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published in
The European journal of neuroscience
2024

DOI (link to publisher)
10.1111/ejn.16227

document version
Publisher's PDF, also known as Version of record

citation for published version (APA)
Jafarzadeh Esfahani, M., Sikder, N., Ter Horst, R., Daraie, A. H., Appel, K., Weber, F. D., Bevelander, K. E., & Dresler, M. (2024). Citizen neuroscience: Wearable technology and open software to study the human brain in its natural habitat. *The European journal of neuroscience*, *59*, 948-965. https://doi.org/10.1111/ejn.16227

Received: 22 January 2023 | Revised: 9 November 2023 | Accepted: 30 November 2023

DOI: 10.1111/ejn.16227

EDITORIAL

EJN European Journal of Neuroscience FENS WILEY

Citizen neuroscience: Wearable technology and open software to study the human brain in its natural habitat

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Funding information
Health Holland, Top Sector Life Sciences & Health

Edited by: Tomás Ryan

Abstract

Citizen science allows the public to participate in various stages of scientific research, including study design, data acquisition, and data analysis. Citizen science has a long history in several fields of the natural sciences, and with recent developments in wearable technology, neuroscience has also become more accessible to citizen scientists. This development was largely driven by the influx of minimal sensing systems in the consumer market, allowing more do-it-yourself (DIY) and quantified-self (QS) investigations of the human brain. While most subfields of neuroscience require sophisticated monitoring devices and laboratories, the study of sleep characteristics can be performed at home with relevant noninvasive consumer devices. The strong influence of sleep quality on waking life and the accessibility of devices to measure sleep are two primary reasons citizen scientists have widely embraced sleep research. Their involvement has evolved from solely contributing to data collection to engaging in more collaborative or autonomous approaches, such as instigating ideas, formulating research inquiries, designing research protocols and methodology, acting upon their findings, and disseminating results. In this

Abbreviations: Acc, accelerometer; AI, artificial intelligence; Amb, ambient; BLE, Bluetooth low energy; BP, body position; COI, conflict of interest; DIY, do-it-yourself; ECG, electrocardiography; EDA, electrodermal activity; EEG, electroencephalography; EMG, electromyography; EOG, electrooculography; (f)MRI, (functional) magnetic resonance imaging; fNIRS, functional near-infrared spectroscopy; GUI, graphical user interface; Gyro, gyroscope; Mic, microphone; PCB, printed circuit board; PPG, photoplethysmography; PSG, polysomnography; QS, quantified-self; REM, rapid-eye movement; RFID, radio frequency identification; SE, sleep efficiency; SpO2, peripheral oxygen saturation; SWS, slow-wave sleep; TMR, targeted memory reactivation; TST, total sleep time.

article, we introduce the emerging field of citizen neuroscience, illustrating examples of such projects in sleep research. We then provide overviews of the wearable technologies for tracking human neurophysiology and various open-source software used to analyse them. Finally, we discuss the opportunities and challenges in citizen neuroscience projects and suggest how to improve the study of the human brain outside the laboratory.

KEYWORDS
citizen neuroscience, do-it-yourself, quantified self, sleep, wearables

1 | SCIENCE AND CITIZEN SCIENCE

Before science became an established and paid profession, most people conducting scientific research were nonprofessionals: Outside their formal occupation, they engaged in scientific investigations based on their intrinsic interest in certain natural phenomena or unanswered questions (Vetter, 2011). Although often referred to as 'amateurs' or 'gentleman scientists', some of these nonprofessionals were among the most knowledgeable people in their respective fields at that time. Many of them had collected large sets of data, which later proved invaluable to modern research. Such occurrences are commonly found in different branches of natural science, archeology, geology, and astronomy. However, since the professionalization of science in the 19th century (Silvertown, 2009), scientific research has gradually become the job of 'experts' or professional scientists, and nonprofessionals have become somewhat sidelined (Kobori et al., 2015).

Nonetheless, people outside the scientific community were still contributing to science but mostly in assisting roles such as data acquisition. Today, such engagement falls under the umbrella of *Citizen Science*, a longstanding practice that collectively refers to various modes of engagement and participation of the general public in scientific studies (Miller-Rushing et al., 2012). The 'North American Bird Phenology Program', organized by ornithologist Wells Woodbridge Cooke in 1883, is the earliest known citizen science project. The 'Christmas Bird Count' project, proposed by US ornithologist Frank Chapman in 1900, is the oldest citizen science project that is still organized every year by the National Audubon Society in the United States. Since then, both the number of citizen science projects and the involvement of amateur scientists have been increasing significantly (Kobori et al., 2015; Silvertown, 2009). Moreover, citizen scientists have moved beyond solely contributing to data collection and have become more involved in collaborative or independent approaches. Nowadays, they initiate ideas, create research questions, develop research protocols and methodologies, collect and analyse data, interpret findings, and share the results. Citizen science is also evolving in new domains, such as the medical and health domains (Den Broeder et al., 2018; Riggare et al., 2019). The popularity of 'citizen science for health' and the practice of tracking and exploring one's own health in 'personal science' projects have risen, leading to new and unconventional applications of science and technology (Sharon, 2017; Wolf & De Groot, 2020).

In the following, we aim to introduce the emerging field of *citizen neuroscience*, highlighting some exemplary projects and communities that are engaging in it. Focusing in particular on the field of sleep citizen neuroscience, we will provide a set of successful projects as well as a comprehensive overview of the open-source software and hardware solutions that allow to engage in citizen neuroscience projects. These solutions will enable the participation of individuals as well as large-scale collaborations between professional and citizen neuroscientists. We close with some reflections on the chances and challenges the field of citizen neuroscience faces.

