Measurements of Sleep and Rest Activity: Where are we and where would we like to go?

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NATIONAL ACADEMIES Sciences Engineering Medicine

Conflict of Interest Disclosures
– Authors/Presenters

☐ The authors do not have any potential conflicts of interest to disclose,

OR

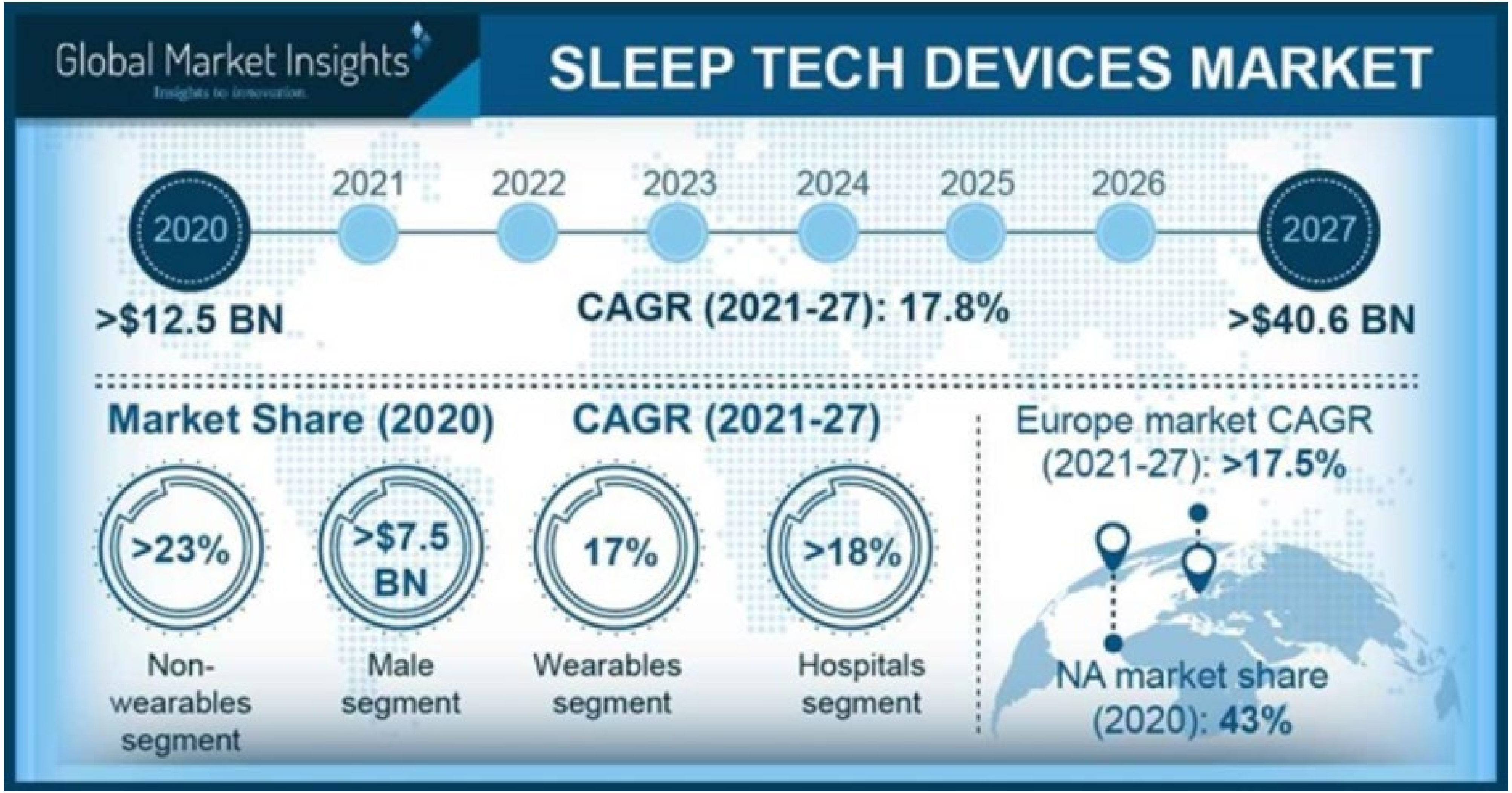
X The authors wish to disclose the following potential conflicts of interest related to content in this lecture:

Type of Potential Conflict	Details of Potential Conflict
Grant/Research Support	
Consultant	SleepScore Labs, Praesidium, EnsoData
Speakers' Bureaus	
Financial support	
Other	

This talk presents material that is related to one or more of these potential conflicts, and the following objective references are provided as support for this lecture:

1. Montgomery-Downs HE, et al. Movement toward a novel activity monitoring device. Sleep Breath. 2012 Sept;16:913-917.
2. Kang S-G, Kang JM, Ko K-P, Park S-C, Mariani S, Weng J. J Psychosom Res. 2017;97:38-44. doi:10.1016/j.jpsychores.2017.03.009.
3. Penzel et al. Dynamics of heart rate and sleep stages in normal and patients with sleep apnea. Neuropsychopharmacology 2003:28;S48-S53.

Where are we?



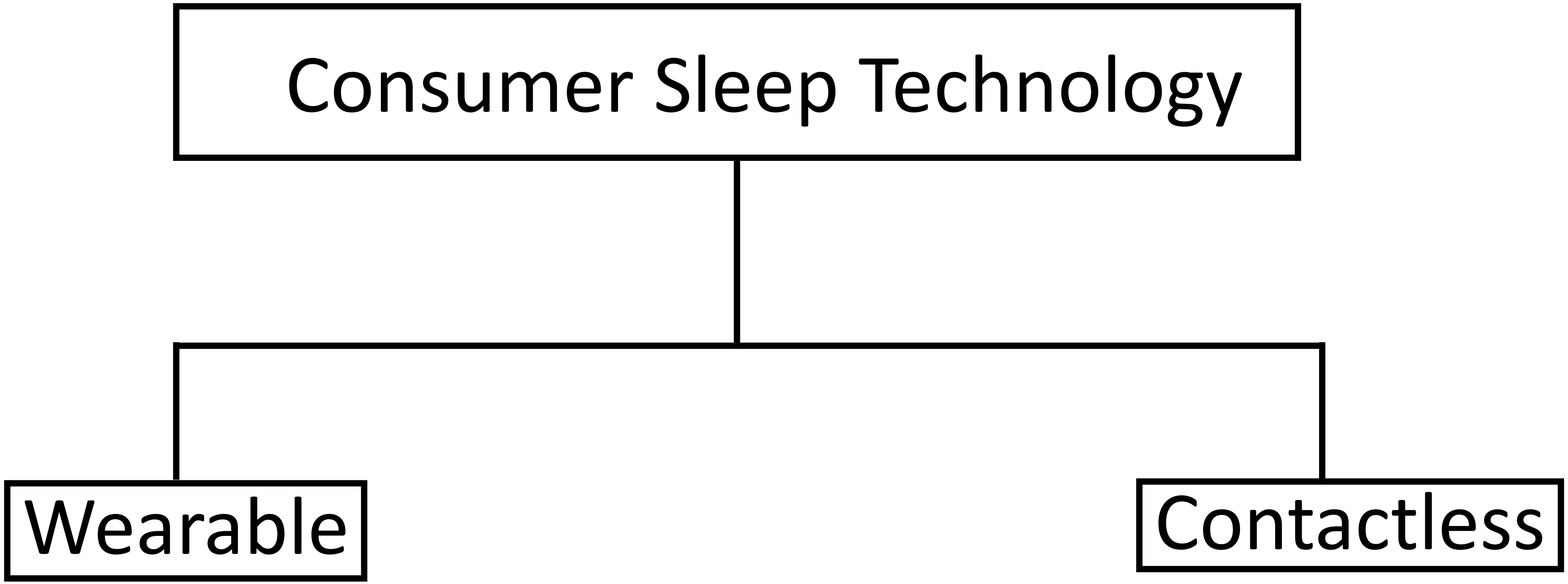
[Sleep Tech Devices Market Forecast Report 2021-2027 (gminsights.com)]

