EEGManyPipelines: A Large-scale, Grassroots Multi-analyst Study of Electroencephalography Analysis Practices in the Wild

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Abstract

■ The ongoing reproducibility crisis in psychology and cognitive neuroscience has sparked increasing calls to re-evaluate and reshape scientific culture and practices. Heeding those calls, we have recently launched the EEGManyPipelines project as a means to assess the robustness of EEG research in naturalistic conditions and experiment with an alternative model of conducting scientific research. One hundred sixty-eight analyst teams, encompassing 396 individual researchers from 37 countries, independently analyzed the same unpublished, representative EEG data set to test the same set of predefined hypotheses and then provided their analysis pipelines and reported outcomes. Here, we lay out how large-scale scientific projects can be set up in a grassroots, community-driven manner without a central organizing laboratory. We explain our recruitment strategy, our guidance for analysts, the eventual outputs of this project, and how it might have a lasting impact on the field. ■

INTRODUCTION

The scientific community in psychology and neuroscience faces increasing pressure to rethink and improve its current culture and practices. Low replicability and reproducibility of research findings have eroded trust in even some of the

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most established results (e.g., Szucs & Ioannidis, 2017; Open Science Collaboration, 2015). At the same time, these issues have made clear that a traditional research structure based on individual laboratories with a solo lead will likely be insufficient to overcome the many obstacles inherent to studying the human brain and mind. Restoring trust and advancing knowledge requires not only evaluating the robustness of a specific field's research outcomes to lay the groundwork for evidence-based, reproducible, and robust scientific standards, but also to develop and implement alternative models of research culture.

Here, we introduce the EEGManyPipelines project to (1) map the real-life analytical flexibility in EEG research and its effects on robustness of reported results, and (2) serve as a blueprint for setting up and conducting research in a grassroots, community-driven manner without a central organizing laboratory.

EVALUATING THE ROBUSTNESS OF EEG RESEARCH "IN THE WILD"