2 | FROM CITIZEN SCIENCE TO CITIZEN NEUROSCIENCE

Citizen science has a long history in different fields of the natural sciences. More recently, 'neuroscientists' also started enlisting the help of citizen scientists in large-scale scientific projects, initially only for data collection but increasingly also for data analysis and pattern recognition, paving the way for 'citizen neuroscience' (Roskams & Popovic, 2016). One of the driving factors of this development is the 'Quantified Self' (QS) movement, where individuals without formal training in medicine, neuroscience, or behavioural sciences are longitudinally logging and analysing physiological as well as behavioural and environmental data, usually as part of an

$N = 1$ self-study (Swan, 2013; Wolf & De Groot, 2020). One of the authors of this paper (RtH) falls into this category of citizen neuroscientists: Trained as a bioinformatician studying the immune system and with no prior knowledge of neuroscience, he started a personal longitudinal $N = 1$ citizen neuroscience project in 2017 with very dense and deep phenotyping, dubbed *The Quantified Scientist* (Sikder et al., 2022; Ter Horst & Dresler, 2022). This ongoing project aims to study individual variations in physiology and psychology over several years using both consumer electronics and scientific equipment. Since 2018, these measurements included weekly magnetic resonance imaging (MRI) brain scans, daily sleep electroencephalography (EEG) measurements, and, until 2020, weekly polysomnography (PSG) and microbiome sampling. Additionally, using wearables, electronics, and questionnaires, different parameters are monitored on a continuous or daily basis. His simultaneous PSG and wearable EEG recordings played an essential role in the large-scale scientific validation study of the EEG wearable, accounting for about a third of the overall analysed data (Esfahani, Weber, et al., 2023). The contribution further paved the way for the early-stage development of the online and offline automatic sleep staging methods used in the open-source dream engineering toolbox (Dreamento; Esfahani, Daraie, et al., 2023), which enabled the largest multicentre lucid dream induction study with physiological data to date (Esfahani et al., 2022). His motivation for the project is to help advance scientific understanding, learn more about himself, and potentially optimize different aspects of his life. From personal experience, he can report that, although he never got any formal training in neuroscience, he gained a lot of knowledge about the fundamentals of sleep physiology and other neuroscientific topics and methods during the project.

More generally, the study of sleep is a field that has received particular attention in recent years from both producers of wearable neurotechnologies for everyday home settings and their users. Everybody spends a considerable proportion of life asleep, and sleep has a direct, noticeable influence on one's perceived quality of life, which makes sleep and related phenomena such as dreaming popular among many citizen neuroscientists. Citizen neuroscience, when focused specifically on sleep, holds potential advantages over conventional studies due to several reasons. First, the last two decades have seen a dramatic increase in the diversity of affordable commercial health tracker technologies, ranging from smartwatches with sleep monitoring features to a growing market of wearable systems for neurophysiological sleep recording. The availability of these technologies could facilitate large-scale citizen neuroscience, overcoming the common challenge of the majority of existing studies: small sample size. Second, sleep self-experiments are relatively easy to set up for anyone, regardless of their skills or education level, and the results can be shared with or compared with other individuals and general sleep norms. Third, longitudinal daily sleep recordings, which pose challenges for conventional sleep study participation, can become feasible through citizen neuroscience engagement. Of note, there are also some cautionary points that should be considered while performing sleep citizen neuroscience studies. For instance, one should establish a protocol to define an 'acceptable' data standard for quality control, which will be followed to review the collected data in an unbiased manner (Roskams & Popovic, 2016). Ethical guidelines should be followed carefully (Naufel & Klein, 2020; Oberle et al., 2019; Remmers et al., 2023).

Beyond investigating one's sleep individually, groups of people have also formed that try to monitor and improve their sleep and dreams collaboratively. Such interest groups range from loose internet communities to more organized crowds of citizen neuroscientists. Examples of loosely connected citizen science groups include web communities in English[1] and German,[2] in which lay enthusiasts as well as professional researchers exchange ideas, methods, and knowledge on the phenomenon of lucid dreaming. There are also citizen science groups that meet regularly in real life to discuss scientific topics or even conduct their own scientific studies: the 'Student Initiative Sleep and Dream' at Osnabrück University (Germany), for example, conducts sleep experiments without any professional supervision in their own polysomnographic sleep laboratory and publishes some of their results in scientific journals (e.g., Appel et al., 2020). Another group of sleep and dream citizen scientists formed an independent nonprofit research institute: the Institute of Sleep and Dream Technologies.[3] Their goal is to "invent technologies for better sleep and better dreams"—from ideation of new sleep concepts and prototyping to conducting sleep research and putting the results into real-world applications. Some of the citizen scientists at this institute have a background in professional sleep research; however, they are not actively pursuing the topic within an academic setting anymore, whereas others bring in skills and ideas from other technological fields entirely outside academia, illustrating how classical science and citizen science can interact and complement each other.

[1]www.dreamviews.com.
[2]www.klartraumforum.de.
[3]www.sd20.org.

In addition to pure monitoring of brain function, emerging biohacking/neurohacking communities aim to explore the technological enhancement of their brains, bodies, and behaviour. These perceived enhancements involve various modifications, ranging from the gain of additional sensing or control functions by implementing magnets or radio frequency identification (RFID) tag in the arm to creating a neural interface by surgically inserting a multielectrode array into the arm to 'telepathically' control a robotic arm (Yetisen, 2018). Less invasive neurotechnologies are increasingly being used not only for passive monitoring but also for active optimization of daily behavioural performance brain function (Dresler et al., 2019). As part of the above mentioned The Quantified Scientist project, RtH tests consumer devices for their accuracy and reports the results on a YouTube channel.[4] A significant part of the >200k subscribers of this channel are generally interested in tracking and improving different parts of their lives using wearable and neural devices, and some of these could thus be considered citizen neuroscientists. Interestingly, a survey among subscribers revealed that all individuals that used neurotechnological devices themselves considered the topic of self-enhancement as a significant matter (Ter Horst & Dresler, 2022), confirming that many citizen neuroscientists aim to modulate and improve aspects of their lives using neurotechnology.

