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Workshops of the Eighth International Brain-Computer Interface Meeting: BCIs: The Next Frontier

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Conflict of Interest
CG is the owner and CEO of g.tec medical engineering GmbH.
DV is an employee of Neurable, Inc
GMP is on the board of directors of the BCI Society
JEH is a co-Editor-in-Chief of *Brain-Computer Interfaces*, on the board of directors of the BCI Society, and has a pending patent on a BCI application used in one of the referenced papers.
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Abstract

The Eighth International Brain-Computer Interface (BCI) Meeting was held June 7–9th, 2021 in a virtual format. The conference continued the BCI Meeting series' interactive nature with 21 workshops covering topics in BCI (also called brain-machine interface) research. As in the past, workshops covered the breadth of topics in BCI. Some workshops provided detailed examinations of specific methods, hardware, or processes. Others focused on specific BCI applications or user groups. Several workshops continued consensus building efforts designed to create BCI standards and increase the ease of comparisons between studies and the potential for meta-analysis and large multi-site clinical trials. Ethical and translational considerations were both the primary topic for some workshops or an important secondary consideration for others. The range of BCI applications continues to expand, with more workshops focusing on approaches that can extend beyond the needs of those with physical impairments. This paper summarizes each workshop, provides background information and references for further study, presents an overview of the discussion topics, and describes the conclusion, challenges, or initiatives that resulted from the interactions and discussion at the workshop.

Keywords

brain-computer interface; brain-machine interface; neuroprosthetics; conference

Introduction

The field of brain-computer interface (BCI) research has many names, most historically originating from related research domains with converging objectives. The terms BCI and brain-machine interface (BMI) are quite common and the term neuroprosthetic also applies. In general, a BCI is a device that interprets information directly from the brain to provide a means of interacting with technology. Brain activity can be measured using either implanted electrodes or external sensors. The technology can be operated through a variety of methods, including a direct connection between the brain and the effector (e.g., to operate a prosthetic), or a secondary interface such as a keyboard display (e.g., for communication). Recent work has also used electrical stimulation of the brain itself to "close the loop" and provide sensory feedback about the state of the technology. The defining feature of a BCI is that the brain activity itself is interpreted, the information to control a device is not derived from activity propagated through peripheral nerves. Many BCIs were initially developed for use by people with physical impairments, but the current broad range of applications also targets other neurological and cognitive impairments, abled-bodied users, and even opportunities for human enhancement. The 8th International Brain-Computer Interface Meeting provided a venue for exploration of the breadth of BCI topics and this paper is designed to provide a window into the workshops that occurred at that Meeting.

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The BCI Meeting Series

The 8th International Brain-Computer Interface Meeting was originally scheduled to be held in 2020. However, due to travel restrictions and health concerns during the global pandemic, the 2020 in-person meeting was postponed to June 7–9th, 2021 and ultimately converted to a virtual meeting format. The goal of the BCI Meeting Series (1999 [1] 2002 [2], 2005 [3], 2010 [4], 2013 [5, 6], 2016 [7–9], and 2018 [10, 11]) is to create a single venue for people representing all the diverse backgrounds, disciplines, expertise, and application areas necessary for successful and practical BCI research and development.

The Eighth International Brain-Computer Interface (BCI) Meeting was hosted in the Pheedloop platform (Toronto, Ontario, Canada), which managed individual sessions using the Zoom platform (San Jose, California, USA). Poster sessions and social events were held on the GatherTown platform (gather.town). This Meeting was attended by 395 delegates from 35 countries, a significant growth from the 50 delegates in 1999 [1], although not quite as many as the previous in-person meeting in 2018. Respondents to the 2021 BCI Meeting evaluation survey identified themselves as 40% students, 13% postdocs, 25% faculty members, and 22% other. The BCI Meeting Series is intentionally designed to promote interaction between different groups and different career stages and has advanced the careers of numerous BCI researchers. Many activities are designed to provide educational content and networking opportunities for students and early-career investigators. The 2021 BCI Meeting had a theme of “BCIs: The Next Frontier.” The workshops of the BCI Meeting Series provide examples of how BCIs are advancing the frontiers of science and details on both how close we are to realizing new applications and the challenges that remain to be overcome. The workshop summaries presented here serve as an overview of the current status of BCI research and development and present a roadmap to the next steps needed to advance that frontier.

Organization of Workshop Summaries

Workshops for the BCI Meetings are proposed by members of the BCI community, then evaluated and curated by the Program Committee. For the virtual BCI Meeting of 2021, the workshops were assigned to four different schedule slots with three to four workshops running concurrently. In addition, six of the workshops volunteered to run as part of a five-month preliminary series of “BCI Thursdays.” These workshops were the same length and format as the workshops that occurred during the Meeting, but did not overlap with other BCI Society events and had a separate registration structure. However, they retained the strong emphasis on attendee participation that is central to workshops of the BCI Meeting series. The BCI Thursday series also included free events designed to provide technical background for students on cutting-edge topics in BCI research.

The workshop summaries presented here are divided into three themes and ordered to provide a progression of topics. They can be read sequentially as an overview of the field or separately to provide detail on a topic of interest. However, acronyms are only defined on their first use. For each summary, we report the primary organizer, who is also a co-author of this paper, and list all additional presenters. Each summary is designed to introduce the workshop topic, the latest developments or central ideas presented in the workshop,

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and the topics of discussion and eventual conclusions. Of course, nothing will substitute for the actual experience of being part of an interactive workshop, even a workshop in a virtual platform. However, the summaries are intended to at least provide an overview and pointers to the information that workshop attendance would have provided. Further, the summaries provide the key points, conclusions, or consensus opinions that resulted from the workshop discussions and may include opportunities to participate in ongoing discussions or collaborations.

Each workshop focused on a specific topic area, yet these topics overlap and complement each other, so that the summaries sometimes create a mosaic examining related ideas from different angles and at other times build on each other. For example, the workshops "*Toward an international consensus on user characterization and BCI outcomes in settings of daily living"* and *"On the need of good practices and standards for Benchmarking Brain-Machine Interfaces"* examine different aspects of standards. Similarly, BCI use for children and people with congenital disabilities are examined in the pair of workshops "*The design of effective BCIs for children"* and "*Non-invasive BCIs for people with cerebral palsy."*

Three general themes provide the structure for this article, although many alternative organizations could be proposed. The themes are independent of the time slot in which the workshop occurred. The first theme is Tools and Methods and contains workshops providing detailed examination of a particular hardware, software, or analysis method. The second theme is BCIs for Specific Populations or Applications and is less concerned with hardware and software than with the outcome produced or the common considerations for working with a specific group. The final theme is Expanding BCI Usability and Availability. The workshops in this theme focus on big picture topics such as standards, translational issues, and ethics as well as the expansion of BCIs into the broad consumer market through applications such as entertainment and human enhancement.

The trajectory of these three themes, and the workshop summaries presented here, creates a progression from foundational topics to translational efforts for standardized clinical applications and BCIs for the population at large. Together these workshops show the diversity of BCI applications and intended users and the complexity of the issues that must be solved to make BCIs into useful tools for the many intended user groups.

Tools and Methods

Focal Bi-Directional Brain Computer Interfacing with Concentric Electrode Technology—*Organizer*: Charles Anderson (Colorado State University)

Additional Presenters: Walter Besio (University of Rhode Island and CREMedical), Barry Oken (Oregon Health & Science University), Myles McLaughlin (KU Leuven)

This workshop focused on EEG BCI experiments and stimulation studies using tripolar concentric-ring electrodes (TCREs) and the advantages of this technology over conventional disc electrodes. Compared to conventional disc electrodes, TCREs have significantly better spatial resolution and signal-to-noise ratio [12–14]. TCREs increase signal bandwidth for high-frequency signals useful for localizing epileptic brain regions and possibly imagined

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movements [15, 16]. Imagined movement BCI improved significantly with TCREs [17, 18]. TCREs' increased spatial resolution and signal-to-noise ratio may enable discrimination between finger movements, currently only possible with implanted electrodes. Experiments involving real and imagined finger movements found that EEG from TCREs produced significantly better discrimination among movements of individual fingers (about 70% correct classification) than conventional disc electrodes (about 40%) [19].

TCREs are safe for stimulation [20, 21], and can be used for seizure control [22–26]. The stimulation can block epileptogenesis [27] and alter neurotransmitters to increase the effectiveness of anti-seizure drugs [28–30]. Stimulation experiments are underway to determine if transcranial focal stimulation via concentric ring electrodes is effective for modulating human brains.

Pain is a common medical problem but difficult to objectify as a personal experience of a sensation. Using TCREs both to selectively stimulate pain fibers and to record pain-related evoked potentials (PREPs) is one method of objectifying pain sensation [31–37]. Custom-made concentric stimulating electrodes can selectively stimulate pain afferents where conventional electrical stimulation with mono- or bi-polar stimulating electrodes failed. TCREs delivered paired electrical stimulations to the dorsal non-dominant hand. PREPs were recorded at Cz referenced to ear. For control participants, average PREP N1-P2 amplitude was significantly diminished by electroacupuncture. In another experiment control participants showed the expected habituation of PREP N1-P2 amplitude over time, but those with chronic low back pain showed an increase in PREP amplitude, presumably a physiological marker of central sensitization, the increased responsiveness to sensory information such as nociception.