Consumer Sleep Technology: An American Academy of Sleep Medicine Position Statement

Seema Khosla, MD[1]; Maryann C. Deak, MD[2]; Dominic Gault, MD[3]; Cathy A. Goldstein, MD[4]; Dennis Hwang, MD[5]; Younghoon Kwon, MD[6]; Daniel O'Hearn, MD[7]; Sharon Schutte-Rodin, MD[8]; Michael Yurcheshen, MD[9]; Ilene M. Rosen, MD, MS[8]; Douglas B. Kirsch, MD[10]; Ronald D. Chervin, MD, MS[4]; Kelly A. Carden, MD[11]; Kannan Ramar, MD[12]; R. Nisha Aurora, MD[13]; David A. Kristo, MD[14]; Raman K. Malhotra, MD[15]; Jennifer L. Martin, PhD[16,17]; Eric J. Olson, MD[12]; Carol L. Rosen, MD[18]; James A. Rowley, MD[19]; for the American Academy of Sleep Medicine Board of Directors

. *J Clin Sleep Med.* 2018;14(5):877–880.

- Clinicians should have a general awareness of CST and a readiness to discuss CST with patients.
- Clinicians should understand the general framework of devices and apps available and have a basic knowledge of available evidence or lack thereof.
- Most CSTs are not FDA cleared or validated clinical devices/ applications, but widespread accessibility and use by patients (and potential patients) may augment patient engagement.
- Data can be utilized as a tool for opening discussions with patients.
- Clinicians should recognize the patient's use of CST as a commitment to focus on sleep wellness.


Consumer Sleep Technology
Wearable
Contactless

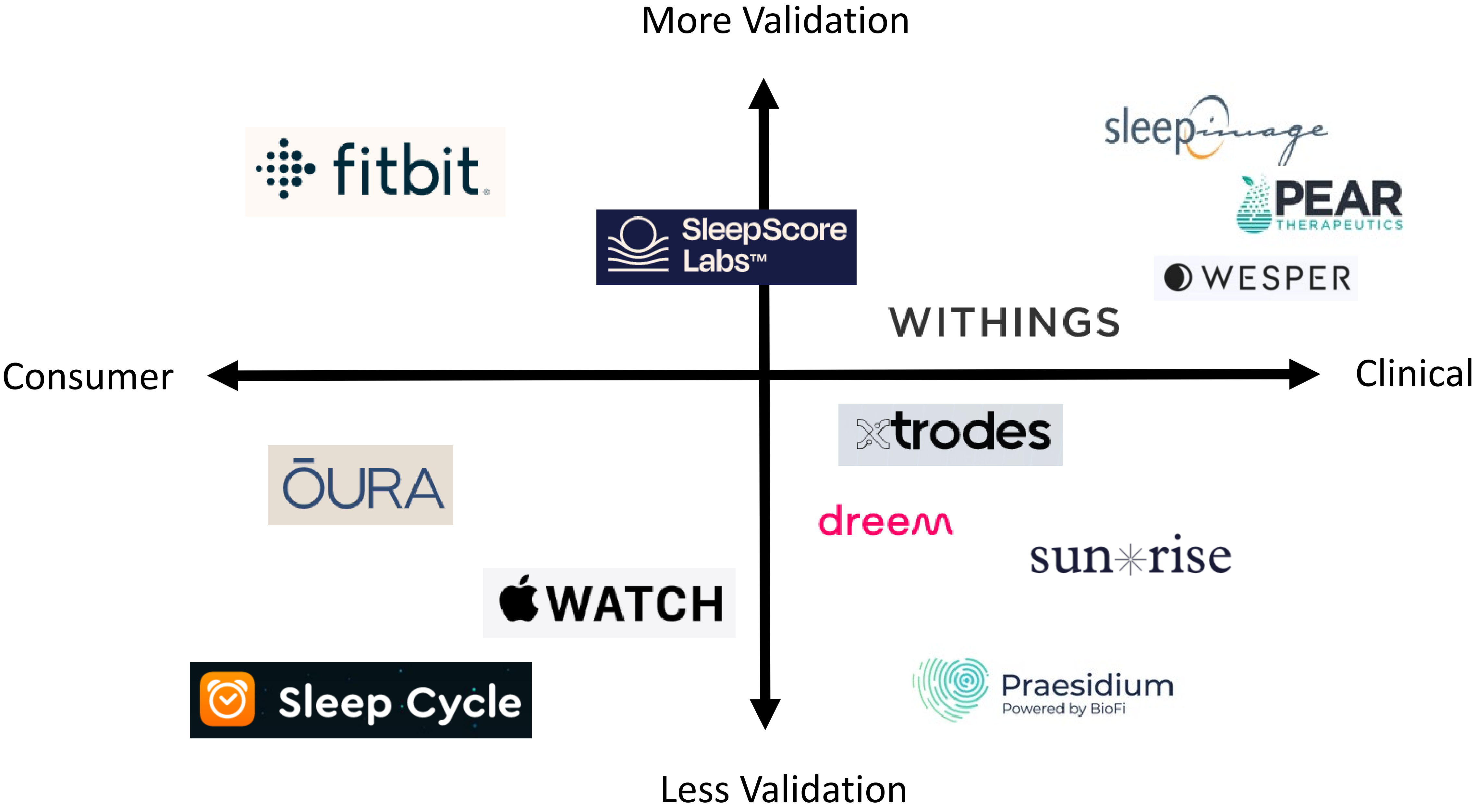
Consumer Sleep Sensing Technologies: History

- First mass market device:

Fitbit Classic, 2009

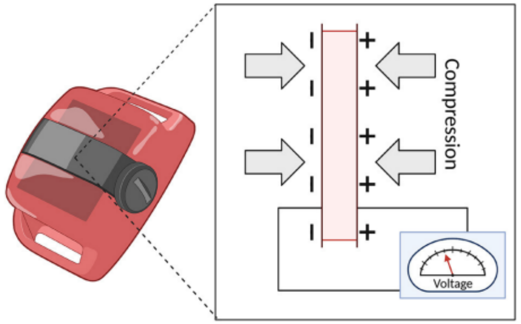
  - Steps
  - Sleep
  - 7 days Battery

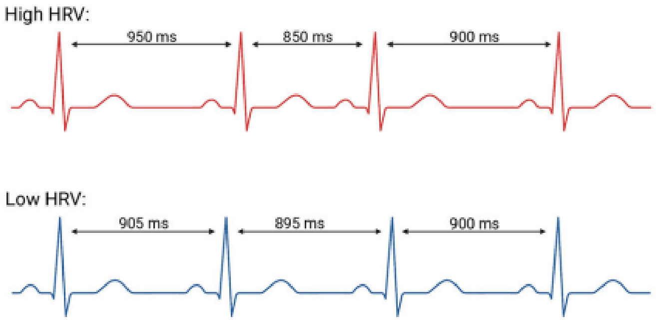
Consumer, Contact, Motion, Single Sensor


