There is no research on a dead planet – Fostering ecologically sustainable open science practices in neuroscience

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Abstract

The rapidly escalating climate crisis poses an existential threat to human wellbeing. Reducing anthropogenic greenhouse gas emissions must therefore become a primary goal of humanity. At the same time, advancing knowledge on human experience and behaviour through empirical research is likewise essential for wellbeing, but can incur substantial negative impact for the environment. Neuroscientific methods are particularly resource intensive and potentially harmful, from the carbon footprint of MRI scanners to the long-term impact of data centres keeping datasets permanently accessible for scientific reuse. This position paper addresses the resulting tension between scientific research, open science principles, and responsible scientific stewardship in times of the climate crisis. We discuss how sustainable open science practices can be implemented in neuroscience at each step of the research cycle following the ARIADNE framework. Specifically, we suggest to (1) re-place new data with open data, (2) re-fine methods to make them more sustainable, and (3) re-duce carbon emission of testing by precisely determining sample sizes and research protocols beforehand.

Keywords: Climate crisis, sustainability; open science; neuroscience; biological psychology

Introduction

Scientific research on human experience and behaviour advances knowledge which contributed to improved wellbeing in humans over the last two centuries. It led and can further lead to a better understanding of why humans think and behave as they do, paving the way for improvements in applied and clinical settings. For some research, benefits are immediate and tangible - for instance, Farah (2018)[1] published an article with direct societal or clinical applications that transformed policies or clinical guidelines. For other neuroscientific research fields, benefits tend to be less immediate, yet still important - such as for basic research at the neurochemical level or for animal models of human behaviour[2].

In face of the rapidly escalating climate crisis, we have to consider the *ecological impact* of scientific research when assessing its societal impact. Governments and coalitions worldwide, including the European Union (EU)[3] made the reduction of greenhouse gas emissions caused by humans a primary and urgent goal. Yet, depending on the methods and procedures used, research on human behaviour can impact the environment, for example through the carbon footprint of data collection, processing, and publishing. While some of these costs are justified by the benefit they bring, they can and need to be reduced in order to assure sustainable research practices (see Figure 1 for an overview of unsustainable research practices). Neuroscience as a field of study grew exponentially over the past decades, often motivated by the promise of solving pressing clinical issues[4,5]. At the same time, it relies on tools with a particularly strong impact on the environment compared to other fields studying human behaviour. For instance, while personality psychology largely relies on questionnaire data, research on humans in neuroscience additionally employs methods such as functional magnetic resonance imaging (fMRI) that requires substantial amounts of electricity for data collection and processing[6,7]or animal models, which require large research and breeding facilities that are energy- and waste-intensive[84]. This implies a responsibility for neuroscientific research to carefully balance promises and costs. Whilst this responsibility initially lies with decision-makers, institutions and governments, there are opportunities for each individual scientist to contribute to a balance between costs and benefits.

Recently, researchers called on the community to acknowledge and act on environmental issues in personal behaviour, research practice, and academic politics, using their influence as researchers, educators, administrators, and public voices[8,9]. Certain institutions and funders, such as the EU and the German Research Foundation (Deutsche Forschungsgemeinschaft, DFG), incorporated sustainability principles into their mission statements[10,11], acknowledging the urgent need to reconsider the scientific process in light of the climate crisis. Yet, despite the pressing need for more sustainable research practices, few guidelines exist on how to effectively implement these. Here, we argue that *open science practices*, if responsibly implemented, can make an important contribution to tipping the cost-value scale towards conducting sustainable human neuroscience. Responsible implementation includes providing step-by-step guidelines and resources for how to implement them in research practice.