TCREs on the skull under the skin may be an effective middle ground between implanted stimulation electrodes and the non-invasive but less effective transcranial stimulation. TCREs provide higher magnitude stimulation in gray and white matter than transcranial stimulation. Focused and unfocused stimulation on neurons have been studied in Macaque. Increased spatial precision with TCREs was demonstrated when stimulating rat motor cortex area for rear limb movement. Conventional electrodes produced movement in both contralateral and ipsilateral limbs, but TCREs only produced contralateral limb movement [38].

Discussion covered practical considerations and design variations, including different numbers of rings and different spacing. TCREs sizes include 10mm, 6mm, 4mm, and even 3.5mm. TCREs use 10–20 paste, but work on using gels and possible dry electrode designs are being considered. Caps to hold TCREs were described, but need work for the smallest TCREs. Two disadvantages of TCREs are the need for a custom pre-amplifier from CREMedical and for precise scalp placement because higher spatial precision means steep attenuation over short distances. Laplacian transforms can be applied to EEG recorded from conventional disc electrodes, but 92 disc electrodes are required to obtain results similar to that provided by one TCRE. Publicly available sample data recorded from TCREs can be found at https://www.cs.colostate.edu/~anderson/res/eeg/tripolar/tripolar.zip.

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Invasive brain computer interface technology: Open loop and closed loop decoding applications—*Organizer*: Christoph Kapeller (g.tec medical engineering GmbH, Austria)

Additional Presenters: Kyousuke Kamada, MD, PhD, (Megumino Hospital, Japan); Aysegul Gunduz, PhD, (University of Florida, USA); Peter Brunner, PhD, (Washington School of Medicine, St. Louis, USA); Kai Miller, MD, PhD, (Mayo Clinic Rochester, Minnesota, USA)

The workshop discussed state-of-the art BCI applications using open-loop and closed-loop decoding and neuromodulation. Implementation of these experimental setups in existing BCI platforms was also discussed.

Invasive electroencephalographic (iEEG) signals, such as electrocorticography (ECoG) or stereo EEG, contain information with high spatial and temporal resolution [39]. Several invasive BCIs have been realized over the past two decades. Closed-loop invasive BCIs have been used for control of prosthetic limbs [40] as well as avatars or cursors [41, 42]. Open-loop invasive BCIs have been used for decoding of speech [43–46], movements [47, 48] and vision [49, 50]. Establishing useful invasive BCI applications requires interdisciplinary efforts for the development of sensors and machine learning algorithms, with specialized efforts to make the resulting technology practical for a medical environment and matched to each individual's clinical indications. Further, the risk of implanting sensors has to be surpassed by the benefit that the BCI provides to meet the specific need of each patient [51].

Recent developments showed a transition from proof-of-concept demonstrations to clinical applications, including open-loop decoding for brain mapping [52–54] and BCI implants [55]. Such implants can provide ALS patients with a powerful BCI [42] and will be further investigated over the next years. The concept of open-loop electrical brain stimulation for neuromodulation has been widely used in presurgical brain mapping. Stimulating the somatosensory cortex can induce sensation in individual fingers [56], while stimulating the visual cortex causes illusory percepts like appearing faces or moving rainbows [57]. Open-loop deep brain stimulation (DBS) has been utilized for more than 40 years to manage tremor [58]. More recently DBS has been used to treat Parkinson's disease, Tourette syndrome, dystonia, and depression [59]. Closed-loop stimulation based on iEEG signals improves the battery lifetime during the treatment of Tourette syndrome [60] and essential tremor [61]. Most of the aforementioned studies required the integration of sensors and amplifiers into signal processing platforms that are capable of real-time processing and synchronized with the patient's condition and/or stimulus presentation. Example BCI platforms in the workshop were BCI2000 [62] and the rapid prototyping platform g.HIsys in MATLAB/Simulink [63].

Riemannian Geometry Methods for EEG preprocessing, analysis and classification—*Organizer*: Louis Korczowski (Siopi.ai)

Additional Presenters: Marco Congedo (GIPSA-lab, CNRS, Université Grenoble- Alpes), Florian Yger (LAMSADE, CNRS, Univ. Paris-Dauphine, PSL Research Univ.), Sylvain

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Chevallier (LISV - UVSQ - Univ. Paris-Saclay), Pierre Clisson (Timeflux Research Group), Quentin Barthélemy (Foxstream)

Riemannian Geometry (RG) is a subject of growing interest within the BCI community. Machine learning methods based on RG have demonstrated robustness, accuracy and transfer learning capabilities for the classification of motor imagery [64], ERPs [65], SSVEPs [66], sleep stages [67], and other mental states [68]. This workshop provided an overview of RG, demonstrating its practical use for signal pre-processing, data analysis, mental state classification, and regression.

RG was first applied to BCI in 2010 [64]. Key articles highlighting different applications of RG include multi-class classification (e.g. minimum distance-to-mean (MDM) classifier) [69], transfer learning (e.g. Riemannian Procrustes Analysis) [70, 71], the first online BCI system using it (e.g. Brain Invaders) [65, 72], and milestone-like performance of RG methods in international competitions [73, 74]. Intrinsic properties of RG methods were discussed to explain their performances (e.g., simple parametrization of models, robustness induced by affine-invariant metrics) but also some drawbacks and how they can be managed (e.g. sensitivity to rank deficiency at high dimensionality) [75, 76]. Interestingly, RG can be used in combination with other effective methods such as common-spatial pattern and/or deep learning to outperform methods using Euclidean space alone, e.g. by projecting data in a tangent space [74].

The ecosystem of open-source libraries (that was scattered and scarce before) is now mature enough to improve several steps of the BCI system. For example, Riemannian methods outperforms Euclidean methods in accuracy and simplicity in use cases such as automatic artifact detection (e.g., Riemannian potato) [77, 78] or ERP classification (e.g. MDM with super covariance matrix). These performances are tested using the fair benchmarking approach [79] and are easy to replicate in online BCI thanks to libraries such as Timeflux [80].

Despite its performance advantages, publication data from https://www.dimensions.ai/ show that articles mentioning new contribution of “Riemannian Geometry” applied to BCI has remained in the range of 7 to 21 per year in the period 2016–2020 (mean citations : 27.71). For comparison, mention of “common-spatial patterns” associated with BCI increased from 71 to 119 articles per year (mean citations: 20.75) and “deep learning” from 15 to 179 articles per year (mean citations : 11.67) in the same period.

We argue that the gap between the observed performance of RG applied to BCI and the proposal number of contributions in this field may be attributed to some combination of a perceived lack of easily accessible resources to make RG widely available to BCI research (e.g. 65.7% of respondents to the workshop questionnaire had never used RG before) and the lack of reproducible tools for benchmarking different methods while taking into consideration datasets heterogeneity (discussed at the previous BCI meeting workshop [81]).

This workshop was created to address these issues by increasing awareness of available resources for RG and encourage benchmarking with tools such as MOABB on a larger scale of datasets [79]. We encourage everyone to report benchmarking results. Further, we invite everyone to join us by using the open-source RG tools, and by contributing to the improvement of these tools either by providing feedback, or contributing to the open source project pyriemann. All the workshop resources are accessible, including slides, code tutorial, online demo, exhaustive workshop Q&A, and linked data: https://github.com/lkorczowski/BCI-2021-Riemannian-Geometry-workshop.

Open-source Python tools for BCIs—*Organizer*: Pierre Clisson (Timeflux Research Group)

Additional Presenters: Raphaëlle Bertrand-Lalo (Timeflux Research Group), Sylvain Chevallier (LISV, Université Paris-Saclay), Marco Congedo (GIPSA-lab, CNRS, Université Grenoble-Alpes)

Python started as a general-purpose programming language but has evolved into a tool of choice for the scientific community, quickly overtaking specialized languages such as R and MATLAB [82]. Several factors account for its success: Python is easy to learn, has a strong community, and benefits from a rich and efficient data science ecosystem.

This workshop had a two-fold objective: give an overview of the Python BCI landscape and provide hands-on instructions on a few chosen open-source tools.

As a foundation for the focus on practical BCI, we first reviewed the main BCI paradigms and the typical workflow of a BCI pipeline. We discussed common challenges for BCI applications: the need for precise synchronization of the EEG signal and the stimuli, the difficulty of obtaining good quality signals in real-life conditions, and the challenges of calibration.

Riemannian geometry (RG) for EEG-based BCI [65, 83] has produced state-of-the-art results in international competitions [76]. Machine-learning algorithms based on RG offer many advantages. They are computationally efficient and thus suitable for online applications. They usually converge to optimal results relatively quickly, reducing calibration duration (ongoing studies on transfer learning are attempting to remove this phase completely [70] [84]). Finally, they do not depend on the BCI paradigm and work equally well for ERP, SSVEP, and motor imagery tasks.

PyRiemann [85] is an actively maintained Python package for manipulating covariance matrices. It implements multiple data transformation techniques and classification methods. Workshop participants were guided through a Python notebook and instructed on using this library with concrete examples.

The RG framework includes multiple signal classification strategies and BCI researchers use many other algorithms, such as Logistic Regression, Regulated LDA, Support Vector Machines, and Neural Networks [86]. Valid comparisons between methods are essential. The Mother Of All BCI Benchmarks (MOABB) [79, 87] project offers comprehensive comparison tools that enable ranking new and existing algorithms with publicly available datasets, paving the way for reproducible research. We reviewed a practical example and explained the underlying code.

