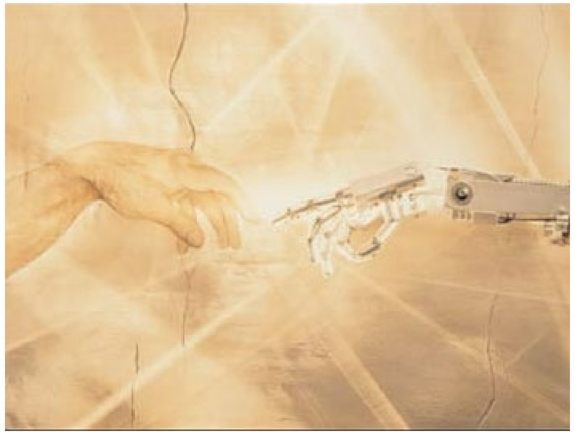
Maha Alattar, MD
Associate Professor of Neurology
Interim Division Chief
VCU Health Center for Sleep Medicine

Virginia Commonwealth University

Artificial Intelligence in Sleep Medicine



Disclosure

- CO-PI. Sleep for Stroke Management and Recovery Trial (Sleep SMART).
- Sub-PI. A Phase 3, Multicenter, Randomized, Double-blind, Placebo-controlled Study to Evaluate the Efficacy and Safety of Suvorexant for the Treatment of Insomnia in Participants with Opioid Use Disorder.
- Member: ABIM, Sleep Medicine Testing Committee
- Artificial intelligence was not used in the creation of this PP

Outline

- Artificial Intelligence (AI): Wish List in sleep medicine
- Definition of AI
- History of AI in medicine
- Data: Wearables, polysomnograms, EKGs, EEGs, MRI
- OSA. PLMS.RBD. Insomnia. Narcolepsy
- Challenges
- The American Academy of Sleep Medicine’s Statement
- VII. Closing remarks

Netflix

Recommendations

Netflix
220 million viewers

- Tracks what you watch----How long---Finished it/not
- Uses information from your past: Shows you have watched (genre, actors, theme), ratings you gave, movies other users with similar preferences watched

- Relies on AI and machine learning. 2006. Algorithms. Spots patterns, trends. Challenging for humans to detect.

- THEN:
  - Match your taste
  - **Customize, individualize service**
  - Makes Tailored Recommendations JUST FOR ***ME***

- Ref: Netflix Recommendations: How Netflix Uses AI, Data Science, And ML. By Simplilearn. Last updated on Sep 24, 2024

- **Screen**
- **Diagnose**
- **Sleep staging, leg movements, and respiratory events**: Automation
- **Insomnia and narcolepsy subtyping**
- **Circadian rhythm:** Gene expression
- **Phenotyping:** obstructive sleep apnea (OSA)
- **Sleep and wake tracking** and **feedback**
- **Risk assessment**
- **Treatment tracking**
- **PAP adherence**
- **Treatment selection**

Current Challenges
Artificial Intelligence can step in to help

- Limitation of the human eye
- Labor intensive-scoring
- Patient access issues:
  - In spite of the growing number of accredited sleep centers, there remains **a significant gap in healthcare access to sleep medicine in the United States,** where the ratio of people to sleep specialists is over 43,000

Watson, N.F.; Rosen, I.M.; Chervin, R.D. The Past Is Prologue: The Future of Sleep Medicine. J. Clin. Sleep Med. 2017

What is Artificial Intelligence?

- Development of computer algorithms, programs, and software systems capable of learning and adapting
- Purpose: Improve performance over time
- Gains experience
- Intelligent behavior

Definitions

NF Watson. Sleep Medicine Reviews. 2021

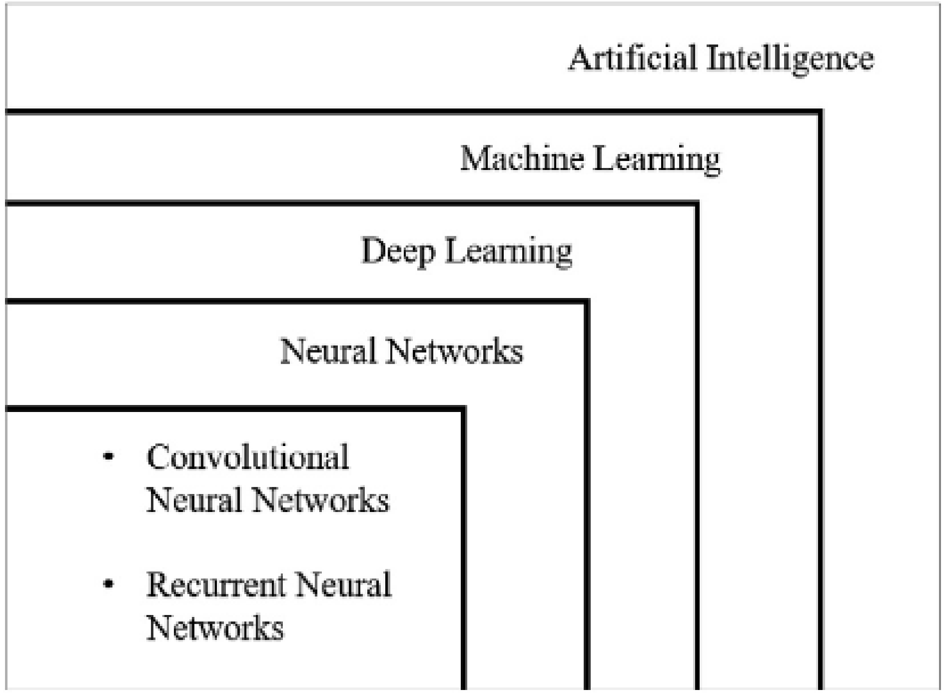


Fig. 2. The relationships of various aspects of artificial intelligence to one another. Artificial intelligence is the most general term encompassing the totality of the field and convolutional neural networks/recurrent neural networks are the most specific.