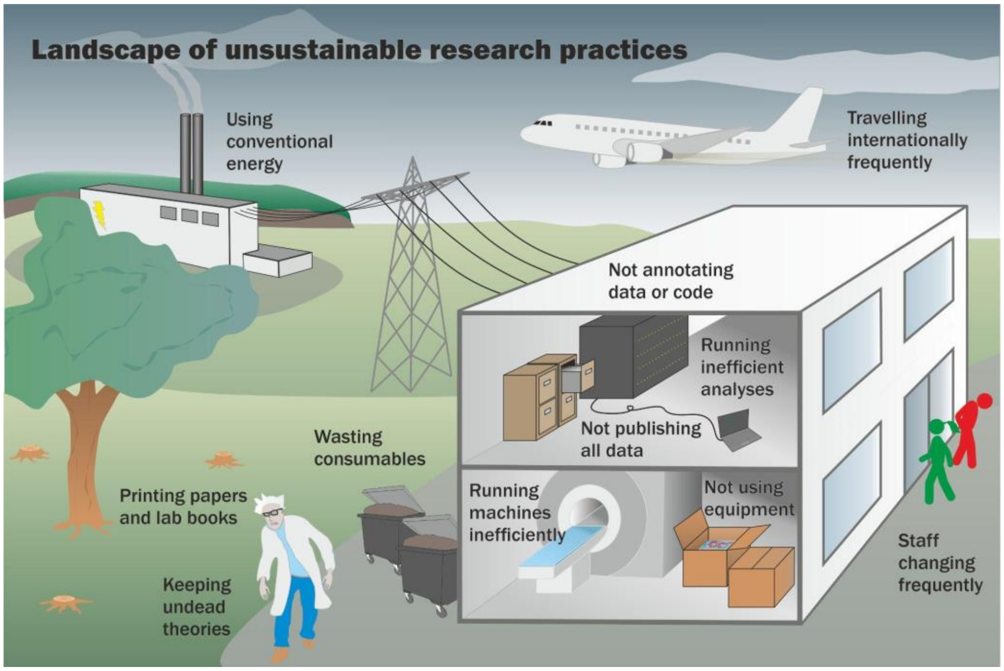

Figure 1. *Landscape of unsustainable research practices. Conducting science impacts the environment. Human cognitive neuroscience, for example, is characterised by energetically expensive techniques and analysis pipelines. This, paired with the relatively large number of neuroscientific studies being run and the considerable environmental footprint of science per se, strongly suggests that neuroscientists should consider the ecological footprint of their work.*

Note. Unsustainable research practices can be directly related to research methods and facilities using conventional energy sources, running inefficient analyses and running machines inefficiently. Unused equipment, wasted consumables and printing papers and lab books add to the ecological footprint as well. Further ecological costs are related to not publishing all data and not annotating code as well as continuing research on undead theories, which generates output with restricted value for the scientific community. Disseminating research via data servers, printed and online publications as well as frequent international travelling to conferences also comes at a cost. Finally, frequent changes in staff counteract the implementation of sustainable research practices.

Conducting Research in Times of the Climate Crisis

The climate crisis threatens human well-being, the ecosystems, and the stability of our planet. Thus, urgent and comprehensive action is necessary to transition to sustainable practices in order to reduce the impact of climate change[12]. The link between the climate crisis and scientific research is multifaceted[13]. First, scientific progress is important for human life and wellbeing. While this is true even for basic research, this benefit is further reinforced when directly aimed at researching and informing about climate change, its causes and its consequences, as is the case for environmental psychology and cognitive sciences[14]. Similarly, neuroscience addresses the mental health impact of the climate crisis by researching phenomena such as climate anxiety[15] and the therapeutic benefits of nature and green spaces[16,17,18], which increasingly fall victim to climate change. Second, the scientific community has the opportunity to lead by example and act in accordance with scientific findings to reduce the ecological impact of their research activities. As such, scientists are torn between conducting relevant research while reducing their climate impact in- and outside of their work[8,9]. The aim is to achieve a *state of sustainability*, which refers to the ability to meet the needs of the present generation without compromising the ability of future generations to meet their own needs[19]. Sustainability involves balancing economic, social, and environmental factors to ensure that resources are used efficiently and responsibly in both the short- and long-term. While the concept of sustainability within the scientific community serves as an umbrella term for various aspects, this position paper focuses on ecological sustainability (while other forms such as the sustainability of academic staff resources and knowledge should be addressed in future work). Alongside the moral imperative and, now, in some countries even legal obligation[20], scientific endeavours often rely on public funding and thus entail acting responsibly towards society and future generations[19]. Thus, we as scientists are responsible - and even more so the institutions and governments that create the framework conditions - for ensuring the ecologically sustainable research practices.

