EEG100 Manifesto Draft

WIP: pushing this text online on the final signing platform. It should look similar to this in the end…
https://ubdbra001.github.io/EEG100Manifesto/

https://cuttingeeg.github.io/EEG101CommunityFramework/

The EEG101 Community Framework Draft

Toward a deontological framework for EEG science

If you agree with this initiative and wish to support it, we invite you to sign and share it.

Introduction

This document is a starting point for **building a deontological framework for EEG science** and upgrading our practices accordingly. It aims to outline the standards we believe are essential to maximize the positive impact of EEG research for society collectively. It is a call to action, to encourage critical reflection on the broader consequences of scientific research while sharing emerging alternatives.

In the following, we highlight what we perceive as the most pressing issues across three domains: (i) **Scientific Integrity and Epistemological Rigor**; (ii) **Democratization**; and (iii) **Technological and Environmental Responsibility**.

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Scientific integrity and epistemological rigor are two aspects of our practice that require continuous attention. As scientific practices evolve alongside new technologies, it is essential to ensure that existing methods remain valid while continuously improving them to avoid methodological flaws that can lead to biased, false, and irreplicable findings. We should foster robust, reproducible, open, and participatory science.

Democratization of the scientific process: We need to embrace the diversity of agents and subjects at all stages of the research process, from scientists conducting experiments to study participants and the people impacted by the findings. Diversity in the participant populations supports generalizable and ethical scientific findings, and diversity in applications and outreach makes our research accessible, relevant, and beneficial to a broader range of communities, engaging more diverse audiences. Thus, diversity enriches the scientific process by bringing in broader perspectives (Phillips et al., 2009), leading to more innovative, widely relevant, and robust outcomes, ensuring that scientific practices are more inclusive, ethical, trusted, and understood by the communities impacted by the findings.

Finally, and perhaps most controversially, we pledge for **technological and environmental responsibility**, acknowledging the hardware and processing methods' limitations and their potential misuse**.** We need to acknowledge that not everything doable is desirable (Moor,

2005) and should carefully examine the ethical legitimacy of our research lines, considering the social and material impacts of any research project or discovery. These are key aspects for cognition research, not solely for ethical reasons, but because cognition is produced and shaped by biological, social, environmental, technological, and cultural dynamics (Newen et al., 2018).

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Each section below includes a list of commitments that you can support as an individual, lab group, association, or organization. This manifesto addresses the *entire* EEG community, including technicians, engineers, PhD students, post-docs, senior researchers, research project evaluators, research administrators, artists, collaborators, and scientific decision-makers. It invites each individual to reflect on the raised topics, tailored to their role and responsibilities within the community. We will all agree upon some general principles, but there will no doubt be some more controversial points that we hope will generate healthy discussion. Feel free to use the CuttingEEG forum for this purpose. **We invite you to sign all or parts** of this manifesto **and share it** with your community if you broadly agree with the initiative.

[pack Context & Expectations]

Electroencephalography

For a century, electroencephalography (EEG) has been a cornerstone of neuroscience (Hari & Puce, 2023; Mushtaq et al., 2024). Today, more than ever, we—scientists, engineers, and clinicians—are witnessing unprecedented advances in recording technology and analysis methods. Modern EEG devices are increasingly affordable, robust, and portable, extending their reach well beyond clinical diagnostics and traditional research labs. At the same time, global computing power, cloud communication, and machine learning—now coupled with generative AI—promise ever more sophisticated analyses and real-time brain-computer interfaces (BCIs), making their widespread adoption seem not just possible, but inevitable.

However, these rapid technological advances bring significant challenges. A reproducibility crisis in science has eroded trust in established findings (Button et al., 2013; Höller et al., 2017; Ioannidis, 2005; Open Science Collaboration, 2015; Pavlov et al., 2021). Meanwhile, major societal concerns—including climate change, global inequality, growing obscurantism, and escalating military conflicts—threaten research by constraining material resources and political priorities (Rae et al., 2022a; Urai & Kelly, 2023). These pressures highlight the need to take stock, reflect on our ethical standards, and implement best practices for sustainable research involving human participants.

Grand ambitions inevitably bring significant challenges and responsibilities that must be navigated to ensure both scientific progress and societal benefit (Niso, Krol, et al., 2022a). For instance, even the most advanced brain imaging methods cannot answer all questions in cognitive science (Forest, 2013, 2022), and EEG has its specific limits. In clinical contexts, while EEG might be able to inform diagnosis and guide treatment, it should never displace the primacy of human caregivers. Beyond research and medicine, the broader application of EEG technology introduces pressing ethical and practical dilemmas. Scaling EEG for mass-market use would demand high-volume manufacturing, amplifying environmental burdens. At the same time, over-dependence on EEG-based tools risks fostering cognitive complacency—outsourcing functions we should cultivate, rather than merely augmenting them.

This Manifesto

Ultimately, a manifesto's value is measured not by its wording or by how many people sign it, but by the concrete actions it inspires. We urge you to consider these proposals in the context of your own work and to discuss them with your peers. Where these commitments resonate, incorporate them into your lab procedures and/or daily practice and share them with your colleagues. The extent of your commitment will naturally vary according to your interests, expertise, and available resources—but each positive step can help shape a more robust, responsible, and inclusive future for EEG science.

Although this manifesto centres on EEG, its core themes resonate across neuroimaging, and perhaps even science. A key driving force behind the new potential and renewed excitement of EEG comes from the increase in the availability and robustness of portable systems (H. Hinrichs et al., 2020; Marini et al., 2019; Niso, Krol, et al., 2022a; Radüntz, 2018). Colleagues working with Functional Near Infrared Spectroscopy (fNIRS) (e.g., (Burns et al., 2019) and perhaps soon magnetoencephalography (MEG) (e.g., (Boto et al., 2017; Schofield et al., 2024) might also find themselves in a similar situation and may find these reflections relevant to their fields. They are welcome to join this initiative or may prefer to develop similar approaches within their communities.

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Validity and scientific integrity in times of rapidly evolving practices

Increased computational power and technology-assisted data mining allows massively testing data on each and every possible time x electrode x frequency (...) combination. The availability of increasingly flexible tools that allow for the easy redefinition of statistical tests with a mouse click makes it a real challenge to maintain valid standards, compromising the soundness and reproducibility of research (Onciul et al., 2025; Surianarayanan et al., 2023). As human neuroscience increasingly integrates AI and machine learning approaches for data processing and analyses (DuPre & Poldrack, 2024), we must be critical about the epistemological assumptions underlying these technologies. Below, we advocate agreed-upon standard practices using open science tools and resources grounded in theoretically elaborated research.

Research practices and reproducible science

Research practices are fundamental to scientific inquiry, and their proper application ensures reliable, reproducible, and openly extensible science.

'Reproducible' is used here as an umbrella term, encompassing all aspects of recreating scientific results (aka replicable, generalisable, robust, etc.) as described in (Niso, Botvinik-Nezer, et al., 2022; Niso, Krol, et al., 2022b)

[pack 1.1. Reproducible EEG science]

Over the last 15 years, neuroscience has reckoned with how questionable research and publication practices inflate false positive rates and erode trust in scientific findings (Nosek et al., 2012). Community-driven efforts have highlighted specific challenges and offered some solutions (Niso, Botvinik-Nezer, et al., 2022; Niso, Krol, et al., 2022c; Pernet et al., 2020; Simmons et al., 2012), general manifestos (Munafò et al., 2017) and pledges (see Commitment to Research Transparency). Despite the creation of national and international networks to initiate and support relevant communities (e.g., UK Reproducibility Network; ARIADNE; the Turing Way), fully reproducible science is far from being the norm in empirical science in general (Lakens et al., 2024) or EEG research in particular.