Deep Neural Network

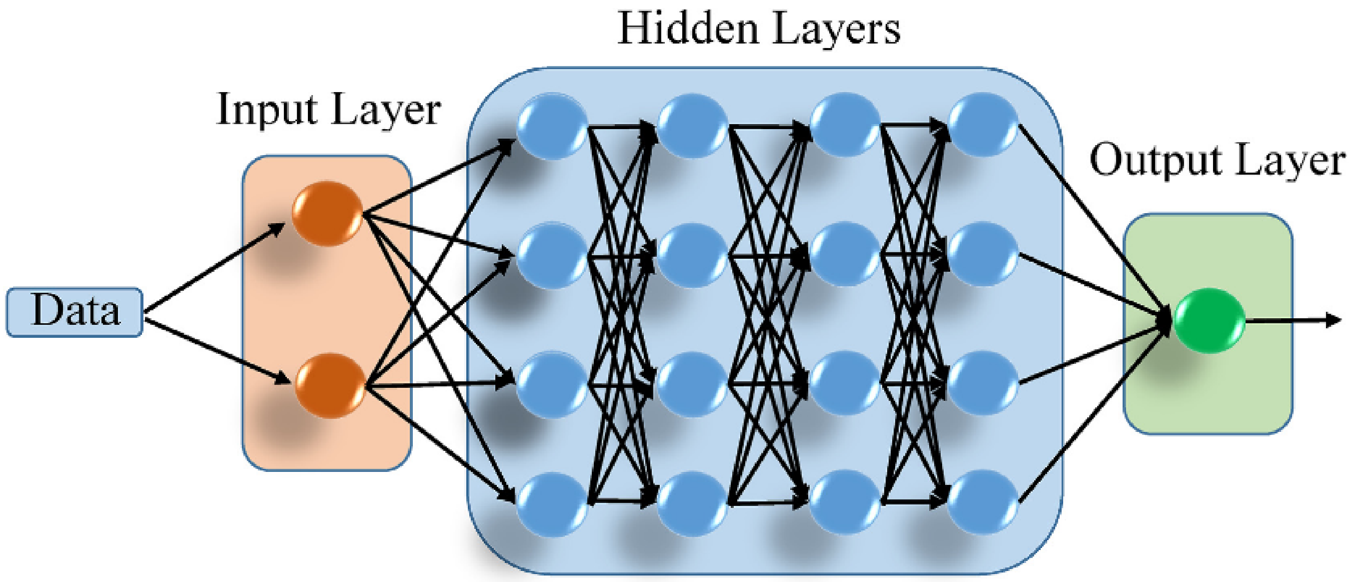
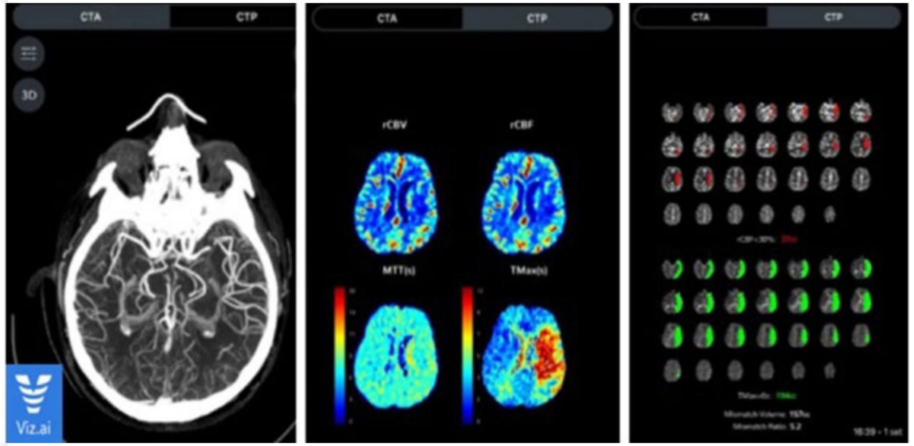
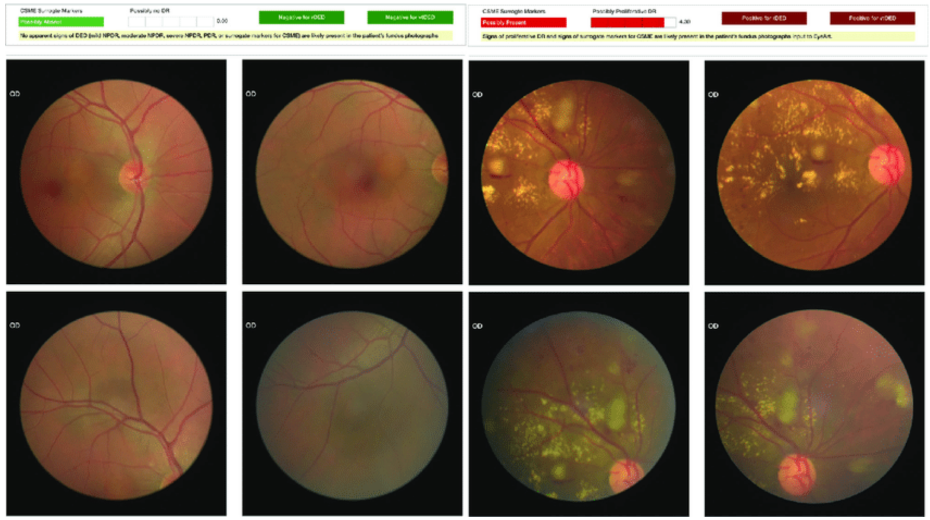


Fig. 1. A simplified view of a deep neural network with an input layer (supervised or unsupervised), hidden layers that can number in the thousands, and a defined output layer. Each node in a layer, represented by the blue dots above (e.g., "neurons") have vertex connections between them (e.g., axonal and dendritic connections). The deep neural network is autodidactic because the final number of layers is not designed by humans, but rather determined by the data itself. (For interpretation of the references to color in this figure legend, the reader is referred to the Web version of this article.)

Precedence

- Neuro-Radiology: Detect a clot. Vis I
- Ophthalmology: Promising use of AI is in field of retinal diseases. "Deep learning" AI system taught itself to accurately detect diabetic retinopathy and diabetic macular edema in fundus photographs
- Oncology: Watson
- Dermatology: classifying skin lesion images into different skin cancer





Artificial intelligence applied in acute ischemic stroke: from child to elderly La Radiologia Medica Oct 2023

Fundus photograph-based deep learning algorithms in detecting diabetic retinopathy. Eye. November 2018

Cluster Analysis

- Used in machine learning to optimize the task of grouping together data
- Seeks to identify a configuration of clusters
- Can identify distinct endotypes of OSA
  - OSA with/out disturbed sleep
  - OSA with/out hypersomnia
  - OSA in different ethnic groups, sex, age
  - Cluster analysis identified three clinical phenotypes of ischemic stroke patients with OSA

Wearable technology uses

Health and fitness
Fitness monitoring, caloric intake, physiological monitoring

Sports
Performance monitoring, body cooling and heating, outdoor tracking and navigation

Entertainment and gaming
Interactive gaming, virtual traveling, AR, video streaming

Healthcare and medical
Vital signs monitoring, heart rate fluctuations, chronic disease management

Fashion
Intelligent clothing, eye-catching fashion with built-in technology for fitness or health monitoring

LEFT: VM/GETTY IMAGES, REKLAMLAR/GETTY IMAGES, TIM ROBBERTS/GETTY IMAGES, DZINA_MROWKA/GETTY IMAGES, YURI_ARCURS/GETTY IMAGES

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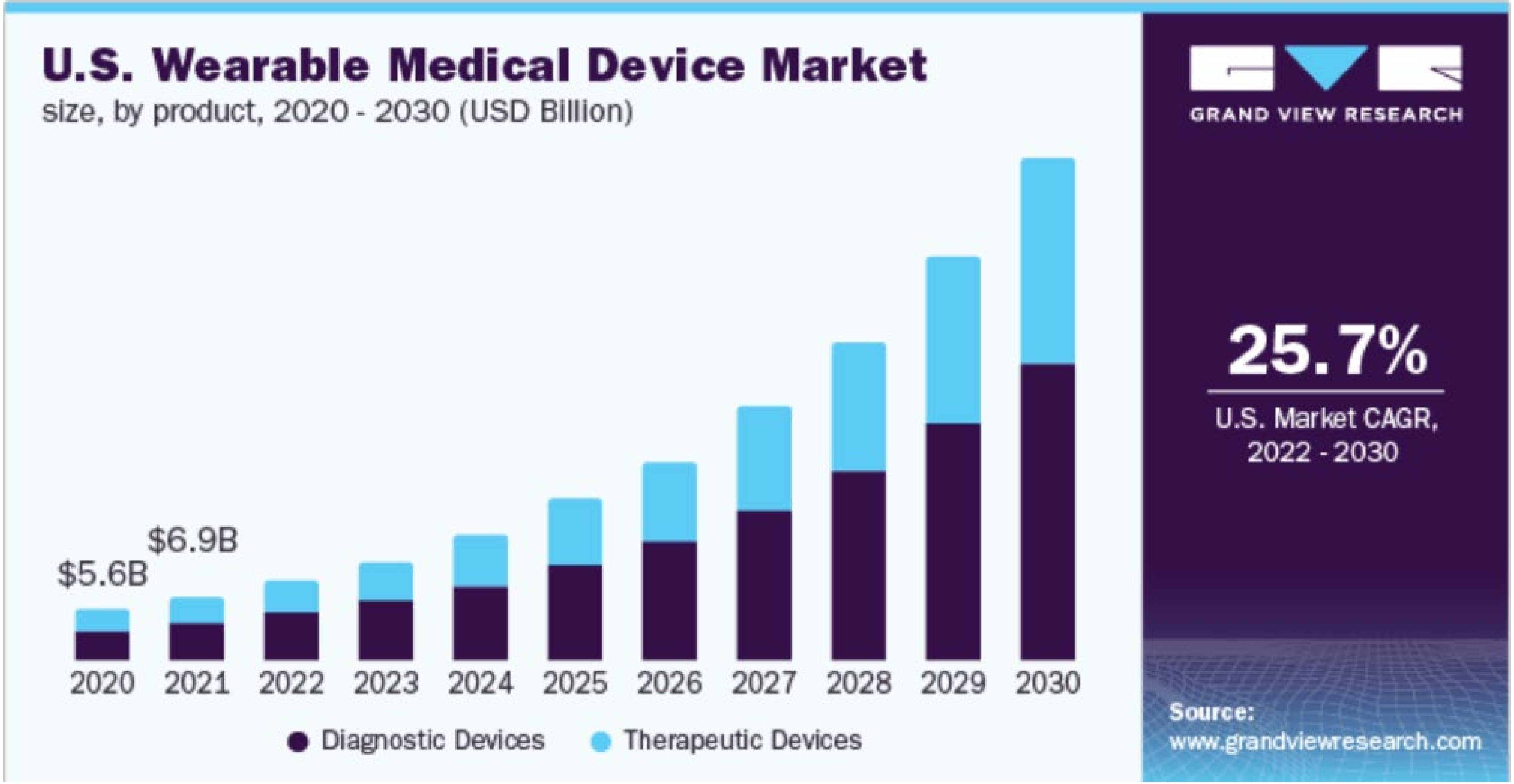