2.1 | Hardware for the citizen neuroscience of sleep

The gold standard technology for studying human sleep is PSG, which includes different biosignals such as EEG, electrooculography (EOG), and electromyography (EMG), with potential additions of electrocardiography (ECG), respiratory rate, and other measures (Iber, 2007). However, PSG comes with several limitations that complicate its involvement in citizen neuroscience: It is typically bulky and thus confined to the lab environment, requires trained experts to place the electrodes, is a time-consuming procedure, and is expensive. The problems with PSG recording increase when it comes to longitudinal recordings, for example, to assess intraindividual sleep regularity or sleep abnormalities, which are not commonly identifiable by a single night of sleep measurement.

Recent developments in relatively low-cost open hardware solutions such as OpenBCI (OpenBCI, New York, USA), and FreeEEG32 (NeuroIDSS) have made PSG more available for citizen neuroscientists. In addition, while many commercial polysomnographs are not readily configurable (e.g., in terms of the number of channels), modular and stackable EEG printed circuit boards (PCBs) offer considerable flexibility to the user, for example, in terms of the number of ExG channels that can be used as a combination of multiple EEG, EMG, EOG, and ECG channels, depending on the application of interest. Moreover, most of these systems are commonly open source, and there is a large community of users continuously developing upon the available features of these technologies.

Close to classical PSG is also the *Traumschreiber* system: a portable sleep mask that can record electrophysiological data such as EEG, ECG, EOG, and EMG and is thus well suited for polysomnographic investigations. It was developed at Osnabrück University, Germany, over the past years and is still being developed further. The *Traumschreiber*[5] is an open tool for researchers and developers, who need a cheap, modifiable device for their experiments that offers high data quality and free access to the raw data, hardware, and software. It is not targeted at the consumer market and not sold commercially but can be obtained via direct contact with the researchers, joining their next bulk orders at cost price (nonprofit). The *Traumschreiber* has a 24-channel ExG PCB with custom, adjustable hardware filters, is battery-powered, and transmits data via Bluetooth low energy (BLE). An Android app and a Python code exist to receive and process the raw data (e.g., on a Raspberry Pi), enabling further processing steps of the data via machine learning or external toolboxes.

Beyond full PSG, various types of sleep tracking systems can be employed by citizen neuroscientists, and these generally aim to estimate sleep quality and score sleep stages and potentially also have clinical applications, such as detecting sleep apnoea (Edouard et al., 2021). These sleep tracking systems include technologies that remotely measure physiological signals from the user, without direct body contact, such as smart home sensors (e.g., Google Nest hub 2) and under-mattress sleep trackers (e.g., the Withings Sleep Analyzer). Additionally, many sleep-tracking systems are in the form of wearable or portable systems capable of collecting signals, such as actigraphy wristbands (e.g., Ancoli-Israel et al., 2003; Lichstein et al., 2006; Martin & Hakim, 2011; Morgenthaler et al., 2007; Sadeh, 2011), smartwatches (e.g., Alfeo et al., 2018; Chang et al., 2018; De Zambotti et al., 2018; Phan et al., 2015; Sun et al., 2017), smart rings (Altini & Kinnunen, 2021; Chaudhry et al., 2020; Malakhatka et al., 2021; Mehrabadi et al., 2020; Koskimäki et al., 2018), and

[4] www.youtube.com/TheQuantifiedScientist.

[5] https://github.com/mvidaldp/Traumschreiber-mobileEEG.

EEG-based systems such as headbands (Arnal et al., 2020; Koushik et al., 2019; Mota-Rolim et al., 2019; Onton et al., 2016).

The earliest forms of commercial sleep tracking were based on actigraphy, which uses an accelerometer to measure motion. Actigraphy was introduced in the early 1990s in the form of a wrist-worn watch or band. This system distinguishes wakefulness from sleep based on the user's movement and generally does not provide more detailed information about the sleep stages. In a systematic overview of the performance of actigraphy compared with PSG, Van De Water et al. (2011) showed that although actigraphy has an appropriate sensitivity to detect sleep, ranging from 87% to 99%, the ability of some actigraphy devices to detect wakefulness is poor, ranging between 28% and 67%, indicating the confusion between restful wakefulness and sleep. It has also been shown that sleep quality parameters such as total sleep time (TST) or sleep efficiency (SE) are overestimated in actigraphic systems when compared with the standard PSG (Montgomery-Downs et al., 2012).

On the other hand, modern smartbands and smartwatches often include additional sensors, for example, photoplethysmography (PPG), to measure pulse and respiration rate, and oxygen saturation sensors to measure the oxygenation of the red blood cells. Thanks to the current developments in sensor fusion techniques and artificial intelligence (AI), these systems provide users with more information than merely a sleep–wake distinction. For instance, in addition to overall sleep metrics such as sleep efficiency, they provide the users with the estimated sleep stages and the latency of each sleep stage. Smart rings have a relatively similar sensor suite to smartwatches and can typically derive similar quantitative metrics. However, the accuracy of these estimates is largely unknown, since many of the algorithms are based on proprietary technology, and the algorithms are continuously being changed and updated. Although research has been done to compare the performance of different devices, this only includes a small subset of available devices and will inevitably lag behind the most recent developments.