More Validation
Less Validation
Consumer
Clinical
fitbit
SleepScore Labs™
sleepimage
PEAR THERAPEUTICS
WESPER
WITHINGS
ŌURA
xtrodes
dreem
sunrise
WATCH
Sleep Cycle
Praesidium
Powered by BioFi

Consumer Sleep Technologies: General Concepts Utilized

- Accelerometry
- Respiratory Frequency and Amplitude
- Heart Rate, Heart Rate Variability, Pulse Waveform and Amplitude
- Acoustic Monitoring
- Binaural Beats
- Photoplethysmography
- Temperature



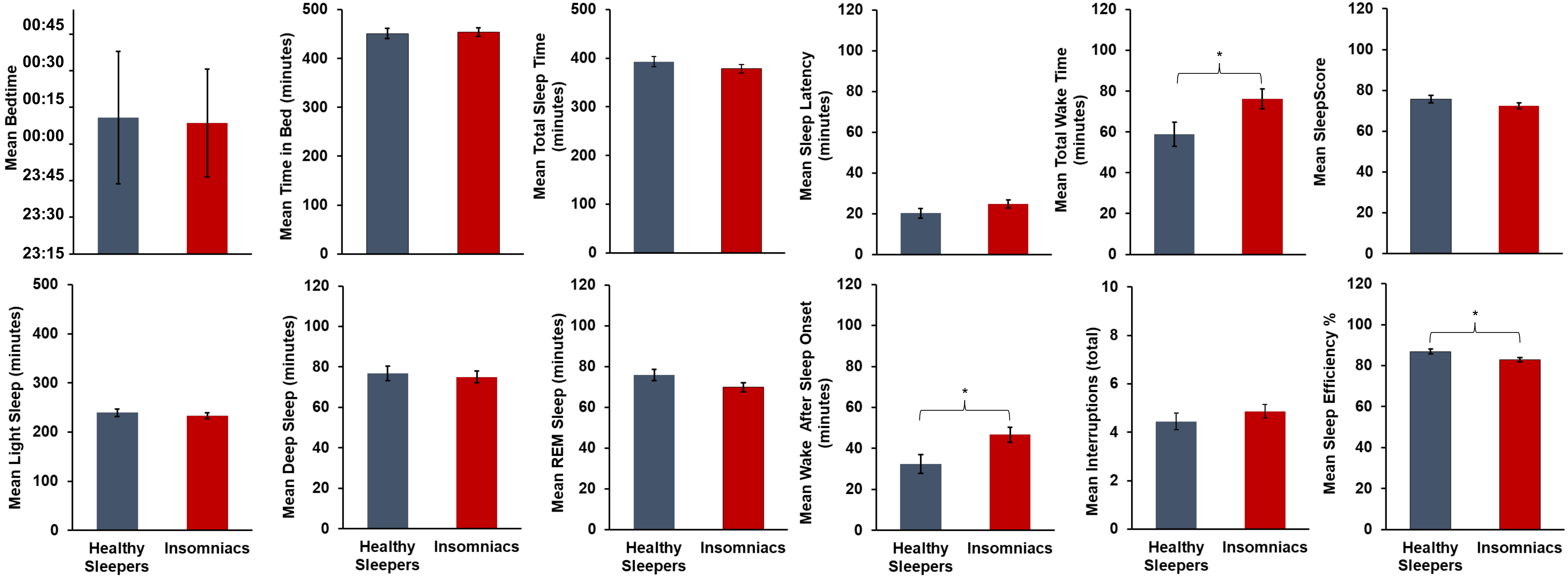


Can CSTs Differentiate Those with Insomnia from Healthy Sleepers?

- N=44 individuals meeting ICSD-3 criteria for chronic insomnia (ages 19-63y, 30 males) and 29 healthy sleeper controls (ages 19-54y, 21 females) participated in an at-home sleep monitoring study
- Participants used the SleepScore Max to record their sleep periods each night for 8 weeks
- Sleep measurements were analyzed for group differences in both means (characterizing sleep overall) and within-subject standard deviations (quantifying night-to-night variability), using mixed-effects regression controlling for systematic between-subject differences

Hansen D, Peterson ME, Raymann RJ, Van Dongen H, Watson NF. Long-Term, Naturalistic, Non-Contact Measurement of Sleep in Chronic Insomnia. SLEEP 2021;44:A130 ; updated analysis submitted to World Sleep 2022

Objective Group Mean Differences



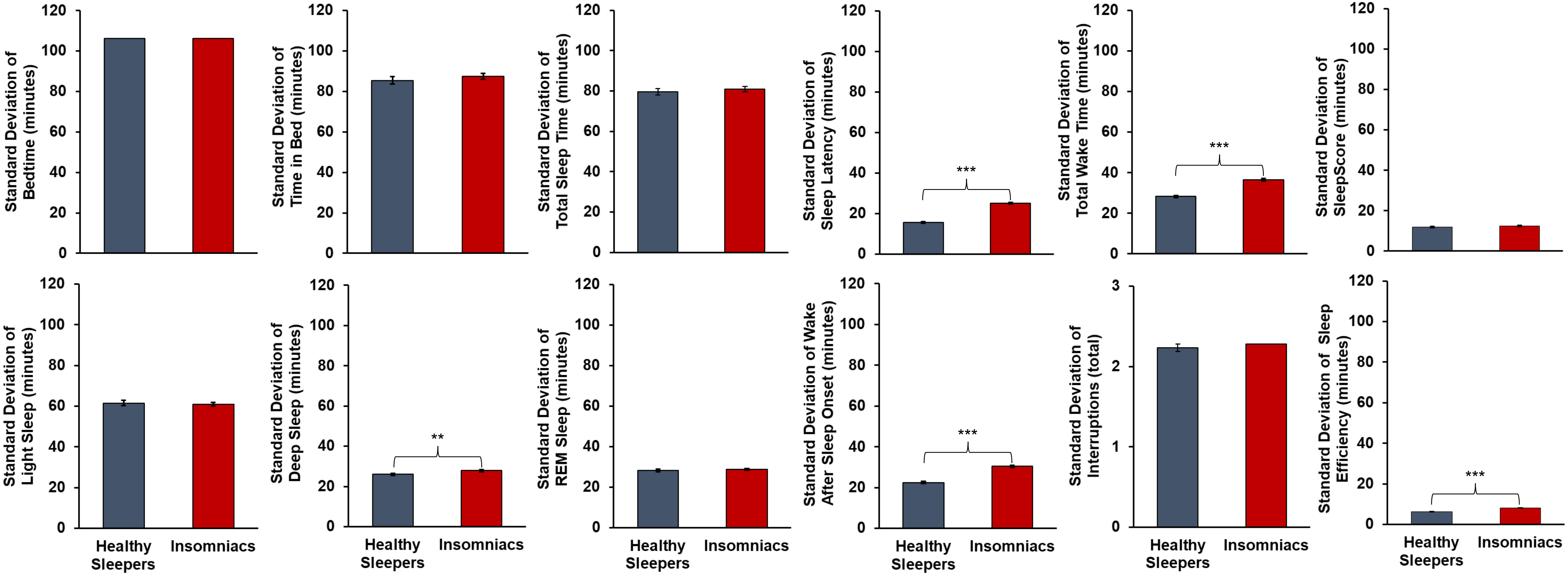
<u>Significant Group Differences</u>:

Total Wake Time $F_{1,\ 2977}$ = 5.24, p=0.0221

WASO $F_{1,\ 2977}$ = 6.00, p=0.0144

Sleep Efficiency $F_{1,2977}$ = 6.07, p=0.0138

Within-Subject Standard Deviations (Quantifying Night-to-Night Variability)



<u>Significant Group Variability Differences</u>:

Total Wake Time $F_{1, 72} = 93.89$, $p<0.001$

WASO $F_{1, 72} = 135.06$, $p<0.001$

Deep Sleep $F_{1, 72} = 7.19$, $p=0.0091$

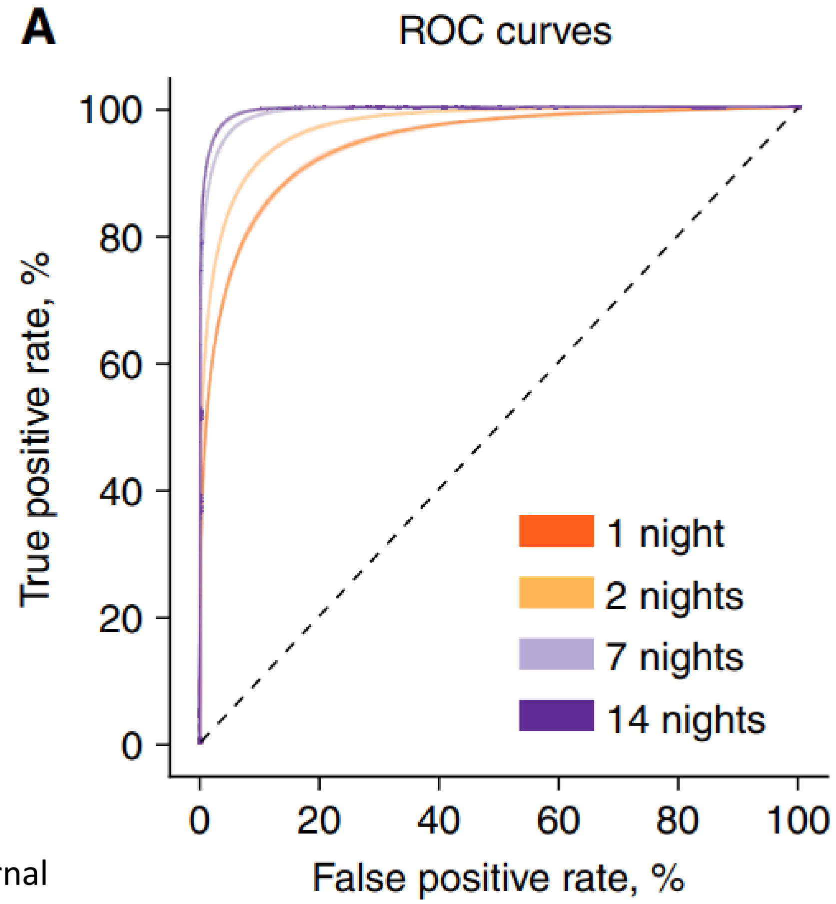
Sleep Latency $F_{1, 72} = 324.53$, $p<0.001$

Sleep Efficiency $F_{1, 72} = 92.53$, $p<0.001$

Multinight Prevalence, Variability, and Diagnostic Misclassification of Obstructive Sleep Apnea

Bastien Lechat[1], Ganesh Naik[1], Amy Reynolds[1], Atqiya Aishah[1,2], Hannah Scott[1], Kelly A. Loffler[1], Andrew Vakulin[1], Pierre Escourrou[3], R. Doug McEvoy[1], Robert J. Adams[1], Peter G. Catcheside[1], and Danny J. Eckert[1]

- 67,278 individuals aged 18 - 90 years underwent in-home nightly monitoring with Withings Sleep Analyzer over an average of approximately 170 nights
- OSA defined as AHI > 15 events/hour
- OSA global prevalence was 22.6%
- OSA misdiagnosis (based on a single night) was 20%
- Misdiagnosis error rates decreased with increased monitoring nights (e.g., 1-night F1-score = 0.77 vs. 0.94 for 14 nights) and remained stable after 14 nights of monitoring.

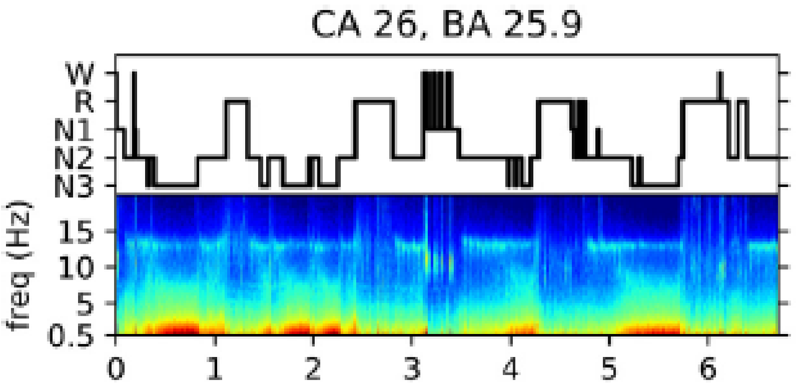


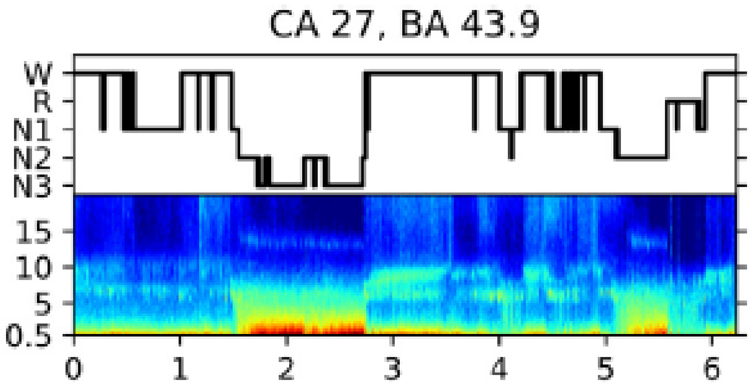
Lechat, Naik, Reynolds, et al.: Night-to-Night Variability of Sleep Apnea Severity. American Journal of Respiratory and Critical Care Medicine Volume 205 Number 5 | March 1 2022

Can “Brain Age” Be Predicted by the EEG?

- Brain age (BA) serves as a potential aging biomarker where the variation of BA between individuals of the same chronological age may carry important information about the risk of cognitive impairment, neurological or psychiatric disease, or death
- Alzheimer’s disease, schizophrenia, epilepsy, traumatic brain injury, bipolar disorder, major depression, cognitive impairment, diabetes mellitus, and HIV, are associated with excess BA (on MRI)
- Machine learning model developed to predict BA based on 2 large sleep EEG data sets: the Massachusetts General Hospital (MGH) sleep lab data set (N = 2,532; ages 18-80); and the Sleep Heart Health Study (SHHS, N = 1,974; ages 40-80).