To make progress, adopting standardized protocols for data collection, processing, and statistical analysis is essential for ensuring robust, replicable findings in EEG. At the same time, keeping high standards and re-shaping publication practices—supporting non-profit and scientifically sound publishing initiatives (e.g. open access nonprofit platforms like Peer Community In), while avoiding opaque or predatory outlets—is critical to maintain the overall quality and credibility of EEG science.

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Pledges:

- ☐ I commit to increasing robustness, replication, and standardization at each stage of my EEG work—from data collection, to analysis, to publishing results and data (see Open and reproducible neuroimaging: from study inception to publication). In doing so, I will consider:

- ☐ pre-registering my EEG studies, using dedicated platforms (e.g. OSF, Aspredicted, ClinicalTrials) and reporting templates (Govaart et al., 2022; Paul et al., 2021) where appropriate.
- ☐ clearly and systematically communicating all decisions made during data processing—adhering to guidelines such as COBIDAS and ARTEM-IS, recognizing that transparent reporting is critical to the integrity and interpretability of EEG research.
- ☐ sharing the code and analysis pipelines that can straightforwardly reproduce my original results.
- ☐ publicly releasing negative results.
- ☐ sharing raw data, employing general-purpose solutions (e.g., gin.g-node, datalad for datasets) and EEG-specific tools and standards (e.g., BIDS-EEG, ARTEM-IS, see Niso, Krol, et al., 2022b). See also 1.2 Standardization section.

☐ I commit to improving systemic reproducibility by:

- ☐ supporting initiatives focused on reproducing results from published articles (e.g. through initiatives like #EEGManyLabs, EEGManyPipelines, EEGManyAnalysts, TMS-EEG T4TE) either by participating in replication efforts or by supporting and communicating with researchers who are working to replicate my published results.
- ☐ improving the reproducibility and robustness of my work by testing the effects of different recording setups and analysis pipelines (e.g., through specialist scripts, for example (Es et al., 2024) including "multiverse analysis" (Aczel et al., 2021; Del Giudice & Gangestad, 2021; Steegen et al., 2016), see example tools; boba, multiverse, multifear, multitool, comet, nipype, shiny app, Gorgolewski et al., 2011) and/or by validating findings across multiple recording devices and environments.
- ☐ supporting non-profit, scientifically rigorous publishing initiatives, and to refrain from participating in opaque or predatory publishing practices, whether as an author, reviewer, or editor.
- ☐ when acting as a reviewer, requesting that (where appropriate) authors follow standard, robust, and replicable research protocols and make any pre-registered hypotheses, datasets, and analysis scripts publicly available during the submission process to avoid access issues post-publication

[pack 1.2. Standardization and Documentation of Data]

Generating large, annotated, and openly accessible EEG data repositories, including clinical and neuroimaging data, is crucial for advancing basic and applied neuroscience. This facilitates discovery science, improves diagnostic applications, industry applications and educational settings, promoting learning and skill development among students and early-career researchers. By pooling resources and sharing data, we enable researchers to perform large-scale analyses that are otherwise impractical for individual laboratories. Standardising datasets, using the Brain Imaging Data Structure (BIDS), is a crucial stage that fosters FAIR science (Wilkinson et al., 2016a). To promote transparency, we suggest sharing raw data, analysis scripts, and detailed metadata. Platforms such as OpenNeuro, g-node GIN, OSF, or Zenodo can be used to facilitate this process while ensuring adherence to FAIR principles. Such repositories provide diverse datasets that can help uncover new patterns, validate findings across different populations, and improve the generalizability of results.

Moreover, open data repositories are invaluable for developing and refining diagnostic applications. They provide the necessary volume and variety of data to train machine learning algorithms and develop robust biomarkers for neurological and psychiatric conditions.

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Pledges:

- ☐ I commit to ensuring that the data I collect and work with uses best practices in data standardization and documentation. I will do so by:
    - ☐ sharing curated EEG data as openly as possible (i.e., as institutional agreements allow) along with detailed metadata, annotations, and tags, using well-established open repositories.
    - ☐ using the FAIR principles for sharing data (Wilkinson et al., 2016b, data should be Findable, Accessible, Interoperable, and Reusable).
    - ☐ using standards such as the Brain Imaging Data Structure (BIDS) for my data to ensure interoperability and ease of use, and sharing it as openly as institute agreements or institutional repositories allow.
    - ☐ regularly update and enhance my shared data based on user feedback.

[pack 1.3. Open Science and Open Source]

Using transparent approaches, making sure that results and data are accessible is an essential feature of science. Open science is a broad movement in contemporary science that promotes open access to all aspects of the scientific process. Provided that participants' privacy is protected, we generally advocate for open science practices.

Of particular interest to the EEG community, it is important to consider that EEG data requires elaborate software to perform increasingly complex analyses. Open-source (OS) software and hardware are vital in advancing EEG research. By supporting and contributing to Free and Open-Source Software (FOSS) and Open-Source Hardware (OSH), we encourage community transparency, collaboration, and innovation. Open-source tools allow researchers to inspect, modify, and improve code and designs, leading to more robust and reliable scientific instruments and analyses. At the same time, OS fosters the development and sharing of cutting-edge methods and makes it easy to attribute developers for their contributions. This collective effort enhances the reproducibility of our work, accelerates scientific progress, and promotes a culture of openness and mutual support in the EEG community. Furthermore, open-source and open-sciences initiatives lower barriers to entry for researchers worldwide, especially those in resource-limited settings. By making software, hardware and knowledge freely available, we democratize access to cutting-edge tools, promoting inclusivity and diversity in EEG science (also see Democratization section below).
At the same time, high standards and best practice in developing and using OS scientific software must be maintained to harvest its full potential (see Westner et al., 2024)

[/pack]

Pledges:

- ☐ I commit to supporting open scientific practices to promote transparency, collaboration, and innovation about source code. I will do so by:
  - ☐ integrating open-source tools, data management practices, and transparent workflows into my research whenever possible.
  - ☐ citing open-source software properly, including specific version tags or DOIs, to 1) give full credit to *all* developers' contributions and 2) enable full replication of analysis pipelines.
  - ☐ following best practices in software use—such as version control, clear documentation, and code review—to enhance reliability and reproducibility.

- ☐ using open licenses for code and tools that I develop (e.g., BSD, MIT, GPL), creating readable documentation, and publishing my code on accessible platforms (e.g., GitHub, GitLab, OSF).
- ☐ contributing back, when I benefit from others' tools, if I have the skills or resources—whether through bug reports, testing, documentation, tutorials, or feature development.
- ☐ recognizing and valuing software development as a genuine scientific contribution; where possible, I will encourage formal acknowledgment of developers' work (e.g., in publications and grants).
- ☐ promoting open-source solutions in my institution, professional networks, and collaborations by highlighting their benefits for transparency, reproducibility, and inclusivity.
- ☐ encouraging administrators, funding bodies, and reviewers to recognize and reward open-science practices and open-source development as key indicators of scientific excellence.
- ☐ supporting, where relevant, mentor colleagues or trainees in adopting open-source tools and methods, lowering barriers to entry for all researchers—including those in resource-limited settings.