Although credibility issues in psychology and cognitive neuroscience concern a wide range of topics and methodologies, EEG research represents an ideal candidate to investigate current scientific practices. Not only is EEG one of the most widely used tools to study human cognition, its large analytical flexibility may render it particularly susceptible to low replicability and robustness (Figure 1A).
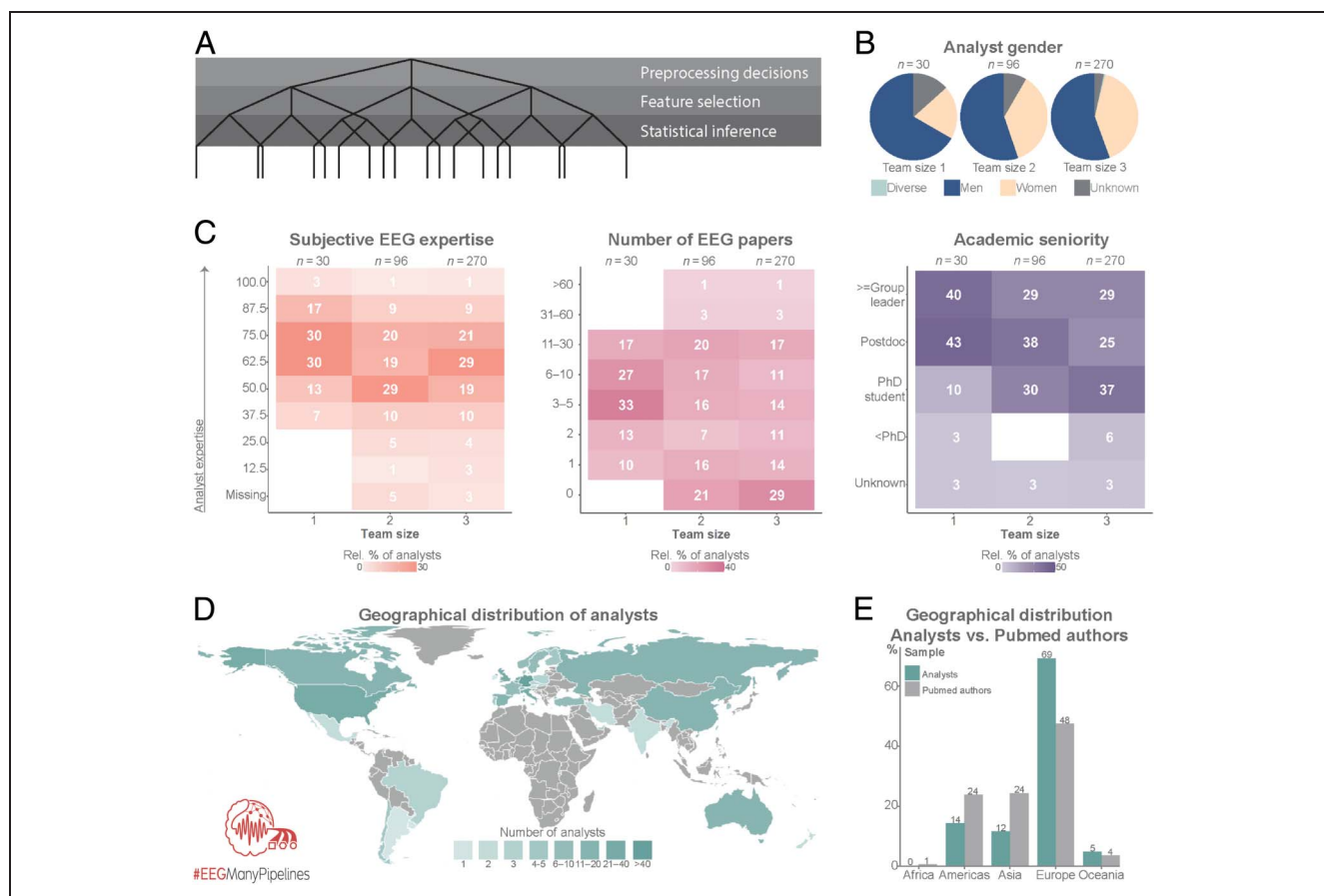
Figure 1. Theoretical motivation and demographic composition of the EEGManyPipelines sample. (A) Significance of variability in analysis pipelines. Raw EEG data are both high-dimensional (i.e., there is a large number of channels and time points) and noisy. Common analysis techniques (e.g., time–frequency transforms) increase dimensionality further. As a result, EEG analysis pipelines involve substantial signal processing, with many degrees of freedom at all analysis stages from preprocessing to statistical testing and inference. Variability in analysis pipelines might thus be a driving factor for variability in reported results. (B) Gender distribution of the EEGManyPipelines analysts as a function of team size. Analysts reported their gender in a forced-choice questionnaire. Each pie chart depicts the relative percentage of analysts self-identifying as diverse (green), female (yellow), and male (blue). The relative percentage of analysts who preferred not to disclose their gender is shown in gray. Sample sizes for different team categories are shown above the pie charts. (C) Indicators of analysts' expertise based on self-reports at sign-up split by team size. Each matrix depicts the relative percentage of analysts possessing a given level of expertise (with EEG). (Left) Analysts' subjective EEG expertise. Analysts rated their expertise in the following 10 categories: EEG preprocessing, EEG ERP analysis, EEG time–frequency analysis, statistical analysis of EEG data, memory research, visual long-term memory research, cognitive neuroscience, the N1 component, fronto-central theta power, and posterior alpha power. Answers were recorded on a 100-point scale, ranging from 0 (*no expertise*) over 50 (*average expertise*) to 100 (*expert*). Here, we present the single-analyst average level of expertise across all 10 categories, divided into eight equally spaced bins between 0 and 100. y axis labels denote the upper limit of each bin. (Middle) Analysts' self-reported number of published peer-reviewed articles involving EEG or related methodologies (i.e., MEG, ECoG) grouped according to the categories on the y axis. Note that, for visualization purposes, junior research positions outside academia were considered as part of the "Postdoc" category, whereas senior research positions outside academia were grouped together with the "Group leader" category. In all three matrices, exact relative percentages per bin are shown in white numbers and darker hues signal higher relative percentage. The total number of analysts per team are indicated above each matrix column. (D) Geographical distribution of the analysts. Total number of analysts reporting a given country as their current place of residence is shown. Darker hues signal increasing numbers. (E) Representative comparison between place of residence of EEGManyPipelines analysts (in green) and geographical origins of the larger EEG community (in gray), extracted from author affiliations of EEG articles indexed on PubMed and published between 2017 and September 2022 ($n = 31,440$; search term "EEG").

