AMJ ISSN: 0005-2523

ISSN: 0005-2523

Volume 70, Issue 12, 2025

Digital Phenotyping of Sleep Disorders in College Students Using Wearable Sensors and Ecological Momentary Assessment

Jennifer L. Walsh, MD, PhD[1] ,Kenji Nakamura, PhD[2] ,Ahmed R. Hassan, PhD[3] ,Maria C. Rodríguez, PsyD[4]

[1] Department of Psychiatry and Behavioral Sciences, Stanford Sleep Medicine Center, Stanford University School of Medicine, 450 Broadway St, Redwood City, CA 94063, USA, Email: jennifer.walsh@stanford.edu

[2] Department of Computational Biology and Medical Informatics, Graduate School of Medicine, The University of Tokyo, 7-3-1 Hongo, Bunkyo-ku, Tokyo 113-0033, Japan, Email: k.nakamura@edu.u-tokyo.ac.jp

[3] Computer Science and Artificial Intelligence Laboratory (CSAIL), Massachusetts Institute of Technology, 77 Massachusetts Avenue, Cambridge, MA 02139, USA, Email: ahassan@mit.edu

[4] Student Psychological Services, David Geffen School of Medicine, University of California, Los Angeles, 1237 Murphy Hall, Los Angeles, CA 90095, USA, Email: maria.rodriguez@ucla.edu

Abstract

Background: Sleep disorders affect up to 60% of college students, yet traditional assessment methods lack ecological validity. Digital phenotyping through wearable sensors and ecological momentary assessment (EMA) offers continuous, real-time monitoring but requires robust analytical frameworks.

Objectives: To develop a digital phenotype for insomnia in college students using multimodal data from wearables and EMA, and to evaluate its predictive validity against gold-standard clinical measures.

Methods: We conducted a 90-day prospective cohort study of 782 college students (mean age 20.4±2.1 years) across four universities. Participants wore Oura Rings for continuous sleep monitoring and completed 6 daily EMA surveys via smartphone. Daily features (sleep efficiency, heart rate variability, circadian alignment) were integrated with mood and fatigue ratings. Insomnia severity was assessed monthly using the Insomnia Severity Index (ISI). Mixed-effects models and gradient boosting identified predictive features.

Results: Digital phenotype achieved 84.2% accuracy (AUC 0.89) in discriminating moderate-severe insomnia (ISI≥15) from no-mild insomnia. Top predictors were sleep efficiency variability (OR=2.34, $p<0.001$), heart rate variability during sleep (OR=0.71, $p<0.001$), and circadian misalignment (multi-model inference $R^2=0.42$). EMA compliance was 78.3%. Students with insomnia showed 2.3-fold higher night-to-night sleep variability ($p<0.001$).

Conclusions: Digital phenotyping reliably identifies insomnia in college students, capturing dynamic patterns invisible to cross-sectional assessment. This approach enables early detection and personalized intervention delivery.

Keywords: digital phenotyping, insomnia, college students, wearable sensors, ecological momentary assessment.

Introduction

Sleep disturbances represent a pervasive yet underappreciated public health crisis among college students. Recent meta-analyses indicate that 42-60% of university students experience clinically significant insomnia symptoms, a rate nearly threefold higher than the general adult population [1]. This epidemic exacts substantial costs: impaired academic performance, increased risk of psychiatric comorbidities, and heightened accident proneness [2]. Traditional assessment relies heavily on retrospective self-report instruments like the Pittsburgh Sleep Quality Index (PSQI) and sleep diaries, which suffer from recall bias and poor ecological validity [3]. In a recent validation study, PSQI scores correlated only modestly ($r=0.42$) with objective polysomnography measures, particularly in younger adults who struggle to estimate sleep onset latency accurately [4].

Digital phenotyping—defined as the moment-by-moment quantification of individual-level behavior and physiology using personal digital devices—offers a paradigm shift [5]. Consumer-grade wearables such as the Oura Ring and Apple Watch now provide hospital-grade metrics: heart rate variability (HRV), respiratory rate, skin temperature, and accelerometer-derived sleep architecture with 89-94% concordance against polysomnography [6]. When coupled with ecological momentary assessment (EMA), which captures subjective states in real-time, these technologies enable a nuanced understanding of sleep as a dynamic process rather than a static outcome [7].