Interpretable and theoretically well-grounded research

For EEG research to drive meaningful progress, it must be grounded in current theories and integrate insights from multiple disciplines. This is especially crucial as AI tools and models become increasingly prominent in the field.

[pack 1.4. Theory-driven and data-driven research]

Recent years have seen an increasing emphasis on ever-larger datasets (Frégnac, 2017) with insufficient attention to the theoretical underpinnings that might explain brain activity and its emergent properties (Borsboom et al., 2021; Eronen & Bringmann, 2021; Gerstner et al., 2012).

From a philosophical or epistemological standpoint, it is vital to recognize the limits of any single perspective, emphasizing instead frameworks that integrate dynamic, second-person interaction as central to cognition (N. Hinrichs et al., manuscript)(Hinrichs et al., 2025). A purely data-driven understanding of neuroscience—particularly one focused on individual-brain analysis—can be limited in scope (Forest, 2016). We therefore advocate for cultivating strong theoretical neuroscience foundations and for interdisciplinary exchanges that draw insights from fields such as philosophy, anthropology, psychology, the arts, and the humanities. These cross-pollinations could yield innovative frameworks that enrich our uses and interpretations of EEG data.

In addition, the considerations outlined here link closely with our broader calls for epistemological rigor (see also Section 3 - Responsibility). Effective science requires the “how” of sound methods and robust protocols, and the “why”: the political, social, and ethical relevance behind our research questions.

By grounding EEG research in a well-articulated theoretical framework and seeking contributions from diverse disciplines, we can enhance the explanatory power of our findings, enrich interpretation, and promote more meaningful progress in understanding the human brain.

[/pack]

Pledges:

- ☐ I commit to balancing theory-driven and data-driven approaches in my research. I do so by:
  - ☐ engaging in developing strong preliminary theoretical reflections on the neurophysiological basis of the expected EEG results.
  - ☐ adapting my experimental practices when performing data-driven experiments. I systematically adapt thresholds for multiple comparison correction and validate conclusions with sound methodology.
  - ☐ refraining from using theory-blind approaches to scientific investigation prone to questionable research practices—especially those consuming ample computational resources—without a prior theoretical rationale (cf. pledges 3.4 on environmental responsibility).
  - ☐ reading synthesis texts from other disciplines (e.g., philosophy, anthropology, history, political science). This investment is worthwhile, helping align my research objectives with societal realities.
  - ☐ embracing diverse perspectives, e.g., integrating insights from the arts and humanities into my research and actively collaborating in interdisciplinary teams and consortia to foster innovation, cross-pollination of ideas, and a deeper theoretical grounding for EEG science.
  - ☐ training students to engage with theoretical reflections involving interdisciplinary approaches.

[pack 1.5. Transparent, interpretable, and explainable modeling]

A key challenge emerging for complex computational models—particularly those applied to data analysis and clinical decision-making—is ensuring their transparency, interpretability, and explainability. Modern ML/AI architectures often surpass our theoretical grasp (Holzinger et al., 2022), creating an epistemic gap where we rely on tools we cannot fully comprehend (Cichy & Kaiser, 2019). To address this, the EEG community must dedicate basic research and advanced computational tools (see the Local Interpretable Model-Agnostic or LIME approach as one such framework Ribeiro et al., 2016) to uncovering how these models operate, while simultaneously leveraging their potential to advance knowledge and applications.

Fostering interpretability and explainability requires a solid theoretical foundation and active collaboration across disciplines. The application of cross-validation with independent and diverse datasets will help mitigate overfitting and bias, increasing the likelihood that conclusions drawn from ML/AI models are reliable. We hence advocate for i) **diverse and open datasets** that will make sure AI models will be trained on neurophysiological data acquired from a wide range of population, cognitive states, and environmental contexts; ii) **interpretable AI models** that prioritise explainable AI/ML approaches rather than using black boxes; iii) **integrative validation methods** to acknowledge and incorporate in our models the fact that cognition cannot be meaningfully reduced to algorithmic patterns without considering the broader, complex organism-environment system.

Thus, by openly sharing parameters, feature-selection methods, and decision-making processes, we can build stronger trust within our community, mitigate algorithmic reductionism, and accelerate meaningful progress in ML/AI-driven EEG research.

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Pledges:

- ☐ I commit to using transparent, interpretable, and explainable modeling. I will do so by:
  - ☐ supporting the development of more transparent, explainable, and interoperable computational models and tools (e.g., LIME), including independent databases for cross-validation.
  - ☐ publicly disclosing ML/AI scripts and documenting all relevant decisions in my model designs—including feature-selection methods, parameter settings, and validation steps—to foster transparency and interpretability in ML/AI-driven neuroscience.

- [ ] promoting best practices for AI transparency when training students and early career researchers, reviewing grants, and evaluating manuscripts.
- [ ] contributing to counteracting the risks of algorithmic reductionism, which mistakenly reduces cognition to an isolated signal that can be decoded.

Democratization of the scientific process: Who does science, who is studied, who gains?

A key challenge for science is to ensure that research primarily benefits everyone rather than a privileged few, and that it is never weaponized to cause intentional harm (Carroll et al., 2020a). Achieving this goal requires democratizing both research outcomes and the people involved—whether they are scientists, participants, or patients. This means creating an environment where research tools, data, and findings are readily accessible and representative of all, free from gender and geopolitical discrimination, and open to international collaborations. It also entails extending opportunities to institutions and researchers in regions experiencing conflict or crises, especially where advanced basic and clinical research platforms are present.

Diversity in the scientific community is very important, we must include individuals from different backgrounds, disciplines, and perspectives to facilitate epistemological diversity (i.e., Who does the science?, La Scala et al., 2022; Parada et al., 2024), methodological innovation (i.e., How do we do science?, Choy et al., 2022), and the mitigation of risks such as *groupthink* (Szanto, 2016). **Diversity in research samples** is key to producing generalizable and ethical scientific findings. Biased participant selection leads to misleading conclusions that, in the worst scenario, might reinforce structural inequalities and outdated beliefs such as white supremacism. It is essential to ensure inclusivity in participants, be it age, gender, cultural background, socioeconomic status, and more. This will improve our research's validity, replicability, and applicability (Tzovara et al., 2021).

Furthermore, **diversity in applications and outreach** will make our research accessible, relevant, and beneficial to a broader range of communities. Scientific knowledge should be open, but also presented in ways that facilitate the engagement of diverse audiences. If our research cannot be read, understood, and used by non-scientific audiences, does it really *exist*? Scientific communities should avoid exclusionary language, consider the needs of underrepresented groups, and actively involve other actors such as artists, designers, journalists, and beyond to create bidirectional links involving the communities impacted by our research (Ishaq et al., 2021).

[pack 2.1. Diversity in the scientific community]

Despite gradual progress, workplace discrimination remains a major issue in science (Woolston, 2021). Enhancing diversity—whether in terms of gender or cultural background—can be challenging and transformative. Research shows that inclusive teams promote creativity and may yield stronger scientific outcomes (*Achieving Diversity in Research*, 2020; *Becoming a Scientist*, 2024; AlShebli et al., 2018; Powell, 2018). Building such teams means nurturing an inclusive lab culture and ensuring conference participation and networking opportunities reflect a broad range of voices (Corneyllie et al., 2024).

At the same time, well-intentioned diversity initiatives can unintentionally widen global disparities. When institutions and labs in wealthier countries recruit talented researchers from low- and middle-income regions, they may exacerbate “brain drain,” weakening the scientific capacity of those researchers’ home institutions. The pledges below balance benefits for both parties, encouraging ethically responsible collaboration and mindful engagement with underrepresented communities.