One possible source of such a lack of replicability and robustness of research findings could be that reported results are affected by differences in analysis pipelines (Wagenmakers, Sarafoglou, & Aczel, 2022). Systematically and meaningfully mapping the variability of reported results to the variability in analysis pipelines can only be achieved by applying multiple genuine and plausible analysis pipelines to the very same data set. Recent reviews highlighted considerable variability in analysis pipelines, even when researchers pursued similar research questions (Šoškić, Jovanović, Styles, Kappenman, & Ković, 2022). Likewise, permuting analysis parameters in multiverse approaches (Steegen, Tuerlinckx, Gelman, & Vanpaemel, 2016) has shown strong effects on EEG results (Clayson, Baldwin, Rocha, & Larson, 2021).

However, neither of these approaches can fully relate meaningful variability in analytic choices to meaningful variability in results. Evaluating robustness of research outcomes in the context of published literature relies on comparing analysis pipelines applied to different data sets,

thereby introducing uncontrolled variability. By contrast, systematically permuting analysis parameters does not necessarily produce analysis pipelines the community of researchers would actually use or deem plausible.

To address this important blind spot and reveal the true extent of diversity in existing analytical practices and the ensuing variability of findings, we launched the EEG-ManyPipelines project in 2020. Complementing the EEG-ManyLabs project (Pavlov et al., 2021), a large-scale effort to replicate experimental findings in EEG research by pooling data collection efforts across multiple laboratories, here, we rely on a multi-analyst approach to investigate EEG analysis practices: Many independent analysis teams test the same set of hypotheses on the same data and report their analyses in detail, providing a record of their results and analysis code. In that sense, our project targets EEG analyses as conducted "in the wild": (1) It goes beyond summarizing analysis practices reported in published EEG studies by observing in detail how such analyses are conducted and implemented in actual research environments; (2) the analyses are executed by a large, representative sample of analysts rather than a single team; and (3) the analysts are granted the autonomy to make their own analytic choices, mirroring their own "natural" research work.

Multi-analyst studies of a similar kind have already been successfully conducted or are currently underway in other domains and fields. For instance, the Neuroimaging Analysis Replication and Prediction Study (NARPS; Botvinik-Nezer et al., 2020) analyzed fMRI pipelines and demonstrated large methodological flexibility, affecting the reported results for a subset of the tested hypotheses. Similarly, the recently announced Coscience EEG Personality project (Paul et al., 2022) as well as the Team 4 TMS-EEG project (Bortoletto et al., 2023) complement our project with more targeted approaches, aiming at leveraging multi-analyst or multilab components to investigate personality and individual differences with EEG recordings or the robustness of TMS-EEG data to heterogeneous data collection situations and analytic strategies, respectively.

So far, however, this type of multi-analyst approach has never been taken to evaluate the robustness of EEG research as a whole and, as such, contributes to the expansion of comparative research on analytical variability across research fields and designs. What is more, although previous multi-analyst studies (e.g., NARPS) have already started alerting the community about variability and its consequences in domain-specific analysis practices, there is much more to be learned about more general research culture and scientific decision-making. In contrast to NARPS, in the EEGManyPipelines project, analysts did not only report the outcomes of their analysis in the form of a detailed questionnaire and yes/no answers to whether hypotheses were confirmed by the data, but also wrote a free-text "results section" interpreting their findings and submitted their actual analysis code. We expect that the free-text results section might shed light on how people

draw conclusions from their statistical findings, while keeping data and hypotheses constant. Moreover, comparing these reports to the analysts' actual code promises to reveal novel patterns about, for instance, where and how scientists are most error-prone in reporting and interpreting their results. Findings such as these should be relevant not only to the EEG community but also to cognitive neuroscientists at large. In the context of multi-analyst studies from different fields, the EEGManyPipelines project is one of the largest ever conducted and yields an unprecedented rich data set of choices, outcomes, and analyst-level variables, enhancing meta-scientific opportunities to investigate determinants of variability.