EEG is the most information-rich physiological signal for the investigation of sleep stages and, as a direct readout of neural activity, the most interesting tool for citizen *neuro*science. As an interesting compromise between full PSG and peripheral sleep trackers, several EEG-based wearables have been developed that are lightweight and easy to use. These include headbands, which are the most widely used, and ear-EEG systems that can detect EEG either from the inside of the ear, that is, in-ear EEG, or from behind the ear. It is feasible to integrate other sensors such as PPG (to measure heart rate and heart rate variability), a pulse oximeter (respiration rate and oxygen saturation), electrodermal activity (EDA) sensor (to measure skin conductance), ambient light, ambient noise, and accelerometer sensors to a headband to have a more complete system for sleep measurement. While various EEG wearables are available for consumers (see Niso et al., 2023), Table 1 reviews the ones tailored for citizen neuroscience projects: Our selection encompasses EEG wearables with an appropriate design for sleep studies (e.g., reasonable battery life and amplifier location), which can be utilized independently by the citizen neuroscientists with minimal help and assistance required from researchers. As an example, the *ZMax* headband employs two frontal EEG channels, F7–AFz and F8–AFz, that are attached to the forehead with a wet hydrogel patch. It has a proper signal correlation to the PSG, proprietary automatic sleep scoring (autoscoring) algorithm, and can measure sleep assessment statistics and detect microstructural sleep features, for example, K-complexes, spindles, and rapid eye movement (REM) reliably (Esfahani, Weber, et al., 2023). This headband is open source, and therefore, any developer can build upon the existing features of the technology (e.g., Esfahani, Daraie, et al., 2023). Another headband commonly used for research purposes is the *Dreem* headband, which has five dry EEG electrodes (F7, FpZ, F8, O1, and O2) in addition to supplementary sensors such as an accelerometer sensor and a pulse oximeter. This headband has been validated in a scientific study by Arnal et al. (2020) and performed robustly when compared with the polysomnographic ground truth by achieving satisfactory EEG quality, heart rate, breathing rate, and respiration rate estimation as well the accuracy of the autoscoring.

Rather than a one-size-fits-all solution, selection of the most suitable hardware to conduct a citizen neuroscience study is subject to the study-specific objectives. More advanced systems, such as (modular) high-density EEG systems, should only be used for studies aiming for in-depth brain activity analysis, whereas minimal sensing systems, such as EEG headbands, may be preferable in the majority of cases.

3 | OPEN SOFTWARE FOR THE CITIZEN NEUROSCIENCE OF SLEEP

Open software is often preferable in research, and when it comes to citizen science, its importance is even greater. Benefits of open-source software for citizen neuroscience include the adaptability to the research goals, no additional cost for scaling due to licensing, and the possibility to involve the citizens in the development and improvement of the software.

TABLE 1 List of the applicable EEG-based wearable and modular technologies useful for citizen neuroscience of sleep. Systems are sorted based on their category (modular PCBs, headbands, ear EEG, and patches), and within each category, they are sorted alphabetically. Acc: accelerometer, Amb.: ambient, BP: body position, ECG: electrocardiography, EEG: electroencephalography, EMG: electromyography, EOG: electrooculography, fNIRS: functional near-infrared spectroscopy, Gyro: gyroscope, LSL: lab streaming layer, mic: microphone, PCB: printed circuit board, PPG: photoplethysmography, REM: rapid eye movement, SDK: software development kit, SpO2: peripheral oxygen saturation, SWS: slow-wave sleep, Therm: thermometer. N/A: not available.

Device name	Category	Sensors/channels	Specifications and features	Open source?	Sale status	Price ($)
FreeEEG32	Modular PCB	32 channels (can be used as EEG, ECG, EMG, fNIRS)	• 512-Hz sampling frequency • Stackable up to 256 channels • Loose or pre-soldered headers • SD card storage • Stackable up to 256 channels	Yes	Crowdfunding	<500
Mentalab Explore	Modular PCB	8 channels (can be used as EEG, EMG, EOG, ECG)	• Configurable sampling rate up to 1 kHz • Wireless • Scientifically validated	Yes	Available	5k–10k
OpenBCI- Cython + Daisy	Modular PCB	16 channels (can be used as EEG, ECG, EMG)	• 125-Hz sampling frequency • Programmable Bluetooth dongle • 3-axis accelerometer • Micro SD card storage • Various data output formats • Scientifically validated	Yes	Available	1k–5k
OpenBCI- Cython	Modular PCB	8 channels (can be used as EEG, ECG, EMG)	• 250-Hz sampling frequency • Programmable Bluetooth dongle • 3-axis accelerometer • Micro SD card storage • Various data output formats • Scientifically validated	Yes	Available	500–1k
OpenBCI- Ganglion	Modular PCB	4 channels (can be used as EEG, ECG, EMG)	• 200-Hz sampling frequency • Programmable Bluetooth dongle • 3-axis accelerometer • Micro SD card storage • Scientifically validated	Yes	Available	<500
SOMNOwatch plus	Modular PCB	7 (+8) channels BP, Resp, EEG	• 256-Hz sampling frequency • 7 internal channels and up to 8 external channels (via AUX) • Leg movement analysis if worn on ankle • Marker button • Scientifically validated	No	Available	1k–5k
Traumschreiber	Modular PCB	24 channels (can be used as EEG, EMG, EOG, ECG)	• 200-Hz sampling frequency	Yes	Available for research	<500

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TABLE 1 (Continued)

Device name	Category	Sensors/channels	Specifications and features	Open source?	Sale status	Price ($)
			• Sticky or cup electrodes that can be placed freely on head and body • Full access to raw data via BLE in real-time • Scientifically validated • Open source			
Unicorn naked BCI	Modular PCB	8-channel EEG, Acc, gyro	• Hybrid electrodes (dry or wet) compatibility • Real-time data analysis through a programmable API	Yes	Available	500–1k
Bitbrain Neuroband	Headband	5-channel EEG, Acc	• 256-Hz sampling frequency • Garment design with 5 dry EEG channels • Real-time data representation • Medical certification in progress • Customizable design for different applications • LSL and SDK tools	No	Available	1k–5k
Bitbrain Air	Headband	8-channel EEG, Acc, SpO2	• 256-Hz sampling frequency • 8 dry EEG channels • Real-time data representation • Online impedance measurement • SDK compatibility with Matlab, Python	No	Available	1k–5k
Dreem (gen. 1, 2, 3)	Headband	EEG, PPG, SpO2, Acc	• 256-Hz sampling frequency • Five dry EEG channels: F7, F8, Fpz, O1, O2 • Bone-conduction: audio stimulation • Scientifically validated	No	Available For Research	<500 (before relaunch)
Emotiv—Epoc	Headband	EEG, Acc	• 14 dry EEG channels (saline soaked felt) • 9-axis motion sensor • Rotating headband • Setup time: 3–5 min • Scientifically validated	No	Available	500–1k
Emotiv—Insight	Headband	EEG, Acc	• Five EEG sensors (semi-dry polymer) • 9-axis motion sensor • Fixed (no rotation)	No	Available	<500