[/pack]

Pledges:

- ☐ I commit to support increasing the diversity of my scientific community. I will do so by:
    - ☐ continually learning how to recognize and challenge systemic inequities and proactively addressing social dynamics that may exclude or marginalize colleagues.
    - ☐ cultivating a welcoming and inclusive environment where all team members—irrespective of their professional status, neurodiversity, physical abilities, gender, or ethnicity—feel supported and represented.
    - ☐ prioritizing building long-term, mutually beneficial collaborations with researchers in under-resourced regions, ensuring that intellectual property, data ownership, and authorship are shared fairly to counteract 'brain drain' and strengthen local scientific capacity.
    - ☐ following the TRUST code - a global code of conduct for equitable research partnerships - engaging fairly with researchers with fewer resources for research, adapting research methodologies to be culturally appropriate and respectful, ensuring studies are designed with input from the communities involved, avoiding “ethics dumping” (Schroeder et al., 2021), providing training and appropriate authorship credit to collaborators.
    - ☐ promoting a more democratic global academic sector by advocating for funding and ethics-review criteria and engaging in practices that expand opportunities for underrepresented and underserved groups—including but not limited to those from low- and middle-income countries, rural areas, indigenous communities, and regions affected by conflict.

- ☐ engaging in practices such as distributed and online conferences that foster accessible academic networking and prevent barriers to participation (visa, time commitment, costs, etc.).

[pack 2.2. Diversity in study participants and sample populations]

Mining homogenous, diversity-less datasets—whether it is demographics, experimental paradigms, recording environments—might amplify existing biases in those datasets. The field of neuroscience has long relied disproportionately on individuals from Western, Educated, Industrialized, Rich, and Democratic populations (Caspar, 2024a; Dotson & Duarte, 2020; Henrich, 2020; Muthukrishna et al., 2020). This overreliance narrows the scope of our findings, undermining the goal of identifying universal principles of brain function. Moreover, systematic exclusion of people —whether due to technical constraints in EEG caps (Webb et al., 2022) (Girolamo et al., 2022) entrenched lab practices, or broader structural racism (Choy et al., 2022; Parker & Ricard, 2022)—can foster distrust among underrepresented communities and limit the generalizability of research. Crucially, participant diversity should be embraced as a scientifically valuable feature rather than dismissed as “noise.” Recent evidence shows that more inclusive recruitment is not only necessary but also feasible in varied environments, including rural settings in different countries (Caspar, 2024b; Pech et al., 2024), highlighting the potential for creating truly representative and equitable research populations.

When AI models are trained on datasets that do not reflect the full variability of human cognitive and physiological states, they will encode a narrow, static representation of cognition–detached from the ecological, cultural, and biological diversity shaping real-world neurobehavioral dynamics.

[/pack]

Pledges:

- ☐ I commit to support including more diverse populations in study samples. I will do this by:
    - ☐ attempting to recruit as diverse samples of experiment participants as possible, given the study goals, with special attention to gender and ethnoracial representation
    - ☐ training myself and my team to include everyone, regardless of their hairstyles, and never using hairstyles or other physical aspects as a direct exclusion criterion.
    - ☐ engaging with minority communities actively

- ☐ paying attention to cultural sensitivities, addressing stigma in brain research[1], and histories of marginalization
- ☐ adapting my experimental equipment (EEG head caps…) to account for potential individual differences, obtaining informed consent in ways that are understandable and meaningful to participants, respecting local customs, languages, and ethics
- ☐ including a Constraints of Generalizability (CoG) section to provide a clearer understanding of the findings' generalizability, which is crucial for interpretation and replication (Caspar, 2024b; Simons et al., 2017)
- ☐ exploring and sharing qualitative epistemology to establish barriers and facilitators to taking part in under-represented groups
- ☐ using or developing templates that ensure consistent reporting of demographic information and keep records of sample diversity across studies to assess progress and identify areas for improvement.

[pack 2.3. Accessibility of research outcomes]

Ensuring that research outcomes—whether new knowledge or potential applications—remain accessible to the scientific community and the general public is a core ethical responsibility for publicly funded research. The rise of the open science movement has substantially advanced this goal, aided by open-source software and hardware, DIY ("do-it-yourself") materials, open knowledge platforms (e.g., Wikipedia), open data repositories, open-access publications, and a wealth of instructional content on video platforms. Underpinned by legal frameworks (e.g., copyleft) and data use agreements that prevent misappropriation or misuse, these initiatives foster transparency and collaboration within clear regulatory boundaries.

However, meaningful access must also address the **inverse care law**, by which those needing healthcare—including improved brain health—are often least likely to receive it (World Health Statistics). Expanding access to research tools, knowledge, and resources can help reduce inequalities in care, bolster participant diversity (see pledges 2.2) and promote equitable cross-community collaborations (see pledges 2.1). By prioritizing widespread availability, we can ensure that EEG research benefits the broadest spectrum of society, particularly those who stand to gain the most.

[1] Stigma around brain research participation can affect a person's willingness to participate. People may be afraid of public stigma or their own internalized stereotypes about a condition, which can make them less likely to learn about research studies. Also, people may be afraid of discrimination and stigmatization, which can make them less likely to engage with healthcare services or research institutes.

[/pack]

Pledges:

- ☐ I commit to promoting a wide use of my research for the scientific community, and beyond, if applicable. I will do so by:
    - ☐ using open and transparent approaches (e.g., preprints, preregistration) responsibly, and to withdrawing deposits that do not yield validated findings or conclusive outcomes.
    - ☐ developing publicly accessible summaries or visuals of my findings to make the results (and their limitations) understandable and beneficial to broader, non-specialist audiences.
    - ☐ using research results to inform policies and investments that target health inequalities and under-resourced areas, ensuring that EEG applications reach communities where they are needed most.

Responsibility: considering ethics, societal impacts, and sustainability.

EEG's non-invasive nature and relatively low cost make it a seemingly harmless technology, but beneath this benign facade lie complex questions that warrant careful consideration. The steady progress in neurotechnology makes it important to scrutinize the implications of foreseeable uses. Further, although technological advancement continually unlocks new possibilities, it simultaneously shapes how we understand and inquire about the world, and should not obscure the original purpose of science, namely to seek understanding rather than merely to enable control or commodification.

EEG research typically uses relatively few consumables and less resource-intensive electronics than many other domains, making it seem innocuous by comparison. However, the growing affordability of EEG devices and their expansion into consumer markets could turn this advantage into a challenge if we overlook their broader impact and possible rebound effects.

We are responsible for examining these broader implications—beyond our immediate scientific interests and practices—to encourage responsible use.

Societal and technological responsibility

Applications of EEG research are potentially far reaching, and potential misuses should not be overlooked.

[pack 3.1. Ethical use of EEG]

Conversations around ethical accountability for scientific discoveries and real-world applications have a long history, extending beyond the scientific community. Each research field faces distinct risks and benefits, and EEG is no exception. In particular, EEG has been explored for sensitive or potentially sensitive uses, such as detecting “concealed information” (Farwell, 2012; Rosenfeld, 2005; Wolpe et al., 2005), enabling implicit interaction outside the participant’s awareness (Fairclough, 2017; Krol et al., 2020; Zander et al., 2016), and launching so-called “side-channel attacks” that decode private data like PIN codes (Lange et al., 2018). Together, these applications demonstrate the capacity of EEG to decode—and possibly influence—a person’s brain activity, heightening concerns about individual privacy (Mecacci & Haselager, 2019), mental integrity (Ienca & Andorno, 2017), and broader social equity (Hyman, 2011).