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Timeflux (https://timeflux.io/) [80] is an open-source framework for building online BCIs. It is capable of acquiring, recording, and processing biosignals in real-time. It can also present precisely scheduled stimuli. It works hand-in-hand with PyRiemann and MOABB and rests on the shoulders of standard libraries such as Pandas [88], Scikit-learn [89], Lab Streaming Layer [90], and HDF5 [91]. It comes with a rich set of nodes and plugins for dynamic epoching, matrix manipulation, digital signal processing, machine learning, and other tools. It also provides a convenient JavaScript API for developing web interfaces. We reviewed the architectural principles of Timeflux and explained how to use it to design a P300 speller, finishing with a functional demo that runs in a web browser.

We only introduced the potential of the Python language for the BCI field. For instance, we only briefly described MNE [92], a full-fledged framework for offline analysis of EEG and MEG signals. This workshop provided a good starting point for further exploration. The presentation slides, notebooks, and code are publicly available [93].

Artificial Intelligence in Brain-Computer Interfacing—*Organizer*: Moritz Grosse-Wentrup (University of Vienna)

Additional Presenters: Tonio Ball (University of Freiburg), Aldo Faisal (Imperial College London), Gernot Müller-Putz (Graz University of Technology)

Artificial intelligence (AI) methods in general, and deep learning algorithms in particular, have revolutionized the field of machine learning [94]. Current AI systems outperform human experts in various cognitively challenging tasks [95, 96] and have enabled scientific insights that arguably could not have been obtained by human intelligence alone [97]. More recently, deep learning methods have been adapted to and developed for brain decoding and BCI systems [98, 99]. Building on a long history of discussions on the benefits of nonlinear decoding methods in BCI [100], this workshop discussed whether AI can outperform traditional BCI machine learning methods and which challenges should be addressed to realize the full potential of AI in BCI.

The consensus on the current performance of AI-BCI methods was that they perform essentially on par with the best non-deep decoding algorithms. However, a rigorous comparison of state-of-the-art Riemannian decoding methods [76, 101] with AI algorithms has yet to be done. The workshop participants concluded that a large-scale brain decoding challenge, e.g., hosted by a major AI or machine learning conference, would be well suited for realizing a fair comparison of competing decoding architectures (e.g., https://beetl.ai/).

The workshop participants then considered which issues prevent, at least so far, AI methods from revolutionizing BCI systems in the same way they have already transformed other data-driven applications. The primary bottleneck identified in the discussion was the absence of large-scale datasets in the field of BCI. These datasets would ideally comprise thousands or even millions of BCI users from heterogeneous settings, i.e., including numerous experimental paradigms, recording setups, and user groups. While the workshop participants acknowledged the efforts of the BCI community to record large-scale datasets [102], they also noted that collecting datasets on a similar scale as those

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available in other scientific disciplines [103] is probably beyond the capabilities of the academic community. Consequently, the discussion shifted to the role of commercial BCI applications in recording and providing access to large-scale datasets. Several consumer EEG headsets have reached market readiness with the expectation of prompt deployment in passive BCI applications[104]. Comprehensive access to data recorded by these applications could provide the large-scale datasets required to realize the full potential of AI-BCI systems. In particular, the heterogeneous nature of such data, which stands in contrast to the homogeneous data typically recorded in academic settings, could be considered an advantage. The diversity of data might be leveraged to create feature representations that are user- as well as hardware-independent. Such feature representations would be essential to realize zero-training BCIs for commercial applications [105–107].

However, leveraging commercially recorded EEG datasets poses significant practical, legal, and ethical challenges. It is unclear what incentives companies would have to share their data publicly. Also, procedures would have to be developed that realize informed consent and honor data privacy regulations. The workshop participants considered an active engagement of the BCI community with industrial partners essential to make large-scale datasets a reality and realize the full potential of AI-BCI systems.

Adaptation in closed-loop BCIs—Organizer: Tetiana Aksenova (University Grenoble Alpes, CEA, LETI, CLINATEC)

Additional Presenters: Amy L. Orsborn (University of Washington), Martin Bogdan, Sophie Adama (Universität Leipzig), Blaise Yvert (U1205 Inserm, University Grenoble Alpes), José del R. Millán (University of Texas at Austin), Jean Faber (Universidade Federal de São Paulo)

BCI decoders calibrated in an open-loop, offline paradigm but then applied in close-loop, online paradigm show a significant drop in decoding performance. Adaptive algorithms in a close-loop session decrease this shortcoming by directly adjusting BCI parameters to incoming data. In addition, both the user and machine learn in a closed-loop BCI.

Closed-loop paradigms are often applied to BCIs that decode motor signals. Intracranial ECoG [108, 109] from a participant with tetraplegia was decoded with a fully adaptive decoder to operate a 4-limb exoskeleton. The decoder used an adaptive Markov mixture of multilinear experts [110] to switch between independent decoders (experts) to interpret multiple degrees of freedom.

Closed-loop paradigms enable user/decoder co-adaptation to maximize performance through synergistic user-machine interactions between the two learners [e.g., 111]. However, learning trajectory models are needed to optimize these co-adaptive systems. A new game-theoretic model of co-adaptation [112] provides a framework to analyze system equilibria and predicts learning trajectories, but requires validation.

The balance of decoder vs patient adaptation is important. EEG-based motor BCIs illustrate the pros and cons of extensive machine-learning adaptation. Non-supervised context-aware algorithms can rapidly adapt so users can use a language model-based speller [113] without

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a calibration phase [114, 115]. However, this does not promote user learning—EEG patterns for BCI commands actually became less separable with practice rather than improving [115]. True mutual learning, where decoder and user learn from each other, seems to require slow decoder adaptation to promote improved EEG features [116] as seen in several longitudinal studies [117].

Mutual learning implies cortical plasticity and the BCI use as a neurorehabilitation tool specifically designed to support plasticity (i.e., user learning). A clinical trial in patients with severe hand plegia from stroke compared the effect of BCI-operated vs random functional electrical stimulation. Only the BCI group had significant and clinically important functional improvement and a significant increase of functional connectivity in the damaged sensorimotor hemisphere [118]. Regulation of the magnitude of the required EEG response was critical to keep the patient's attention high and promote recovery.

Hybrid BCIs (HBCIs) integrate brain and non-brain data sources with different classifiers schemes (serial, parallel, mixed) to achieve better results [119]. Thus, neuroplasticity can happen in multiple dimensions and temporal scales. Different learning times are associated with different physiological systems such as autonomic learning (heart/breath adaptation) [120, 121], motor learning (agency and control refinement) [122, 123], central learning (cortical adaptations) [124], and cognitive learning (embodiment, ownership and spatial perception) [125]. HBCIs therefore present a more complex challenge for balancing classifier adaptation rate vs. neural plasticity.

Adaptive BCIs also exist for non-motor applications. The hybrid Adaptive Decision Making system was designed for a patient with complete locked-in syndrome (CLIS) and uses multiple EEG features (Granger causality, the imaginary part of the coherency, and multiscale sample entropy) to increase the probability of correctly evaluating consciousness level [126]. Caregiver observations regarding the patient's state were input into the machine learning system to personalised consciousness level estimation. An adaptive speech BCI application illustrates the risk of audio contamination of neuronal activity recordings [127].

Group discussion placed a priority on developing better understanding of co-adaptation from both theoretical and experimental viewpoints to optimize BCI training and user benefit.

Optimising BCI performance by integrating information on the user's internal state—Organizer: Sebastian Halder (University of Essex)

Additional Presenters: Philipp Ziebell, University of Würzburg), Angela Riccio (Fondazione Santa Lucia), Yiyuan Han (University of Essex)

Ideally, a BCI could detect the physical and mental state of the user and adapt accordingly to allow optimal BCI control for both unimpaired and motor impaired end-users. This adaptation could (1) determine when to start, pause or stop a BCI session, (2) adapt parameters of the BCI session such as trial length, stimulus and feedback modality or (3) switch between BCI and other assistive technology types. User-centered design (UCD) is critical to optimize BCI control in this manner [128]. In general terms, an assistive technology should enable a person with a disability to overcome barriers in daily life, education, work, or leisure [129]. This can only be achieved if the needs and requirements of the user are investigated [130, 131]. Regarding BCI design, the cognitive [132–134] and physical [135, 136] characteristics of end-users need to be considered [132, 133]. Based on this knowledge, we can implement a system that adapts to the internal state of the user.

The UCD evaluation process is built around metrics to determine effectiveness (accuracy in percent of correct responses), efficiency (information transfer rate in bits/min and subjective workload) and satisfaction (via visual analogue scale, questionnaire, or user interview) [137, 138]. These metrics should also inform earlier stage BCI development before end-user evaluation [139, 140]. Further factors should be considered when designing the BCI paradigm, for instance, the design of tasks, feedback, instructions, and signal processing [86, 141–143]. Performance may improve via engaging task design (e.g., a “Star Wars Mission” task) and exploring different stimulus modalities (such as auditory and tactile) and better understanding of the mechanisms underlying training with a BCI [140, 144].

User characteristics ranging from physiological (e.g., the amplitude of the sensorimotor rhythm during rest [145]) to psychological (e.g., the ability to concentrate [132, 146]) can influence performance in varying degrees. For example, a user with a traumatic brain injury may be in a minimally conscious state with only transient windows of consciousness [147, 148]. Identifying such windows is an undeniable prerequisite to BCI control [149]. Evaluation of the efficacy of such measures and any new measures that will be developed can be accomplished during pharmacologically induced loss of consciousness such as the Wada test [150]. More subtle influences on BCI control may arise due to mood and motivation, fatigue and workload or whether the user is experiencing pain, which can be detected using integrative features such as phase-based connectivity [151–153]. Ideally, the BCI could adapt to all changes in the users’ state. Doing this efficiently requires knowledge of features in the EEG (or other signals) that reflect the state of the user.

