Smart Sleep: How AI is Revolutionizing Sleep Medicine and Health Monitoring

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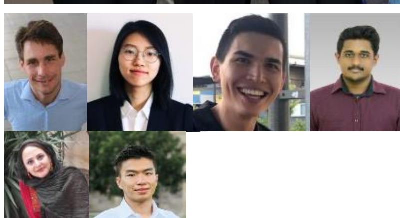
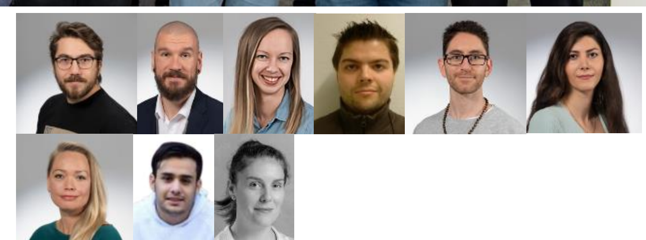
Current situation in sleep medicine

Sleep disorders are highly prevalent	Affects a significant portion of the general population, disrupts sleep, impairs daytime functioning , and is connected to severe health outcomes
The golden standard of diagnosis is an overnight polysomnography (incl. EEG, cardiorespiratory signals, leg EMG etc.)	Expensive and require extensive manual post processing and analysis Home-based solutions also used but often leave out the EEG -> no information on sleep microstructure
The information of the multisignal recordings usually condenced into a few simplistic metrics	Counting of the events; dates back to the times with analog paper-based recordings

Sleep Technology and Analytics Research (STAR)





Who we are?

1. Group consists of mainly physicists and engineers interested in sleep-related diseases
2. The group was founded in 2017
   - 2 professors/Assoc. Professors (Töyräs, Leppänen)
   - 6 senior research fellows (Kulkas, Kainulainen, Korkalainen, Nikkonen, Terrill, Myllymaa)
   - 7 postdocs (Pitkänen, Karhu, Rusanen, Howarth, Sillanmäki, Ferreira-Santos, Behbahani)
   - Lab engineer (Laitinen) and research nurses (Häkkinen, Hiltunen)
   - 18 Ph.D. students + couple of M.Sc. Students
3. Focus on signal analysis, neural networks, and electrode development
4. > 4,2 million € of research funding
   - EU Horizon 2020, (2021, 15M€); Sleep apnea
   - Horizon Europe (2022, 4,4M€); Data security
   - Horizon Europe (2023, 5M€); Data security
   - Nordforsk (2018, 2.4M€); Sleep apnea
   - NHMRC (2021, 260K€); Sleep apnea
   - Kuopio University Hospital (2021-2023, >1M€); Sleep
   - Private Foundations (2021-2023, ~0,5M€); Sleep
5. Active collaboration with commercial partners and high-level international research institutions

STAR
Sleep Technology & Analytics

UNIVERSITY OF EASTERN FINLAND

KUOPIO UNIVERSITY HOSPITAL

THE UNIVERSITY OF QUEENSLAND AUSTRALIA

Future directions in diagnosing sleep disorders

Beyond manual analysis

More comprehensive analysis not restricted to visual inspection

Portable diagnosis and long-term measurements

Simple, low-cost sensors that do not disrupt sleep

Enhancing research

Open-access datasets

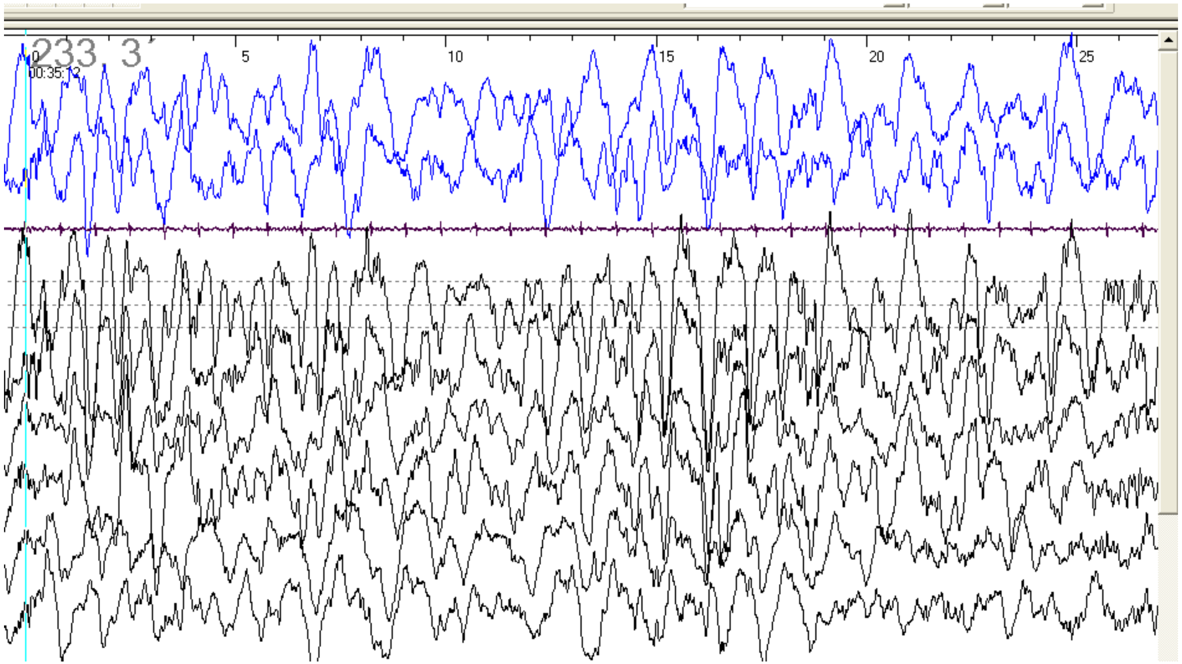
New research not limited with current practices