The Role of Open Science for Achieving Sustainability

Open science practices bear a potential to solve some of these sustainability problems in science and especially cognitive and behavioural neuroscience, but could also cause harm[21]. Neuroscience as a field has a substantial environmental footprint with high consumption of resources like energy and materials. Notably, it relies on costly and resource-intensive techniques such as fMRI or magnetoencephalography (MEG), lab materials, psychopharmacological designs, or high usage of technological resources like databases, shared servers, and high-performance computing. Moreover, complex computational modelling techniques are frequent in state-of-the-art analysis of neuroimaging data and, together with the management of large and ever-growing neuroscientific datasets, highly resource-intensive[22]. Unfortunately, the exact power consumption and the resulting environmental impact of high-level computing are often unknown to individual researchers. This invisibility of their own ecological footprint is problematic, as there are choices in the hands of the researchers that have the potential of a positive impact, for example in computational architectures (e.g., data centres vs. personal computers), computational specifications (e.g., how many cores and parallel processing), as well as the associated energy consumption and sources of that energy[23].

There is an inherent but often neglected trade-off between the assumed benefits of research findings to individuals and society and the ecological costs of the research conducted to achieve them. Increased and timely sharing of research outputs offers crucial benefits to tip this trade-off in the right direction: the shared use of data conserves resources by reducing doubling of efforts (e.g., via interdisciplinary collaboration), and publishing one's work as a preprint can prevent multiple studies from being run on the same research question. Moreover, publishing null findings avoids the "file drawer" issue[24] and future resources from being invested in research pursuits unlikely to generate meaningful insights. Publishing the dataset of an unsuccessful study may prevent other researchers attempting the same potentially futile experiment and help contest the immortality of "undead" theories[25]. Such publications should include analyses focusing on equivalence that allow differentiating relative evidence for the null compared to the alternative hypothesis from inconclusive results[26]. Moreover, resources are saved when researchers conduct secondary analyses using open data instead of collecting new data, or use open-access publishing.

In contrast, it is also crucial to recognize areas where open science practices might inadvertently harm the environment. Valid questions arise regarding the environmental impact of, for instance, running inefficient algorithms or multiverse analyses on openly available data, the long-term management of open data storage, and the quality and usability/reproducibility of openly shared materials[21]. For example, the environmental impact of computationally intensive analyses would be immediately doubled or even tripled if analysis results were routinely checked for computational reproducibility. In turn, not checking for errors may invalidate entire research lines and thus likewise waste resources. Here, the use of cloud computing services to optimise the use of resources or deduplication (i.e., eliminating excessive copies of data) could be a more sustainable alternative. More concretely, it should be determined, which degree of pre-processing should be performed before data sharing, rather than sharing raw data, where intensive computational steps must be repeated by each research team before usage.

Targeted mitigation strategies in research practice are necessary to achieve a balance between neuroscientific research and open science on the one side and sustainability on the other side. At the same time, providing such strategies remains a challenge. While recent calls and initiatives signal a growing awareness for this dilemma within the (neuro-)scientific community[9,22,23], the complexity of current issues and potential solutions can be paralysing - especially for younger researchers, who are often the bottom-up drivers of cultural change.

Implementing Sustainable Research

Research in neuroscience occurs in repeating cycles of project planning, study design, data collection, data analysis, manuscript writing, and dissemination (Figure 2). Accordingly, all of these steps should be considered in a sustainable research cycle. Finding appropriate resources for each step can be challenging, in particular for early career researchers. Tools such as ARIADNE[27] alleviate decision-making to prevent researchers from constantly reinventing the wheel, and therefore serve as prime examples of sustainable open science practices. Specifically, ARIADNE offers easy access to resources required for performing sustainable research.

Figure 2. *Guidelines for sustainable research: Starting a project: Sustainable research starts with finding a useful question that needs an answer and checking if it can be answered using existing data. A cost-benefit analysis should be conducted to ensure the scientific benefit warrants the ecological costs. When planning, scientists should focus on a realistic time schedule for the experiment that allows collecting an informative sample size that has been determined using power analysis (analytically or using simulation techniques). A good way to reduce the amount of required repetitions is a focus on measurement precision. While*