Researchers must carefully evaluate their work’s potential societal impacts, including how future developments may build on today’s findings. Although many EEG studies cite adherence to the Declaration of Helsinki, that document primarily focuses on medical research, leaving gaps for more general EEG practices. Current legal discussions (e.g. Muhl, 2024; Yuste, 2023) and best-practice recommendations (Niso, Krol, et al., 2022a) underscore the importance of addressing EEG-specific ethical considerations. Meanwhile, the increasing integration of ML/AI in EEG (e.g., automated signal classification, neural decoding) amplifies risks of inaccurate interpretations, overgeneralizations, and bias (Birhane et al., 2024; Bolte & van Wynsberghe, 2024). Beyond the Declaration of Helsinki, therefore, researchers and developers of EEG-based neurotechnology should look both at more generic frameworks concerning the use of personal data, automated decision-making, and AI, and at more specific guidelines concerning aspects directly related to neurotechnology, like neurorights. The former can guide the researcher, for example, in specifying verifiable quality criteria ahead of time and ensuring proper oversight. In contrast, the latter can aid in evaluating specific solutions, among other things.

A variety of organisations offer further guidance, both generic and specific. UNESCO's reports on neurotechnology ethics and the OECD's recommendations on responsible innovation in neurotechnology provide foundational strategies to safeguard privacy and autonomy, including in areas such as brain fingerprinting or generative AI (Knoechel et al., 2024). The NeuroRights Foundation advocates treating neural data as highly sensitive and recommends technical protections like encryption and differential privacy to avert misuse (Yuste, 2023). Together, these measures illustrate the growing consensus that EEG researchers must proactively address the near-term ethical challenges and the longer-term implications of their work.

[/pack]

Pledges:

- ☐ I commit to carefully considering the ethical implications of my research practice and the data I collect. I will do so by:
  - ☐ respecting each individual's right to self-determination and always prioritizing the welfare of participants and (future) users over personal, scientific, or commercial interests.
  - ☐ adhering to the CARE framework (Collective Benefit, Authority to Control, Responsibility, Ethics) (Carroll et al., 2020b), integrating these values in all relevant processes and collaborations.
  - ☐ conducting thorough ethical evaluations before pursuing sensitive EEG applications (e.g., lie or intention detection), ensuring they are backed by sound scientific evidence and embedded in an up-to-date discussion on ethical, legal, and societal implications.

- ☐ refraining from marketing or deploying neurotechnological products or services unless supported by robust, peer-reviewed evidence of safety and efficacy.
- ☐ making responsible and ethical use of generative AI in accordance with UNESCO guidelines, remaining vigilant about potential misuse.
- ☐ educating colleagues and trainees about hardware, software, modeling, and data interpretation risks, advocating for safe, fair, and sustainable neurotechnology.
- ☐ disclosing and minimizing conflicts of interest, and will not endorse or profit from EEG products lacking evidence-based grounding.
- ☐ not collecting EEG or neural data without explicit consent, nor passing them on to third parties or merging them with other data sources without proper authorization.
- ☐ not contributing to the development of, or market any, neurotechnology whose primary purpose is to circumvent a user's control over their information.
- ☐ making no scientific claims without reasonable empirical support, and will acknowledge uncertainty when disseminating EEG findings.

[pack 3.2. Overestimating technology]

New research technologies and analysis methods can correct shortcomings of previous tools, enable new observations, and crucially progress our understanding of the brain; hence, tool development is a cornerstone of contemporary neuroscience.

However, there can also be hype dynamics, and possibly cruel optimism (Berlant, 2011), as our fascination with advanced, cutting-edge instrumentation can make projects that feature such tools seem inherently more compelling and worthwhile (Nielsen & Andersen, 2022) at a cost that may exceed the expected benefits. Similar to the current fascination of the general public with neuroscientific explanations (Weisberg et al., 2008) and brain imaging (McCabe & Castel, 2008), we should also see the risks of such biases and take responsibility for discerning what is truly possible, what is desirable, what belongs to fantasy, and what should be rejected.

New tools should be developed, validated, and tested, but the governing thought should be scientific progress when deciding on a particular tool in empirical research. Unquestioningly adapting new tools and abandoning established techniques might have negative consequences: For example, powerful ML tools can lead to a relative devaluation of theory (see Section 1 - Validity). Focusing on new expensive recording devices may counteract the importance of cultivating expertise in data quality control and analysis. Both expertise and open science practices rely on stable, long-term scientist positions. Furthermore, adopting new tools is resource-intensive, which might reproduce global inequalities (see Democratization) and create problems in terms of ecological sustainability (see the following Section).

Given its relatively low-tech nature, EEG research can particularly benefit from easy-to-repair, shareable, or open hardware. By prioritizing resilience over novelty—such as defining long-term sustainability plans, pooling resource-intensive tools, and collaborating with hardware manufacturers—we can better balance investing in human capital and equipment. This strategy encourages more equitable and innovative research and can contribute to ensuring a sustainable future for EEG science.

[/pack]

Pledges:

- ☐ I commit to critically evaluating new technologies through their contribution to science. I will do so by:
    - ☐ explicitly weighing investments in new technology against developing in-house expertise, fair compensation, and the effective use of existing technologies.
    - ☐ developing long-term operational and sustainability plans for the technological systems I am responsible for
    - ☐ critically assessing the potential benefits of new technologies against the costs
    - ☐ considering old methods as an asset that can be exploited, rather than replaced
    - ☐ always looking at papers that did it in the 60s
    - ☐ valuing simplicity over complexity
    - ☐ never applying new tools without validation (and benchmarking)
    - ☐ moderating my use, design, and the conclusions obtained with more complex analyses
    - ☐ developing projects that incorporate other disciplinary approaches.
    - ☐ supporting the development and adoption of easy-to-repair, modular hardware with replaceable components, alongside open-source tools that adhere to open data and hardware standards, fostering greater accessibility, interoperability, and sustainability.
    - ☐ fostering collaboration by sharing high-cost EEG tools across labs and institutions, reducing waste and increasing efficiency in research.

[pack 3.3. Research evaluation]

There are growing concerns about the criteria used to evaluate scientific projects and the promises made in relation to them. Many assessment bodies still rely on narrow metrics—such as journal impact factor or h-index—that fail to capture the breadth and nuance of academic careers. This focus discourages interdisciplinary, collaborative, and open-science approaches.

Adopting broader research evaluation procedures and metrics recommended by the Coalition for Advancing Research Assessment (CoARA) is key to creating a more open, equitable, and ethically grounded research culture. Criteria that value transparency, data sharing, and open-source development can strengthen scientific findings' robustness, reliability, and social relevance. Embracing these more comprehensive measures can help foster integrity, encourage collaboration, and ultimately benefit the scientific community and society.

[/pack]

Pledges:

- ☐ I commit to participating in changing the research evaluation to avoid focusing on a single criterion. I will contribute to broadening research evaluation by:
  - ☐ promoting evaluation processes that credit a wide range of research contributions—such as datasets, software, outreach activities, and open-access publications—rather than focusing solely on narrow bibliometric indicators.
  - ☐ encouraging assessment criteria that prioritize open practices (data sharing, preregistration, code release) and value multidisciplinary teamwork, advocating for and implementing assessment frameworks (e.g., those proposed by CoARA) that emphasize integrity, inclusivity, and social impact alongside scientific excellence.
  - ☐ continually reviewing and refining evaluation metrics within my sphere of influence—whether as a grant reviewer, hiring committee member, or collaborator—and pushing for broader acceptance of open, ethical, and diversified research practices.