Informed decision making

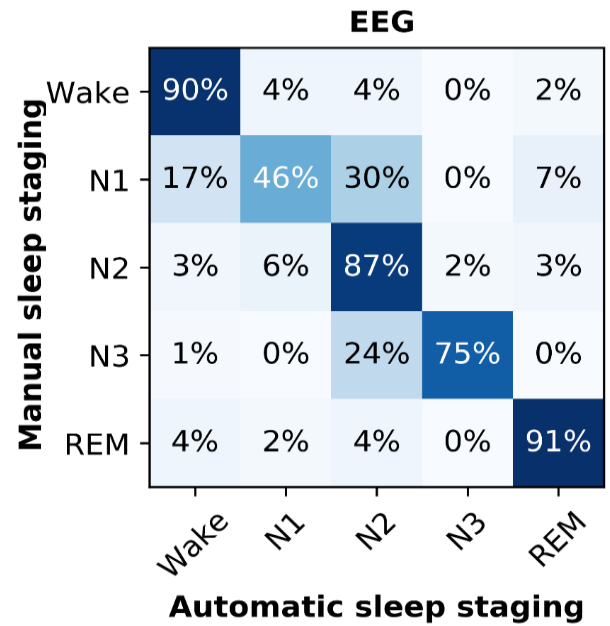
More comprehensive overview of symptomology and identification of patients benefitting most from treatment

Scoring of sleep stages

- Manual detection based on 30 sec



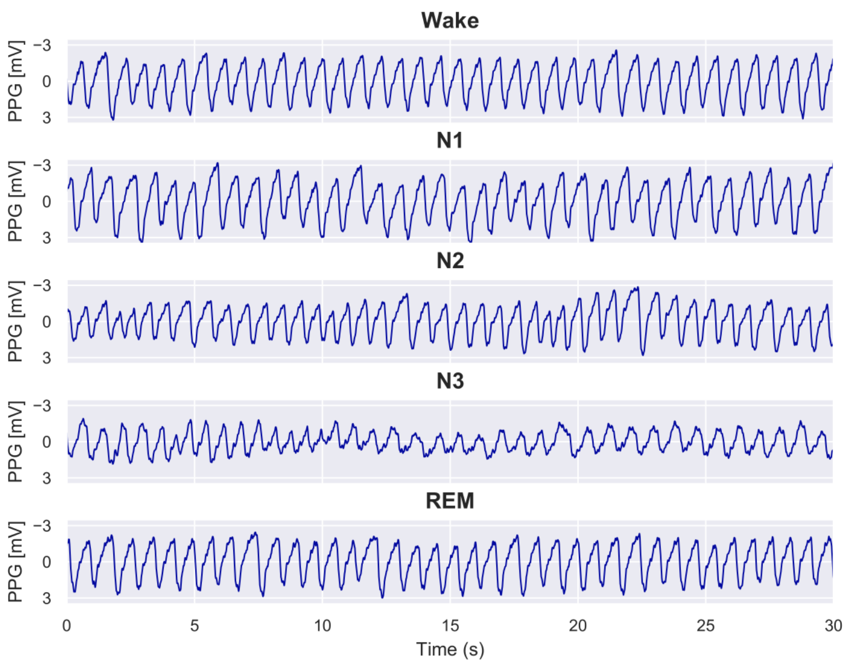
Deep learning –based automatic scoring

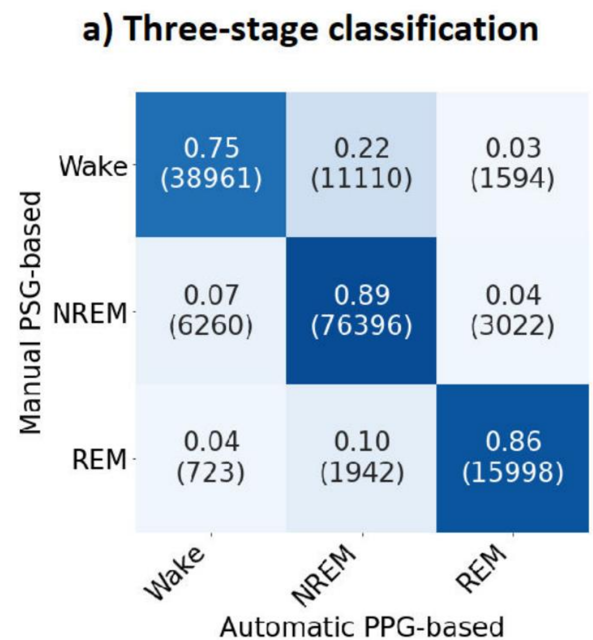


Without EEG? -> photoplethysmography

- **Accuracy:** Wake\N1\N2\N3\REM: **68.7%** (κ=0.60)

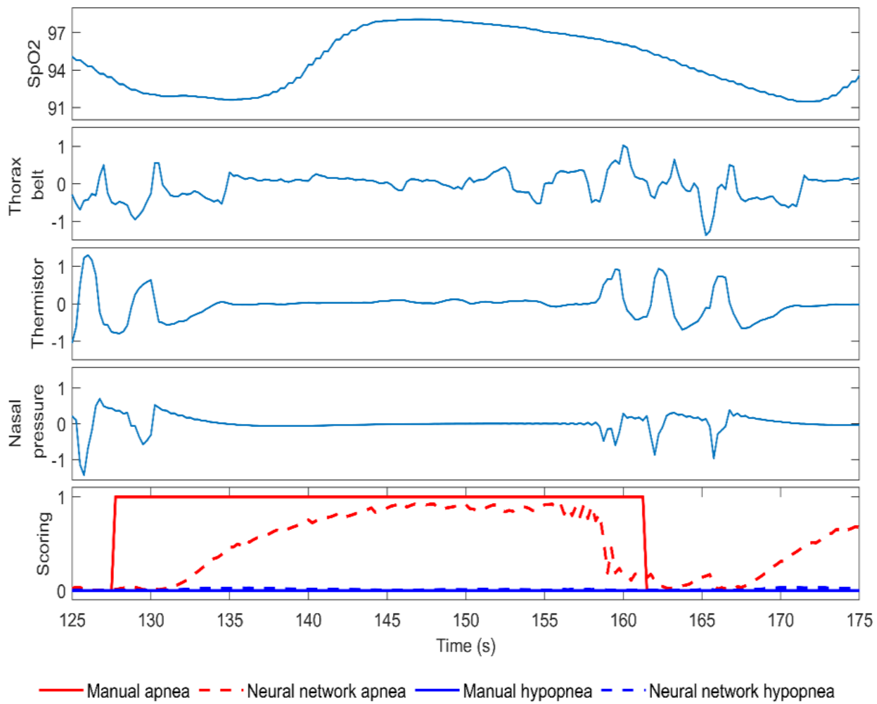
  Wake\NREM\REM: **83.3%** (κ=0.72)