U.S. Wearable Medical Device Market
size, by product, 2020 - 2030 (USD Billion)
$5.6B
$6.9B
2020
2021
2022
2023
2024
2025
2026
2027
2028
2029
2030
Diagnostic Devices
Therapeutic Devices
GRAND VIEW RESEARCH
25.7%
U.S. Market CAGR, 2022 - 2030
Source: www.grandviewresearch.com

Consumer sleep technology (CST)

Smartphones, sleep apps, in-bed sensors as well as devises that are designed as therapeutic or sleep enhancing including bio-feedback sensors and neurostimulators

Track basic physiological functions including motion, heart rate, skin conductance, and temperature and extrapolate sleep and wake data

Advantages: Low cost, accessible for healthcare providers. User friendly for users. Cloud-based

Disadvantages: Not validated against evidence-based interpretations, assessment and management. Lack of consensus among clinicians and researchers. Various apps, various algorithms-lack of consistency for standardized instrumentation

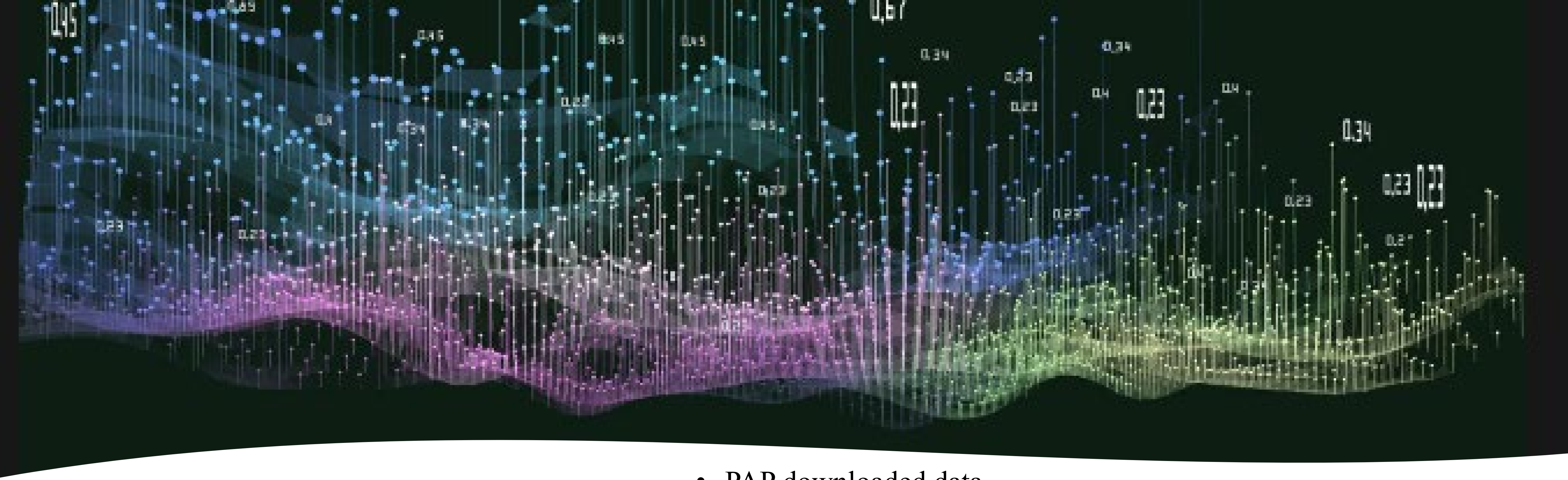
MUSE S (Gen 2): The Brain Sensing...

The Software Precertification (Pre-Cert)

- Launched in 2017 and completed in September 2022
- **Regulatory oversight** of medical device software and to monitor real-world performance of products that is being developed by organizations around the world when they reach US market
- FDA does *not* regulate consumer wearable devises but merely provide information

- (https://www.fda.gov/medical-devices/digital-health-center-excellence/digital-health-software-precertification-pre-cert-pilot-program).