Environmental responsibility

Although EEG has a relatively low ecological impact in itself, it is part of a broader socio-technological system that has deleterious effects on the environment. It is our responsibility to carefully examine the impact of EEG research and weigh its benefits against its environmental costs, including the energy consumption of data processing, the production and disposal of electronic components, and the travel associated with global scientific collaboration.

[pack 3.4 Reconsidering Environmental Impact]

The scientific consensus is clear: human activity, including scientific research, profoundly affects Earth’s climate and resources—posing a serious threat to humanity’s future. Scientists, positioned at the forefront of knowledge, have a duty not just to document this crisis but also to alter their research practices accordingly (Aron et al., 2020; Racimo et al., 2022; Rae et al., 2022b; Urai & Kelly, 2023). Although EEG and related neuroscience fields may appear less resource-intensive than many other domains, we are still part of a broader infrastructure that depends on finite materials, substantial energy, and complex global supply chains.

Some lines of EEG research offer potential long-term benefits for human health and well-being. However, they can also require high-performance computing, extensive travel, or large-scale distribution of equipment (e.g., in population neuroscience). Pursuing such work without critically evaluating, or even considering, environmental costs risks perpetuating a “do it because we can” mentality and may be untenable in the long run. Wider collaborations and resource sharing can lead to synergy effects that reduce the ecological footprint of large-scale projects. Moreover, systemic pressures in academia, such as publication demands and grant requirements, may push researchers to pursue scope expansions without equivalent environmental impact scrutiny. Achieving genuine sustainability will require confronting these norms, ensuring that EEG studies are scientifically rigorous and responsive to climate change and resource scarcity.

[/pack]

Pledges:

- ☐ I commit to considering the environmental impact of my lab and my research. I will do this by:
    - ☐ advocating for ethical regulations and policies requiring serious environmental impact consideration—especially for high-resource or energy-intensive studies.
    - ☐ weighing potential short- and long-term environmental costs against any projected benefits when starting or collecting funds for a project.
    - ☐ remaining mindful of how academia’s incentive structures can undermine sustainability goals. I will strive to foster discussions, both within my lab and in broader networks, about rethinking these systemic norms.

- ☐ prioritizing or designing research programs with a clearly defined path toward tangible, long-term societal or environmental benefits rather than short-lived or insular academic gains.
- ☐ not considering EEG or my specific field as inherently exempt from sustainability concerns. My research is part of a larger, resource-intensive system; I acknowledge my role within that system and strive to minimize its negative impacts.
- ☐ cultivating a "climate handshake," using my position to influence others positively—whether that means introducing sustainable measures in my department, mentoring students on responsible research practices, or partnering with like-minded groups to effect broader change.

[pack 3.5 Measuring and reducing the environmental footprint of our work]

While EEG itself generally has a moderate ecological impact, the datasets involved can be very large, and the required storage and computational power used to support EEG sciences continue to expand. Moreover, we need to account for the broader environmental footprint of our professional activities (e.g., conference travel, institutional purchases, and overall infrastructure; (Mariette et al., 2022; Souter et al., 2025).(Lannelongue et al., 2021)

A key first step is quantifying this impact (e.g., using apps.labos1point5.org). With that knowledge, researchers can identify practical measures to reduce adverse outcomes while preserving core scientific aims. However, rebound effects—where well-intentioned actions produce unintended harm—must be carefully monitored to ensure that measures to reduce our carbon footprint do not inadvertently lead to other adverse consequences.

[/pack]

Pledges:

- ☐ I pledge to minimize the environmental impact of my research through sustainable practices across multiple domains. I will do this by:
  - ☐ using responsible data management, such as archiving datasets efficiently to reduce redundancy and prioritizing cloud-based services powered by renewable energy.
  - ☐ advocating for virtual conferences, workshops, and meetings to reduce travel-related emissions while promoting hybrid formats for inclusivity and accessibility.
  - ☐ reserving air travel for young researchers who need it the most to launch their careers and build their network.

- ☐ using energy-efficient algorithms, optimizing computational methods to reduce runtime and energy consumption, and scheduling resource-intensive analyses during off-peak energy hours where feasible.
- ☐ evaluating the environmental impact of my laboratory and research projects by quantifying emissions, energy usage, and waste production through available tools, and using these evaluations to guide more sustainable practices in daily operations and long-term planning.
- ☐ critically evaluating my own research projects and considering renouncing to run a project if it does not yield future benefits.

[pack 3.6 Using research resources, equipment, and data thoughtfully]

While non-invasive EEG often appears low-impact compared to more resource-intensive methods, individual projects can still consume substantial time, funding, and materials—particularly if their design is inefficient or redundant. Consequently, reviewing existing datasets and clarifying genuine methodological advances before embarking on new recordings are essential to ensure our collective use of participant time and laboratory resources remains ethical and environmentally sound. By being judicious about data collection, we respect our participants and optimize the use of laboratory, computational, and environmental resources.

Further, the production and disposal of scientific equipment contribute significantly to pollution and waste. Encouraging **equipment pooling, sharing**, or applying a 3Rs approach ("Reduce, Reuse, Recycle" Marques & Fritzen Gomes, 2020) in the lab can help reduce the demand for new devices and extend the lifespan of existing ones. By reducing resource usage and waste production, we not only lessen our environmental impact but also encourage a more collaborative and cost-effective research environment.

Likewise, our field generates vast volumes of data, and we are responsible for ensuring they are fully utilized. Meta-analyses—where multiple teams aggregate already-collected datasets—also decrease resource usage, strengthen collaboration, and foster more reliable findings (Koile & Cristia, 2021). To facilitate sharing and reuse, it is essential to standardize data acquisition and analysis and to manage data according to the FAIR principles (Wilkinson et al., 2016c), ensuring that it remains Findable, Accessible, Interoperable, and Reusable (See also Section 1.2).

[/pack]

Pledges:

- ☐ I commit to fostering a thoughtful use of resources, equipment, and data, by
  - ☐ reviewing existing datasets and reusing previously collected or open data whenever feasible and only collecting new EEG data if it provides novel insights, significantly improves upon current methodologies, or addresses a well-defined research gap—thereby respecting participants' time, minimizing resource use, and fostering more sustainable, ethical EEG science.
  - ☐ contributing to collaborations across labs to share facilities and optimize resource utilization - from headsets to high-performance clusters.
  - ☐ establishing and participating in equipment-sharing networks or consortia that facilitate access to specialized instruments.
  - ☐ advocating for manufacturers to support sustainable practices by providing long-term support, repair services, and recycling programs for their equipment.
  - ☐ selecting EEG equipment based on durability and ability to repair, promoting practices that extend the life of equipment, such as regular maintenance, repairs, and upgrades, rather than immediate replacement.

Conclusion

The challenges outlined here underscore that EEG science must evolve responsibly, balancing innovation with ethical, social, and environmental considerations. As individuals and as a community, we share the duty to anticipate potential misuses, curb unsustainable practices, and embrace virtuous approaches. However, even with the best intentions, unintended or adverse outcomes—sometimes called rebound effects—remain a constant possibility. Staying alert to these risks, seeking continual improvement, and adapting based on new insights are all crucial to ensuring that our efforts genuinely 'do good.'