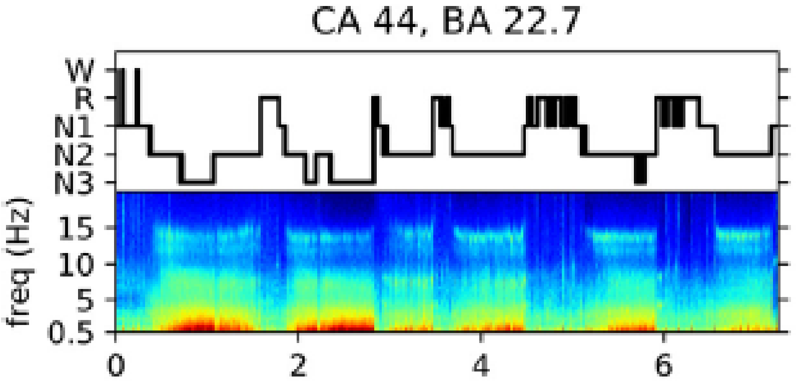
Sun et al. Brain age from EEG of sleep. Neurobiology of Aging 2019;74:112-120
Nygate YN et al. EEG-Based Deep Neural Network Model for Brain Age Prediction and Its Association with Patient Health Conditions. *SLEEP* 2021;44:A214

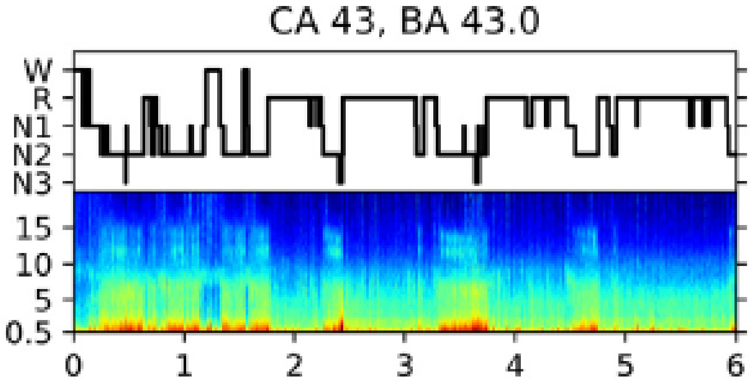


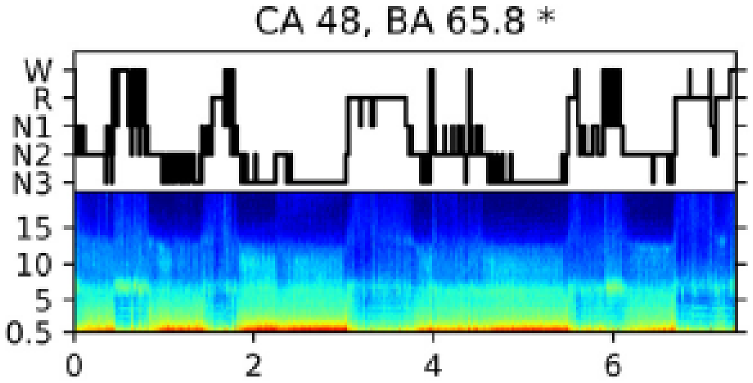


Covariates that have significant correlation with BAI (BA-CA)

Covariate	Spearman's correlation
N3 time	−0.11
N3 percentage	−0.087
Sleep efficiency	−0.082
Total sleep time	−0.076
N2 time	−0.065
Respiratory disturbance index	0.043
N1 percentage	0.058
Wake time after sleep onset	0.081