(Continues)

TABLE 1 (Continued)

Device name	Category	Sensors/channels	Specifications and features	Open source?	Sale status	Price ($)
			• Setup time: 1–2 min • Scientifically validated			
iBand+	Headband	EEG, Acc	• 256-Hz sampling frequency • Single-channel dry EEG (Fp1–Fp2) • Lucid dream induction and deep sleep enhancement features	No	Delayed Production	<500
iWinks—Aurora	Headband	EEG, Acc	• Auditory and visual stimulation for lucid dream induction • Smart alarm	Yes	Discontinued	<500
Muse S	Headband	EEG, PPG, SpO2, Acc	• Soft-touch EEG sensors: AF7, AF8, TP9, TP10 • Presleep meditation • Multisensor neuro-feedback • Scientifically validated	Yes	Available	<500
Philips SmartSleep Deep Sleep Headband	Headband	EEG, Acc	• Soft fabric headband • Self-adhesive electrodes • Deep sleep enhancement with auditory stimulation • Scientifically validated	No	Likely discontinued	<500
SleepLoop	Headband	8 channels (can be used as EEG, EMG, EOG)	• 250-Hz sampling frequency • Scientifically validated for closed-loop auditory stimulation	Yes	Available for research	N/A
Unicorn black hybrid	Headband	8-channel EEG, Acc, gyro	• 4096-Hz sampling frequency • Hybrid electrodes (dry or wet) compatibility • Real-time data analysis through a programmable API	Yes	Available	500–1k
X.on	Headband	8-channel EEG, Acc,	• Sampling frequency up to 500 Hz • 8 dry EEG channels • Real-time data representation • Compatible with Android smartphones • LSL tools	No	Available	1k–5k
Zeo	Headband	EEG	• 128-Hz sampling frequency • Silver-coated fabric electrodes	Yes	Discontinued	<500
ZMax	Headband	EEG, PPG, Therm, SpO2, Acc, Amb. light, Mic	• 256-Hz sampling frequency • Two-channel EEG: F7-Fpz & F8 - Fpz (wet EEG patches)	Yes	Availablefor research	1k–5k

TABLE 1 (Continued)

Device name	Category	Sensors/channels	Specifications and features	Open source?	Sale status	Price ($)
			• Programmable buttons • Real-time data representation (pro version) • Real-time stimulation: auditory, visual, tactile (pro versions) • Automatic REM and SWS detection (pro versions) • Scientific validation in preparation			
IDUN—Guardian	In-ear EEG	EEG, Acc,	• 250-Hz sampling frequency • 1 ear-EEG channel • Bluetooth low energy data transmission • Python Software Development Kit	Yes	Available for research	N/A
Nextsense	In-ear EEG	EEG	• Multimodal biosensing • API-driven	Yes	N/A	N/A
Neurosteer	Patch	EEG	• Wired connection to electronics • Cloud-computing • Scientifically validated	No	Available	–[a]
Onera	Patch	Can be used as EEG, EMG, EOG, ECG	• Can be used to a setup a wireless, self-administered PSG system • Cloud-computing • Scientifically validated	No	Available	N/A
TMSi—cEEGrid	Patch	EEG	• 250-Hz sampling frequency • Flex-printed 10 around-the-ear EEG channels • Compatible design for self-administered home recordings • Scientifically validated	No	Available	–[b]
Xtrodes	Patch	Can be used as EEG, EMG, EOG, ECG	• Wireless data acquisition • Real-time data representation • Cloud-computing • Scientifically validated	No	Available for research	N/A
Zmachine Insight+	Patch	EEG	• Single-channel EEG system • Requires disposable patches (every night) • Real time display of summary of sleep statistics • Automatic sleep scoring	Yes	Available	1k–5k

[a]Will be available when the device is released for customers.
[b]Available upon contact with the developers.

Sleep staging is typically the first step for sleep data analyses. Given the large-scale data produced in citizen neuroscience studies, employing valid automatic sleep scoring methods should be prioritized over human scoring of the data. While several autoscoring algorithms have been introduced in the literature, the majority require a specific EEG montage (e.g., Hsu et al., 2013; Supratak et al., 2017; Supratak & Guo, 2020; Tsinalis et al., 2016), and the ones compatible with different EEG montages (Perslev et al., 2021; Vallat & Walker, 2021) may not be used 'out of the box' for wearables. This is because wearables typically employ different electronics and nonconventional EEG derivations (Esfahani, Weber, et al., 2023; Esfahani, Daraie, et al., 2023). Therefore, it is essential to further develop autoscoring models exclusively for wearable systems data or to retrain some of the robust existing models with wearable data through transfer-learning.

Table 2 summarizes open-source software that is developed for sleep EEG analysis and may be employed by citizen neuroscientists. This list encompasses the tools including graphical user interfaces (GUI) that can be used for (1) real-time data monitoring, recording, post-processing, analysis, and stimulation such as COsleep (RRID:SCR_017053) and Dreamento (Esfahani, Daraie, et al., 2023), (2) data visualization, post-processing, and analysis including FASST (Schrouff et al., 2009), Luna and moonlight,[6] Sleep (Combrisson et al., 2017), Sleep-Trip (RRID:SCR_017318), SpiSOP,[7] Visbrain (Combrisson et al., 2019), SmartHypnos (Chriskos et al., 2019), Wonambi,[8] and YASA (Vallat & Walker, 2021), and (3) tools that have been explicitly developed for sleep events detection (e.g., spindles or K-Complexes) comprising Spinky (Lajnef et al., 2017), SWA (Mensen et al., 2016), and Tensorpac (Combrisson et al., 2020).