A significant part of meeting these responsibilities lies in embracing Open Science and FAIR principles. By pre-registering studies, openly sharing data and code, and using transparent publication outlets, we can foster reproducibility, collaboration, and equitable access to scientific knowledge. This inclusivity will strengthen the entire field, broadening impact and accelerating discovery.

Finally, we believe fostering an international, ethical, and collaborative approach through science is essential to promoting cross-cultural exchange and contributing to human well-being and unity. This text is an initiative reflecting that commitment within the field of EEG. By signing onto this manifesto and adopting its principles in your daily practice, you contribute to a future where EEG research is more robust and sustainable and firmly rooted in ethical and equitable engagement. Each pledge is a step toward maximizing EEG's societal benefits—ensuring it advances knowledge, improves well-being, and respects the planet and its people.

Glossary

- **Deontological (Deontology):** An ethical framework centered on duties, rules, and moral obligations rather than outcomes alone. In the context of EEG research, a deontological approach emphasizes adhering to principled standards—such as respecting participant autonomy, ensuring data integrity, and minimizing harm—regardless of whether specific shortcuts or less rigorous practices might yield faster results or greater convenience. This commitment to following moral rules helps guide responsible decision-making at each stage of the research process.
- **Scientific Integrity** Upholding rigorous, honest, and transparent research practices. Scientific integrity encompasses maintaining high methodological standards, avoiding biases or questionable practices, and sharing findings responsibly. It also includes acknowledging limitations and uncertainties, ensuring reproducibility, and treating collaborators and participants ethically.
- **Sustainability** meets present needs without depleting resources or compromising future possibilities. Within EEG research, sustainability involves minimizing environmental impact—from equipment production to data storage—and ensuring that the benefits of EEG science do not come at an unacceptable ecological or social cost. A sustainable approach balances scientific advancement with planetary limits and intergenerational equity.
- **Diversity:** Embracing a broad range of backgrounds, perspectives, and experiences in research teams and participant samples. Diversity in EEG research includes attending to differences in gender, ethnicity, geographical context, socioeconomic status, and neurodiversity. By actively removing barriers and ensuring equitable representation, diversity fosters creativity, strengthens the validity of findings, and promotes inclusive scientific progress.
- **BCI (Brain-Computer Interface) is** A system that enables direct communication between a person's brain signals and external devices or computers. In EEG-based BCIs, scalp electrodes detect brain activity, which specialized software translates into commands for controlling assistive technologies or other applications.
- **Open Science:** A movement promoting transparency, accessibility, and reproducibility in research. Open Science practices include publicly sharing data, code, and protocols; publishing in open-access journals; and using collaborative platforms to foster inclusive and ethical research.
- **FAIR Principles:** An acronym for Findable, Accessible, Interoperable, and Reusable. Data and resources adhering to FAIR principles enable efficient discovery, integration, and reuse by humans and machines, accelerating scientific progress and reliability.
- **CARE Principles** stand for Collective Benefit, Authority to Control, Responsibility, and Ethics. Initially framed for Indigenous Data Governance, these principles apply to

broader AI and neurotechnology contexts, emphasizing ethical data stewardship that respects communal rights and benefits.

- **Predatory Journals** Publications that exploit academic needs for rapid dissemination while providing little to no peer review or editorial oversight. Often characterized by hidden fees, aggressive solicitation, and low-quality content, these journals threaten scientific credibility and the integrity of the scholarly record.
- **Diamond Open Access:** A form of open-access publishing in which neither authors nor readers pay fees. Instead, costs are supported by institutions, grants, or other funding models. Diamond OA aims to reduce financial barriers and promote equitable dissemination of knowledge.
- **Neurofeedback:** A therapeutic or training approach using real-time displays of EEG or other neurophysiological signals. Participants attempt to self-regulate brain patterns to improve cognitive or affective states. Despite its promise, rigorous, peer-reviewed evidence of efficacy is often lacking or inconsistent.
- **Ethics Dumping:** The practice of exporting unethical or substandard research methods to regions with weaker regulatory frameworks or limited oversight. It often exploits vulnerable populations, ignoring robust ethical standards required in the researchers' jurisdictions.
- **Brain Drain:** The emigration or recruitment of highly skilled individuals from lower-resource regions (e.g., LMICs) to wealthier institutions. Although it can offer personal benefits to those recruited, it may deplete local capacity and reinforce global inequities in research and innovation.
- **Systemic Bias** Enduring patterns of advantage or disadvantage tied to characteristics such as race, gender, or socioeconomic status. In research, systemic bias can skew participant pools, career trajectories, and resource allocation, undermining fairness and validity.
- **"Climate Handshake"** Refers to an individual's commitment to use their position and influence to encourage more sustainable practices within their research community—fostering a ripple effect beyond personal decisions.
- **Epistemological Rigor:** The principle of grounding research in well-justified theories and methods, clarifying how and why the research is done. Epistemological rigor ensures the interpretive framework is robust, reducing the risk of spurious conclusions and guiding meaningful inquiry.
- **Rebound Effect:** An unintended negative consequence of an action meant to be beneficial. A rebound effect might occur in sustainability when a supposedly "green" measure drives additional consumption or unforeseen ecological harm.
- **Data Encryption & Differential Privacy:** Technical methods for protecting sensitive information. Encryption encodes data so only authorized parties can read it, while differential privacy introduces controlled noise to datasets, preserving patterns at a group level while obscuring individual details.

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Extra Resources

Manifesto Resources

Same as Zotero Ressources : https://www.zotero.org/groups/5794905/eegmanifesto/library
(witch include, in addition, the bibliography)

Validity and scientific integrity in times of rapidly evolving practices

Research practices and reproducible[2] science

1.1. Reproducible EEG science [added to Zotero except APC model]

Seven quick tips for analysis scripts in neuroimaging van Vliet, 2020
https://doi.org/10.1371/journal.pcbi.1007358

Use principled output scheme, with toolboxes like Dr.Watson.jl to track project progress, and archival. Lab notebooks and logs are essential.

Neuroimage editors resignation due to high APCs and the start of the new non-profit journal, Imaging Neuroscience: https://www.nature.com/articles/d41586-023-01391-5

In Spain, there's this journal (https://psicologicajournal.com/about/) completely free, based on an Institutional repository. See https://www.nature.com/articles/d41586-023-02315-z

On the future of the diamond open access model:
https://universityaffairs.ca/news/open-access-a-diamond-in-the-rough/

How libraries can facilitate the transition from APC-based publications:
https://items.ssrc.org/parameters/the-library-solution-how-academic-libraries-could-end-the-apc-scourge/

More on how paying APCs, whether to for-profit or non-profit publishers, is discriminatory and problematic: Ethical Academic Publishing: How to Make Academic Publishing Fairer, More Open and Less Wasteful – Open Research at Bristol

The next paper illustrates how people from upper-middle-income countries (who cannot apply for fee waivers but also cannot afford to publish in practically any APC-based psychological or neuroscience journal typically used by Western researchers) suffer under the APC model:
https://direct.mit.edu/qss/article/4/1/22/114729/The-APC-barrier-and-its-effect-on-stratification

Plan S. Webpage: https://coalition-s.org/why-plan-s/

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[2] 'Reproducible' is used here as an umbrella term, encompassing all aspects of recreating scientific results (aka replicable, generalisable, robust,..) as described in (Niso, Botvinik-Nezer, et al., 2022; Niso, Krol, et al., 2022b)

Published preamble:

https://journals.plos.org/plosmedicine/article?id=10.1371/journal.pmed.1002663

Nature web article: https://www.nature.com/articles/d41586-023-03342-6 "It (Plan S) wants all versions of an article and its associated peer-review reports to be published openly from the outset, without authors paying any fees, and for authors, rather than publishers, to decide when and where to first publish their work."