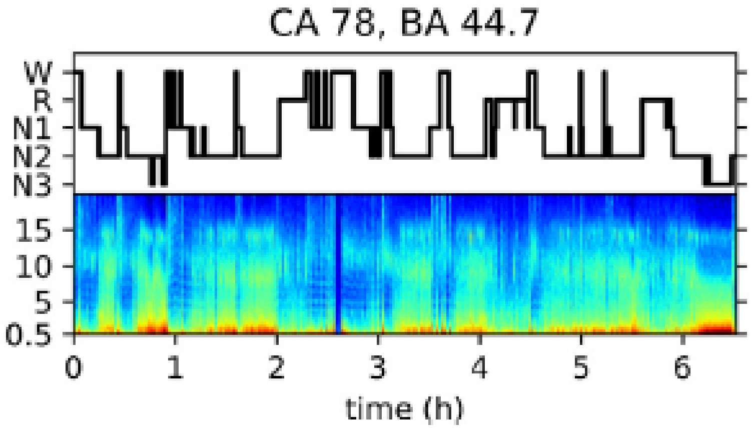


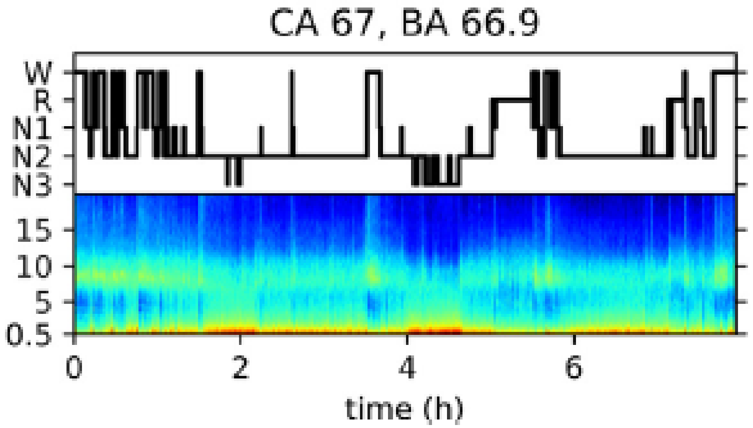


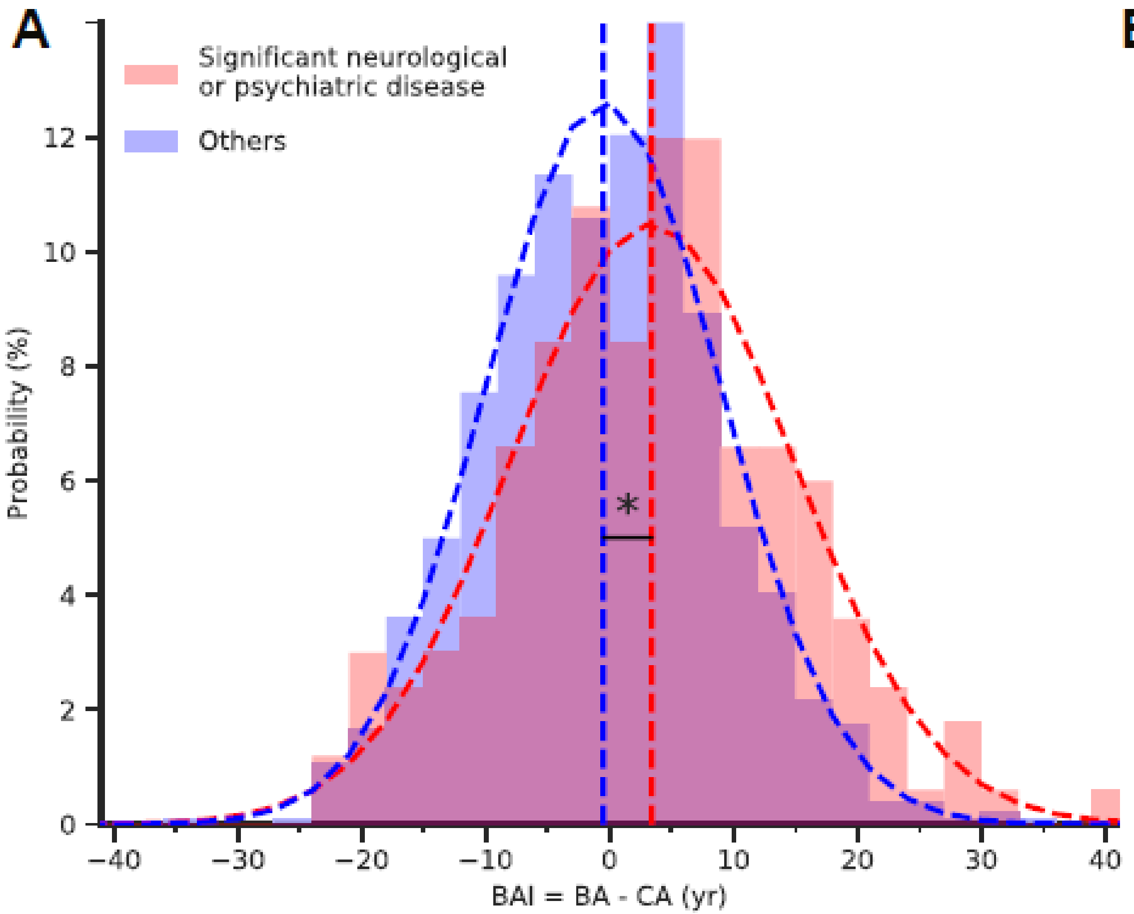


Sun et al. Brain age from EEG of sleep. Neurobiology of Aging 2019;74:112-120

Nygate YN et al. EEG-Based Deep Neural Network Model for Brain Age Prediction and Its Association with Patient Health Conditions. *SLEEP* 2021;44:A214