Similar to hardware, the software selection for citizen neuroscience projects should align with the study objectives. By listing the required features to achieve the study objectives, one may refer to the details outlined in Table 2 to make the most appropriate choice.

In the following, we further elaborate on two examples, selected based on their comprehensive features ranging from data monitoring and recording to potential stimulation capabilities and post-processing of the results. The first example, COsleep, can be used for citizen neuroscience projects employing complex EEG systems such as OpenBCI (see Table 1) and is configurable as a full-PSG with open standards, whereas the second example (Dreamento) is developed to support minimal sensing systems such as EEG wearables.

3.1 | Open software for open hardware: COsleep

We developed COsleep[9] (RRID:SCR_017053, Figure 1a): an open-source python software suite to record full-PSG and drive stimulation using auditory closed- and open-loop protocols with relatively inexpensive open-source OpenBCI hardware (see Table 1; all Cyton boards v1 or later, 125 Hz or 250 Hz, 8 or 16 channels). COsleep is flexible to the experimental setup and helps to set up an OpenBCI Cyton board automatically to record and display PSG-signals according to a user-defined channel montage. A variety of setups can be chosen in COsleep for (1) stimulation studies, (2) real-time recording without stimulation, or (3) just recording on the micro-SD card of the OpenBCI Cyton board without real-time monitoring/stimulation.

COsleep has tools in helping to (a) create, mix, and manage stimulation sounds, (b) accurately determine the hearing threshold, and (c) obfuscate the stimulation/sham condition for blinded experimentation. COsleep comes with slow-wave/sleep spindle detection and targeting algorithms to stimulate at slow-wave downstates and upstates or sleep spindles. These features allow COsleep to reproduce most published auditory stimulation research in sleep like targeted memory reactivation (TMR; Hu et al., 2020; Rudoy et al., 2009), or slow-wave/sleep spindle triggered stimulation (e.g., Ngo et al., 2013; Wang et al., 2022) with relatively higher sample size. In summary, as the importance of transferring appropriate technologies to investigate the clinical applications of auditory stimulation during deep sleep has been recently emphasized (e.g., Esfahani, Farboud, et al., 2023), COsleep enables citizen scientists to conduct full-PSG experiments in a naturalistic home environment, allowing to gain more insights into the topic.

4 | OPEN SOFTWARE FOR EEG WEARABLES: DREAMENTO

Objective modulation of sleep is an intriguing topic for citizen neuroscience, especially when it comes to the topics that most citizens are engaged in, for example, sleep staging, sleep quality assessment, and (lucid) dreaming. Recently, we developed an open-source dream engineering toolbox (currently only) for the ZMax EEG

[6]https://zzz.bwh.harvard.edu/luna/moonlight/.
[7]https://www.spisop.org.
[8]https://wonambi-python.github.io.
[9]https://www.spisop.org/cosleep.

TABLE 2 List of the applicable open-source software (and source code language) employing a graphical user interface to monitor and analyse sleep EEG data as well as providing sensory stimulation tools during sleep. CLAS: closed-loop auditory stimulation. ERP: event-related potential. fMRI: functional magnetic resonance imaging. GPU: graphics processing unit. SO: slow-oscillation. TMR: targeted memory reactivation.

Software (source code language) & purpose	Selected features
COsleep (Python): Real-time data monitoring, recording, post-processing, analysis, and stimulation	• Accurately timed sensory stimulation and annotation • Full-PSG support with different montages • Enabling double-blind studies and study simulation • Real-time automatic SO, spindles and arousal detection • Designed for CLAS and TMR studies or both • Live ERP analysis • Bootable from USB-stick via Debian Linux • Comprehensive documentation and examples • Designed for full-PSG
Dreamento (Python): EEG wearable, real-time data monitoring, recording, post-processing, analysis, and stimulation	• Comprehensive automatic sleep scoring, analysis and curation tools with documentation including: automatic sleep staging (real-time & offline), hypnograms, various spectral analyses (real-time & offline), SO, sleep spindles, REM events identification[b9]Sleep event identification functions employed from YASA. • Accurate manual and automatic annotations • Sensory stimulation (visual, auditory, text-to-speech, tactile) • Synchronization features to align simultaneous recordings • Designed for EEG wearables
Mobile sleep lab (Android): Real-time data monitoring, recording, post-processing and analysis	• Phone-based app • Potential for medical usage • Synchronization features to align simultaneous recordings • Designed for EEG wearables
SleepTrip,[a] SpiSOP (Matlab & Octave): Data visualization, post-processing, pipelining and analysis	• FieldTrip extension, thus already extensive EEG analysis features • Assisted sleep scoring, visualization of events in high density (>128-chan.) PSG • Comprehensive automatic sleep analysis and curation tools with documentation including: extended hypnograms and scoring handling, various spectral analyses, SO, sleep spindles and REM detection, event co-occurrence, topographic maps • Efficient computational costs, pipeline, and grammar based transformation tools adapted for big sleep data analysis
SmartHypnos (Matlab): Data visualization, post-processing, and analysis	• Automatic sleep scoring features • Automatic sleep events detection • Detection of sleep apnoea events
Spinky (Matlab & Python): Sleep events detection	• Automatic spindle and K-complex identification
SWA (Matlab): Sleep events detection	• Sleep scoring and visualization in high-density (>64 chan.) PSG • Automatic SO, spindle and sawtooth wave detection • Enabling manual correction of the automatically detected events
Tensorpac (Python): Sleep events detection	• Enabling various phase-amplitude coupling methods • High computation efficiency
Visbrain, Sleep (Python): Data visualization, post-processing, and analysis	• High-performance 2D and 3D plots. • Rapid and GPU-based computation • Sleep scoring interface • Enabling topographic maps • Automatic sleep events detection • Rapid and GPU-based computation • Comprehensive documentation and examples