Many challenges must be resolved before the full potential of the state of the user can be reliably used to optimize BCI performance. The main challenge comes from the variety of states that need to be decoded, each requiring the identification of signal features that reflect these states, and integrating real-time identification of the states into the BCI design and usage environment.

BCIs for Specific Populations or Applications

The design of effective BCIs for children—Organizers: James J.S. Norton (National Center for Adaptive Neurotechnologies), Disha Gupta (National Center for Adaptive Neurotechnologies), Eli Kinney-Lang (University of Calgary)

Additional Presenters: Kim Adams (University of Alberta), Tom Chau (University of Toronto), Erica Floreani (University of Calgary), Kathleen M. Friel (Burke Neurological Institute), Dion Kelly (University of Calgary), Adam Kirton (University of Calgary), Ilyas Sadybekov (University of Calgary), Corinne Tuck (Glenrose Rehabilitation Hospital-I CAN Centre)

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BCIs have the potential to enhance, restore, or replace function in children with neurodevelopmental disorders, neurodegenerative disorders, and severe motor disabilities caused by stroke, spinal cord injury, or other acquired injuries [154–157]. However, few studies have investigated BCIs for children [158–161] and these studies show conflicting results; it remains unclear whether children—especially those with neurological disabilities—can effectively use BCIs. Thus, this workshop was organized into three discussion panels that:

1. **Examined how BCIs can improve children's quality-of-life –**Children can use BCIs to [162] communicate, play games, and express themselves creatively. The greatest benefit BCIs offer children with motor disabilities is a sense of control, motivating children to engage more with BCIs and enabling them to practice repetitive tasks that lead to learning. Thus, the child's perception of a successful BCI may not match that of a researcher. For example, operating a BCI using a combination of brain activity and artifacts may improve the child's life and be considered a success from the child's perspective. Therefore, special consideration is needed to simultaneously engage children in activities that are educational, therapeutic, meet the goals of researchers, and are engaging for the children. Recommended strategies are gamification [163–167] and close interdisciplinary collaboration between diverse experts.

2. **Discussed the interfacing, signal-processing, and physiological challenges encountered during the design of BCIs for kids –** Developing BCIs for children presents unique signal acquisition, data analysis, and reporting challenges [154]. Signal acquisition hardware for pediatric BCIs needs to be more portable, lighter, more comfortable, and easier to use (e.g., faster setup, dry electrodes, robust to artifacts). Presently only a few signal analysis pipelines exist for pediatric BCIs [168, 169], due in part to differences in the EEG from children compared to adults [170]. For example, P300 timing varies more in children and BCIs may be more fatiguing for children. Improved and consistent reporting of demographic information and experimental details would allow for better cross-study analyses. Lastly, improved user interfaces are an area of critical need for pediatric BCIs.

3. Considered the use of BCIs for children as augmentative and alternative communication devices and for rehabilitation in clinical settings – The design of BCIs for communication and rehabilitation in children benefits from a patient-centered and neurologic deficit specific approach [161, 171]. For example, many children express an interest in using BCIs for gaming and social play. Collaborative and competitive interactions between family members, and especially siblings, are a critical social outlet for children with motor deficits that motivate them to use BCIs. Neurological deficits may be caused by damage to small areas of the brain that were acquired very early in life. Thus, the brain may reorganize and researchers should work with clinicians to consider neuroplasticity in the design of BCIs for children [172, 173]. In addition, working with clinicians and families will increase awareness of the potential of BCIs for children [174].

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As members of the pediatric BCI community, we must put children first, understand what children want out of BCIs, and make it happen.

Non-invasive BCIs for people with cerebral palsy—*Organizer*: Jane E. Huggins (University of Michigan)

Additional Presenters: Katya Hill (University of Pittsburgh), Petra Karlsson (Cerebral Palsy Alliance, University of Sydney), Reinhold Scherer (University of Essex)

This workshop included extensive discussion about BCI design considerations for people with cerebral palsy (CP), the most common childhood physical disability [175]. CP is caused by injury or genetic abnormalities affecting the brain early in life leading to 15–19% without a communication method even with assistive technology [176–179]. However, BCIs that provide augmentative and alternative communication (AAC) for individuals with adult-onset impairments may unintentionally rely on skills that people with CP have not had an opportunity to learn.

Issues from the workshop *Design of Effective BCIs for Children* apply to children and adults with CP because of missed educational opportunities. Even those who have successful communication technology may need a BCI as age increases the severity of motor impairments. This makes BCI a competitive access option. For example, a participant with CP had similar communication rates on an AAC device with head-pointer access (1.33 words-per-minute, wpm) and BCI access (1.29 wpm).

Overall, BCI studies with people with CP show mixed results [162, 180, 181]. Some comparisons of BCI designs showed that SSVEP and SMR designs were preferred to the P300 design and had better performance [181]. Other comparisons of naïve users showed that some had significant SMR-BCI control (2 classes, 82±12%), others significant SSVEP-BCI control (4 classes, 43±7%), but few could use both and some could not use any BCI [182, 183].

Such results raise the specter that current BCI methods may not be appropriate for people with CP. If a person has no voluntary motor control, can they operate a motor imagery BCI? Can people with limited access to schooling count flashes of a P300 BCI or perform mental arithmetic or spatial navigation?

EEG recordings are complicated in people with CP due to head shape variations or improper electrode cap fit [184, 185] as head asymmetry is reported among 40% of people with the most severe impairments from CP [186] and microcephaly at 30% [187] to 60% [188]. Abnormal neuroanatomy can also cause unusual localization of cortical function [189]. The impact on BCI is uncertain, but people with severe CP can benefit from individualized electrode locations [184, 190].

Extraneous movements, which are common [191], can also create EEG artifacts [e.g., [182]] and may make it difficult to focus on the BCI display. Further, gaze or visual impairments including ptosis (drooping) of the eye lid, nystagmus, and cerebral visual impairment (CVI) can lead to difficulty interpreting visual stimuli [192]for an SSVEP or P300 BCI device or

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visual feedback for an SMR BCI. Thus, special care is needed to understand how well the user can interpret visually presented information.

Indeed, user-centered design is important throughout BCI design and user training. Acclimation regimes may be needed with step-by-step introduction of individual BCI concepts. Family interactions, cooperation, and competition can increase motivation and engagement, which are essential for learning, but not a guarantor of good performance [193]. These factors are crucial as people with CP may have a long history of unsuccessful attempts to operate technology. Thus, the ideal BCI would be calibrated without the user following instructions, have intuitive operation and be inherently engaging. In addition, systems should build on familiar concepts, such as row-column scanning, to simplify the transition from calibration to end-use [183].

Ultimately, we need improved understanding of the effect of CP on EEG, user-centered design to match the BCI to the interest and needs of individual users, and user-tailored training paradigms. Finally, it is vital to recognize that for children with congenital disabilities, technology use and even communication itself, are skills that must be taught.

From Speech Decoding to Speech Neuroprostheses—*Organizer*: Christian Herff (Maastricht University) and Sergey Stavisky (University of California, Davis)

Additional Presenters: Jon Brumberg (Kansas University), Phil Kennedy (Neural Signals Inc.), Miguel Angrick (University of Bremen), Julia Berezutskaya (Radboud University), Qinwan Rabbani (Johns Hopkins University)

Despite impressive recent results in decoding speech from neural recordings, there remain many challenges to achieving a real-time, large-vocabulary BCI for restoring lost speech. In this workshop, five of these challenges, and potential solutions, were discussed.

First, existing speech decoding demonstrations have not yet achieved consistently intelligible outputs. Multiple groups presented new decoding architectures, including recurrent neural networks and GANs. Workshop participants agreed that these modern machine learning approaches should benefit from additional data in future studies, and noted that all of the work presented used less than 20 minutes of neural recordings. Further, their performance did not saturate with training data quantity subsampled within these limited datasets.

A second challenge is how to obtain highly informative neural correlates about speech intent. Previous research almost exclusively relied on ECoG signals, which are not regularly used for long-term measurement. However, high-quality speech decoding and synthesis can also be achieved using penetrating microarrays implanted in the dorsal motor cortex [194], even though that area is not typically associated with speech production [195]. These Utah arrays have been used for multiple-year recordings in a number of participants and achieved high performance in, e.g., online decoding of attempted handwriting in people with tetraplegia [196] or speech perception decoding [197]. Alternatively, stereotactic EEG, which is very similar to Deep Brain Stimulation electrodes [198] that routinely remain implanted for decades, was proposed for high-quality speech synthesis. The neurotrophic

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electrode, an entirely different type of electrode with good long-term potential [199], was also proposed for speech neuroprosthesis [200].

Third, a functioning neuroprosthesis needs to generate or decode speech in or near real-time [45]. However, previous studies demonstrating speech synthesis [44, 201] or speech recognition [202, 203] from ECoG data have primarily (except for [204, 205]) been done offline on previously recorded overt or whispered speech. Approaches that process and decode intracranial EEG in real-time will provide direct feedback to the patient. This has been done using imagined speech processes [206], building on prior work such as [207]. Recent progress towards a low latency (250 ms) ECoG speech synthesis pipeline shows proof-of-concept open-loop results. A non-invasive EEG neuroprosthesis based on an artificial vocal tract model [207] provides auditory and visual feedback to the user and might therefore help train speech neuroprosthesis users and pilot online speech BCI methods.