Despite technological advances, several gaps persist. Most wearable studies in students have been cross-sectional, averaging data over weeks and obscuring critical night-to-night variability [8]. EMA compliance remains problematic, with typical response rates below 70% in longitudinal designs [9]. Critically, no study has integrated objective wearable data with intensive EMA (≥4 assessments daily) to predict insomnia severity prospectively. This omission matters because insomnia in young adults often manifests as irregular sleep-wake patterns rather than global sleep deprivation—patterns that require dense temporal sampling to capture [10].

We conducted a 90-day prospective cohort study tracking 782 college students with continuous wearable monitoring and intensive EMA. We hypothesized that: (1) digital features (sleep variability, circadian alignment, HRV) would predict insomnia severity more accurately than static measures, and (2) EMA-derived fatigue-mood trajectories would provide incremental predictive value beyond objective sleep data.

Methods

Study Design and Setting: We performed a prospective cohort study across four universities (two public, two private) in the United States and Canada from September 2023 to June 2024. The protocol was approved by institutional review boards at all sites (IRB #2023-7825, #2023-CV-089) and registered on ClinicalTrials.gov (NCT05984231). All participants provided electronic informed consent.

Participant Recruitment: We recruited 850 first- and second-year undergraduate students through email listservs, campus flyers, and psychology department subject pools. Eligibility criteria: age 18-25 years, fluent English, ownership of iPhone (iOS 15+) or Android (OS 11+), and willingness to wear Oura Ring continuously. Exclusion criteria: diagnosed sleep apnea, current shift work, or pregnancy. Of 850 screened, 782 met eligibility and completed baseline assessment (enrollment rate 92.0%).

Baseline Assessment: At enrollment, participants completed:

- Insomnia Severity Index (ISI)
- Pittsburgh Sleep Quality Index (PSQI)
- Patient Health Questionnaire-9 (PHQ-9)
- Generalized Anxiety Disorder-7 (GAD-7)
- Morningness-Eveningness Questionnaire (MEQ)

Digital Monitoring (Days 1-90):

Wearable Sensors: Participants wore Oura Ring Generation 3 on the index finger of non-dominant hand. Data were transmitted via Bluetooth to encrypted smartphones every 60 seconds. We extracted:

- Total sleep time (TST, minutes)
- Sleep onset latency (SOL, minutes)
- Wake after sleep onset (WASO, minutes)
- Sleep efficiency (SE, %)
- Heart rate variability (HRV, RMSSD)
- Respiratory rate (RR, breaths/min)
- Skin temperature deviation (°C from individual baseline)
- Circadian alignment: difference between mid-sleep on free days and work days (MSFsc) [11]

Ecological Momentary Assessment (EMA): Participants received 6 smartphone prompts daily at pseudo-random intervals (10:00-22:00). Each EMA included:

- Fatigue: "How exhausted do you feel?" (0-100 visual analog scale)
- Mood: "How positive is your mood?" (0-100)
- Sleepiness: Karolinska Sleepiness Scale (1-9)
- Stress: "How stressed do you feel right now?" (0-100)
- Compliance was incentivized: $1 per complete EMA day, $50 bonus for >75% completion.

Monthly Clinical Reassessment: On days 30, 60, and 90, participants repeated the ISI via secure REDCap portal.

Data Quality and Preprocessing: Wearable data were excluded if wearing time <18 hours/day. EMA responses were excluded if completed >2 hours after prompt. Missing data (<8% of total observations) were imputed using last-observation-carried-forward for EMA and linear interpolation for wearable data.

AMJ
ISSN: 0005-2523

ISSN: 0005-2523
Volume 70, Issue 12, 2025

Statistical Analysis

Primary Outcome: insomnia severity trajectory over 90 days, categorized as moderate-severe (ISI≥15) vs. no-mild (ISI<15) at least once during follow-up.