(Continues)

TABLE 2 (Continued)

Software (source code language) & purpose	Selected features
YASA (Python): Data visualization, post-processing, and analysis	• Automatic sleep scoring features independent of EEG montage • Comprehensive automatic sleep analysis tools and documentation including hypnograms,various spectral analyses, SO, spindles and REM, detection and event phase locking • Comprehensive documentation and examples
Wonambi (Python): Data visualization, post-processing, and analysis	• Sleep scoring interface • Time-frequency and power-spectrum analysis • Comprehensive automatic sleep analysis and curation tools • Automatic SO, spindle detection • Comprehensive documentation and examples • Compatibility with various data formats/devices
Luna, Moonlight (C/C++ & *R*): Data visualization, post-processing, and analysis	• Sleep recording visualization in big data • Automatic SO, spindle detection • Comprehensive automatic sleep analysis and curation tools with documentation including: automatic sleep staging, hypnograms, various spectral analyses • Web-based application
FASST (Matlab): Data visualization, post-processing, and analysis	• Visual data exploration via Moonlight • Comprehensive automatic sleep analysis and curation tools with documentation including: automatic sleep staging, hypnograms, various spectral analyses, SO, sleep spindles, coherence and cross-frequency coupling, topographic maps • Efficient computational costs and pipeline, and data transformation tools for big sleep data analysis • Simultaneous EEG-fMRI or sole EEG analysis • Comprehensive documentation and examples

[a]The functions that necessitate a graphical interface are included, but the majority of functions despite being easy-to-use lack graphical elements.
[b]Sleep event identification functions employed from YASA.

headband, dubbed Dreamento[10] (Figure 1b), capable of recording, monitoring, modulating (using sensory stimuli such as visual, auditory, and tactile), and analysing (e.g., automatic sleep scoring, power spectrum, and time-frequency representation) sleep in *real-time* as well as postprocessing the resulting data in an interactive GUI (Esfahani, Daraie, et al., 2023). These features give Dreamento the capability to not only be a practical tool for data collection but also be a user-friendly solution to analyse sleep data by citizen neuroscientists.

While the performance of Dreamento as an all-in-one package for (lucid) dream engineering is currently being validated in a multicentre study (Esfahani et al., 2022), it has potential applications for the upcoming citizen neuroscience topics. As a case in point, citizen neuroscientists may use Dreamento to present light, audio, and vibration stimuli during their REM sleep as a valid method to induce lucid dreams (Stumbrys et al., 2012) or use the text-to-speech feature of the toolbox to establish a medium for communication while dreaming (Konkoly et al., 2021).

[10]https://github.com/dreamento/.

5 | CITIZEN NEUROSCIENCE: OUTLOOK

The advances in wearable neurotechnologies have likely facilitated the increasing number of citizen neuroscience projects. Still, citizens need a certain level of expertise to contribute to or conduct citizen neuroscience projects. They may experience difficulties in understanding the project's goals, following data collection protocols or complex procedures to integrate data, or adhere to privacy and ethical guidelines. Therefore, some studies have questioned the quality and reliability of data collected by citizen scientists and scrutinized their role in scientific research (Aceves-Bueno et al., 2017; Meschini et al., 2021; Resnik, Elliott, & Miller, 2015; Riesch & Potter, 2014). For example, citizen science projects are suggested to be at higher risk of data fabrication, result falsification, tempering, participation bias, plagiarism, or partial data presentation or analysis (Gilbert & Denison, 2003; Haklay, 2016). Furthermore, the involvement between the citizen neuroscientists and nonprofit, private, or political organizations (or personal relationships with the study subjects) may raise a conflict of