collecting data, energy demands of a research method should play an important role. Also, researchers using consumables (e.g., EEG or blood analyses) should use those sparingly and consider the ecological impact of their production and degradation. When analysing, researchers should ideally conduct analyses of data quality while the study is ongoing to avoid unusable data due to missing information. At the same time computations should not be wasted to conduct many analyses that are later not reported. Saving preprocessed data at a reasonable stage will avoid recomputing them on demand. Especially during writing, researchers should report which measures were taken to avoid impact on the environment to enable other researchers to learn. No research should be left in the file drawer, since then the cost-benefit ratio is basically infinite. At the same time, researchers need to write accessibly so that their results can have maximal effect outside of their specific field, thereby enhancing the benefit. Lastly, when disseminating their research, all data, materials, and analyses should be made FAIRly (Wilkinson et al., 2016) available to incentivise re-use instead of de novo data production. Re-use is only possible if these resources are correctly documented. Of note, to prevent doubling of data etc. researchers should decide which raw data or derivation is most useful to the scientific community instead of dumping all data onto a repository.

In the following, we use the framework proposed by ARIADNE to discuss each part of the research cycle in terms of its impact on the environment. We take readers along each step of a research project, suggesting specific mitigation strategies and in particular, how carefully implemented open science practices can contribute to research sustainability. Some of them are easier to implement than others. However, it is crucial that we rigorously evaluate and integrate these measures, if we want to continue doing robust and reproducible research in human neuroscience in the next decades.

1) Starting a project - from literature research to research questions

A thorough literature search is indispensable to ensure that a study is warranted. During this process, printing out papers can be avoided. If reliable findings already exist, it should first be checked if a replication is useful[29] or would not contribute further information (but instead cost money, work hours, and CO_2). Also, search of the literature, data repositories (for a list: e.g., OpenNeuro[30,31]), or even one's own data archives can identify pre-existing data that can be used to answer the research question (see also section of data sharing in point 6 below). If de novo data collection is warranted, it should be planned according to open science principles, to maximise sustainability in advance[22]. For example, new practices among institutions, such as equipment exchanges (an often neglected form of open science) can optimise the use of resources. Often, institutions accumulate equipment that is either underutilised or set aside after limited use. This contrasts with other institutions that struggle to afford such resources, hindering their research capabilities.

Following consensus guidelines ensures that the collected data can be used to address the respective research question with sufficient accuracy or be used by meta research (e.g., Enhancing Neuroimaging Genetics through Meta-Analyses, ENIGMA[32,33]). A preregistration should be made publicly available from the beginning as it helps conserve resources by keeping groups from working on the same question in parallel (though a planned independent replication may also be useful), or even provides an opportunity to work together in a multi-site study, which may help to obtain reliable and generalizable results[34] and yield higher statistical power (see step 2).

2) Designing and creating experiments - from ethics and sample size to task programming and stimulus control

The environmental burden might be less immediate for many behavioural experiments/online surveys or relatively energy efficient methods such as electroencephalography (EEG) or functional near infrared spectroscopy (fNIRS). However, conducting fMRI experiments has a high energy expenditure. A Siemens MRI scanner, for example, uses about 80 kW for demanding functional scans[6,35]. While energy demands spike during scanning, most energy is required to maintain the scanner in the idle and power-saving states annually as an MRI machine requires cooling with liquid helium at all times[36], which itself is a costly resource that needs to be replaced regularly[22]. On average, the annual energy cost of a 3T MRI is around 80 to 90 MW[36], which translates to 31.000-35.000 kg CO^2eq (carbon dioxide equivalent) per scanner. The energy costs of running fMRI measurements can be reduced by conducting a priori sample size estimations to avoid unnecessary testing of too few (or too many) participants. When conducting sample size planning, researchers should maximise information gain[38], since investing resources only makes sense if the research produces reliable information. Here, one can consider adequately powered sample sizes as an important factor for research robustness[39]. When power analyses are not straightforward to conduct, as is often the case for fMRI analyses, it is important to consider and report other sample size justifications[38]. For other kinds of data, however, where power analyses are well established, these should be routinely conducted as a core step of the research cycle.