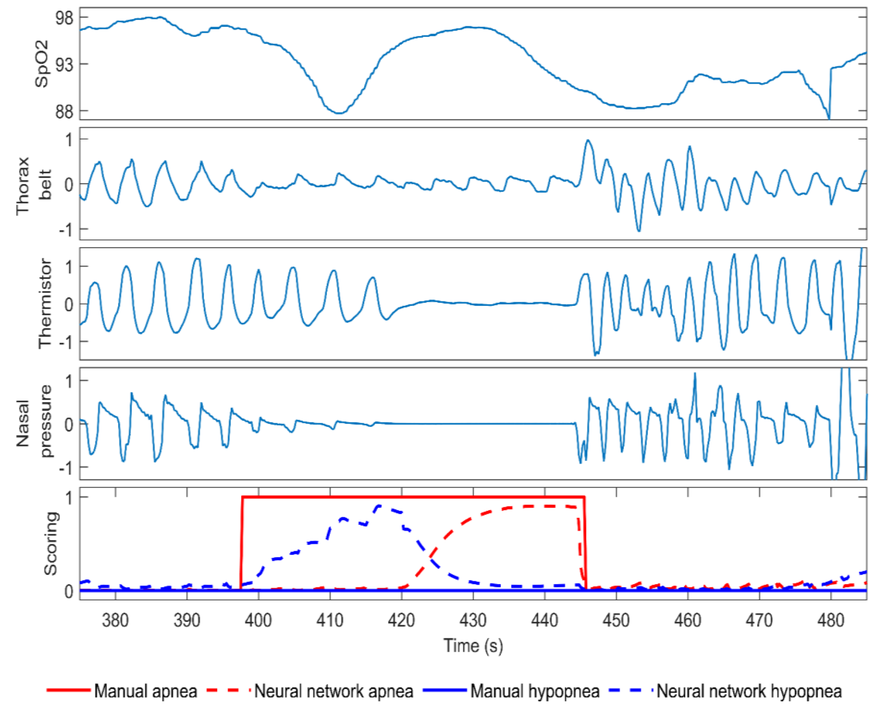




Huttunen et al. Assessment of Obstructive Sleep Apnea-Related Sleep Fragmentation Utilizing Deep Learning-Based Sleep Staging from Photoplethysmography *Sleep*
Korkalainen et al. Deep learning enables sleep staging from photoplethysmogram for patients with suspected sleep apnea , Sleep, zsaa098, 2020. 10.1093/sleep/zsaa098

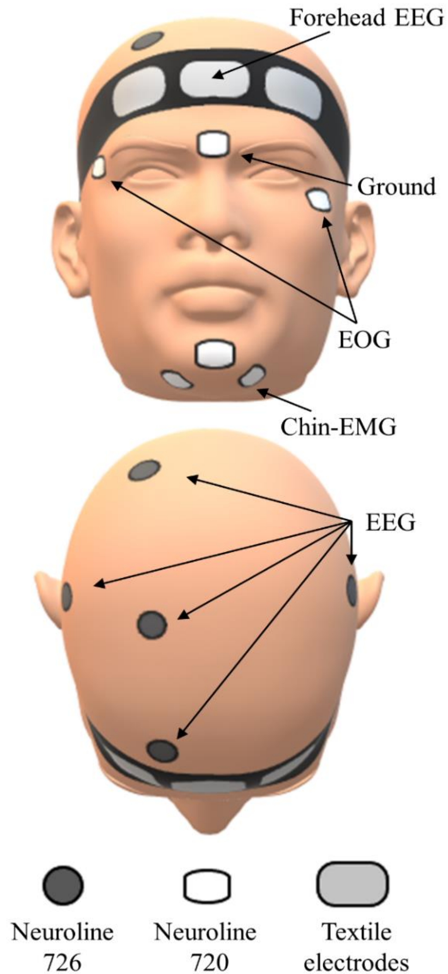
Automatic respiratory event scoring for detecting obstructive sleep apnea