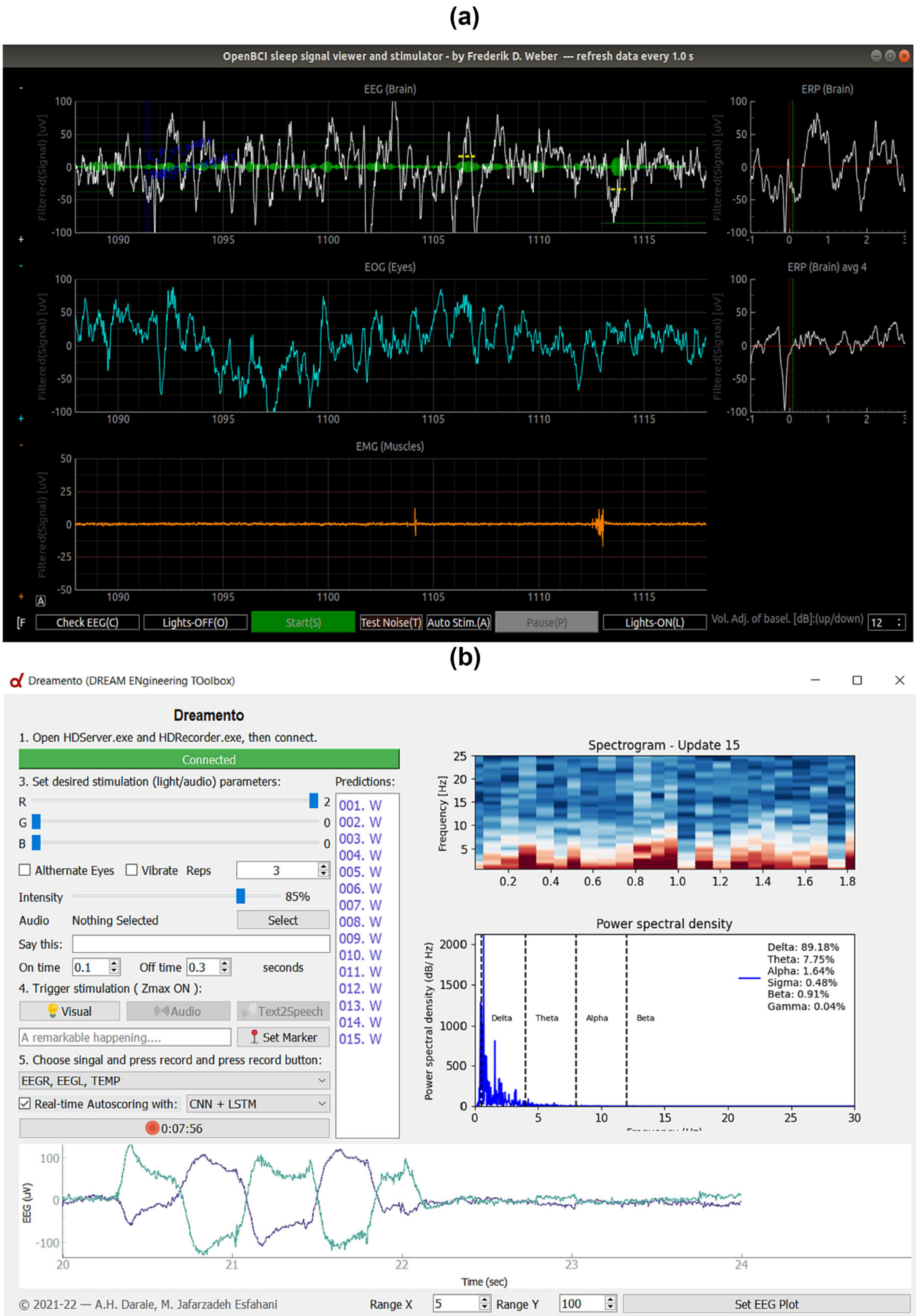

FIGURE 1 The user interface of (a) COsleep and (b) Dreamento software. They both assist citizen neuroscientists in conducting sleep experiments with recording, monitoring, logging, real-time simulation, and analysis of data based on open sleep EEG hardware or wearables.

interest (COI) in the study (Resnik, 2007; Resnik, Elliott, & Miller, 2015). In addition, possibilities for exploitation were mentioned, which occurs due to lack of consent, inequity, mistreatment, or if people are harmed somehow (Guerrini et al., 2018; Riesch & Potter, 2014). Although many countries follow well-established policies to avoid issues related to research misconduct (Resnik, Rasmussen, & Kissling, 2015), they have not yet been appropriately transited into citizen science projects. To overcome these challenges, we suggest that the active involvement of professional researchers can mitigate the issues by providing citizen neuroscientists with the essential training, tools and resources, and assistance for practical works such as data collection, analysis, and integration. Citizen neuroscientists can be informed about the rules and regulations of data sharing, transparency, and ethical research transparently to ensure that these guidelines are strictly followed in every stage of the project (Remmers et al., 2023). Furthermore, the researchers can equip citizen scientists with the necessary devices for data collection and infrastructure for big data management and sharing. For successful knowledge discovery from citizen neuroscience projects, both groups must work hand-in-hand, co-create, and progress methodically towards achieving the goals of the project (Roskams & Popovic, 2016).

Small sample size, lack of generalizability, confinement to the lab settings rather than naturalistic home environments, and restricted amount of recordings per participant are among the major reasons that contributed to several controversial findings in different fields of neuroscience, such as sleep. Given the potential of citizen science, if the challenges are carefully considered, the contributions of citizen neuroscientists are indispensable to advancing the field. Along with the proper tools and skillset to achieve best research practices, they must possess a certain motivation and interest in doing science to make their participation meaningful and worthwhile. They contribute to projects due to their desire to learn, understand, and improve their own sleep patterns as well as the sleep of others, establish networks, or obtain a good reputation in the (scientific) community (Asingizwe et al., 2020). The collaboration between citizen neuroscientists and professionals can contribute to the motivation and commitment of citizens to a project (Hobbs & White, 2012). Creating a welcoming and collaborative environment and rewarding citizen neuroscientists for their contributions are some crucial things that researchers can do to promote citizen science. Rewards could include personalized sleep reports or detailed dream analyses, certificates for participation, acknowledgments or co-authorship in publications, or even monetary rewards (Cappa et al., 2018; Hunter & Hsu, 2015).

Recently, several research groups started to perform home studies with wearable EEG systems (e.g., Debellemaniere et al., 2018; Esfahani, Weber, et al., 2023; Healthy Brain Study consortium et al., 2021; Lustenberger et al., 2022; Talamini et al., in preparation; Ter Avest et al., 2023; Xi et al., 2023). However, the majority of home studies, including the aforementioned ones, still recruit participants using conventional methods. We believe that it is time for a bold translational effort to make citizen neuroscientific studies more common—topics that meet the interest of the wider public, such as sleep monitoring or enhancement and (lucid) dreaming, seem a particularly well-suited starting point for such an endeavour.

Citizen science projects benefit both researchers and citizen scientists, which is why this practice has been growing worldwide (Vohland et al., 2021). It allows researchers to generate large longitudinal datasets and get direct input from the public. From the citizen scientists' point of view, participating in these projects can have numerous benefits (Den Broeder et al., 2018). From a societal point of view, these projects engage people in scientific studies, which have a lot of benefits (Pocock et al., 2019). Such engagement promotes science and technology among populations outside academia and familiarizes them with scientific thinking. By training citizen scientists, these projects help to create the next generation of scientists, researchers, thinkers, leaders, and conservationists, who will be knowledgeable and receptive to science and resistant to disinformation, misconception, and false narratives. All things considered, citizen (neuro)science projects are mutually beneficial and have significance for the long-term prosperity of science.

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ACKNOWLEDGEMENTS

This work was supported by the PPP Allowance made available by Health Holland, Top Sector Life Sciences & Health.

PEER REVIEW

The peer review history for this article is available at https://www.webofscience.com/api/gateway/wos/peer-review/10.1111/ejn.16227.

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