RECRUITING A LARGE AND REPRESENTATIVE SAMPLE OF ANALYSTS TO BUILD A RICH, OPEN-ACCESS DATA REPOSITORY AND DERIVE PRACTICAL RECOMMENDATIONS

Multi-analyst approaches can reveal how real-world variability in research outcomes relates to variability in analysis pipelines. At the same time, they provide the necessary empirical data to derive evidence-based, reproducible, and robust standards for data analysis and reporting (Aczel et al., 2021). This full potential, however, can only be unlocked if the analysts contributing the pipelines as well as the contributed pipelines are themselves representative of researchers and actual analyses in the field.

To achieve this objective, we selected a data set as representative as possible. Consisting of an EEG experiment on visual long-term memory for scene photographs—a cognitive process that we expected most analysts to be familiar with—a group of 33 participants saw a stream of scene images from different categories and decided on each trial whether the image was new or had been presented before. Thus, this paradigm featured a conventional factorial design and typical indicators of behavioral performance, allowing us to formulate several "research questions." The data set itself was recorded with standard parameters and comprises a typical range of noise and signal artifacts (see Algermissen et al., 2022 for details). Importantly, previous studies using similar paradigms have reported significant but modest overall effect sizes for memory-related effects (e.g., Van Strien, Hagenbeek, Stam, Rombouts, & Barkhof, 2005; Burgess & Gruzelier, 2000; Friedman, 1990), rendering the results potentially more susceptible to variations induced by different analysis pipelines and avoiding strong expectations about the presence or absence of an effect. We provided the data in an almost completely unprocessed form, except for downsampling to facilitate data sharing, referencing, and export to a variety of formats, such as the EEG-Brain Imaging Data Structure (BIDS) standard (Pernet et al., 2019). No analyses or results associated with this data set were published at the time of sharing to avoid any potential bias in analytical decisions because of prior knowledge of the data or results. Instructions to analysts were carefully worded to encourage an analysis approach

typical of analysts' standard analysis pipeline and real-life approach to hypothesis testing.

Recruiting as large and representative a sample of analysts as possible was a guiding principle for our decisions at all stages of the EEGManyPipelines project, from its very conceptualization to analyst recruitment and guidance. We defined—and later verified—inclusion criteria, such that each team of analysts (composed of up to three individual researchers) had to include at least one member with expertise in electrophysiological data analysis (i.e., one or more publication(s) in a peer-reviewed journal). This recruitment strategy combined with outreach efforts (on social media, major software mailing lists, and through direct contact with research institutions and colleagues outside of Europe and the United States) allowed us to recruit, to the best of our knowledge, the largest multi-analyst sample to date: 396 researchers across 168 analysis teams. Importantly, this sample also seems to capture some of the main features of the research community at large. Team composition in terms of gender distribution (Figure 1B) and level of expertise with EEG and cognitive neuroscience as measured by subjective ratings, number of EEG publications, and academic seniority (Figure 1C) suggests a profile of diversity similar to what is encountered in real life. In particular, the geographical origin of individual analysts (Figure 1D) mirrors the geographical distribution of the authors of EEG articles published in the last 5 years (Figure 1E).

With such a large and fairly representative sample of analysts, any variability in analytical choices and/or reported outcomes we may discover will likely capture analytical decisions and flexibility as encountered in the wild, that is, in the community's everyday research work that forms the basis of the scientific literature. Thus, we will be in a position not only to infer the robustness of published findings but also to identify those parameters and analytic choices that shape observed results the most. We hope that this knowledge will help sensitize researchers to the impact of their analytical decisions and lay the ground for the development of evidence-based, robust, and standardized analysis pipelines and reporting guidelines.