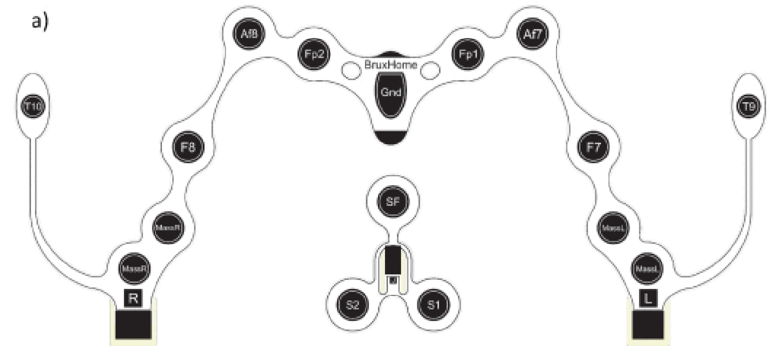


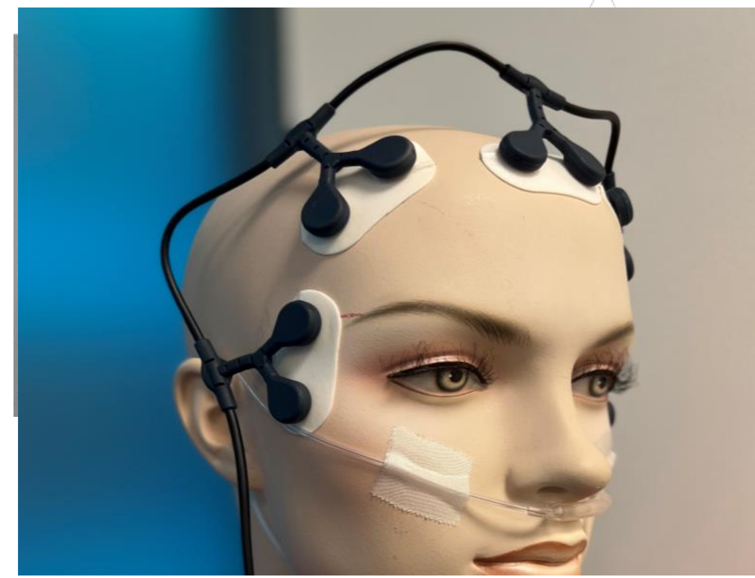


Wearable devices

- Further work with excellent results:
  - Self-applicable EEG set
  - A wearable EEG headband





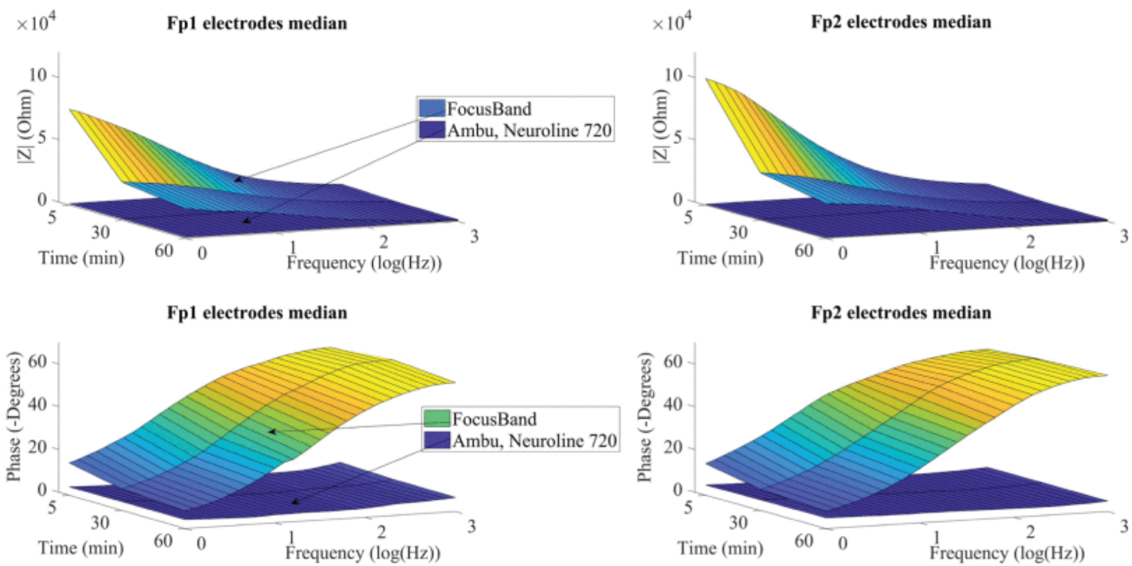


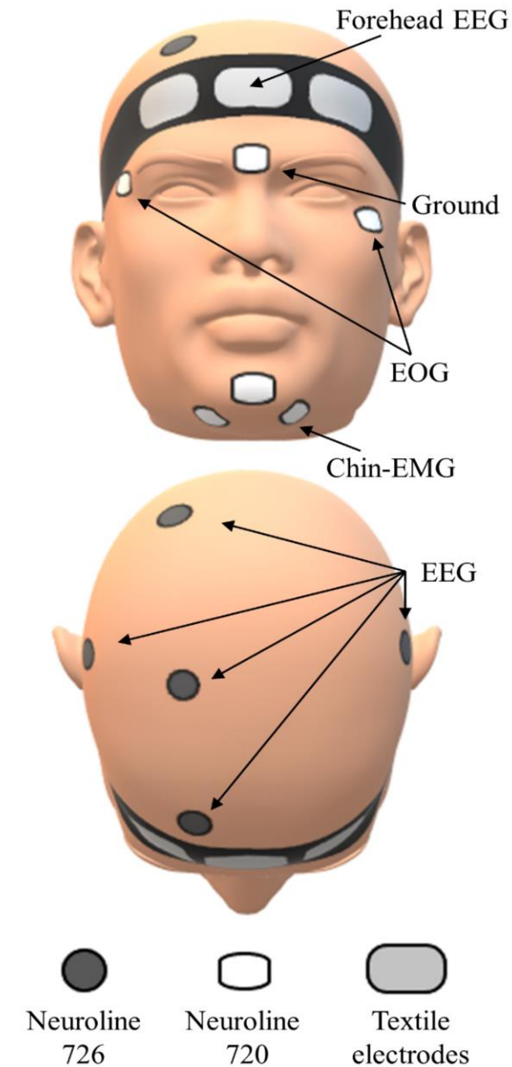
Difficulties in validation

- Data collection together with a clinical standard polysomnography
  - Expensive and time-consuming
- Often only healthy participants are used when validating the devices
  - Generalizibility?
- Data collection from devices
- Rapid development of devices
- Reliability and understanding the sources of error

Images: DALLE-3 with a prompt “validation of consumer-grade devices for SDB screening”

Example: wearable EEG devices - validation is required





SLEEP REVOLUTION

Sleep staging

Study population: 877 PSGs (suspected OSA) for training; testing on 10 wearable EEG recordings of healthy participants

Forehead EEG, accuracy = 82 %

True Label \ Predicted Label	Wake	N1	N2	N3	REM
Wake	0.80	0.02	0.13	0.00	0.05
N1	0.19	0.21	0.46	0.01	0.13
N2	0.03	0.01	0.86	0.04	0.05
N3	0.01	0.00	0.22	0.77	0.00
REM	0.03	0.00	0.10	0.01	0.86