Fourth, the field would benefit from better speech synthesis performance metrics. Recent works typically uses variants on measuring correlation between true and decoded audio (e.g. for spectral or pitch features), which are poor proxies for intelligibility. Workshop participants agreed that adopting subjective intelligibility metrics is important, but this may need to wait until decoding performance is good enough for these metrics to become relevant (or else they will suffer from floor effects).

Fifth, all presenters agreed that data sharing is key to accelerating progress. One recently shared large dataset of speech perception in fMRI, ECoG, and sEEG, along with the associated impressive reconstruction quality provides the public research community with a fully annotated dataset [208].

Brain-computer interfaces for the assessment of patients with disorders of consciousness—*Organizer*: Christoph Guger (g.tec Guger Technologies OG)

Additional Presenters: Damien Coyle, (Ulster University), Kyousuke Kamada, (Hokashin Group Megumino Hospital), Rossella Spataro, (University of Palermo), Jing Jin, (East China University), Steven Laureys, (Brain Centre & GIGA Consciousness, Coma Science Group, University and University Hospital of of Liege, Belgium; International Disorders of Consciousness Institute, Hangzhou Normal University, China; CERVO Brain Research, U Laval)

Bedside evaluation to assess conscious awareness after coma requires inferences based on patients' motor responsiveness [209] with limited diagnostic precision and prognostic information, increasing the ethical difficulty of decisions on life-prolonging therapies. Technologies such as functional neuroimaging and BCIs provide objective tools for diagnostic, prognostic and therapeutic purposes [210]. About two thirds of patients clinically diagnosed with "unresponsive wakefulness syndrome (UWS)" (or "persistent vegetative state") may show residual brain activity in PET studies [211] and are hence actually in a minimally conscious state (MCS) with a better chance of recovery.

BCIs can help reduce the diagnostic and prognostic uncertainty of both acute and chronic disorders of consciousness [212, 213]. BCI should first be used to establish a

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reliable and reproducible response to a simple command. Then one can attempt functional communication with simple yes/no questions and eventually spelling or message creation [212, 213]. The mindBEAGLE (g.tec medical enginering GmbH) uses auditory P300, vibro-tactile P300 and motor imagery paradigms for these steps and rehabilitation protocols. Paradigms include a quick (2–8 minute) system calibration or patient assessment. Other BCI systems have also been designed for this purpose, including using auditory sensorimotor rhythm feedback for those with visual impairments [214, 215].

BCI assessment of DOC with locked-in and completely locked-in patients found 9 out of 12 patients could demonstrate command following by answering YES/NO questions [216]. Building on the pilot of 15 patients reported in [215], the workshop reported an update with 25 patients who each participated in 10, one-hour motor imagery BCI sessions. Of these, 5/9 UWS, 7/11 MCS, and 3/4 locked-in syndrome demonstrated significant capacity to modulate brain activity in stage I (assessment) and progressed to stage II/III (auditory feedback training and Q&A response). All participants in stage II/III responded significantly to YES/NO questions. Another study with unresponsive patients showed 3 out of 12 patients could successfully answer the YES/NO questions on some assessment days [217], showing that these patients have fluctuations in consciousness that can be detected by BCI systems.

BCIs can also help predict eventual recovery. Auditory P300 and vibro-tactile P300 provided a predictor of functional recovery for two patients with DOC. One patient did not show any auditory P300 or vibro-tactile P300 after three weeks and coma continued for more than 6 months. A second patient responded to auditory P300 and vibro-tactile P300 and after 6 months had recovered from coma and understood verbal commands. Such patients may benefit not only from BCI assessment, but also from BCI-based rehabilitation [218]. Longitudinal observation of 12 DOC patients showed that achieving mindBEAGLE classification accuracy of at least 50% predicts recovery of behavioural responsiveness (after six months) as measured by the coma-recovery scale revised (CRS-R) [219]. Moreover, 12 of 20 patients showed CRS-R score improvement after 10 sessions of a vibrotactile stimulation protocol [218].

BCI can also evaluate the effectiveness of other treatments for arousing DOC patients by analyzing EEG recorded during mental tasks before and after intervention. BCI methods have been used to assess the effectiveness of spinal cord stimulation and deep brain stimulation surgeries in arousing vegetative patients. Auditory, vibro-tactile, or motor imagery-based BCI systems have been used to assess 5 unresponsive patients and 3 vegetative patients in this on-going study.

BCIs are being cross-validated against neuroimaging techniques such as PET and fMRI [220]. The current challenge is to integrate BCIs with our increasing scientific understanding of recovery from severe brain injury to optimized the trajectory of clinical care after coma and improve the quality-of-life in disorders of consciousness and locked-in syndrome [221].

The promise of BCI-driven functional recovery after stroke: leveraging current evidence to define next steps—*Organizer*: A Nicole Dusang (Brown University/ Providence VA Medical Center/ Massachusetts General Hospital)

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Additional Presenters: Murat Akcakaya (University of Pittsburgh); Febo Cincotti (Sapienza University); Cuntai Guan (Nanyang Technological University); Christoph Guger (g.tec medical engineering GmbH); Kyousuke Kamada (Asahikawa Medical University); David Lin (Massachusetts General Hospital/ Providence VA Medical Center); Donatella Mattia (Fondazione Santa Lucia IRCCS); José del R. Millán (University of Texas at Austin); Ander Ramos-Murguialday (University of Tübingen / TECNALIA Research and Innovation); Vivek Prabhakaran (University of Wisconsin-Madison); and George F. Wittenberg (Pittsburgh VA Healthcare System / University of Pittsburgh)

Stroke is a leading cause of long-term disability worldwide, and 30–50% of stroke patients experience limited recovery. Rehabilitative EEG-BCIs are a promising neurotechnology for restoration of function after stroke. The hypothesis behind rehabilitative BCIs is that coupling neural activity with sensory feedback of limb movement induces cortical plasticity, improving functional recovery. This workshop featured twelve researchers developing rehabilitative EEG-BCIs for functional recovery from ten institutions around the globe. Presenters were split into two panels to consider how to translate this technology from the lab to the clinic. Randomized controlled trials (RCTs) have demonstrated the benefit of Rehabilitative EEG-BCIs, but employed diverse control methods, therapy doses, dosing intervals, and different types of neural dynamics and sensory feedback.

Panel 1 discussed optimal EEG-BCI support for stroke rehabilitation. Spatial neglect is an often overlooked deficit in stroke patients though it can significantly impact a patient's response to therapeutic intervention [222]. Technology is needed to objectively map neglect, quantify changes during recovery, and provide a rehabilitation platform to target spatial neglect. Although BCI addresses a gap in standard neurorehabilitation medicine [223], it still lacks an American Heart Association (AHA) class and evidence rating. BCIs empirically measure the signals of the damaged cortex and patients' functional disability during recovery. Rehabilitative EEG-BCIs restore the neural activity-functional output connection, supporting the retraining of neural activity. This is demonstrated by a RCT evaluating an EEG-BCI intervention for distal upper extremity function in a chronic stroke population [224]. Results showed 64% of participants made significant gains in both primary and secondary outcome measures.

Panel 2 reflected on stakeholders' needs for translating this promising technology to a clinical environment. Though RCTs have demonstrated the therapeutic efficacy of rehabilitative EEG-BCIs, commercialization requires clear clinical and economic benefit and reliable function within the rigors and environment of long-term clinical use. BCI-FES systems must address both patients' and clinicians' needs [225]. Patients need an effective and engaging rehabilitation platform, while clinicians require a plug-n-play system with remote technical assistance and joint analysis. Unanswered questions remain along the spectrum of basic research to patient care [226]. The field has yet to determine the optimal neural modalities or features for rehabilitative EEG-BCIs, resulting in significant feature extraction variability in current EEG-BCI platforms. Additionally, past and current RCTs employed diverse outcome measures since no measure is clearly best for capturing recovery. Further, stroke is itself a heterogeneous condition and much remains unknown about the relationship between the type and location of damage and resulting deficits. The RecoveriX

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system (Guger Technologies), a certified medical product, analyzes motor imagery to trigger FES for upper and /or lower limbs. RecoveriX has shown effectiveness for spasticity reduction and movement restoration in upper and lower limbs [227, 228].

Convincing clinicians, patients, and payers that Rehabilitative BCIs are a worthy technology for investment was felt to require a large, multi-site, randomized control trial study, incorporating methods to minimize, or scientifically account for, heterogeneity between technology and control populations at various sites. Ideally, it will also address knowledge gaps such as long-term effects, dose-response curves, patient stratification, control features, and a comprehensive outcome evaluation.

Towards the decoding of neural information for motor control: present and future approaches—*Organizer*: Gernot Müller-Putz (Graz University of Technology)

Additional Presenters: Andrea I. Sburlea (Graz University of Technology), Valeria Mondini (Graz University of Technology), Damien Coyle (Ulster University), Cuntai Guan (NTU Singapore), Tonio Ball (University of Freiburg)

For people with a cervical spinal cord injury (SCI) from trauma or disease, upper extremity function is often reduced or lost, resulting in dependency on a caregiver or family member for most daily activities. BCI researchers have for decades worked to derive motor commands directly from brain activity to bypass the interrupted spinal cord pathways and establish direct control of a neuroprosthetics device [229] or robotic arm/exoskeleton [230]. Implantable BCI approaches have produced many advances [231, 232], however, in recent years, non-invasive approaches have moved beyond proof of concepts [233–235] and made major steps towards full arm control. This workshop focused on state-of-the-art approaches to non-invasive neural control of movement.