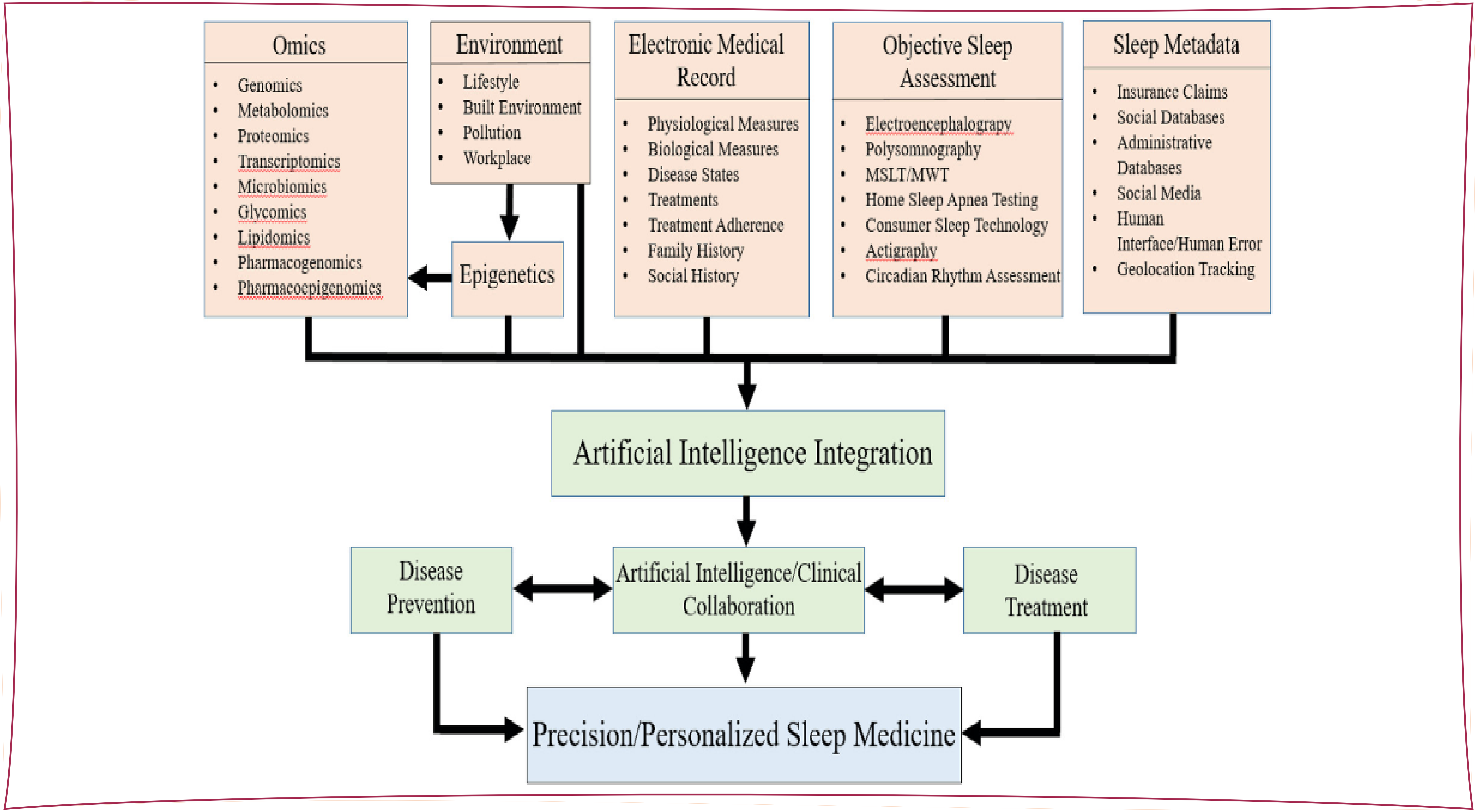
Harnessing Data for Sleep Medicine



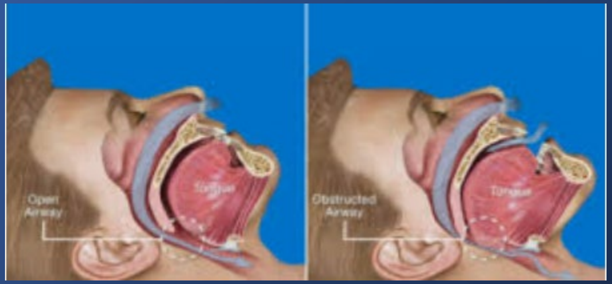
Data already in Use

- PAP downloaded data
- Polysomnograms
- Mean sleep latency tests
- Actigraphy
- Coupled with patient’s demographics and medical history
- EKG: >100 million performed in US annually
- EEG: 25 million performed in US annually
- Others…wearables?

- Drazen, E et al. A. Survey of computer-assisted electrocardiography in the United States. *J. Electrocardiol.* **1988.**



NF Watson. Sleep Medicine Reviews. 2021



Sleep Disordered Breathing

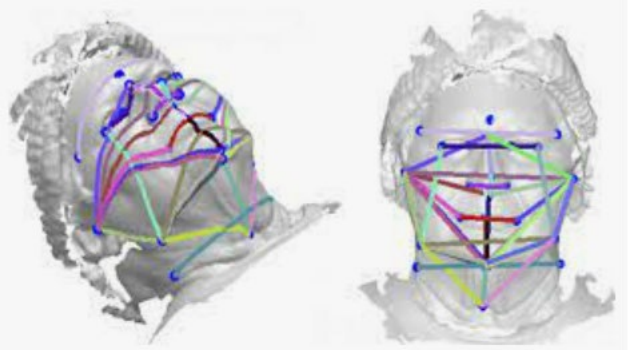
- AHIs < 5 + clinical symptoms of sleep apnea= Dilemma

- Subtypes of OSA
  - Upper airway resistance syndrome
  - Primary snoring
  - ? others

- Machine learning:
  - Identifies subtypes, endotype, genetic expression
  - Tailor treatment

- Eckert DJ Am J Respi Crit Care Med 2013 to discuss OSA traits. Sleep disordered breathing subtypes remain unknown

AI and **Endotyping** personalized, precision medicine



Craniofacial anatomy, oropharyngeal adipose tissue deposition, airway dilatation reflexes and muscle recruitment, arousal threshold, chemotactic breathing stability (loop gain), fluid distribution from upright to supine sleep

Severity and *subtype*

Differential response to therapy

PAP, oral appliance, surgical, other treatments

Applied: RLS, circadian sleep disorders, narcolepsy, insomnia

CHEST

Diagnostic Performance of Machine Learning-Derived OSA Prediction Tools in Large Clinical and Community-Based Samples

INTERPRETATION: OSA prediction tools using machine learning without patient-reported symptoms provide better diagnostic performance than logistic regression. In clinical and community-based samples, the symptomless ANN tool has diagnostic performance similar to that of a widely used prediction tool that includes patient symptoms. Machine learning-derived algorithms may have utility for widespread identification of OSA.

CHEST 2022; 161(3):807-817

Take-home Points

Research Question: What is the diagnostic performance of machine learning-derived OSA prediction tools using readily available data without patient responses to questionnaires, and how do they compare to the STOP-BANG tool in clinical and community-based samples?

Results: OSA prediction tools using machine learning without patient-reported symptoms provide better diagnostic performance than the LOG model. In clinical and community-based samples, the symptomless ANN tool has similar diagnostic performance to the STOP-BANG questionnaire, a widely used prediction tool that includes patient symptoms.

Interpretation: Machine learning-derived algorithms may have utility for a more widespread identification of OSA.

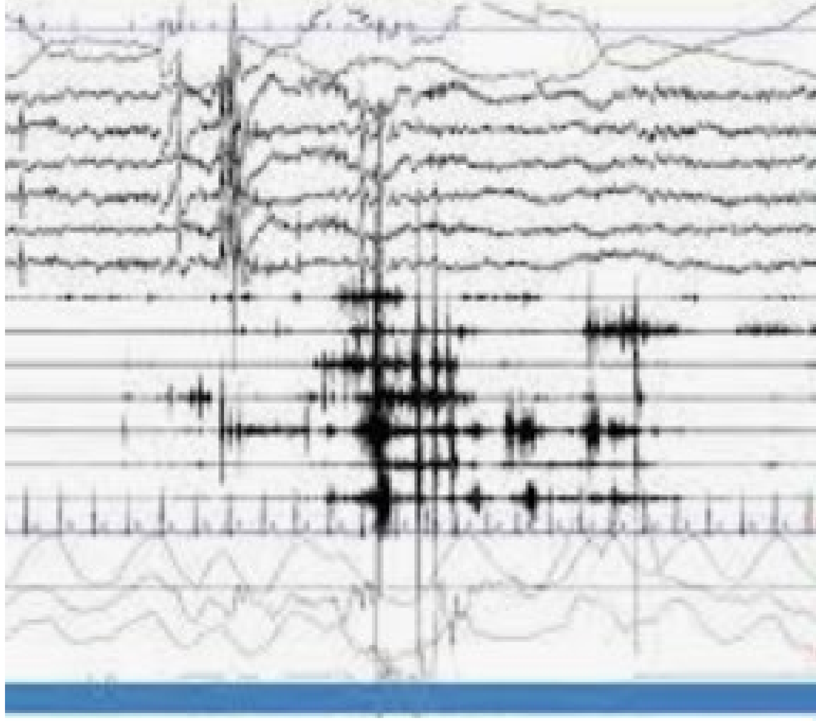
TABLE 2] Demographic Characteristics of Subjects in the Prospective Datasets Used for Machine Learning Model Testing and Comparison With STOP-BANG