We will also release all project materials (i.e., raw EEG data, data/code provided by analysts, data/code derived as part of the EEGManyPipelines project) in an open-access database. This database will represent a rich repository of easily accessible, searchable, and (re-)usable data that we hope will inspire further inquiries into cognitive, methodological, and meta-scientific questions for years to come. Ultimately, we aim to deliver insights that matter—not only for the EEG community but also for those relying on related tools, such as magnetoencephalography, intracranial EEG, or electrocorticography.

SHAPING THE FUTURE OF (NEURO-)SCIENCE BY PROVIDING A BLUEPRINT FOR CONDUCTING LARGE-SCALE, GRASSROOTS, COMMUNITY-DRIVEN SCIENCE

The EEGManyPipelines project is a child of the COVID-19 pandemic: Sparked by a single Tweet,[1] it was envisioned entirely online by a group of researchers from around the world as well as at all career stages (i.e., the "steering committee"; https://www.eegmanypipelines.org/#ref-steering-committee). Unlike traditional laboratory-style science or previous big team science collaborations (e.g., adversarial collaborations, ManyLabs, and NARPS), from the get-go, the EEGManyPipelines project has been a bottom–up, community-driven effort without a rigidly defined hierarchy or a central lead laboratory or researcher. In particular, although there is a clear hierarchy between the steering committee and further contributors to the project (e.g., analysts, advisory board), the internal structure within the steering committee is flat. Moreover, apart from invaluable financial support for one full-time research position and in-person meetings acquired 1.5 years into the project's lifetime (i.e., during the data collection phase in March 2022), the bulk of the efforts of the vast majority of steering committee members—both in terms of overall duration and man–hours—has not been supported by a dedicated source of funding and instead relies entirely on voluntary contributions.

Running a large-scale science collaboration without a clearly identifiable (quasi-)solo lead in the current scientific "incentive" structure poses challenges at all stages: For instance, different ideas, perspectives, and priorities have to be translated into a coherent, feasible, and testable research agenda, and results have to be shared respecting individual contributions, whereas, at the same time, project roles might be fluid. Some of these obstacles (e.g., data sharing) may also be faced in the context of traditional laboratory or collaborative science. However, in a grassroots, community-driven setting without a central lead, these can be amplified. We highlight some of the most pertinent challenges encountered and lessons learned in setting up and running this kind of decentralized, big team science effort in Box 1.

Box 1: Early challenges encountered and lessons learned to run a decentralized, large-scale science collaboration

The steering committee of the EEGManyPipelines project has a flat hierarchy—with "decision power" being equal among its members, irrespective of career stage (i.e., doctoral/postdoctoral vs. independent researcher) or resources (i.e., funding, time) to contribute. Setting up and running a large-scale scientific project in such a community-driven, decentralized fashion poses particular challenges at all stages of the scientific process—from

initial conceptualization, over implementation, all the way to interpretation, sharing, and dissemination of results. We hope that the EEGManyPipelines project may serve as a blueprint for further collaborative and community-driven projects, as well as a flatter science culture in the future. It is in this spirit that we want to highlight some of the initial challenges we encountered and the ways in which we solved them.

- *Challenge 1: How to make decisions in the absence of a clearly identifiable lead?*
  Unlike in a typical laboratory setup with a single PI or other large-scale collaborations with a clearly identifiable lead, the EEGManyPipelines project is led by a large (i.e., currently 13 members) steering committee that not only has a flat hierarchy, but also changes over time. There is thus no single individual in charge to make decisions.

  To overcome this issue, in the EEGManyPipelines project, we adopted a democratic decision-making process: All members can contribute to the meeting agenda and raise points to discuss or decide. Different perspectives on each point under consideration are first collected and discussed among all members of the steering committee, and then decided on by unanimous agreement or ultimately by democratic majority vote. The decision is recorded in our "Meeting minutes" stored online and accessible by all members of the steering committee. Meetings are moderated by a designated committee member, who leads the discussion and can suggest to resolve points by voting or by postponing them, but has no executive power and whose role can be taken up by any alternative committee member. Some of the most important decisions solved in the past include, for instance, the questions of which data set to use, when (and how) to announce the EEGManyPipelines project to the public, or which type of infrastructure to use for internal documentation, data sharing and data collection, or internal/external communication.