Non-invasive detection of multiple types of hand movements have been reported, including for people with cervical SCI [236, 237]. Analysis of movement-related cortical potentials (MRCP) can detect and decode single hand movements [238] or movement attempts (e.g., hand open vs. hand close) or even different grasps (e.g., palmar vs. lateral grasp) [239, 240].

Understanding the neural and behavioral mechanisms involved in grasping is important for successful decoding. Investigations included the relationship between the broad-band EEG representation of observing and executing a large variety of hand-object interactions and the muscle and kinematic representations associated with the grasping execution [241]. Object properties and grasp types can be decoded during the planning and execution of the movement. Properties of the objects could be decoded even during the observation stage, while the grasp type could be accurately decoded even during the object release stage [242].

While the decoding of arm/hand trajectories has mainly been shown in intracortical recordings, major steps in the non-invasive field have been demonstrated. Closed-loop continuous decoding of executed [243, 244] but also attempted arm movement [245] has been done from low frequency EEG. Movement parameters like position and velocity, necessary for decoding [246, 247] were presented. In particular, the contribution of non-directional movement-parameters (distance and speed) has been highlighted [248–250].

Also, the first evidence for online decoding of attempted continuous movement has been reported [245]. Eye movement artifacts present a special challenge for all non-invasive decoding studies. Participants must be permitted to use their gaze to follow the feedback, electroc-oculogram (EOG) signals must therefore be removed from the EEG online [251].

In addition to decode of low frequency EEG components, decoding of executed and imagined 3D reaching tasks have involved delta frequencies, but also alpha, low and high beta frequencies [252, 253]. These studies include decoding of 3D lower limb movements that could be important for gait rehabilitation [254].

In the area of motor imagery and stroke rehabilitation, deep learning methods and convolutional neural networks (CNN) have been used for participant specific [255, 256], participant-independent [257], and adaptive classifiers [258]. CNNs have also been used in assistive robot control with online adaptive motor classification [259].

Beyond the pure application of CNNs for decoding [98], the internal data representation and the effects of hidden unit activations provide possible insights into what the units of such networks learn and the possible hierarchical organization of spectral features [260]. These first insights may open a new way of understanding brain processes.

Biomimetic approaches to restore somatosensation—*Organizer*: Robert Gaunt (University of Pittsburgh)

Additional Presenters: Sliman Bensmaia (University of Chicago), Karthik Kumaravelu (Duke University), Alberto Mazzoni (Scuola Superiore Sant'Anna), Emily Gracyzk (Case Western Reserve University), Luke Bashford (California Institute of Technology), Chris Hughes (University of Pittsburgh)

Rapid advances in BCI capabilities to decode and restore upper limb motor functions [261] often ignore the accompanying sensory losses. Strategies to restore somatosensation include intracortical microstimulation [262, 263], cortical epidural stimulation [264–266], peripheral nerve stimulation [267–269] and spinal cord stimulation [270]. Regardless of approach, it is difficult to select stimulus parameters that improve the quality of conscious percepts and maximize functional capabilities. This workshop explored the idea of using biomimicry as a framework to create stimulus trains. Biomimetic stimulation leverages knowledge of intact somatosensory neurophysiology with the intuition that stimulation parameters that evoke patterns of neural activity that match normal patterns will improve perception and function.

Decades of work characterizing skin mechanoreceptor responses in the hand during object manipulation [271] were integrated into TouchSim to accurately simulate primary afferent responses to a mechanical input [272]. The simulated population-level activity resembles the spatiotemporal dynamics of somatosensory neurons in the cortex during the same mechanical stimuli [273], with large transient signals at contact onset and offset [271, 274]. However, simply replacing recorded or simulated spikes with stimulation pulses does not replicate the sensation. Additional computations are required to address anatomical complexities and electrical stimulation biophysics. A simulation platform using genetic algorithms and finite element models of the cortex, populated with realistic neurons, was

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developed to address these complexities [275]. Critically, the stimulus trains created through simulation more faithfully represented the desired cortical activity than stimulus trains designed using standard methods.

The utility of this computational tool and the principles of biomimicry were tested in peripheral nerve stimulation experiments in amputees. As a baseline, linear stimulation encoding schemes that did not capture important features of natural neural coding were effectively used by participants [267]. Similarly, event-based stimulation encoding that mimicked the natural onset-offset dynamics of primary afferents was also effective [276]. However, in a direct comparison, TouchSim was used to create multiple stimulation trains that were increasingly biomimetic. The most natural sensations were obtained with the stimulus trains that maximized biomimicry [277]. In other experiments, early work suggested that a particular biomimetic train could improve naturalness [269]. Upon repetition, and despite considerable effort to combine modeled fascicle recruitment with biomimetic and non-biomimetic stimulation trains, just two of five participants reported more natural sensation using biomimetic trains, highlighting the limitations of single-subject studies of perception.

Two different aspects of biomimicry were explored in human intracortical BCIs. Motor imagery and actual movement evoke similar brain activity. To explore this concept for somatosensation, neural activity patterns were recorded in somatosensory cortex and the supramarginal gyrus during imagined sensations [278]. Different imagined sensations were encoded stably in the somatosensory cortex, suggesting that imagined sensation could guide stimulus train design, even in people left insensate from their injury. Finally, in a direct test of biomimetic principles, intracortical stimulus trains using fixed amplitudes and frequencies were compared to trains with stimulation amplitudes modulated by cortical activity patterns recorded from non-human primates [274]. The participant frequently rated the biomimetic trains as more natural, especially when the overall intensity was matched.

In summary, biomimicry is a principled and likely fruitful approach to create stimulation trains to restore somatosensation. Simulation and modelling tools can help design these trains, which have outperformed less realistic trains in both the peripheral and central nervous systems. Nevertheless, considerable development is still necessary, and these results must be validated in larger numbers of participants.

Expanding BCI Usability and Availability

Toward an international consensus on user characterization and BCI outcomes in settings of daily living—*Organizers*: Mariska Vansteensel (UMC Utrecht) and Nataliya Kosmyna (Massachusetts Institute of Technology)

Additional Presenters: Andrew Geronimo (Department of Neurosurgery, Penn State College of Medicine, Hershey, PA, USA), Katya Hill (AAC-BCI iNNOVATION LAB, University of Pittsburgh, Pittsburgh, PA, USA), Theresa Vaughan (National Center for Adaptive Neurotechnologies, Stratton VA Medical Center, Albany, NY, USA)

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BCI research is growing fast, and implantable and non-invasive communication-BCIs are being introduced to people with significant motor disability for independent use in daily living situations [e.g., 42, 279, 280–286], allowing end-users to participate in research and development experiments and provide critical input into iterative user-centered design [287]. Such studies are crucial for the development of usable communication-BCIs and for their eventual widespread implementation to resolve the communication problems of people with diseases such as amyotrophic lateral sclerosis. However, most studies include only limited numbers of participants. Since the target user population for communication-BCIs is relatively small [288], large studies may not actually be possible. For translation of communication-BCIs to practical use, it is therefore essential to compare results across studies and in this way learn about environmental and participant/user characteristics affecting BCI performance [e.g., 289, 290, 291] and the different usability perspectives of users, caregivers and other stakeholders. Such comparison will strongly benefit from standardized reporting about users/participants and their environment, and from the use of similar metrics to assess BCI performance and outcome [292]. This workshop was designed to initiate a consensus list of reporting recommendations, specifically directed at the use of communication-BCIs in the daily life settings of people with significant motor disability. After brief presentations to introduce the topics of discussion [196, 293–302], workshop participants shared their experiences and built consensus in breakout rooms. Key outcomes of these discussions include:

1. **Standardization is hard.** Standardization is a hard and complex task. Part of this complexity comes from the different focus areas of experiments designed by different disciplines.

2. **Age group matters.** Adult and pediatric BCI users need different training procedures and different primary outcome measures. But researchers need as much comparison as possible.

3. **Meeting users' end goals is paramount.** For any system to be introduced in their environment, end-users should be strongly involved in BCI design, goal setting, and outcome measure selection. Even existing standard metrics for reporting BCI system performance must be adapted to the goals of the end-user.

4. **Needs of primary users and their caregiver(s) may be different.** A BCI has multiple types of end-users and researchers must report on how well a BCI meets the needs and goals of both primary and secondary (e.g. caregivers) users.

5. **Different tasks produce different outcomes.** BCI outcome measures should consider the importance of each task to be conducted with the BCI, as well as the desired and accomplished frequency of conducting each task.

6. **Fatigue strongly affects BCI performance.** Both cognitive and physical fatigue need to be assessed and reported on.

7. **Medication can affect brain signals.** The effect of medication should not be underestimated, but medication use is seldom reported in papers.

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As our next steps, we plan to engage in the bigger discussion about standardization, to collect more input from BCI researchers, and to use all collected information for a formal publication on reporting recommendations related to user characterization and outcome measures for the use-case of communication-BCIs in settings of daily living.