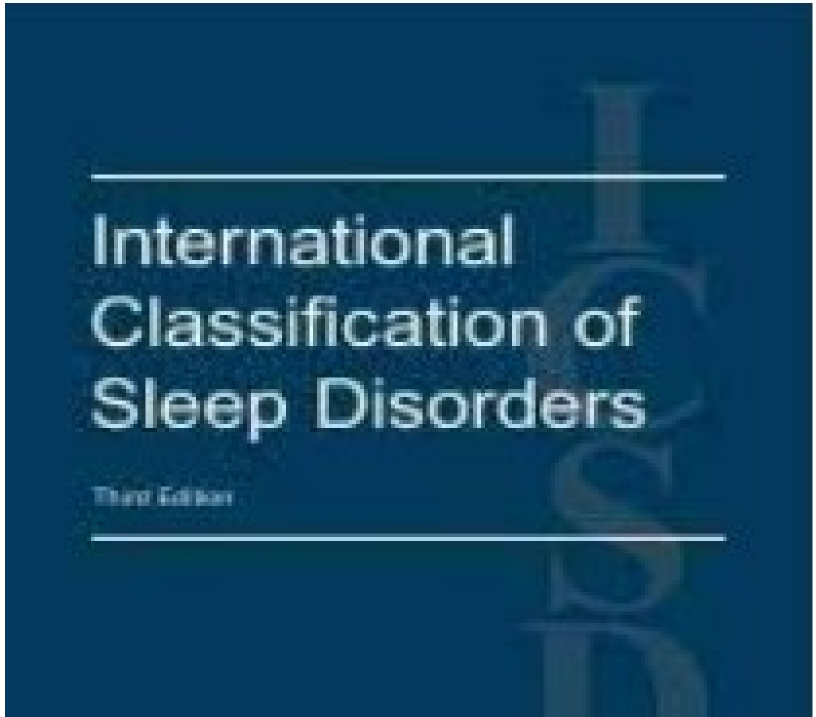
Variable	Prospective Dataset: SAGIC	Prospective Dataset: SHHS	*P* Value[a]
No.	1,613	5,599	
Age, mean ± SD, y	50.1 ± 14.1	63.3 ± 11.2	< .001
BMI, mean ± SD, kg/m^2	30.9 ± 8.1	28.2 ± 5.1	< .001
Male sex	1,033 (64.0%)	2,673 (47.7%)	< .001
Race			
Caucasian	730 (45.3%)	4,783 (85.4%)	< .001
African American	87 (5.4%)	454 (8.1%)	< .001
Other	100 (6.2%)	362 (6.5%)	< .001
Asian	693 (43.1%)	NA[b]	...
AHI, mean ± SD, events/h	27.7 ± 28.5	10.2 ± 13.6	< .001
OSA prevalence AHI ≥ 15 events/h	53.5% (n = 863)	21.2% (n = 1,189)	< .001

AHI = apnea-hypopnea index; SAGIC = Sleep Apnea Global Interdisciplinary Consortium.
[a]*P* value from Student *t* test (for continuous data), two-proportion *z* test (for categorical data), or a χ^2 test (race).
[b]Not applicable (NA). Small proportion of Asian subjects automatically classified as Other in the Sleep Heart Health Study (SHHS) to avoid identifiable information.

REM Sleep Behavioral Disorder

- Interpretation is a challenge
- PSG for detecting tonic RWA for the evaluation of RBD: "*Any (tonic/phasic) chin EMG activity combined with bilateral phasic activity of the flexor digitorum superficialis muscles in **> 27%** of REM sleep (scored in 30-second epochs) reliably distinguishes RBD patients from controls.*"
- Safety issues for patients and bed partner
- Therapeutics





REM Sleep Behavioral Disorder

Article

Assessing REM Sleep Behaviour Disorder: From Machine Learning Classification to the Definition of a Continuous Dissociation Index

Irene Rechichi [1,*], Antonella Iadarola [2], Maurizio Zibetti [3], Alessandro Cicolin [2,*] and Gabriella Olmo [1]

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2 Sleep Disorders Center, Department of Neuroscience, University of Turin, 10126 Turin, Italy; antonella.iadarola@unito.it
3 Department of Neuroscience, University of Turin, 10126 Turin, Italy; maurizio.zibetti@unito.it
* Correspondence: irene.rechichi@polito.it (I.R.); alessandro.cicolin@unito.it (A.C.)

Abstract: Objectives: Rapid Eye Movement Sleep Behaviour Disorder (RBD) is regarded as a prodrome of neurodegeneration, with a high conversion rate to α–synucleinopathies such as Parkinson's Disease (PD). The clinical diagnosis of RBD co–exists with evidence of REM Sleep Without Atonia (RSWA), a parasomnia that features loss of physiological muscular atonia during REM sleep. The objectives of this study are to implement an automatic detection of RSWA from polysomnographic traces, and to propose a continuous index (the Dissociation Index) to assess the level of dissociation between REM sleep stage and atonia. This is performed using Euclidean distance in proper vector spaces.

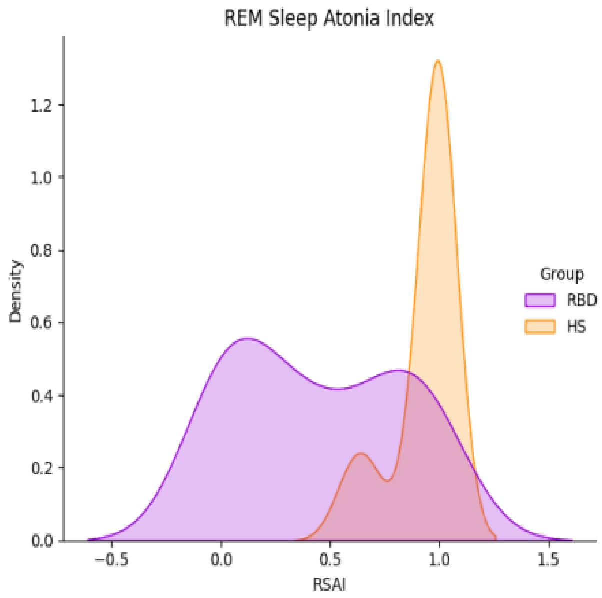
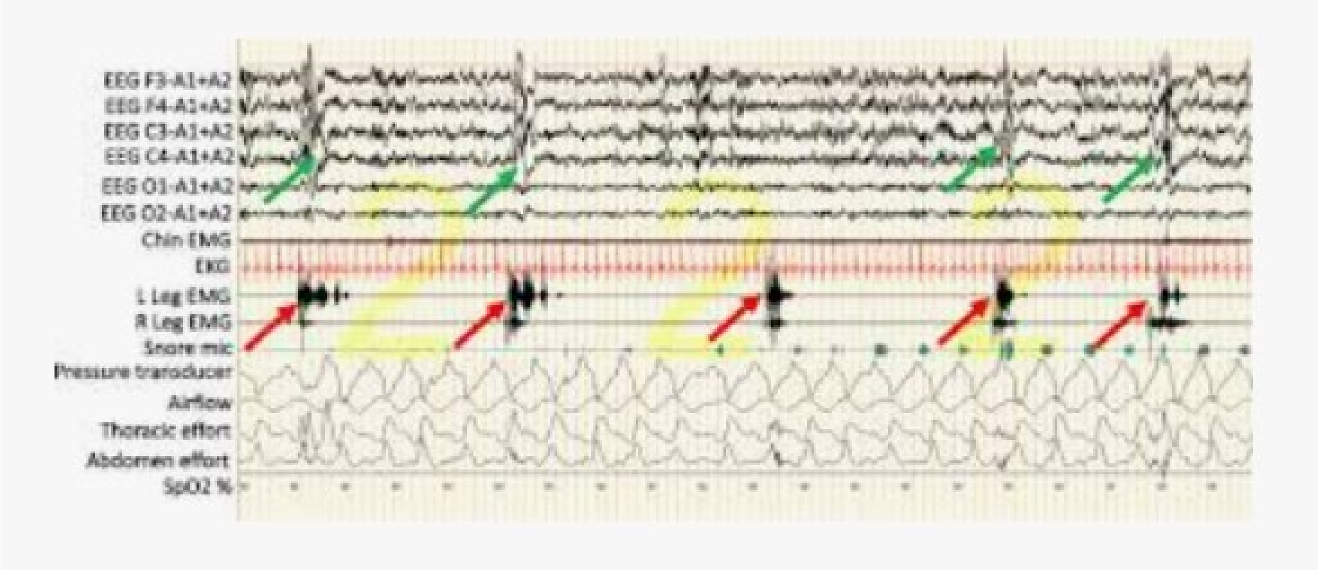


Figure 5. REM Sleep Atonia Index (RAI) Kernel Density Distribution in HS (orange) and RBD subjects (purple), in the CAP Sleep Database. RBD subjects present with a wider RAI distribution.