Standard EOG, accuracy = 87 %

True Label \ Predicted Label	Wake	N1	N2	N3	REM
Wake	0.83	0.03	0.09	0.00	0.05
N1	0.23	0.39	0.25	0.00	0.13
N2	0.02	0.03	0.87	0.03	0.04
N3	0.01	0.00	0.12	0.85	0.02
REM	0.01	0.00	0.02	0.00	0.97

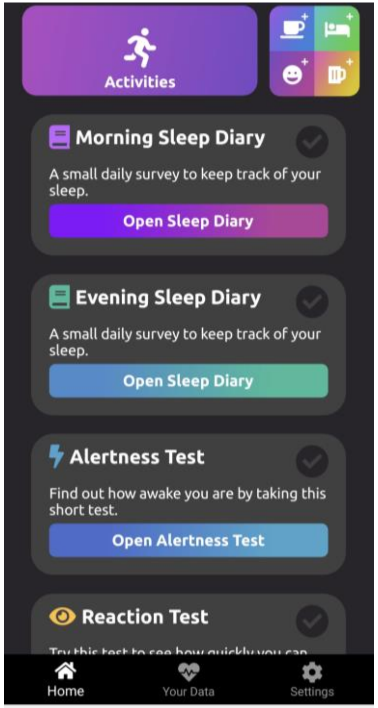
Snoring detection and sleep apnea screening
-Smartphone apps

- Several apps available
  - Promising results for detecting snoring (e.g. Camacho et al., 2015; Chiang et al., 2022; Figueras-Alvarez et al., 2020; Klaus, Stummer, & Ruf, 2021)
  - Specificity, variability between devices, real-world situation (e.g. bed partner)?

SLEEP REVOLUTION

Snoring detection and sleep apnea screening -Smartphone apps

- OSA estimation
  - Respiratory sounds and/or movement with a smartphone
  - Perform fine in controlled cases, can have low specificity (Cho et al., 2022; Nakano et al., 2014; Narayan et al., 2019; Tiron et al., 2020).
- Sleep diaries also possible with apps to enable simple collection of subjective data



The Sleep Revolution app

Sleep apnea screening – nearables

- Nearables: bed sensors, radar technologies
  - Require an additional sensor for the sole purpose of sleep measurements
  - Potential to estimate cardiac signals and respiration (Balali 2022)

Figure courtesy of Withings

Sleep apnea screening – consumer-grade oximetry

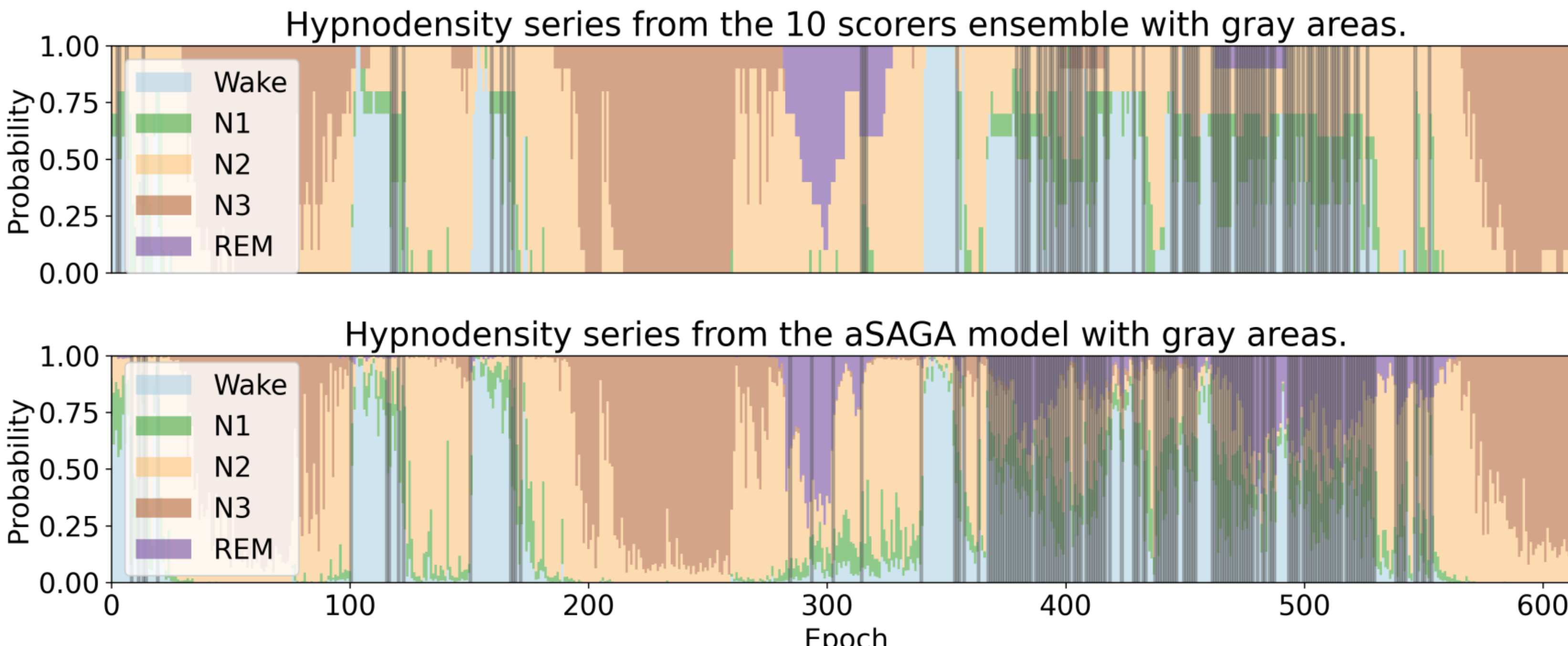
SLEEP REVOLUTION

- Fitness trackers, smartwatches, rings
  - Sensor quality is often sufficient
  - Physiologically relevant data
  - Screening accuracy, sensitivity, and specificity vary across devices between ~40% to 90% (Chen, Wang, Guo, Zhang, & Xie, 2021; John, Nundy, Cardiff, & John, 2021; Mokhtaran et al., 2022; Papini et al., 2020)