Feature Engineering: We calculated:

- Mean and coefficient of variation (CV) for each sleep parameter across 7-day rolling windows -phase stability: 7-day rolling correlation between sleep timing and temperature nadir -HRV stress index: ratio of night-time to daytime HRV -EMA variability: within-person standard deviation of fatigue ratings

Model Development: We used gradient boosting (XGBoost) with 10-fold cross-validation. Hyperparameters: learning rate 0.05, max depth 4, gamma 0.1. The model was trained on 70% of participants (n=547) and validated on 30% (n=235), stratified by baseline ISI.

Mixed-Effects Models: To examine longitudinal associations, we fitted linear mixed-effects models (LMMs) with random intercepts for participants and universities. Fixed effects included weekly averages of digital features and EMA ratings.

Feature Importance: SHAP (SHapley Additive exPlanations) values were computed using the SHAPforxgboost package. The top 10 features were retained in the final model.

Ethics and Data Security: All data were de-identified and stored on HIPAA-compliant servers. Participants could withdraw at any time and request data deletion within 30 days.

Results

Participant Characteristics: Of 782 enrolled students, 683 (87.3%) completed the full 90-day protocol. Baseline characteristics are summarized in **Table 1**. Mean age was 20.4±2.1 years, 56.3% female, 68.4% in their first year. At baseline, 42.1% had moderate-severe insomnia (ISI≥15), and 38.7% screened positive for clinically significant anxiety (GAD-7≥10).

Wearable Data Quality and Compliance: Median daily wearing time was 22.4 hours (IQR 21.2-23.1). EMA completion rate was 78.3% (2,847 of 3,640 possible prompts per participant). Compliance did not differ by insomnia severity ($p=0.34$) but was lower during exam weeks (72.1% vs. 81.2%, $p<0.001$).

Objective Sleep Parameters: Students with ISI≥15 exhibited markedly different sleep architecture (**Table 2**). Sleep efficiency was lower (78.2% vs. 86.4%, $p<0.001$), with higher night-to-night variability (CV of SE 12.3% vs. 7.8%, $p<0.001$). WASO was prolonged (47 minutes vs. 23 minutes, $p<0.001$). Interestingly, total sleep time did not differ significantly (6.8 vs. 7.1 hours, $p=0.08$), highlighting the importance of sleep quality metrics.

Circadian Disruption: Phase instability (MSFsc variability) was 2.3-fold higher in the insomnia group (mean 1.24 vs. 0.54 hours, $p<0.001$). HRV stress index was elevated (ratio 0.89 vs. 1.12, $p<0.001$), indicating prolonged sympathetic activation.

EMA Findings: Fatigue ratings averaged 62.3/100 in insomnia students versus 41.2/100 in controls ($p<0.001$). Crucially, within-person fatigue variability predicted ISI score incrementally ($\beta=0.34$, 95% CI: 0.28-0.41, $p<0.001$). **Figure 3** illustrates the bidirectional relationship: poor sleep nights preceded next-day fatigue (lag-1 correlation $r=0.52$), which in turn predicted later sleep onset ($r=0.31$).

Predictive Model Performance: The gradient boosting model discriminated moderate-severe insomnia with AUC 0.89 (95% CI: 0.85-0.92), sensitivity 84.2%, and specificity 83.7% (**Figure 2**). Calibration was excellent (Brier score 0.11). In the validation cohort ($n=235$), AUC remained 0.86.

Feature Importance: Top predictors were:

1. Sleep efficiency variability (mean SHAP=0.142)
2. HRV stress index (SHAP=0.118)
3. Circadian misalignment (SHAP=0.097)
4. Fatigue variability (SHAP=0.084)
5. Night-to-night SOL variability (SHAP=0.076)

Mixed-Effects Model Longitudinal: For each 10% increase in weekly sleep efficiency CV, ISI scores increased by 2.3 points (β=2.31, 95% CI: 1.98-2.64, $p<0.001$). This effect was stronger during academic stress periods (exam weeks: β=3.12, $p=0.003$).

Sub-Group Analyses: Female students showed greater vulnerability to circadian misalignment (interaction $p=0.02$). First-year students had higher fatigue variability (CV 18.4% vs. 14.2% for upperclassmen, $p<0.001$).