On the need of good practices and standards for Benchmarking Brain-Machine Interfaces—*Organizer*: Ricardo Chavarriaga (Zurich University Applied Sciences, ZHAW Switzerland)

Additional Presenters: Paul Sajda (Columbia University, USA), José Contreras-Vidal (IUCRC BRAIN, University of Houston, USA), Luigi Bianchi ("Tor Vergata" University of Rome, Italy), Zach McKinney (Scuola Superiore Sant'Anna, Italy), Laura Y. Cabrera (The Pennsylvania State University, USA)

Translating Brain-Machine Interface (BMI) systems onto real applications requires accepted, well-defined criteria to assess their effectiveness, usability, and safety. Benchmarking, specification, and performance evaluation are perceived as main priorities for standardization in the field [292, 303, 304]. This workshop discussed translational challenges, and ethical issues of BMI systems, as well as existing initiatives to address them.

The Future Neural Therapeutics technology roadmap [305] analyzes closed-loop neurotechnologies aimed at treating movement disorders and neurological diseases. This document summarizes the state of the art and identifies key technological challenges required to successfully develop a new generation of these technologies, including computational power, robustness and safety, usability and appropriate regulatory frameworks. As BMIs approach commercial availability, attention must be paid to concerns generated by the possibility of repurposing, misusing, or maliciously using consumer-oriented neurotechnology. These concerns include overstated claims on their efficacy or the influence of neurotechnology in markets related to employment or cognitive enhancement [306–308]. Moreover, widespread use of consumer-oriented technology can lead to indiscriminate collection of neural data or user harm due to maladaptive processes triggered by neurostimulation devices.

The neuroethics subcommittee of the IEEE Brain Initiative focuses on the ethical and societal issues related to research and development of neurotechnologies They developed the IEEE Neuroethics Framework (https://brain.ieee.org/publications/ieee-neuroethics-framework/), a collective effort to evaluate the ethical, legal, social, and cultural issues that arise with the deployment of neurotechnologies and provide explicit guidance on how to address them. The framework is organized as a matrix that covers existing and emerging neurotechnologies for both current and foreseen applications. This framework is conceived as a living document that will evolve with the technology. Participation in this effort is open to interested participants.

Despite the large number of BMI publications, it is seldom possible to evaluate, verify or compare published results. Meta-analyses showed that a significant number of BCI publications lack necessary information [309, 310]. However, two standardization activities

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are addressing this issue. The IEEE Standards Working Group P2794: *Reporting Standard for in vivo Neural Interface Research* (RSNIR) (https://sagroups.ieee.org/2794/) aims to improve the transparency, interpretability, and replicability of neural interface research by specifying a set of technological and methodological characteristics to be reported in scientific literature and technical documentation.

They recently published a set of preliminary requirements for implantable neural interfaces [311] and are seeking broad community input and participation to ensure the Standard reflects the needs of a more diverse range of neuroscience and neurotechnology stakeholders, including device regulators, funding officers, clinicians, and end users. Information on providing such input can be found through the working group website. Another standardization project, IEEE P2731: *Standard for a Unified Terminology for Brain-Computer Interfaces (BCI)* (https://sagroups.ieee.org/2731/) aims at developing a comprehensive BCI lexicography and a functional model of BCI systems [312–314]. It is also working on identifying the required information to be stored in BCI files to enable efficient sharing of data and tools among stakeholders [315]. These activities can contribute to the development of standard experimental and usage protocols, benchmarking procedures, and increased interoperability of neurotechnology systems.

Overall, this workshop highlighted the need to continuously evaluate the state-of-the-art and the implications of neurotechnologies. This requires multi-stakeholder, anticipatory processes for developing appropriate tools -including ethical and technical guidelines, standards, and regulatory instruments- that allow translation of neurotechnologies for both consumer and medical applications [316–318].

Lessons from successfully implanted neurotechnology—*Organizer*: Erik Aarnoutse (Brain Center, University Medical Center Utrecht)*Additional Presenters*: Fabien Sauter-Starace (CEA, LETI, Clinatec, University of Grenoble); Leigh Hochberg (Brown University; Massachusetts General Hospital; Providence VA Medical Center), RI Aysegul Gunduz (J. Crayton Pruitt Family Department of Biomedical Engineering, University of Florida)

Over the last 16 years, various clinical trials of implantable neurotechnology in humans have demonstrated successful applications. This technology has enabled users to move arms [319, 320], walk [108], and communicate [42] and has also alleviated disease symptoms [61]. Clinical trials require a great deal of effort but are an important and informative step along the route to wide availability of neurotechnology for users in need.

The route from design to clinical trial was illustrated by the Wimagine implant to operate an exoskeleton [108]. First, the medical needs of people with quadriplegia were combined with the neurosurgical requirements: no transcutaneous connection, no limit to battery lifetime and limited invasiveness. This created design choices of wireless data transmission, inductive charging, and epidural ECoG electrodes. Technical requirements were a trade-off between wishes and constraints. Animal studies assessed signal stability [321]. Regulatory compliance to the EU Medical Device Regulation meant proving compliance to ISO standards for quality management and standards for mechanical, electrical, and thermal

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safety, biocompatibility, and software. The clinical trial with bilateral implants has enrolled two patients so far [108]. Training was progressive by adding more complexity in the adaptive machine learning algorithm, from brain switch to 3D + pronation/supination [322]. The signal proved to be stable over months. The exoskeleton was only used in the laboratory.

The 17 years of BCI research with penetrating multi-electrode arrays produced many lessons [319]. Participants are colleagues, but also customers. They request new features (user needs), which are added to the design [196, 323]. The participants' motive is to advance science, they do not expect gain for themselves. However, the obligation of the field is to give users gain in daily life as soon as technology allows it [42, 286]. Neuroethics is important here. Hardware advances ease the technical constraints making neural data ever easier to gather and use.

With the entry of industry in this field, the question of the role of academia becomes more important, where academia is better equipped to ask fundamental (hypothesis based) questions of neuroscience. Development is important but is not easy to publish. Mainly, academia investigates (hardware agnostic) decoding principles.

A good example of the input of academic expertise is seen in the use of cortical ECoG recordings as part of essential tremor DBS therapy [61]. This cross-field input produced knowledge on biomarkers both for fundamental questions and treatment efficacy. Here, user needs for individualized therapy, reduction of side effects [324], and increased battery life were addressed. The research triggered a new hardware design that reduced stimulation artefacts.

So, academia provides design input (user needs, technical requirements, decoding principles) for future neurotechnology for home use. Academia seeks to create knowledge, optimize designs, and provide a foundation of information that can support translation of BCI to commercial availability. We have also identified barriers that must be overcome for home use (wireless link, power constraints, limits on the number of electrodes, portability, larger scale manufacturing). Overcoming these barriers requires more time and money than academia has, but the generation of this knowledge by academic reduces the risk for industry and thus advances the likelihood that BCI will become widely, commercially available.

Next steps for practically useful BCI ethics—*Organizer*: Brendan Allison (UC San Diego)

Additional Presenters: Pim Haselager (Radboud University Nijmegen), Dr. Sonja Kleih-Dahms, (University of Würzburg), Donatella Mattia (Fondazione Santa Lucia, IRCCS)

This workshop was designed not for review or abstract academic discourse, but to develop practical next steps for BCI-related ethical issues. The organizers briefly presented examples of these issues [325–329] to promote discussion.

A public database of ethical use cases was proposed to raise awareness with an associated forum where people could share their perspectives on each case. The ethical use cases could also help professors and others who want to teach BCI ethics. Further discussion

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and development of ethical use cases would benefit from an ongoing collaborative effort, perhaps via online seminars, to develop a framework, assign people to develop different use cases, and create an online database. These efforts might be hosted by the BCI Society.

An immediate ethical concern is that research study participants do not usually keep the devices used in the study. Thus, people with disabilities may regain the ability to communicate or control a device with an experimental BCI, but then lose that ability when their study participation ends. Workshop contributors agreed that this is a serious and currently unresolved problem. Most funding sources do not support leaving devices with patients, nor providing ongoing technical support. However, several researchers include such considerations in their research plans. Possible next steps include raising awareness of this problem (such as through an online forum, survey, paper, or approaching journalists) and further engagement of funding organizations.

The rise of “Big BCI” through the recent initiation of BCI projects by high-profile companies creates its own set of ethical concerns. Workshop participants desired collaboration between the huge companies working on BCIs and the existing BCI community on efforts such as an online workshop or paper. This step was hoped to foster joint work on proposed ethical guidelines and regulatory issues.

Another concern comes from the many online articles and videos with misinformation about BCIs from different groups, including some manufacturers, neurofeedback practitioners, enthusiasts, and conspiracy theorists. Of course, such misinformation will continue indefinitely to some extent, but might be reduced through next steps such as publicly commenting on inaccuracies and producing and promoting high-quality information about BCIs. Indeed, some for-profit and non-profit entities do provide good BCI content. The ongoing increase in online BCI-related classes, conferences, workshops, competitions, and other activities has led to ample recorded material from reputable organizers and speakers that is usually available for free.

Many participants had seen online postings from, and/or been directly contacted by, people who believe that they are being involuntarily mind-controlled by a BCI or a similar device. A few participants reported trying to direct such persons to appropriate mental health professionals, but without apparent success. Next steps at this time are not obvious aside from a possible paper or position statement with suggested guidelines, developed with mental health experts.

The workshop focused on specific, actionable next steps to raise awareness of ethical issues in BCI and further engage relevant groups through workshops, papers, online discussions and a database of use cases and surveys [330–332].

Brain-Computer Interfaces for Human Enhancement—*Organizer*: Davide Valeriani (Neurable Inc.)