Figure courtesy of Withings

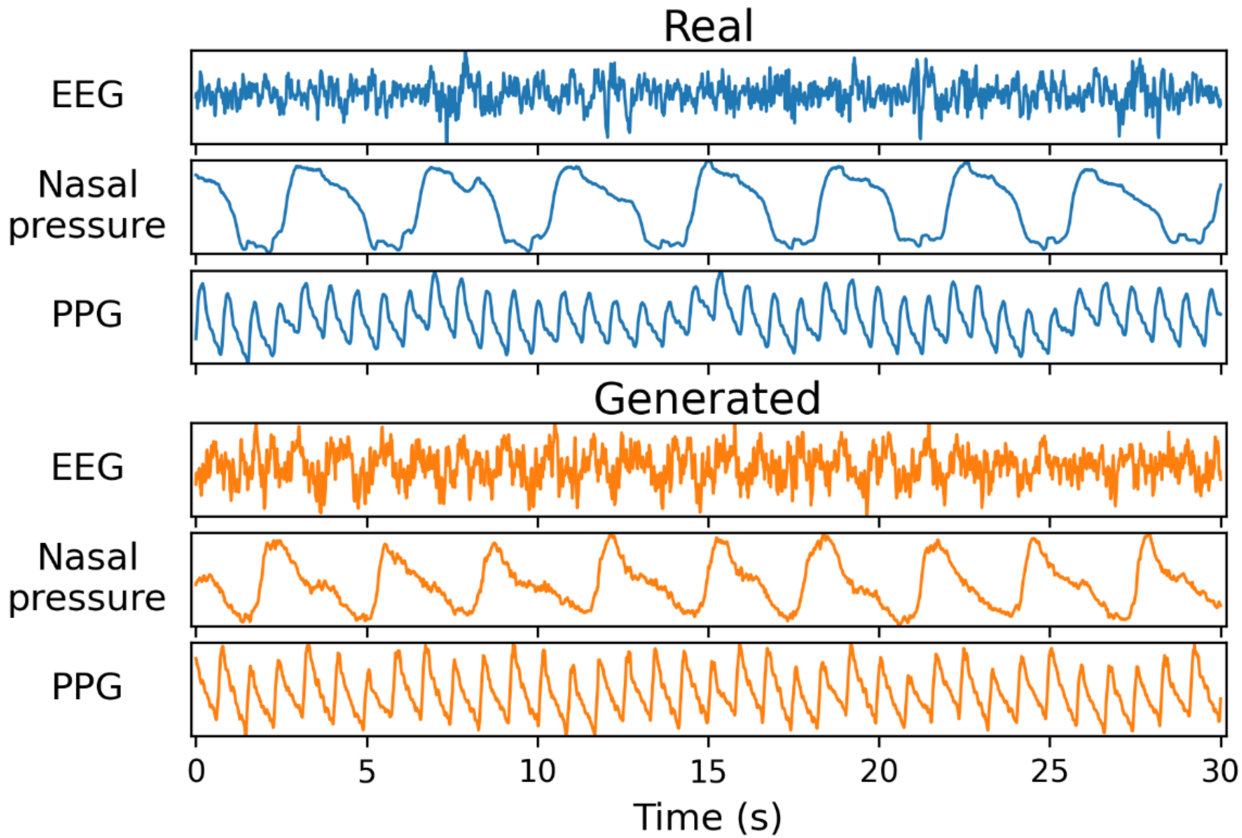
Figure courtesy of Oura

Explainable AI:
Gray areas



Rusanen M *et al.*, Empowering Sleep Medicine with Human-in-the-Loop Scoring Approach: Automatic Sleep Analysis with Gray Areas. MS under review. 2023

Generative AI



R Huttunen et al. Synthesizing polysomnography signals with generative adversarial nets. Proceedings of the EMBC 2023.