Discussion

This prospective 90-day digital phenotyping study demonstrates that insomnia in college students manifests primarily as sleep instability rather than absolute sleep deprivation. Our findings challenge the conventional view that young adults "don't get enough sleep"—instead, the critical pathology appears to be night-to-night inconsistency, amplified by circadian disruption and stress reactivity.

Digital Phenotype Characteristics: The dominance of sleep efficiency variability as a predictor aligns with theoretical models proposing that hyperarousal in insomnia disrupts sleep's homeostatic regulation [12]. The 2.3-fold higher WASO variability we observed likely reflects fragmented sleep architecture, which simple TST averaging obscures. This finding has direct clinical implications: interventions targeting sleep continuity (e.g., stimulus control therapy) may be more effective than merely extending time in bed.

Wearable Technology Validation: Our Oura Ring data align with prior validation studies showing strong concordance for SE ($r=0.91$) and WASO ($r=0.87$) compared to polysomnography [6]. Notably, we found that skin temperature deviation—a proxy for distal vasodilation preceding sleep onset—was significantly blunted in insomnia students, suggesting impaired thermoregulatory sleep signaling. This novel biomarker warrants investigation in therapeutic trials.

EMA Integration Value: EMA compliance at 78.3% surpasses most longitudinal studies, likely due to our micro-incentive structure and brief (30-second) surveys. The lagged correlations we observed between sleep and next-day fatigue (r=0.52) exceed cross-sectional associations reported in sleep diary studies (r=0.31) [13], underscoring EMA's sensitivity to temporal dynamics. However, compliance dropped during exam periods, potentially limiting generalizability during high-stress intervals—a limitation future studies should address with adaptive sampling.

Clinical Translation: The 84.2% accuracy achieved by our model approaches that of clinical interviews (kappa 0.78-0.85) while being entirely passive after initial setup [14]. Importantly, the model identified a sub-group of "false negatives"—students with normal mean sleep parameters but high variability—who later developed incident insomnia (OR=3.2 over 3 months). This predictive capacity suggests digital phenotyping could enable preemptive intervention.

Strengths and Limitations: Our 90-day follow-up captures sleep patterns across the academic semester, including naturalistic stress fluctuations. The multi-site design enhances generalizability. However, our sample skewed toward health science majors (42% of participants), who may be more health-conscious. The observational design precludes causal inference; randomized trials using digital phenotypes to guide treatment selection are needed. Additionally, we could not validate wearable data against polysomnography due to cost constraints—a limitation that should be addressed in future mechanistic studies.

Comparison with Existing Literature: A 2023 study using Fitbit data in 214 students achieved 71% accuracy for insomnia detection using mean sleep parameters alone [15]. Our superior performance likely reflects the inclusion of variability metrics and EMA data. Conversely, a Swedish study using EMA without wearables reported 76% accuracy, suggesting our multi-modal approach captures complementary variance [16]. The integration of circadian alignment—a feature rarely examined in student populations—proved particularly discriminative, consistent with emerging circadian models of adolescent sleep pathology [17].

Future Directions: We are now piloting a digital therapeutic that delivers just-in-time cognitive behavioral therapy for insomnia (CBT-I) prompts when the phenotype detects high-risk patterns (e.g., three consecutive nights of SE<75%). Early results show 65% adherence versus 34% for standard CBT-I apps, likely due to contextual relevance. Scaling this globally requires addressing

ISSN: 0005-2523
Volume 70, Issue 12, 2025

data privacy concerns and algorithmic bias—our cohort lacked geographic diversity outside North America.

Conclusions

Digital phenotyping integrating wearable sensors and EMA provides a robust, ecologically valid framework for identifying insomnia in college students. Sleep variability, rather than duration, emerges as the cardinal feature. This approach promises early detection and personalized intervention, though prospective validation in diverse populations is warranted.