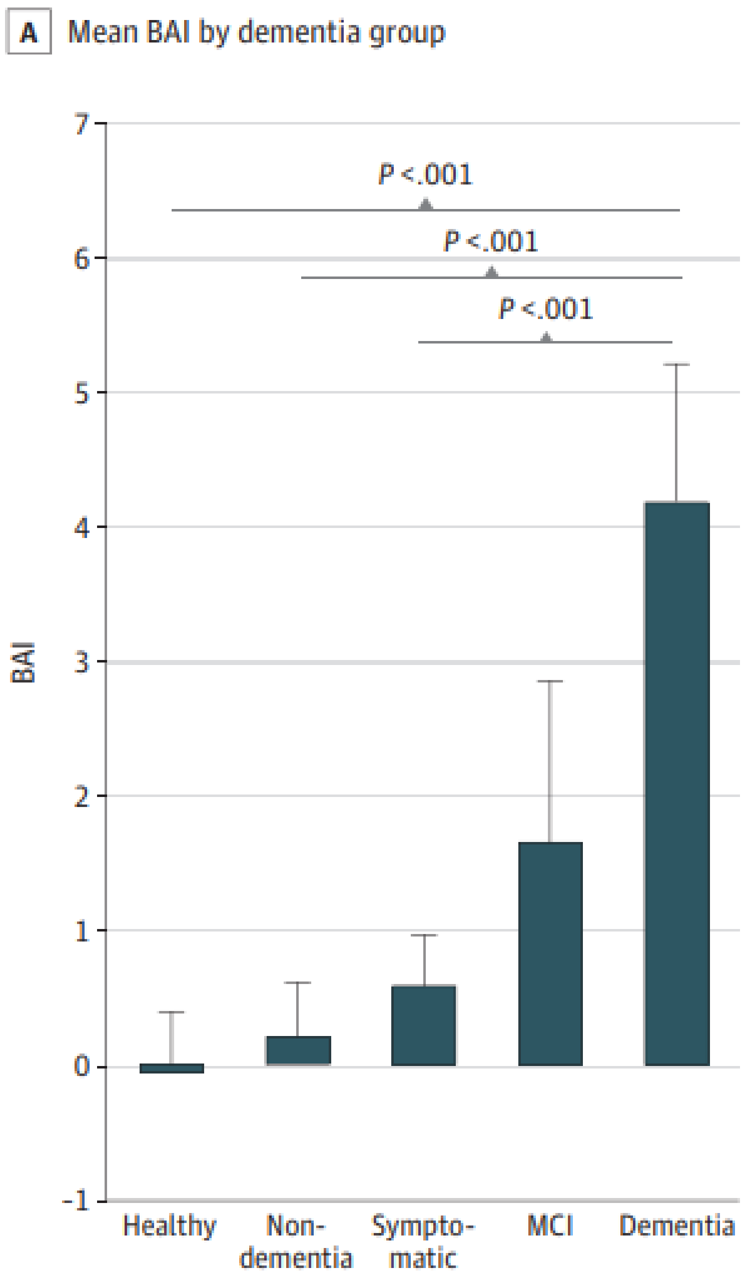


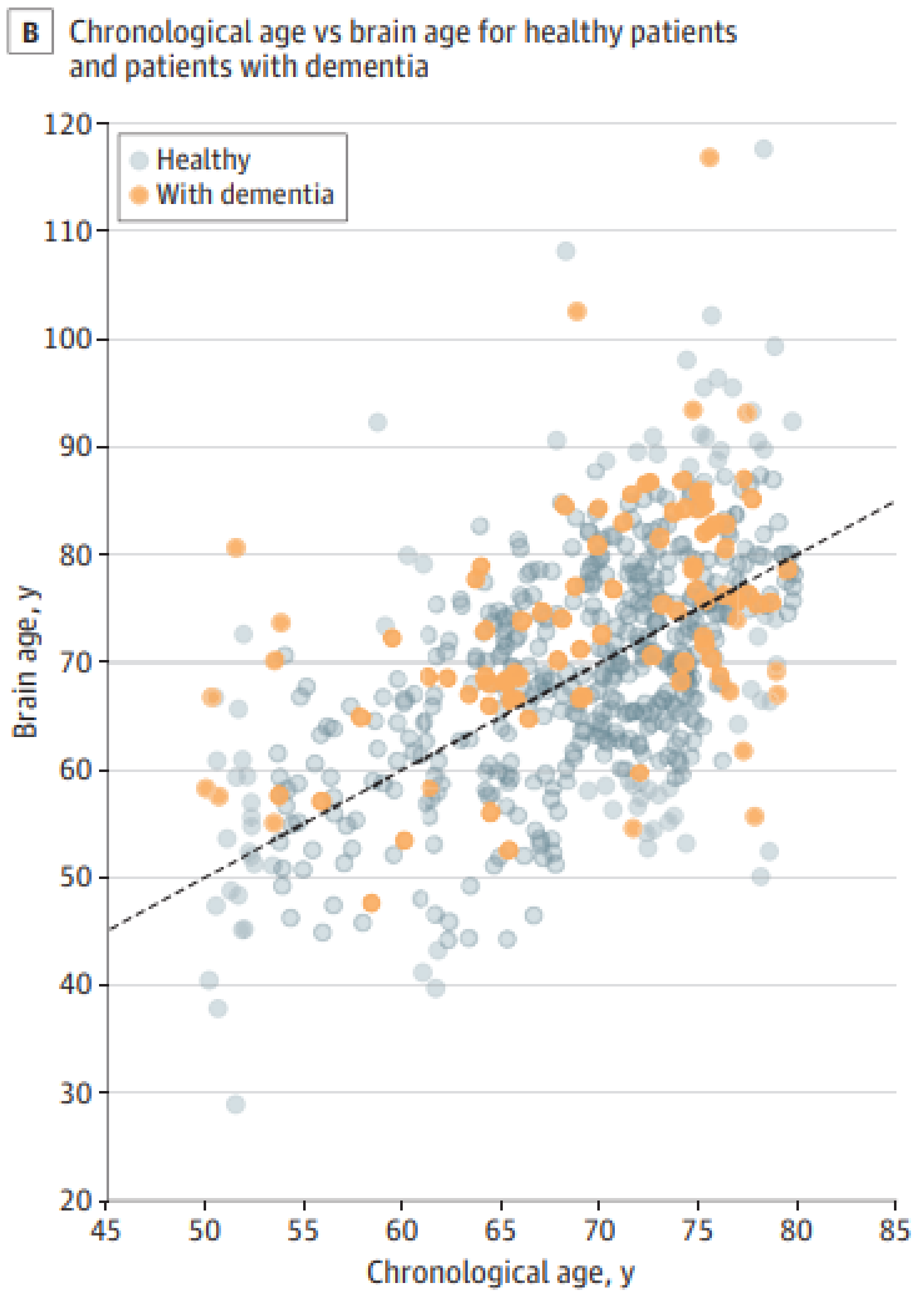




- Gender
- ESS ≥ 16
- BMI
- Diabetes
- HTN
- Depression
- Memory/Concentration
- Sleep Efficiency

Sun et al. Brain age from EEG of sleep. Neurobiology of Aging 2019;74:112-120
Nygate YN, Rusk S, Fernandez CR, Glattard N, Arguelles J, Shi JM, Hwang D, Watson NF. EEG-Based Deep Neural Network Model for Brain Age Prediction and Its Association with Patient Health Conditions. *SLEEP* 2021;44:A214

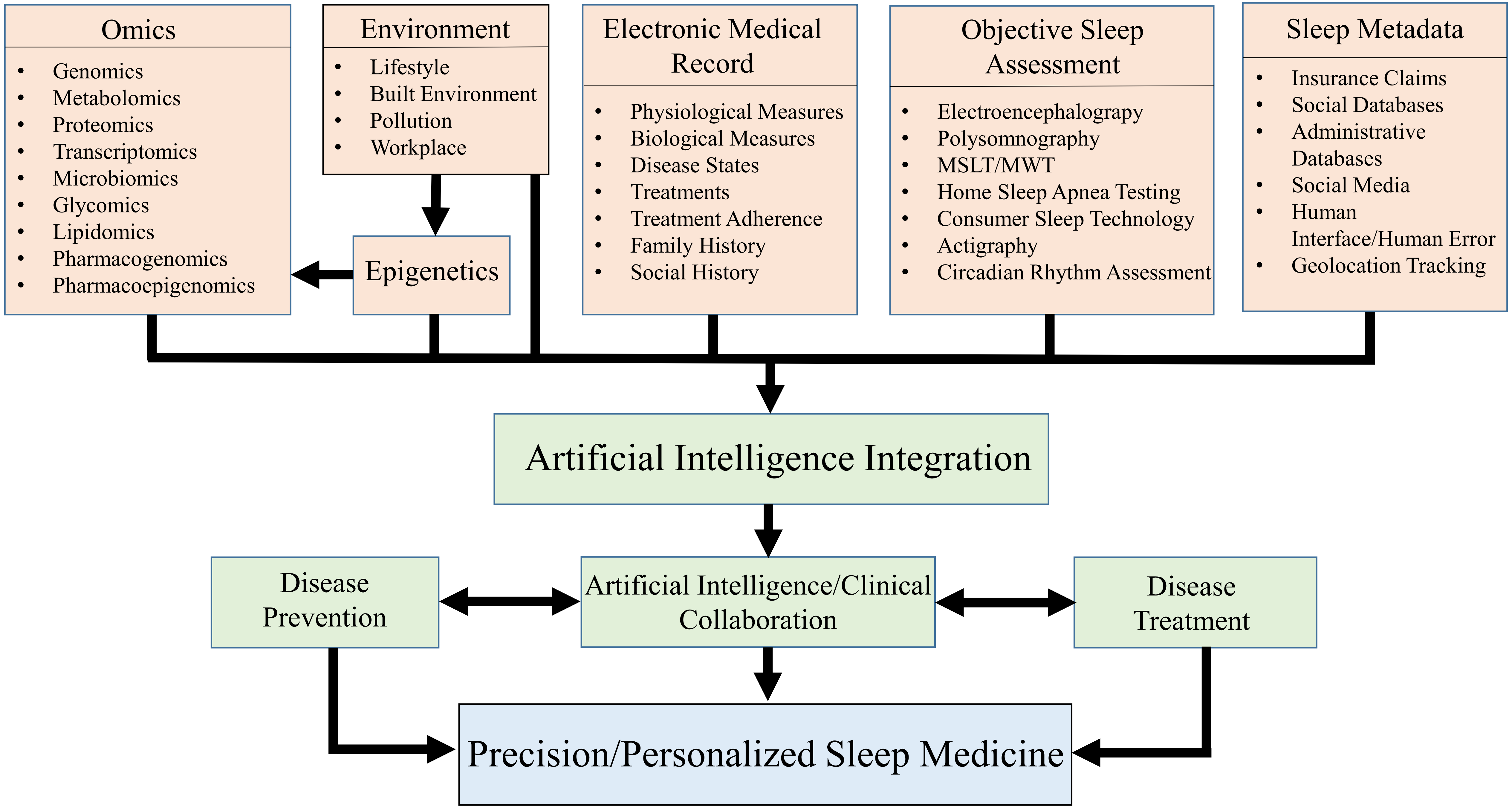




Ye et al. Association of Sleep EEG-Based Brain Age Index with Dementia. AMA Network Open. 2020;3(9):e2017357

Where we would like to go…


Questions?


Omics
Genomics
Metabolomics
Proteomics
Transcriptomics
Microbiomics
Glycomics
Lipidomics
Pharmacogenomics
Pharmacoepigenomics
Environment
Lifestyle
Built Environment
Pollution
Workplace
Epigenetics
Electronic Medical Record
Physiological Measures
Biological Measures
Disease States
Treatments
Treatment Adherence
Family History
Social History
Objective Sleep Assessment
Electroencephalograpy
Polysomnography
MSLT/MWT
Home Sleep Apnea Testing
Consumer Sleep Technology
Actigraphy
Circadian Rhythm Assessment
Sleep Metadata
Insurance Claims
Social Databases
Administrative Databases
Social Media
Human Interface/Human Error
Geolocation Tracking
Artificial Intelligence Integration
Disease Prevention
Artificial Intelligence/Clinical Collaboration
Disease Treatment
Precision/Personalized Sleep Medicine

Does Good Sleep Produce More Happiness?