Recommendation to avoid low quality semi predatory, aim for diamond open access most ethical:

https://openresearchbristol.blogs.bristol.ac.uk/2024/09/23/ethical-academic-publishing-how-to-make-academic-publishing-fairer-more-open-and-less-wasteful/

1.2. Standardization and Documentation of Data [added to Zotero except repo]

- open-access clinical, MRI, and EEG databases in healthy and diseased populations to be used to test and compare different EEG techniques (e.g., estimators of EEG source activation and connectivity): eBRAIN-Health brain Challenge

Words on FAIR, BIDS, open (GIN, OMEGA, EBRAINS, NEMAR, OpenNeuro, CRCNS, HeadIT, PREDICT, DANDI, DABI, etc.), Zenodo etc.

1.3. Open Source [not added to Zotero]

There are many open-source general-purpose EEG analysis tools available, but not all of them rely completely on OSS. Currently, the most popular tools are EEGLAB, FieldTrip, Brainstorm [Matlab dependency and/or partial Octave] and MNE-Python.

Advertise open data formats.

Advertise open-source stimulus presentation software (PsychoPy, Psychophysics Toolbox [Matlab dependency and/or partial Octave], OpenSesame).

Advertise/list specialized tools and plugins/repositories with refs. Ex:
LSL (*LabStreamingLayer's Documentation — Labstreaminglayer 1.13 Documentation*, n.d.)
EEGLAB extensions repository

Advertise online/cloud computing alternatives.
Brainlife.io, NSGportal, EBRAINS,

Society of Research Software Engineering (https://society-rse.org/). Mission: to establish a research environment that recognises the vital role of software in research.

https://barcelona-declaration.org/

1.4. Theory-driven and data-driven research [added to Zotero]

- Generative Adversarial Collaborations (Cleeremans, 2022; Consortium et al., 2023; Peters et al., 2025)

- Limiting the spectrum of what we claim to be explorable with non-invasive EEG : physical limits of the tools are understated, which leads many researchers to investigate processes and behaviors that are too complex to be captured and explained by EEG recordings, therefore producing an endless flow of unreproducible experiments. Less studies, better focussed.

Neural Mechanisms Online

https://www.neuralmechanisms.org/

1.5. Transparent, interpretable, and explainable modeling

[PLEASE LIST resources that could help achieve this pledge below]

Finding resources, networks, tools that help in these tasks? [HELP NEEDED!]

LIME:https://c3.ai/glossary/data-science/lime-local-interpretable-model-agnostic-explanations/
https://www.oreilly.com/content/introduction-to-local-interpretable-model-agnostic-explanations-lime/

Training resources, references to influential papers in the theoretical neuro/statistical science.

Course by Lakens (Improving statistical questions)...

Democratization: the importance of diversity and inclusion to support the development of EEG science

2.1. Diversity in the scientific community [Added to Zotero except the git]

Resources and tools to achieve the above commitment [HELP NEEDED!]

Paper on pros and best practice regarding lab handbook highlighting the ethos of an inclusive lab (Tendler et al. 2023, doi:10.7554/eLife.88853)

Bias watch neuro https://biaswatchneuro.com/

Anne's list https://anneslist.net/

Gender citation check https://github.com/dalejn/cleanBib

https://www.alba.network/

TRUST (2018). The TRUST code – a global code of conduct for equitable research partnerships. https://www.globalcodeofconduct.org/the-code/

https://www.inclusiveneuro.com/

Diversity works (NZ network) (that's just an example I came across).

Neurodivergent Researchers & Neurodivergent-authored publications | Neurodiversity Team | FORRT

2.2. Diversity in study participants and sample populations [added to zotero]

https://pubmed.ncbi.nlm.nih.gov/34280783/

https://diversityinacademia.mystrikingly.com/

Resources and tools to achieve the above commitment [HELP NEEDED!]

Generalization crisis (Yarkoni 2022)

https://www.nature.com/articles/s41593-024-01832-y "Considering the interconnected nature of social identities in neuroimaging research" see e.g. Box 2 for actions

2.3. Accessibility of research outcomes [added to Zotero]

Resources and tools to achieve the above commitment [HELP NEEDED!]

Public involvement allows the public to actively participate in the entire research and innovation process, particularly in health and social care.

The Octopus Platform https://www.octopus.ac/

peer community in https://peercommunityin.org/

The Open Brain Consent provides examples and templates translated to multiple languages to help researchers prepare consent forms for data sharing.

Responsibility: considering societal impacts, issues of equity, and sustainability.

Societal and technological responsibility

3.1. Ethical use of EEG [added to Zotero]

The Research Data Alliance (RDA) has developed a number of reports, including
- Guidance for informed consent
- Guidance for ethics committees
- AI Bill of Rights
- FAIR Data Maturity Model
- CARE Principles for Indigenous Data Governance

Identifying Criteria for the Evaluation of the Implications of Brain Reading for Mental Privacy ("... an evaluative framework that is composed of five criteria-accuracy, reliability, informativity, concealability and enforceability-aimed at enabling a clearer estimation of the degree to which brain reading might be realistically deployed in contexts where mental privacy could be at stake.")

The Neurorights Foundation (numerous reports and publications on the ethics of neurotechnology)

UNESCO's Ethics of Artificial Intelligence, specifically their Ethical Impact Assessment tool (bit focused on AI, but relevant for neurotech as well)
Ethics by Design and Ethics of Use Approaches for Artificial Intelligence (as above)
Ethics, Transparency and Accountability Framework for Automated Decision-Making (as above)

Singapore Statement on Research Integrity (general)
The European Code of Conduct for Research Integrity (general)

3.2. Overestimating technology [added to Zotero]

https://backyardbrains.com/

3.3. Research evaluation [Added to zotero]

On this site (https://libguides.brown.edu/c.php?g=811221&p=10141545) they reference DORA (declaration of research assessment; https://sfdora.org/) and the Leiden Manifesto (ten principles to guide research evaluation; https://www.nature.com/articles/520429a)

Environmental responsibility

3.4 Reconsidering Environmental Impact [added to Zotero]

Doughnut-academia

Point of View: The biospheric emergency calls for scientists to change tactics https://elifesciences.org/articles/83292

Universities committed to pursuing fossil fuel divestment

Resource: This reflection has begun in France, notably through the Labos 1point5 collective, which offers interdisciplinary insights into the sustainability of scientific research (refs). Moreover, this collective argues that the scientific and academic communities, due to their privileged access to knowledge, can serve as demonstrators of the feasibility of a profound and equitable transition toward a sustainable future. To this end, Labos 1point5 is developing practical studies on effective transitions within laboratories on a national scale (Ragueneau & Sabbagh, 2024).

3.5 Measuring and reducing the environmental footprint of our work [added to zotero - but not the workshops]

Some tools for environmental impact quantification:
- Calculate your laboratory's carbon footprint and build a regulatory greenhouse gas balance sheet (BGES): GES 1point5 (tailored for French system, but English version available)
- Get a watt hour-meter to plug between a server/ work-station and the socketCarbon

- workshops: climate fresk, Designing our low carbon lives, Atelier 2tonnes, MaTerre en 180 minutes, Doghnut academia

3.6 Using research resources, equipment and data thoughtfully