Periodic Limb Movements of Sleep



- Challenges: Labor intensive scoring
- ICSDIII definition: AT EMG shows repetitive contractions, each lasting 0.5 to 10 seconds. There must be at least 5 seconds and no more than 90 seconds between limb movements. There must be at least 4 limb movements in a series. If limb movements occur in both legs, they are scored as a single movement unless they are separated by at least 5 seconds
- Phenotyping with/out RLS
- Separate or part of OSA

Periodic Limb Movements of Sleep

Computer-Assisted Detection of Nocturnal Leg Motor Activity in Patients with Restless Legs Syndrome and Periodic Leg Movements During Sleep

Raffaele Ferri, MD[1]; Marco Zucconi, MD[2]; Mauro Manconi, MD[2]; Oliviero Bruni, MD[3]; Silvia Miano, MD[1]; Giuseppe Plazzi, MD[4]; Luigi Ferini-Strambi, MD[2]

[1]Sleep Research Centre, Department of Neurology I.C., Oasi Institute (IRCCS), Troina, Italy; [2]Department of Neurology, Sleep Disorders Center, H San Raffaele Scientific Institute, Università Vita-Salute San Raffaele, Milan, Italy; [3]Centre for Pediatric Sleep Disorders, Department of Developmental Neurology and Psychiatry, University of Rome "La Sapienza", Rome, Italy; [4]Department of Neurological Sciences, University of Bologna, Bologna, Italy

Study Objectives: To assess the performance of a new method for automatic detection of periodic leg movements during sleep.
Methods: Leg movements during sleep were visually detected in the tibialis anterior muscles recordings of 15 patients with restless legs syndrome and 15 normal controls. Leg movements were detected automatically by means of a new computer method with which electromyogram signals are first digitally band-pass filtered and then rectified; subsequently, the detection of leg movements is performed by using 2 thresholds: one for the starting point and another to detect the end point of each leg movement. Sensitivity and false-positive rate were obtained; the American Sleep Disorders Association parameters were also computed, and the results analyzed by means of the Kendall *W* coefficient, the linear correlation coefficient and the Bland-Altman plots.
Setting: N/A.
Participants: Fifteen patients with restless legs syndrome and periodic leg movements and 15 controls.
Measurements and Results: High values of the Kendall *W* coefficient of concordance between automatic and visual analysis were found with values close to 1 and the linear correlation coefficient for leg movements index and total leg movements index was >0.950 (p<.000001). The Bland-Altman plots provided the limits of agreement between visual and computer detection, which were -9.01 and +9.89 for the periodic leg movement index. None of the normal controls was found to have periodic leg movement indexes >5 after automatic analysis.
Conclusions: Our method can be applied to the clinical evaluation of periodic leg movements during sleep, with some caution in patients with a low periodic leg movement indexes. Large-scale research application is possible and can be considered as reliable.
Keywords: Restless legs syndrome, periodic leg movements, sleep scoring, computer-assisted detection, visual detection
Citation: Ferri R; Zucconi M; Manconi M et al. Computer-assisted detection of nocturnal leg motor activity in patients with restless legs syndrome and periodic leg movements during sleep. *SLEEP* 2005;28(8):998-1004.

diagnostics

MDPI

Article

Deep Learning for Automatic Detection of Periodic Limb Movement Disorder Based on Electrocardiogram Signals

Erdenebayar Urtnasan [1,†], Jong-Uk Park [2,†], Jung-Hun Lee [3], Sang-Baek Koh [4] and Kyoung-Joung Lee [5,*]

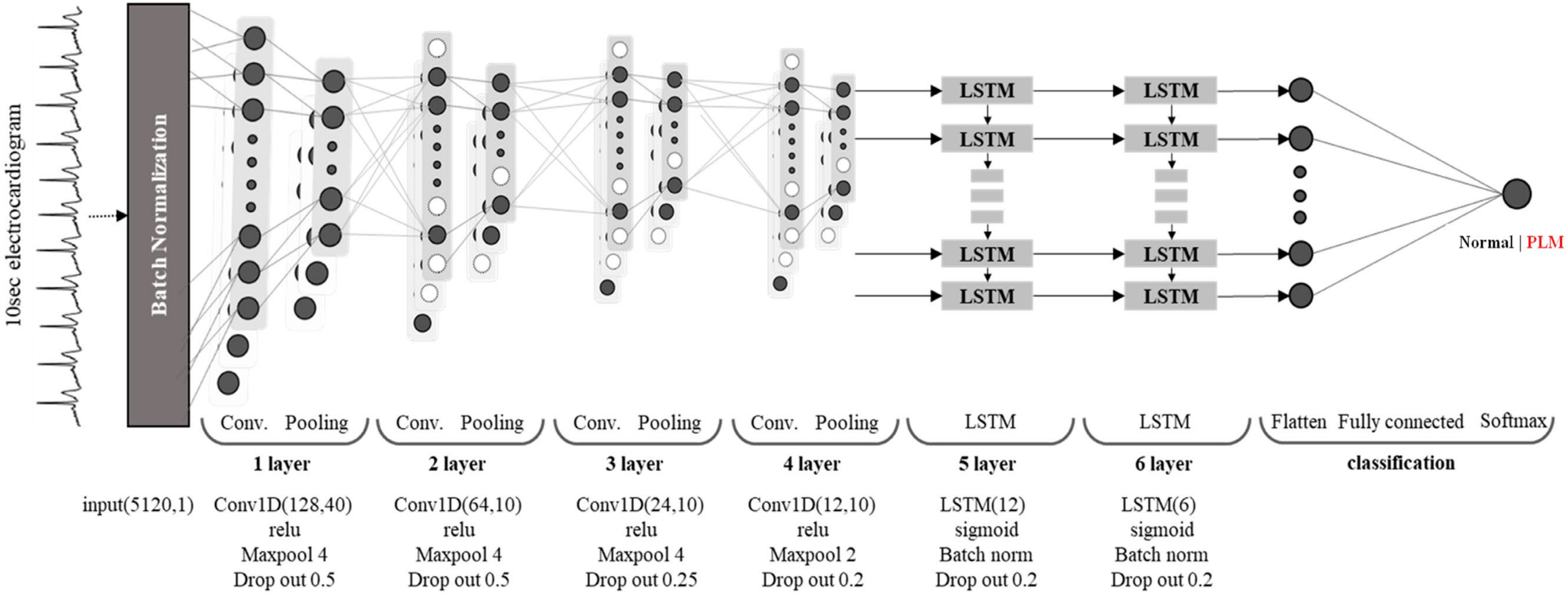


Table 3

The performance of the deepPLM model for the automatic detection of PLMS patients.

Datasets	Segment	Precision	Recall	F1-Score	Accuracy
Training set	Normal	0.94	0.97	0.96	0.89
	PLM	0.97	0.94	0.96	
Validation set	Normal	0.90	0.94	0.92	0.92
	PLM	0.94	0.90	0.92	
Test set	Normal	0.90	0.93	0.92	0.92
	PLM	0.93	0.90	0.92	

Insomnia

Deep Learning and Insomnia: Assisting Clinicians With Their Diagnosis

Mostafa Shahin, Beena Ahmed, Sana Tmar-Ben Hamida, Fathima Lamana Mulaffer, Martin Glos, Thomas Penzel

PMID: 28092583 DOI: 10.1109/JBHI.2017.2650199

Abstract

Effective sleep analysis is hampered by the lack of automated tools catering to disordered sleep patterns and cumbersome monitoring hardware. In this paper, we apply deep learning on a set of 57 EEG features extracted from a maximum of two EEG channels to accurately differentiate between patients with insomnia or controls with no sleep complaints. We investigated two different approaches to achieve this. The first approach used EEG data from the whole sleep recording irrespective of the sleep stage (stage-independent classification), while the second used only EEG data from insomnia-impacted specific sleep stages (stage-dependent classification). We trained and tested our system using both healthy and disordered sleep collected from 41 controls and 42 primary insomnia patients. When compared with manual assessments, an NREM + REM based classifier had an overall discrimination accuracy of 92% and 86% between two groups using both two and one EEG channels, respectively. These results demonstrate that deep learning can be used to assist in the diagnosis of sleep disorders such as insomnia.