Tools in practice

SmartSleep Lab

Research infrastructure

Two full polysomnographic examination rooms in sleep laboratory

Medical technology testing facility

RESEARCH

DEVELOPMENT

CLINICAL EVALUATION

COLLABORATION

TEACHING

Internationally unique sleep research center

Regional visibility and talent attraction

Services for health tech companies

Open access data

Novel scientific approaches

High-quality scientific publications

Innovations

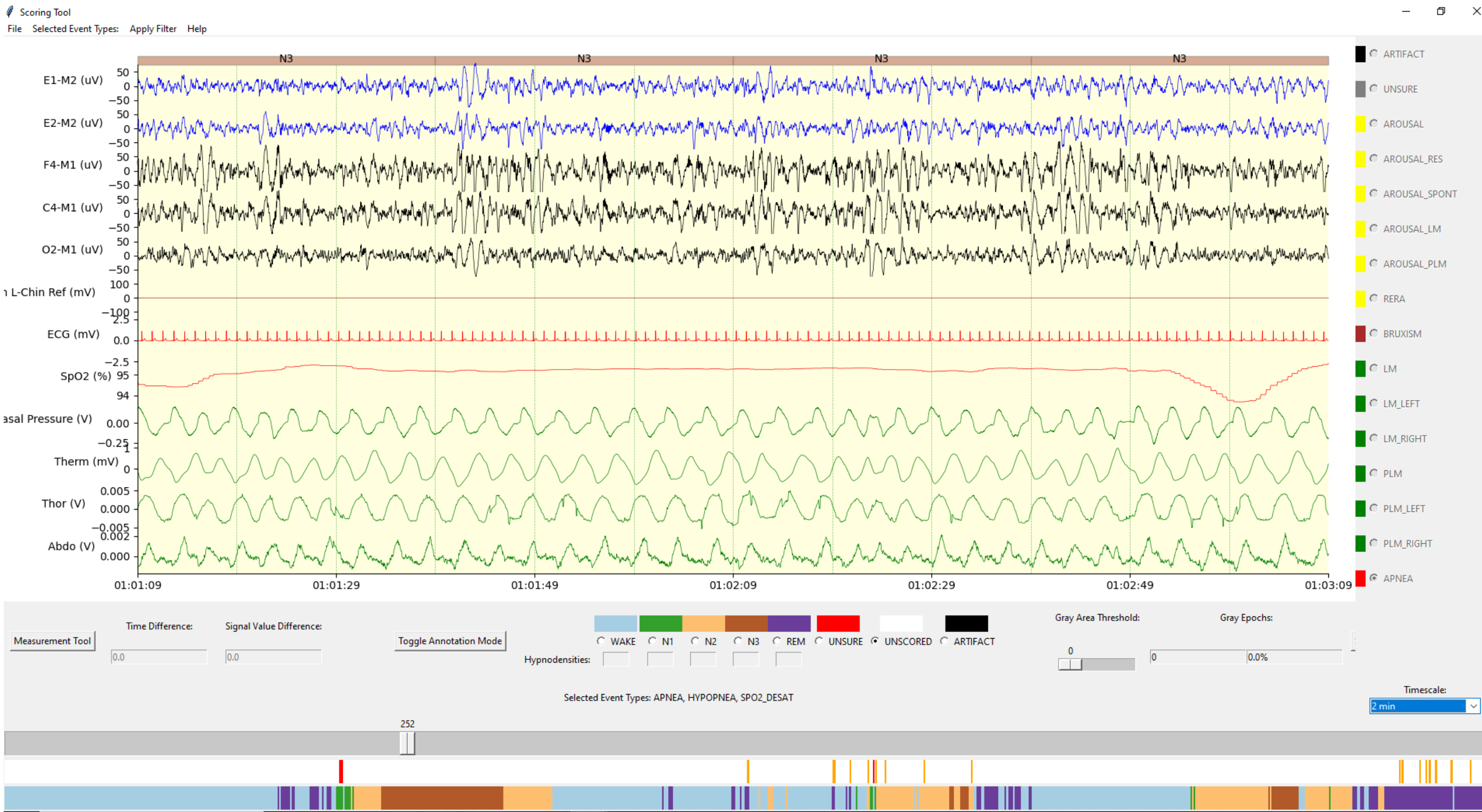
Multidisciplinary training

https://sites.uef.fi/star/smartsleeplab/

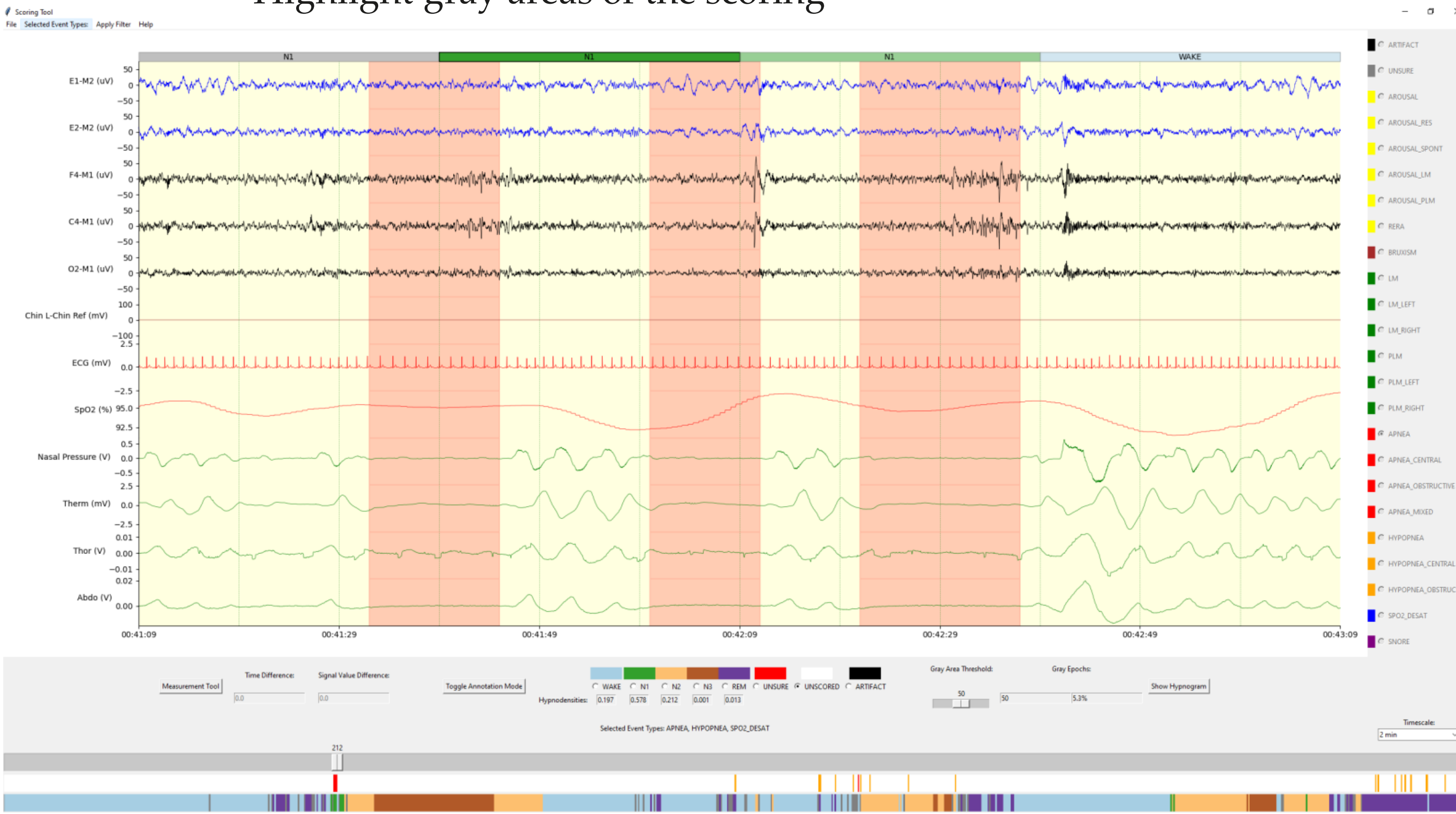
European Union
European Regional Development Fund