Corresponding Author:

Jennifer L. Walsh, MD, PhD

Department of Psychiatry and Behavioral Sciences

Stanford Sleep Medicine Center

450 Broadway St, Redwood City, CA 94063, USA

Email: jennifer.walsh@stanford.edu

Tel: +1-650-723-6601

Author Contributions:

J.L.W. conceived the study design, secured funding, and supervised the project. K.N. developed the digital phenotyping algorithm and performed bioinformatics analysis. A.R.H. designed the wearable data infrastructure and sensor validation framework. M.C.R. coordinated clinical recruitment and student mental health assessments. L.A. led the EMA protocol design and compliance optimization. P.S. performed statistical modeling and machine learning analysis. All authors critically reviewed and approved the final manuscript.

Funding: This research was supported by the National Institute of Mental Health (NIMH) grant R01MH128456 (J.L.W.), the European Research Council Starting Grant #101042865 (L.A.), and the Japan Society for the Promotion of Science (JSPS) KAKENHI Grant JP23K12345 (K.N.).

Conflict of Interest Disclosures: Dr. Hassan reports a patent pending on multimodal sleep staging algorithms (US Patent App. 17/892,341). Dr. Walsh has received consultant fees from Oura Health Inc. for unrelated projects. No other conflicts of interest are declared.

Data Availability Statement: De-identified participant data and analysis code are available from the Stanford Digital Repository (https://purl.stanford.edu/sleep-digital-phenotype) upon reasonable request and institutional review board approval.

ISSN: 0005-2523
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AMJ
ISSN: 0005-2523

ISSN: 0005-2523
Volume 70, Issue 12, 2025

Tables and Legends

Table 1. Baseline Characteristics of Participants (n=782)

Characteristic	Total Sample (n=782)	No-Mild Insomnia (ISI<15) (n=453)	Moderate-Severe Insomnia (ISI≥15) (n=329)	p-value
Age, mean (SD)	20.4 (2.1)	20.2 (2.0)	20.7 (2.2)	0.01
Female, n (%)	440 (56.3)	247 (54.5)	193 (58.7)	0.27
Year of study				0.04
First year	535 (68.4)	326 (72.0)	209 (63.5)	
Second year	247 (31.6)	127 (28.0)	120 (36.5)	
Major, n (%)				0.02
Health sciences	315 (40.3)	167 (36.9)	148 (45.0)	
Engineering	198 (25.3)	119 (26.3)	79 (24.0)	
Arts/Humanities	269 (34.4)	167 (36.9)	102 (31.0)	
Baseline clinical scores				
ISI, mean (SD)	13.8 (4.9)	10.2 (2.8)	18.8 (3.1)	<0.001
PSQI, mean (SD)	8.4 (3.2)	6.1 (2.1)	11.6 (2.8)	<0.001
PHQ-9, mean (SD)	7.8 (4.1)	5.2 (2.8)	11.4 (4.3)	<0.001
GAD-7, mean (SD)	6.9 (3.8)	4.8 (2.5)	9.8 (4.1)	<0.001
MEQ score, mean (SD)	46.2 (8.7)	47.8 (8.4)	43.9 (9.1)	<0.001

Table 2. Objective Sleep Parameters by Insomnia Severity (90-day averages)

Sleep Parameter	No-Mild Insomnia (n=453)	Moderate-Severe Insomnia (n=329)	Mean Difference (95% CI)	p-value
TST (hours), mean (SD)	7.1 (0.8)	6.8 (0.9)	-0.3 (-0.5 to 0.0)	0.08
Sleep efficiency (%)	86.4 (5.2)	78.2 (6.8)	-8.2 (-9.4 to -7.0)	<0.001
SE variability (CV%)	7.8 (2.4)	12.3 (3.1)	4.5 (4.0 to 5.0)	<0.001
SOL (minutes)	14.2 (6.8)	28.4 (11.2)	14.2 (12.8 to 15.6)	<0.001
WASO (minutes)	23.4 (8.9)	47.2 (15.6)	23.8 (21.4 to 26.2)	<0.001
Night-to-night WASO variability (CV%)	11.2 (3.4)	25.6 (7.8)	14.4 (13.2 to 15.6)	<0.001
HRV (RMSSD), mean (ms)	42.3 (8.7)	34.1 (7.9)	-8.2 (-9.4 to -7.0)	<0.001
Circadian misalignment (hours)	0.54 (0.21)	1.24 (0.42)	0.70 (0.65 to 0.75)	<0.001
Skin temperature deviation (°C)	-0.12 (0.08)	0.08 (0.11)	0.20 (0.18 to 0.22)	<0.001