However, running experiments on huge samples can be extremely resource intensive. Therefore, special focus may be placed on maximising measurement precision[40], thereby reducing the amount of trials and/or participants required to answer a research question. Notably, precise measurements, efficient algorithms, and knowledge about the relevant open questions in the field all require a high level of expertise that is currently undermined by the precarious job situation leading to high fluctuation of non-tenured scientists[41]. Furthermore, engineering companies should work on increasing the energy efficiency of neuroimaging techniques in the future, which may include improving measurement precision by technological advances (e.g., as has been achieved with active electrode EEG-systems) and room temperature superconductors[42]. When experimental ideas are discussed, it should always be evaluated whether a specific method is suitable and necessary to answer the research question or whether it can be substituted by other, less energy-consuming methods. Notably, new MRI scanners should only be acquired if there is enough staff to conduct high-quality MRI research on a continuous basis - ideally on permanent contracts to avoid knowledge loss, errors, and inconsistency[43]. Lastly, we encourage researchers to quantify the carbon footprint of their software and algorithms using tools such as CodeCarbon[44] and the Green Algorithms project[23].

Another domain that has not yet received much attention from a sustainability perspective is using animal models in neuroscience in order to understand human conditions and pathologies. Although precise numbers of emissions have not yet been quantified, there are many aspects in animal research that lead to high carbon emissions. Animals need to be bred, transported, housed, fed, their wastes removed, humanely killed, and their bodies need to be disposed of. Facilities need to be cleaned, ventilated, and maintained. In the EU alone, almost nine million research animals are used each year[3], highlighting the relevance of animal research not only for carbon emissions but also regarding the release of potentially hazardous biomedical waste[45]. Many animal research institutes around the world have therefore already established so-called “green labs” that aim for increasing sustainability practices inside the institute such as reducing freezer temperatures and re-using materials whenever possible. While these efforts are helpful, the responsibility to adhere to these practices lie with the individual institute or even laboratory and thus do not strongly contribute systemically. To reduce the environmental impact produced by animal research at the systemic level, practices such as preregistration and registered reports must be implemented on a broad scale to improve precision in animal research and avoid the re-doing of experiments due to null findings remaining unpublished and thus unknown to the research community. Unfortunately, the number of registered protocols in biomedical animal research is still very low compared to research in humans where preregistration has become normative[46]. A dedicated website for the registration of animal protocols has only recorded 102 registrations in five years of service of which only around 20% were preregistered despite governmental support[47]. Thus, more effort is required to establish and facilitate registered protocols in the domain of animal research in the future, for example by creating detailed registration templates for animal experiments.

3) Collecting the data - from piloting to testing

Data collection consists of piloting, manipulation checks, data simulation, documentation, participant recruitment, and testing. It is crucial that data quality is checked consistently during the acquisition period to avoid a useless and costly dataset (see also step 4). Smaller but effective solutions to reduce the carbon footprint might, for example, be digitising data collection and avoiding wasting of resources as much as possible (e.g., only printing out information sheets if expressly wished by participants, reusing instruction and stimulus material, collecting data in online documents, etc.). Reduction of waste and improvement of sustainability practices is also important when working with biological samples, e.g., saliva or blood samples (in so called wet labs). These samples come with a particularly high carbon footprint due to the energy needed to store and analyse data (e.g., freezers, safety hoods, autoclaves, etc.) and result in an estimated 5.5 million tons of discarded single-use plastic products per year[48]. Several wet labs have started to set up individual sustainability programs (e.g., Biomedical Center Munich[85]) and non-governmental organisations like www.mygreenlab.org support scientists working at the laboratory to reduce their carbon footprint. Turning to reusable materials may further be considered as a valid option.

Sustainable research practices also pertain to the long-term usability and usefulness of one's research outcomes. Proper documentation from the beginning, such as detailed log books and method descriptions, is vital in this regard. This involves detailed metadata, clear data dictionaries, and comprehensive recording of methodologies. Tools and platforms that facilitate collaborative documentation, such as electronic lab notebooks and data management systems, can enhance the reproducibility and standalone nature of research projects[49]. This documentation can then be shared together with the publication and might avoid investing resources in repeating the same mistakes in new or follow-up studies.

Similarly, it needs to be ensured that the collected data and materials are regularly backed up and saved in case of hardware or software breakdowns (e.g., saving large amounts of data on servers/cloud services, or saving biosamples in freezers with backup-batteries). On a macro-scale, researchers should share resources as much as possible thus ensuring that large machines (e.g., MRI and MEG) as well as smaller machines (e.g., EEG, NIRS, centrifuges, and eye trackers) are used as frequently as possible instead of each lab maintaining their underused infrastructure. Here, also good scheduling practices must be implemented to prevent last-minute cancellations of usage as much as possible. Core facilities offer a good model to increase usage of scientific machinery and dedicated staff ensures that all machines are maintained to offer high measurement precision[40]. In this context, ensuring permanent employment of trained staff is essential not only for research quality[41], but also for sustainability.