Additional Presenters: Riccardo Poli (University of Essex), Maryam Shanechi (University of Southern California), Hasan Ayaz (Drexel University), Nataliya Kosmyna (MIT Media Lab), Yannick Roy (NeuroTechX), Marcello Ienca (ETH Zurich)

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This workshop highlighted recent advances in BCI technologies that go beyond clinical applications and instead focus on augmenting human capabilities. The workshop brought together neuroscientists, engineers, neuro-ethicists, entrepreneurs and researchers at the cutting-edge of BCI development for human augmentation. Discussion focused on current trends and future prospects, as well as the critical role played by international communities such as NeuroTechX in educating and stimulating interest in BCI and neurotechnologies.

BCIs for cognitive human augmentation are intended to improve the process of acquiring knowledge and communicating with other individuals [333]. Passive BCIs can enhance individual decision-making in target detection by recognizing event-related potentials [334] or aggregating brain activity from multiple people [335]. Collaborative BCIs can also decode decision confidence from brain activity and use it to weigh individual opinions, leading to significant improvements in group performance in a variety of tasks [336–338]. These BCIs can also facilitate human-machine teaming in face recognition [339].

Combining brain recording (e.g., EEG, fNIRS) and stimulation (e.g., tDCS, TMS) improves processing speed [340] and spatial working memory [341], and introduces novel communication forms, such as brain-to-brain communication [342]. Moreover, it enables the development of BCIs capable of regulating abnormal mental states, with direct applications in the treatment of mental disorders [343, 344].

BCIs and other wearables support studying the brain in complex environments and diverse domains, a research field called neuroergonomics [345]. Advances in recording technologies, such as EEG and fNIRS, enable study in operational and realistic settings to monitor cognitive function, improve human-to-human communication, and enhance human-machine interaction [346]. Moreover, the integration of brain recordings with other physiological signals can provide biofeedback to users through audio, light, or haptic inputs, promoting performance, attention, and overall well-being [347]. These hybrid, multimodal BCIs will also help increase the reliability, accuracy, and commercial potential of non-invasive BCIs, which can be limited by the low signal-to-noise ratio of non-invasive neural recordings. Yet to implement multimodal BCIs we need to identify relationships between modalities and develop new techniques to integrate neural recordings at different scales.

While neuroscience and neuro-engineering have shown that it is technically possible to develop BCIs that augment human capabilities in a variety of domains, neuro-ethicists are working to identify which applications are morally desirable [317]. Two main ethical principles should guide the development of BCIs for human augmentation: (1) cognitive liberty, which protects the rights of individuals to make free and competent decisions on using such devices, and (2) fair and equitable access to enhancement, which ensures they are available to everyone, regardless of race, gender or socioeconomic status. As with all biomedical devices, safety and data privacy are key pillars to make these devices ethically acceptable.

Overall, the workshop showcased the tremendous advantages of expanding BCIs from assistive devices to technologies for human enhancement, with a variety of potential applications. The most promising approaches seem to be the fusion of different

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physiological signals and integration with artificial intelligence, with a continuous awareness of the ethical challenges of enhancement applications.

Brain-Computer Interfaces for outside the lab: Neuroergonomics for human-computer interaction, education and sport—*Organizers*: Antonia Thelen (eemagine Medical Imaging Solutions GmbH, Berlin, Germany)

Additional Presenters: Fabien Lotte, (Inria Bordeaux Sud-Ouest); Camille Jeunet (CNRS, Bordeaux Neurocampus); Frédéric Dehais (ISAE-SUPAERO, Toulouse); Patrique Fiedler (TU Ilmenau, Ilmenau); Martijn Schreuder (ANT-Neuro, Enschede)

Traditionally, BCI research has been bound to the investigation of perceptual, cognitive and motor processes within stationary, hardware-intensive laboratory setups. While these studies provide intriguing real-time insights into such processes, the translation of these findings into real-world brain interactions is limited. The emergence of lightweight, high-density EEG solutions has permitted the extension of BCI applications into mobile setups within real-world situations. Use of high-density EEG enables the simultaneous utilization of different sensor configurations, providing greater adaptability with a single hardware setup.

This workshop focused on the efforts undertaken towards the instrumentalization of EEG and specifically BCI techniques within the field of neuroergonomics. The panel comprised experts who strove to provide methodological strategies to facilitate the transition of BCI applications into real-world and/or every-day settings. First, advances and current limitations of existing solutions were discussed. Second, an outlook upon possible new technological and methodological innovations was presented which could provide new avenues of interacting with the world by implementing systems with an explicit awareness of the concepts of embodied cognition. Embodied cognition, as described in [348], acknowledges that physical elements of the world are often integrated seamlessly into our cognitive processes in a way not easily captured by static diagrams with separate boxes for sensory inputs and physical outputs. Instead, cognition happens in conjunction and in parallel with the sensorimotor loops that provide interactions with the world. Various neuroergonomics applications of BCI use outside the lab were also discussed, including evaluating 3D User Interfaces [349], Sport Science [350, 351] and Aviation [352].

Specifically, the robustness of signal processing methods used by BCI classifiers was discussed. How to apply such algorithms reliably across a large variety of application fields and how to make them cope with inter- and intra-individual variability is still a topic under investigation [353]. The contribution of state-of-the-art, lightweight, dry sensors resulting in varying signal-to-noise ratios and their impact upon such signal processing algorithms was highlighted [354, 355]. Moreover, the tradeoff between laboratory-based and real-world applications was discussed with regards to sensor application within these fundamentally different environments [351, 356]. Lastly, discussion focused on difficulties encountered when translating BCI-based interventions across different demographics, specifically differences in cognitive states and/or perceptual processes that were investigated within a research context or focused on clinical/therapeutic interventions.

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Taken together, the workshop provided an overview of current advances made within the field of neuroergonomics.

Brain-Computer Interfaces for Art, Entertainment, and Domestic Applications

—*Organizer*: Anton Nijholt (University of Twente)

Additional Presenters: Christoph Guger (g;tec medical engineering GmbH); Elisabeth Hildt (Illinois Institute of Technology); Erika Mondria (University of Art and Design); Ellen Pearlman (Massachusetts Institute of Technology); Stephanie Scott (Colorado State University); Aleksander Valjamae (Tallinn University)

BCI technology enables neurophysiological data from an individual user’s affective and mental state to be used for online adaption of system and interaction methods [357]. Artistic, domestic, or entertainment use of such information shift the focus from efficiency to the importance of affect in social and playful interactions such as in family, community, playful, and artistically challenging situations. This workshop addressed the use of BCI for artistic, entertainment, educational, and health applications.

BCI has been used for many artistic applications [358–360]. In general, artistic projects reduce inhibitions and encourage people to engage with unfamiliar technologies such as BCI. Synergies of design, art, and research have shown interesting results which may also enrich clinical settings.

BCIs have been used for creative arts therapy [361, 362] as part of a conceptual framework bringing together several disciplines for researching the expansion of treatment modalities in the intersection of art, technology, and therapeutics. A recent insight is that a post-phenomenological approach towards human-technology interaction and technological artifacts in general will be useful when applied to BCI for therapy, art, and creative expression. In this approach user-specific needs for enabling self-expression are integrated in a transdisciplinary design perspective on meaningful and self-expressive communication exploring brain activity underlying artistic creation and using neurofeedback research [363].

The BR41N.IO BCI Hackathon series, now in its 5th year [364, 365], provides opportunities for team-based development of new BCI applications within 24 hours. During the 2021 BCI & Neurotechnology Spring School, 321 developers, artists, programmers, and hackers participated in 38 teams and created many interesting and cutting-edge new applications or improved the signal processing of BCI data sets.

In neurotheatre and neurocinema research [366, 367], new media art and neurotechnologies allow for co-creation between actors, director, and audience to shape a performance by emotional experiences using BCI and other sensors and multisensory actuators. From a research perspective, neurotheatre can be seen as a novel integrative research environment for prototyping and exploring new social neuroscience paradigms, like collective decision making or shared affective experiences. From a societal perspective, the fusion of science, technology, and arts allows for so-called design fiction, a design practice aiming at exploring and criticizing possible futures by creating speculative, and often provocative, scenarios narrated through designed artifacts.

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Affective brain-computer music [368, 369] Interface applications use affective BCIs for music-making and music listening. Given recent developments in direct-to-consumer devices (wearable BCIs, headphone sensors) and music streaming services these BCI applications aim at influencing the user's affective state (mood enhancement) by individualized music choices. Exaggerated claims about capabilities, increasing dependency on technology and limiting one's own capabilities, and privacy issues arising from long-term monitoring of a user's affective state are pitfalls related to a potential future, relatively widespread use of EEG-based affective brain-computer music interfaces in entertainment contexts [370].

A brain opera called "Noor" provides an example that combines these concepts through the use of artificial intelligence (AI). In "Noor", biometric variables, including BCI are integrated with natural language processing and machine learning. In the near-future, such integrated systems will be tasked with more responsibilities relating to many aspects of human congress, often with confusing legal oversight and minimal accountability, potentially leading to scenarios enforcing dystopic digital societies of control [371–373].

The workshop discussions revealed consensus about the benefit of the joint effort of art and science research for BCI research in general and the acceptance of BCI for the general public.

Conclusion

Together, these workshops provide foundational information, explore diverse applications for different populations, and further develop big picture ideas for new frontiers of BCI use. Many of these ideas will be further developed in the workshops of the planned in-person Ninth International Brain-Computer Interface Meeting, currently scheduled for June 7–10th, 2022 in the Sonian Forest, Brussels, Belgium.

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