Leverage from the EU 2014–2020

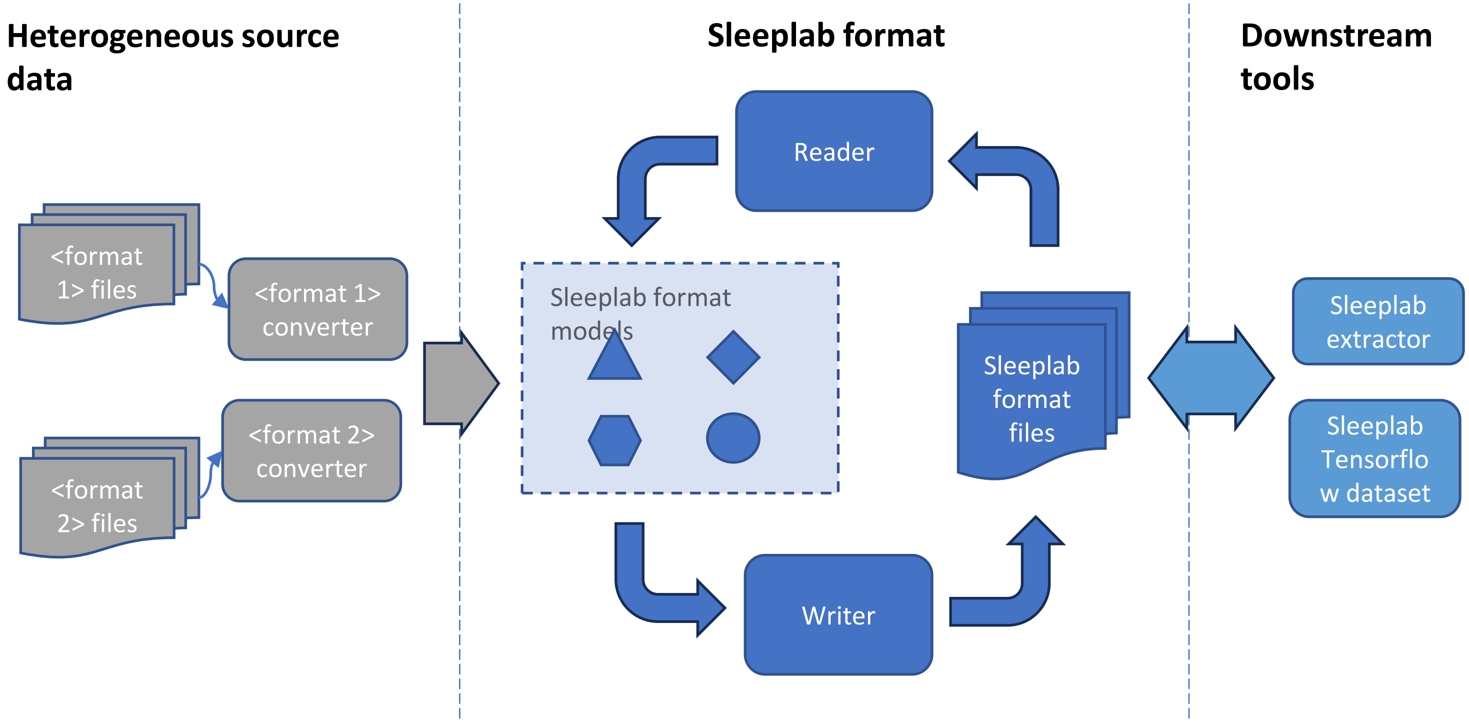
Tools in practice



- Visualize results with signals for review/editing of the scorings
- Highlight gray areas of the scoring



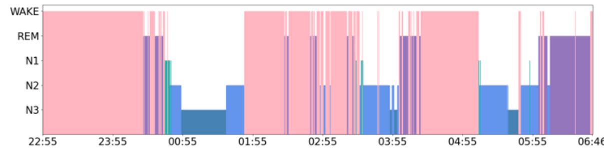
Sleeplab-format ecosystem provides tools for reading, writing and processing of data



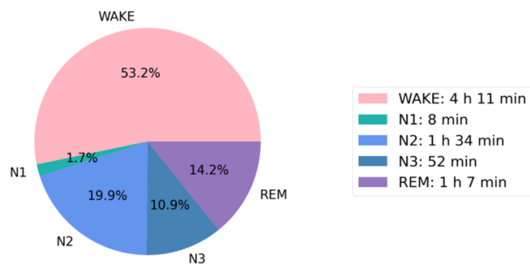
- Create reports automatically

Subject: 10009
Study Date: 06.07.2023

Hypnogram



Sleep Stage Distribution Pie Chart



Sleep Statistics

Parameter	Value
Total sleep time	3 hours and 40 minutes
Sleep efficiency	46.77%
Sleep onset latency	87.5 minutes
Wake after sleep onset	163.5 minutes
REM latency	87.5 minutes

Subject: 10009
Study Date: 06.07.2023

Respiratory Events

	Count	Max length (s)	Mean length (s)
All events	21	31	15.7
Apneas	3	16	13.3
Hypopneas	18	31	16.1

Event Indices

Parameter	Value (1/h)
Apnea-hypopnea index (AHI)	5.7
Apnea index	0.8
Hypopnea index	4.9
REM-AHI	11.6
NREM-AHI	3.1

The quality of the recordings is verified by an expert. All analyses are conducted using automatic tools. Hypnogram and respiratory events are scored using scientifically validated deep learning tools: Huttunen et al., A comparison of signal combinations for deep learning-based simultaneous sleep staging and respiratory event detection, IEEE Transactions on Biomedical Engineering doi:10.1109/TBME.2022.3225268

STAR Sleep Technology & Analytics RESEARCH GROUP

SmartSleep Lab UNI- & TUTKIMUSLABORATORIO

Thank you!

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