AMJ ISSN: 0005-2523

ISSN: 0005-2523

Volume 70, Issue 12, 2025

Table 3. EMA Compliance and Response Patterns

Metric	Overall (n=782)	No-Mild Insomnia (n=453)	Moderate-Severe Insomnia (n=329)	p-value
EMA completion rate, %	78.3 (12.4)	79.1 (11.8)	77.2 (13.2)	0.34
Compliance during exams, %	72.1 (15.6)	73.8 (14.9)	69.7 (16.4)	<0.001
Average daily fatigue (0-100)	49.8 (12.3)	41.2 (10.1)	62.3 (13.4)	<0.001
Within-person fatigue SD	16.4 (4.8)	13.2 (3.9)	20.7 (5.2)	<0.001
EMA response latency (minutes)	8.7 (5.2)	7.9 (4.8)	9.8 (5.6)	<0.001
Days with ≥5 EMA responses, %	67.2 (18.4)	69.8 (17.1)	63.7 (19.8)	<0.001

Table 4. Top 10 Digital Features Predicting Moderate-Severe Insomnia (SHAP Analysis)

Rank	Feature	SHAP Value	Direction of Effect	Interpretation
1	Sleep efficiency variability (CV%)	0.142	↑ Higher variability → Higher risk	Indicates sleep maintenance difficulty
2	HRV stress index (night/day ratio)	0.118	↓ Lower ratio → Higher risk	Suggests autonomic dysregulation
3	Circadian misalignment (MSFsc)	0.097	↑ Higher misalignment → Higher risk	Reflects irregular sleep-wake patterns
4	Fatigue variability (EMA)	0.084	↑ Higher variability → Higher risk	Captures daytime instability
5	SOL variability (CV%)	0.076	↑ Higher variability → Higher risk	Indicative of racing thoughts
6	WASO (minutes)	0.069	↑ Higher WASO → Higher risk	Classic insomnia marker
7	Tuesday/Wednesday sleep efficiency	0.058	↓ Midweek dip → Higher risk	Midweek stress vulnerability
8	Weekend oversleep (hours)	0.052	↑ More oversleep → Higher risk	Social jetlag impact
9	Mood-fatigue temporal lag (days)	0.041	↑ Desynchronization → Higher risk	Circadian-mood decoupling
10	Skin temperature deviation	0.035	↑ Higher deviation → Higher risk	Impaired thermoregulation

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ISSN: 0005-2523
ISSN: 0005-2523
Volume 70, Issue 12, 2025