TABLE II

INSOMNIA VERSUS CONTROL CLASSIFICATION PERFORMANCE SHOWING THE PRECISION AND RECALL OF EACH CLASS (P/R), OVERALL ACCURACY AND COHEN'S KAPPA (κ) FOR BOTH ONE AND TWO EEG CHANNELS

Stages	EEG channels	Manual staging				Automatic staging			
		CL (%) P/R	I (%) P/R	Acc (%)	κ	CL (%) P/R	I (%) P/R	Acc (%)	κ
All Stages	C3 + C4	92/89	90/92	90	0.81	–	–	–	–
NREM + REM	C3 + C4	94/89	90/95	**92**	**0.84**	94/89	90/95	**92**	**0.84**
NREM	C3 + C4	94/89	90/95	92	0.84	94/89	90/95	92	0.84
N2 + N3	C3 + C4	89/84	85/89	87	0.73	88/81	83/89	85	0.7
All Stages	C3	86/84	85/87	85	0.7	–	–	–	–
NREM + REM	C3	89/86	87/89	**88**	**0.75**	84/86	86/84	**86**	**0.71**
NREM	C3	86/84	85/87	85	0.7	84/84	84/84	84	0.67
N2 + N3	C3	84/86	86/84	85	0.71	84/86	86/84	85	0.71

- JBHI 2017 Nov;21(6):1546-1553.

Central Disorders of Hypersomnia

- Narcolepsy presents with unique challenge because excessive daytime sleepiness, its core feature, is also common in other sleep disorders, making it difficult to rely solely on this symptom for an accurate diagnosis
- Narcolepsy type 1 (narcolepsy with cataplexy) is characterized by low or absent cerebrospinal fluid (CSF) hypocretin levels, which serves as a reliable biomarker
- Narcolepsy type 2, have poor retest reliability with the MSLT
- Idiopathic Hypersomnia versus Narcolepsy
- PSG and MSLT is laborious

- Trotti, L.M. Twice Is Nice? Test-Retest Reliability of the Multiple Sleep Latency Test in the Central Disorders of Hypersomnolence. *J. Clin. Sleep Med.* **2020**, *16*, 17–18

Differentiation of central disorders of hypersomnolence with manual and artificial-intelligence-derived polysomnographic measures

FREE

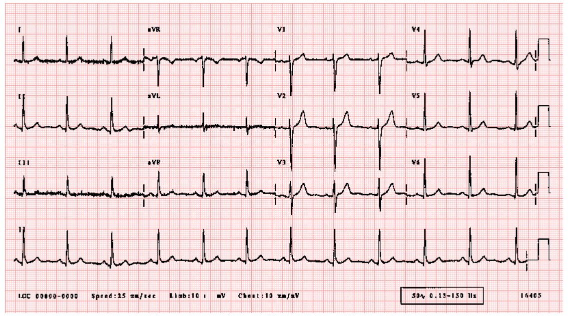
Matteo Cesari ✉, Kristin Egger, Ambra Stefani, Melanie Bergmann, Abubaker Ibrahim, Elisabeth Brandauer, Birgit Högl, Anna Heidbreder

Sleep, Volume 46, Issue 2, February 2023, zsac288,

Statement of Significance

This study is the first one investigating whether biomarkers describing night sleep instability and architecture derived from manual hypnogram and automatic hypnogram and hypnodensity graphs obtained with artificial intelligence algorithms can differentiate between distinct disorders of hypersomnolence. The results confirm the usefulness of scoring sleep with automatic artificial intelligence algorithms and to derive biomarkers from hypnodensity graphs. It was possible to identify narcolepsy type 1 from the other groups with high performances and also to distinguish narcolepsy type 2 from idiopathic hypersomnia with moderate performances. Future multicentre studies should confirm these exploratory findings on a larger cohort and should combine the identified biomarkers with outcomes from other tests to better improve differentiation of disorders of hypersomnolence.

- Polysomnograms might not be the only diagnostic tools to detect OSA or other sleep disorders



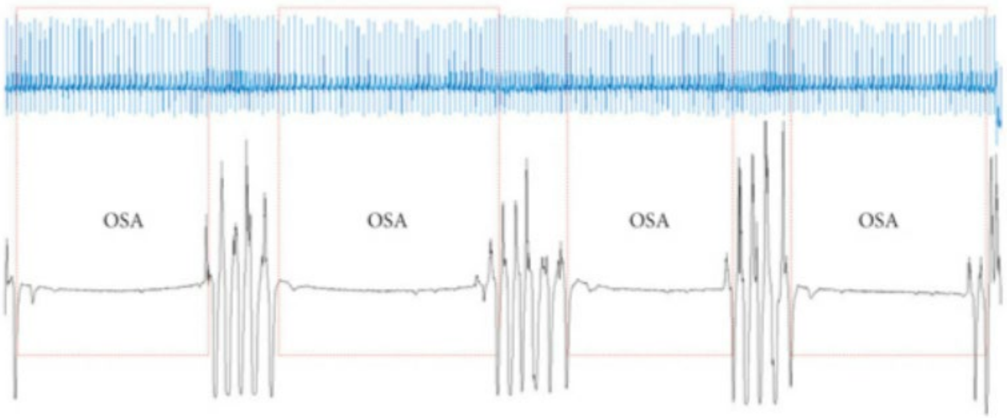


Figure 9

Journal of Medical Systems (2018) 42: 104
https://doi.org/10.1007/s10916-018-0963-0

MOBILE & WIRELESS HEALTH

CrossMark

Automated Detection of Obstructive Sleep Apnea Events from a Single-Lead Electrocardiogram Using a Convolutional Neural Network

Erdenebayar Urtnasan[1] · Jong-Uk Park[1] · Eun-Yeon Joo[2] · Kyoung-Joung Lee[1]

Received: 28 February 2018 / Accepted: 16 April 2018 / Published online: 23 April 2018
© Springer Science+Business Media, LLC, part of Springer Nature 2018

Abstract
In this study, we propose a method for the automated detection of obstructive sleep apnea (OSA) from a single-lead electrocardiogram (ECG) using a convolutional neural network (CNN). A CNN model was designed with six optimized convolution layers including activation, pooling, and dropout layers. One-dimensional (1D) convolution, rectified linear units (ReLU), and max pooling were applied to the convolution, activation, and pooling layers, respectively. For training and evaluation of the CNN model, a single-lead ECG dataset was collected from 82 subjects with OSA and was divided into training (including data from 63 patients with 34,281 events) and testing (including data from 19 patients with 8571 events) datasets. Using this CNN model, a precision of 0.99%, a recall of 0.99%, and an F_1-score of 0.99% were attained with the training dataset; these values were all 0.96% when the CNN was applied to the testing dataset. These results show that the proposed CNN model can be used to detect OSA accurately on the basis of a single-lead ECG. Ultimately, this CNN model may be used as a screening tool for those suspected to suffer from OSA.