- *Challenge 2: How to attribute project roles and avoid diffusion of responsibility?*
  In a grassroots, decentralized collaboration such as the EEGManyPipelines project, with most of its steering committee members neither directly employed by nor funded specifically for this project, it is a challenge to decide on and divide different roles, and also avoid diffusion of responsibility.

  We approach this issue by relying on internal delegation of task ownership: An important lesson we learned early on is that, although there is no overall project lead, most tasks require a clearly identifiable leader in charge of overseeing the task's progress and assigning specific actions to specific people to progress and avoid diffusion of responsibility. For instance, regular communication with analysts necessitates drafting and sending out hundreds of emails and data analysis requires preprocessing of the data, converting them into an easily shareable format, and planning and conducting the analyses. We tend to handle such different tasks in dedicated "subgroups," composed of approximately one to four individuals, who assume leadership and, as such, take on responsibility in exchange for additional "decision power" for a given task as well as appropriate credit in future publications. Although we now have one dedicated postdoctoral researcher, who by virtue of her position is our "lead analyst," in most other cases, formation of those subgroups has been on a volunteer basis.

- *Challenge 3: How to resolve conflict and fairly credit people's individual contributions?*
  As a result of the flat hierarchy of our steering committee and the fluidity of project roles, it can be particularly challenging to fairly credit people's contributions. For instance, how should authorship for the project's main article be determined, when individuals' commitment and contributions will naturally have fluctuated over the course of the project? Similarly, how does one resolve conflict about authorship for a specific article if there is no general consensus on individual contributions to start with?

  In the EEGManyPipelines project, we keep an updated, written record of every member's contributions to the overall project and initiate discussions about co-authorship for each planned article early on—ideally before the writing process. Although these conversations may feel awkward at first and one may consider postponing them to a later date, in our experience, this only prolongs an inevitable process and substantially builds up discomfort.

  A successful part of this strategy involves partitioning authorship questions into smaller, more manageable decisions. For instance, when writing this position article, we identified three broad categories of authors: shared first authors (responsible for taking on the lead and writing the initial draft of the manuscript), shared last authors (having contributed significant resources and/or conceptualization), and shared middle authors (i.e., all remaining active members of the steering committee who contributed to the article). As a group, the steering committee decided on listing middle authors in alphabetical order, whereas first and last authors determined the author order internally in their groups.

- *Challenge 4: How to administer and manage a large-scale collaboration with limited (or no) financial resources?*
  One of the biggest challenges we continue to encounter is how best to administer and manage such a large-scale collaboration, based to a large extent on volunteer efforts and limited (or no) financial resources. Although

we were able to secure some funding, these resources only materialized well into the project's lifetime and, as such, primarily accelerated its execution.

Our philosophy and reliance on open-source, no- (or low-) cost infrastructure, as well as project and time management resources remain unchanged. An important aspect of our strategy therefore relies on making the most use of the resources and/or skills already available to us, without necessarily striving to select the "best tools." For instance, we use the Brainhack Mattermost channel (https://brainhack.org/) for internal offline communication, the Sciebo platform (https://www.hochschulcloud.nrw/) for data sharing, and Trello boards (https://start.atlassian.com/) for overall project management. At the same time, our website and analyst survey were built by a steering committee member with expertise in web design and another set of members have voluntarily taken up the roles of "project coordinators" to guide and structure our regular meetings and keep us on time and focused.

Recognizing the potential vulnerabilities associated with relying heavily on individual members or specific tools, we have proactively implemented measures to safeguard the project's continuity: We have identified potential risks, such as the dependence on a single individual's institutional affiliations or tool access, and have taken steps to diversify our resources and ensure redundancy. This foresight ensures that our project remains adaptable, irrespective of individual member's transitions or tool availability, thereby maintaining the integrity and momentum of the EEGManyPipelines project.