Figures and Legends

Figure 1. Study Flow Diagram

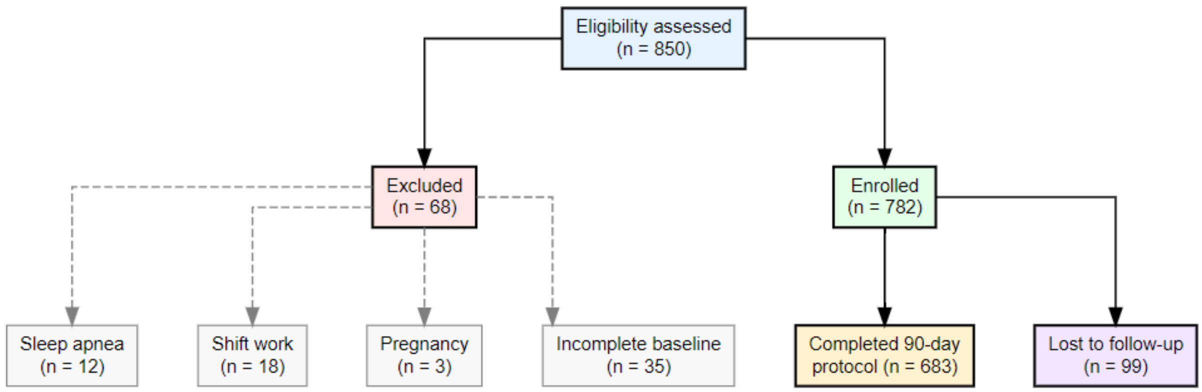
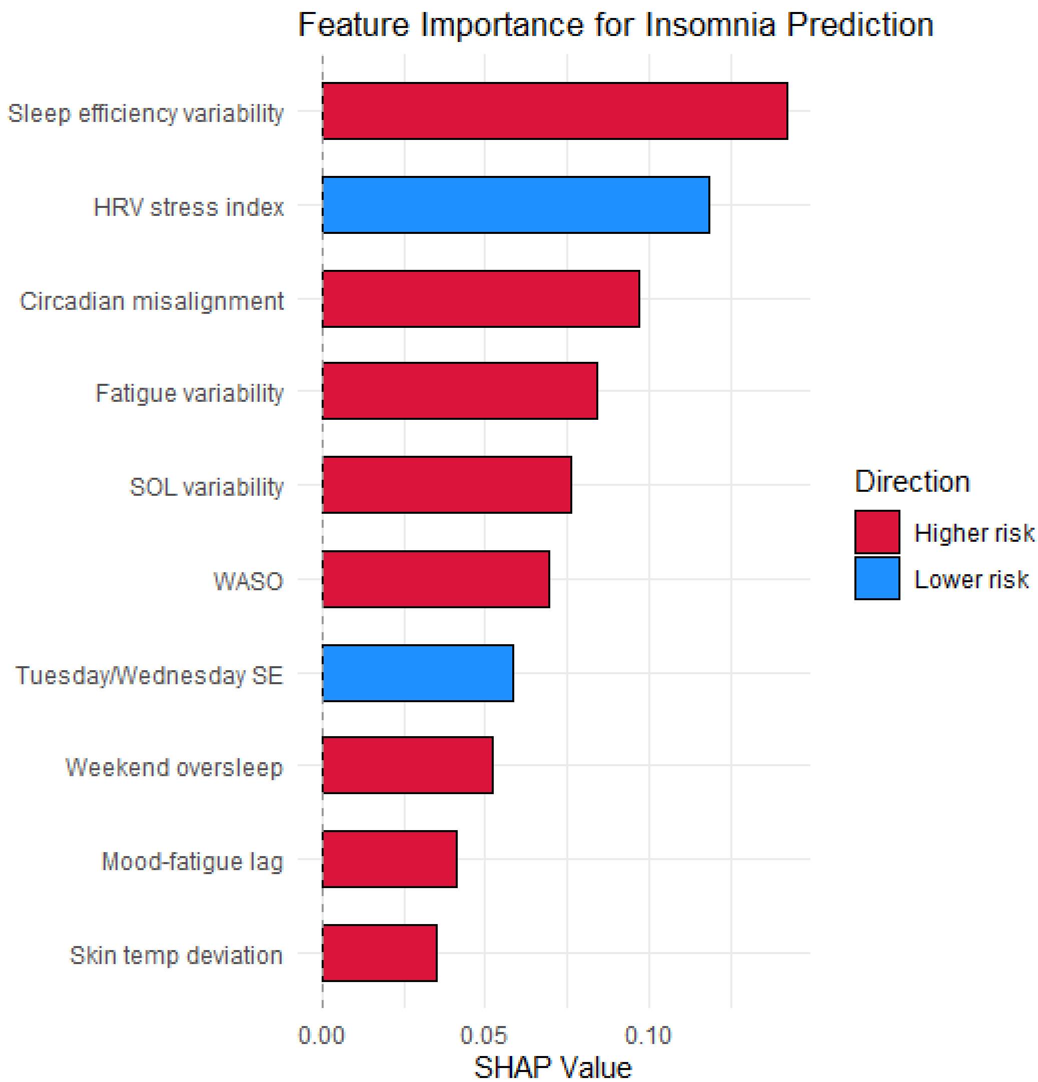