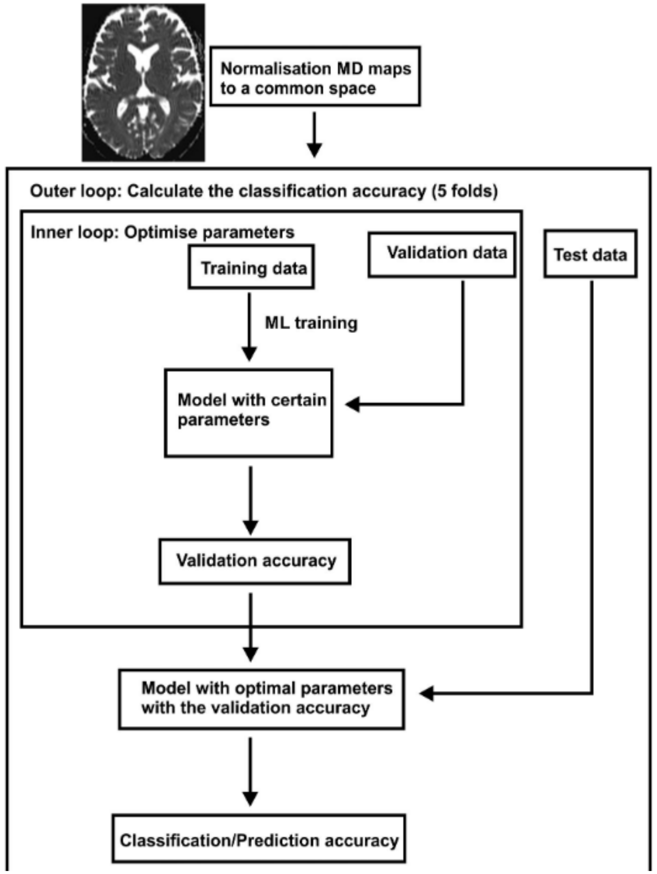


FIGURE 1 Steps for machine learning (ML) models for training, cross-validation, and testing

Machine learning approach for obstructive sleep apnea screening using brain diffusion tensor imaging

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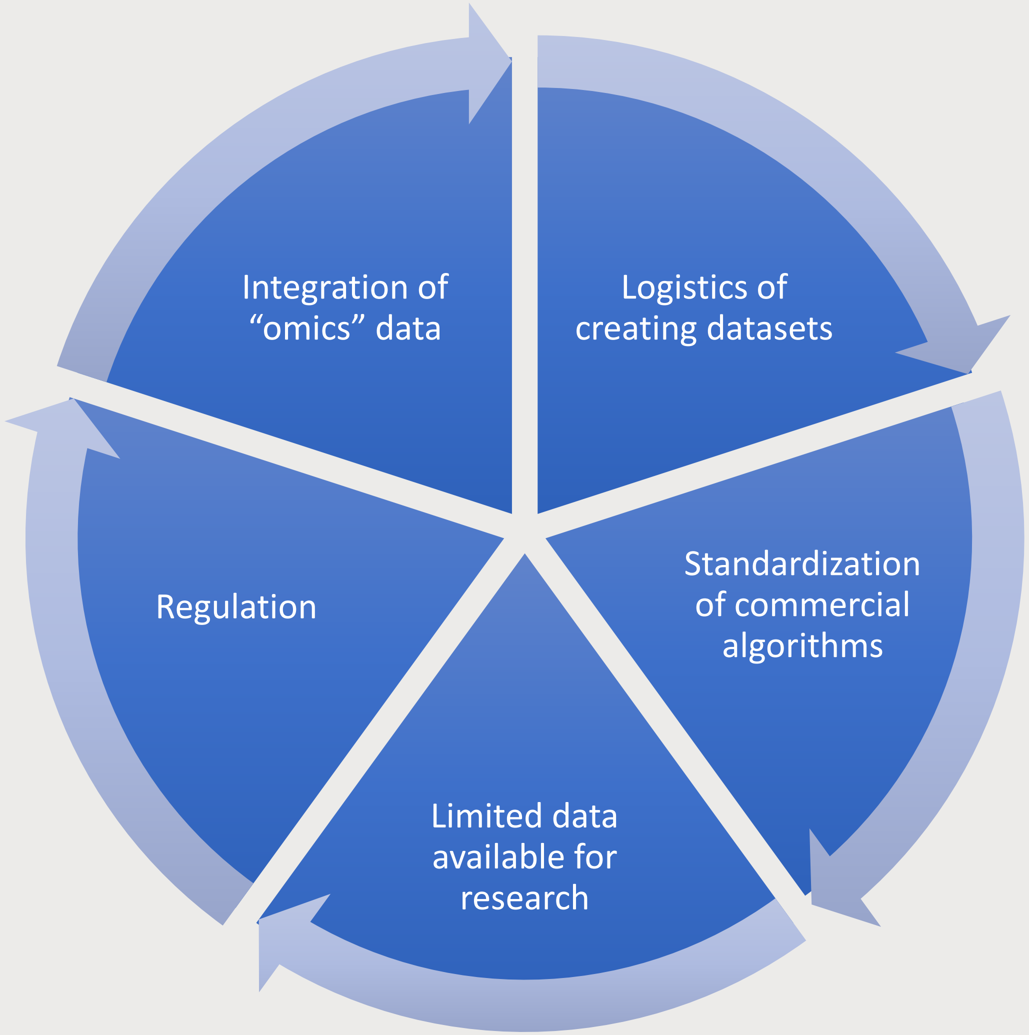
Challenges of Artificial Intelligence in Sleep Medicine



Artificial Intelligence in Sleep Medicine: an American Academy of Sleep Medicine position statement

- Put forth in 2020
- In support of AI for current application for scoring polysomnographic events
- However, analysis of massive physiological data that is already available to use is NOT ready at this time for clinical use
- Future: Allow clinicians to gain greater insight into the data provided by the polysomnogram besides the currently used metrics and moving towards disease subtyping and phenotyping and ultimately tailored management
- Warn: Hurdles that require work including data security and ethical issues

- (Cathy A Goldstein , Richard B Berry et al.. J Clin Sleep Med. 2020 Apr 15;16(4):605-607).

The American Academy of Sleep Medicine Position Statement 2020

- *"It is the position of the AASM that the electrophysiological data acquired during PSG is well-suited for analysis using AI. While AI applications that score sleep and associated events are expected to improve sleep laboratory efficiency and yield greater clinical insights, the goal of AI integration should be to augment, not replace, expert evaluation of sleep data. Guidance addressing logistical, security, ethical, and legal considerations will need to be provided to sleep facilities to enable clinical implementation of AI."*

Systematic Review

Artificial Intelligence Models for the Automation of Standard Diagnostics in Sleep Medicine—A Systematic Review

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Bioengineering **2024**, *11*(3), 206

Abstract: Sleep disorders, prevalent in the general population, present significant health challenges. The current diagnostic approach, based on a manual analysis of overnight polysomnograms (PSGs), is costly and time-consuming. Artificial intelligence has emerged as a promising tool in this context, offering a more accessible and personalized approach to diagnosis, particularly beneficial for under-served populations. This is a systematic review of AI-based models for sleep disorder diagnostics that were trained, validated, and tested on diverse clinical datasets. An extensive search of PubMed and IEEE databases yielded 2114 articles, but only 18 met our stringent selection criteria, underscoring the scarcity of thoroughly validated AI models in sleep medicine. The findings emphasize the necessity of a rigorous validation of AI models on multimodal clinical data, a step crucial for their integration into clinical practice. This would be in line with the American Academy of Sleep Medicine's support

Future of AI in Sleep Medicine

- Sleep disorders are prevalent in the general population and present significant health challenges
- The current diagnostic approach, based on a manual analysis of overnight polysomnograms, is costly and time-consuming
- AI has emerged as a promising tool in this context, offering a more accessible and personalized approach to diagnosis, particularly beneficial for under-served populations
- Assist in diagnosis, monitor progress, identify challenging cases (paradoxical sleep)
- Still require oversight by health care providers
- Need continued advancement in technology
- Population health (big data)
- Personalized medicine
- Allowing more time for physician–patient interaction
- Augment physician–patient relationship

- Thank you
- Questions?