In the EEGManyPipelines project, we signal that a meaningful, interesting, and solid scientific question can be successfully addressed with this kind of bottom–up, community-driven collaboration. Although this particular model of scientific inquiry might be indispensable for research agendas such as ours, we believe that it is not limited to multi-analyst studies or comparable scientific questions. Indeed, decentralized, democratic "big team science," in which researchers pool both their physical and intellectual resources, might confer several critical advantages over a traditional, centralized research approach (Baumgartner et al., 2023; Coles, Hamlin, Sullivan, Parker, & Altschul, 2022): Perhaps among the most important, this kind of decentralized collaboration allows for a larger and, critically, more freely moving pool of ideas. Thereby, it might foster creativity, become larger than the sum of its parts, and open up the door toward potentially unexpected scientific discovery.

Alongside other current big team science projects in neuroscience and beyond (e.g., #EEGManyLabs, Coscience EEG Personality project, Team 4 TMS-EEG), we believe the EEGManyPipelines project to be unique in opening up the discussion about and giving visibility to other models of science. There will not be a "one size fits all" solution. Further inspiration might be drawn from similar projects, such as the Psychological Science Accelerator (PSA; Moshontz et al., 2018) or the International Brain Lab (IBL, 2017), which, in addition to being large-scale collaborations, focus on setting up collaborative infrastructures (e.g., committees to decide which study proposals to put forward, how to allocate funding to collaborators) for running experiments across countries and laboratories (cf. Table 1). We hope that by setting an example; opening up our scientific practices; providing guidance on how to set up and run a grassroots, community-driven project; and successfully finishing this venture, the EEGManyPipelines project may serve as one potential blueprint for a more collaborative, community-driven, flat, and open scientific culture.

Table 1. Comparison of the EEGManyPipelines Project with Other Similarly Spirited Big Team Science Projects

Project	Governance	Decision-making	Membership	Infrastructure	Scientific Focus
EMP	Steering committee with flat hierarchy	Democratic vote in steering committee	Individual researchers	No	Data analysis
IBL	General assembly (i.e., all IBL PIs)	Consent-based within the IBL	Franchise of laboratories	Yes	Data collection
PSA	Hierarchical leadership team with committees	Democratic vote of all members	Individual researchers	Yes	Data collection

We highlight some similarities and differences between the EEGManyPipelines project (EMP) and other big team science initiatives: the International Brain Lab (IBL) and the Psychological Science Accelerator (PSA). Projects are compared across a non-exhaustive list of five different criteria: (1) governance, that is, a decision-making body for setting shared scientific goals and policies; (2) decision-making process; (3) membership, being based either on the decision of entire labs under a PI or individual researchers; (4) development of dedicated infrastructure; and (5) main scientific focus.

CONCLUSION

The fields of experimental psychology and cognitive neuroscience currently find themselves at a critical crossroads: Faced with uncertainties about replicability, reproducibility, and robustness, the community increasingly recognizes the need for a shift toward better scientific practices as well as improving the scientific culture. With the EEGManyPipelines project, we tackle analytical flexibility "in the wild" and explicitly address the impact of methodological choices on research outcomes. Our results will provide a roadmap toward more reproducible, robust, and transparent standards for conducting and reporting EEG studies and, ultimately, contribute to shaping a more credible, inclusive, and collaborative science.

Data Availability Statement

The scripts used to create figures and summaries in this article are available at https://github.com/EEGManyPipelines/metadata_summary.

Diversity in Citation Practices

A retrospective analysis of the citations in every article published in this journal from 2010 to 2020 has revealed a persistent pattern of gender imbalance: Although the proportions of authorship teams (categorized by estimated gender identification of first author/last author) publishing in the *Journal of Cognitive Neuroscience (JoCN)* during this period were M(an)/M = .408, W(oman)/M = .335, M/W = .108, and W/W = .149, the comparable proportions for the articles that these authorship teams cited were M/M = .579, W/M = .243, M/W = .102, and W/W = .076 (Fulvio et al., *JoCN*, 33:1, pp. 3–7). Consequently, *JoCN* encourages all authors to consider gender balance explicitly when selecting which articles to cite and gives them the opportunity to report their article's gender citation balance.

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