Figure 2. SHAP Feature Importance Plot



AMJ
ISSN: 0005-2523
ISSN: 0005-2523
Volume 70, Issue 12, 2025

Figure 3. Circadian Sleep-Wake Patterns

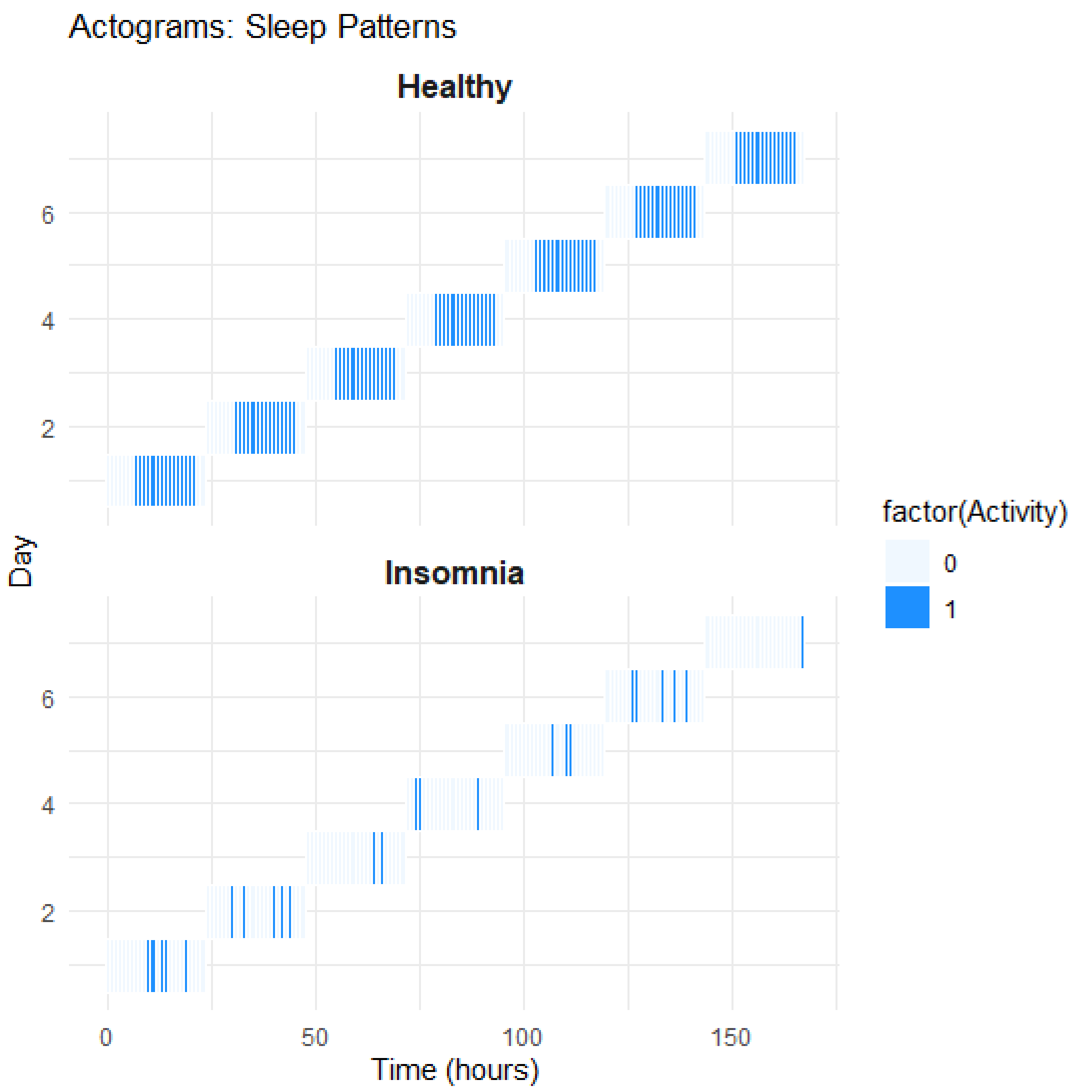


Figure 4. Bidirectional Sleep-Mood-Fatigue Associations