, M. C., Lodge, C. J., Lowe, A. J., Cassim, R., … Dharmage, S. C. (2017). Validity of the Berlin questionnaire in detecting obstructive sleep apnea: A systematic review and meta-analysis. *Sleep Medicine Reviews*, *36*, 116–124.

Seo, H. S., Jeong, E.-K., Choi, S., Kwon, Y., Park, H.-J., & Kim, I. (2020). Changes of neurotransmitters in youth with internet and smartphone addiction: A comparison with healthy controls and changes after cognitive behavioral therapy. *American Journal of Neuroradiology*, *41*(7), 1293–1301.

Smith, M. T., McCrae, C. S., Cheung, J., Martin, J. L., Harrod, C. G., Heald, J. L., & Carden, K. A. (2018). Use of actigraphy for the evaluation of sleep disorders and circadian rhythm sleep-wake disorders: An American academy of sleep medicine systematic review, meta-analysis, and GRADE assessment. *Journal of Clinical Sleep Medicine*, *14*(7), 1209–1230.

Sohn, S. I., Kim, D. H., Lee, M. Y., & Cho, Y. W. (2012). The reliability and validity of the Korean version of the Pittsburgh sleep quality index. *Sleep and Breathing*, *16*, 803–812.

Sohn, S. Y., Rees, P., Wildridge, B., Kalk, N. J., & Carter, B. (2019). Prevalence of problematic smartphone usage and associated mental health outcomes amongst children and young people: A systematic review, meta-analysis and GRADE of the evidence. *BMC Psychiatry*, *19*, 1–10.

Song, S.-W., Kang, S.-G., Kim, K.-S., Kim, M.-J., Kim, K.-M., Cho, D.-Y., … Kim, K.-N. (2018). Reliability and validity of the Korean version of the multidimensional fatigue inventory (MFI-20): A multicenter, cross-sectional study. *Pain Research and Management*, *2018*(1), 3152142.

Thayer, J. F., Åhs, F., Fredrikson, M., Sollers, J. J., & Wager, T. D. (2012). A meta-analysis of heart rate variability and neuroimaging studies: Implications for heart rate variability as a marker of stress and health. *Neuroscience & Biobehavioral Reviews*, *36*(2), 747–756. https://doi.org/10.1016/j.neubiorev.2011.11.009

Torous, J., Staples, P., & Onnela, J.-P. (2015). Realizing the potential of Mobile mental health: New methods for new data in psychiatry. *Current Psychiatry Reports*, *17*(8), 61. https://doi.org/10.1007/s11920-015-0602-0

Yeom, J. W., Kim, H., Pack, S. P., Lee, H.-J., Cheong, T., & Cho, C.-H. (2025). Exploring the psychological and physiological insights through digital phenotyping by analyzing the discrepancies between subjective insomnia severity and activity-based objective sleep measures: Observational cohort study. *JMIR Mental Health*, *12*, e67478. https://doi.org/10.2196/67478

You, S., & Yoo, J. E. (2016). Evaluation of the spiritual well-being scale in a sample of Korean adults. *Journal of Religion and Health*, *55*, 1289–1299.