- Sleep data from the SleepScore Mobile Application
- The data set included 1,234,462 nights (72,819 users, aged 18-85, mean age: 51.03 +/- 15.17 years, 51.04% female, from 26 countries). All nights were recorded in 2019
- In this analysis we only included countries for which there were >1000 subjects
- Happiness Index data were taken from the World Happiness Report 2020. This Index is calculated based on individuals' own assessment of their wellbeing in nationally representative surveys, using a 11-point Cantril scale
- Linear mixed effect modelling was used for analysis

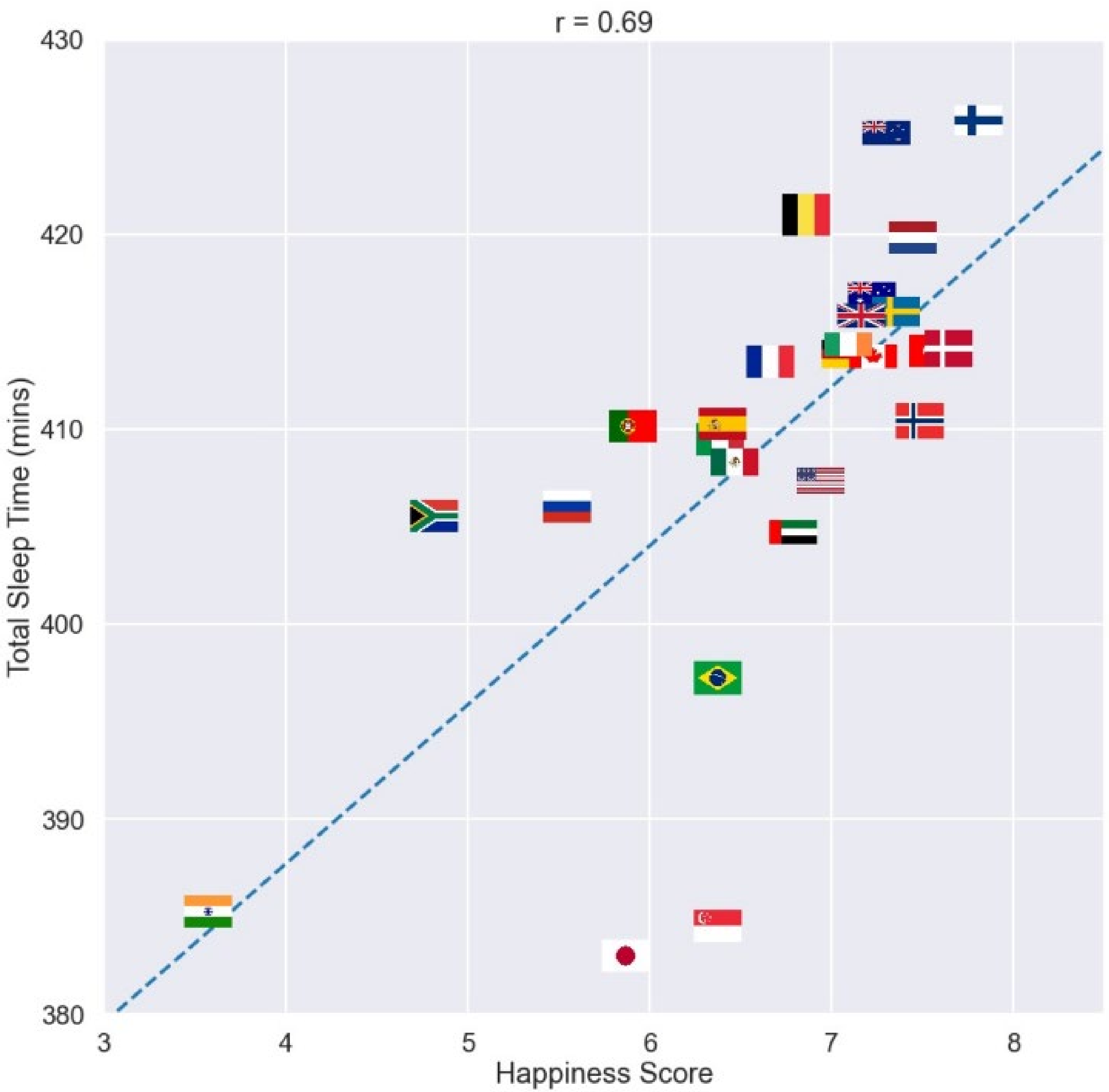
Gahan L, Ruder MJ, O'Mullane B, Raymann R. The Global Connection Between Happiness and a Good Night's Sleep: A Big Data Analysis. 2020 Journal of Sleep Research;29:393

- A significant positive relationship between a country's Happiness Index and the Total Sleep Time (TST) of users who tracked in the respective nations was found ($p<0.001$, $R=0.69$)

- A 1-point increase in Happiness Score was shown to be associated with an extra 8.16 minutes of sleep

- A significant positive relationship between Time in Bed (TIB) and Happiness Index was also revealed ($p<0.001$, $R=0.68$)

- A 1-point increase in Happiness Score was shown to be associated with an extra 9.48 minutes of TIB



CASE REPORTS

Orthosomnia: Are Some Patients Taking the Quantified Self Too Far?

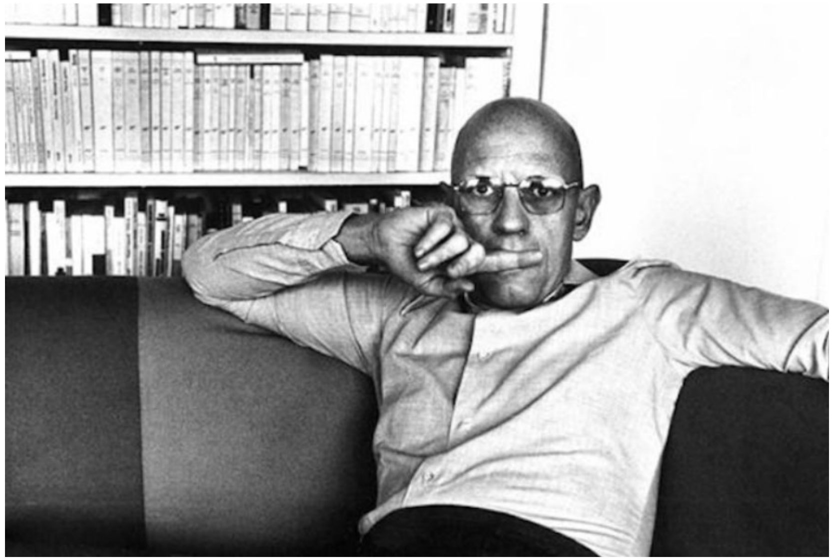
Kelly Glazer Baron, PhD, MPH[1]; Sabra Abbott, MD, PhD[2]; Nancy Jao, MS[2]; Natalie Manalo, MD[2]; Rebecca Mullen, MS[2]

[1]*Rush University Medical School, Chicago IL;* [2]*Feinberg School of Medicine, Northwestern University, Chicago, IL*

The use of wearable sleep tracking devices is rapidly expanding and provides an opportunity to engage individuals in monitoring of their sleep patterns. However, there are a growing number of patients who are seeking treatment for self-diagnosed sleep disturbances such as insufficient sleep duration and insomnia due to periods of light or restless sleep observed on their sleep tracker data. The patients' inferred correlation between sleep tracker data and daytime fatigue may become a perfectionistic quest for the ideal sleep in order to optimize daytime function. To the patients, sleep tracker data often feels more consistent with their experience of sleep than validated techniques, such as polysomnography or actigraphy. The challenge for clinicians is balancing educating patients on the validity of these devices with patients' enthusiasm for objective data. Incorporating the use of sleep trackers into cognitive behavioral therapy for insomnia will be important as use of these devices is rapidly expanding among our patient population.

Keywords: insomnia, technology, cognitive behavioral therapy

Citation: Baron KG, Abbott S, Jao N, Manalo N, Mullen R. Orthosomnia: are some patients taking the quantified self too far? *J Clin Sleep Med.* 2017;13(2):351–354.



On Foucault and Panopticism Today – Pharos. (pharosmagazine.org)