4) Validating and analysing the data - from quality control, data curation, and wrangling to the final results

Validating research data and ensuring its statistical validity is crucial for drawing accurate and reliable conclusions from studies, whereby they crucially contribute to the studies' added benefit. This step should be implemented already during data collection, to prevent collection of large datasets that contain errors that may make them worthless[50]. Sharing datasets openly and ensuring they are well-documented further enables other researchers to verify results and build upon previous work without starting from scratch[51]. Ensuring the reusability of shared data through good documentation places considerable demands on early career researchers in particular, who are often faced with this challenge without centralised support. Again, permanent employment of trained staff can offer the support necessary to assure sustainability.

Following data acquisition, data analysis has further environmental consequences, especially computationally advanced models in the realm of artificial intelligence, which make up almost half of all energy costs in information technology[52]. Adopting energy-efficient methods in data analysis is thus becoming increasingly important. Streamlining data processing techniques, optimising code for efficiency, and using low-power computing resources can significantly reduce the environmental impact of research. Lannelongue and colleagues[22] offer practical guidelines for the latter in their "10 simple rules" paper. To reduce energy-related carbon emissions in data processing, preregistration of pre-processing steps and analyses can substantially reduce the number of re-analyses of the same data[53]. Furthermore, code should be written to optimise data processing efficiently and avoid redundant analysis steps.

5) Writing and publishing - from the manuscript draft to the cover letter and responding to reviewer comments

Once the data have been collected, analysed and their quality has been controlled, the manuscript needs to be written up, even if introduction and methods may have already been produced for the preregistration. The carbon footprint of a scientific publication from writing the paper, searching for the paper, and finally reading it has been estimated to be around an average of 5.44 kg CO_2eq[54]. With this footprint, any completed study that ends up in the file drawer constitutes a considerable waste of resources. In 2024, the primary form of publication in neuroscience is digital. However, some journals retain a double publishing model, where journal issues are available both digitally and in print. Needless to say, the carbon footprint of a journal that is only published digitally is less than that of a hybrid journal offering both options. The carbon footprint of a sheet of office paper from cradle-to-customer is between 4.29 g to 4.74 g CO_2eq[55]. Thus, the paper needed for a 30-page scientific article would have a carbon footprint of around 85.8 g to 142.2 g CO_2eq. Depending on the print run of the journal, this can result in a considerable carbon footprint. It is thus generally advisable to submit to a journal that does not print its issues anymore. Given that most newer open access journals do not print copies, this solution is again a strong argument for open science.

In general, the feedback process during writing, be it internal feedback or peer review, can be conducted online and not on paper (although online work and cloud computing also produce significant CO_2 emissions and need to move towards more energy efficient and sustainable solutions[88,89]. This means researchers should try to reduce printing manuscripts, or at least should reuse the paper in a meaningful way after feedback. For laptops, using a product that has been produced sustainably (e.g., TCO certified, which guarantees that computer products purchased maintain ecological standards and are sufficiently ergonomic) or, even better, a recycled laptop can help in further reducing the carbon footprint of writing and reading papers[56]. For both printed papers and laptops used to write and read digital papers, proper recycling can help in reducing the carbon footprint [56].

6) Disseminating research - from data sharing to science communication

As stated above every study that remains in the file drawer is a waste of resources. Even if results are deemed non-significant or inconclusive, dissemination will help other researchers, because they will not waste further resources on a paradigm that may not work. For example, some Theory of Mind paradigms were shown to be unreliable[57,58], and this information can prompt other researchers to use different paradigms in future research. Proper platforms for disseminating such non-significant or inconclusive findings may be hard to find, as many scientific journals still (inadvertently) foster the publication bias. Dissemination as preprint or publication on an archive server with an explicit emphasis on the added value of the availability of these findings might be an alternative - here however findability is largely limited as such platforms are often not listed in the relevant databases. A solution option might be additional commentaries or brief communications in peer-reviewed journals referring to the archive/preprint publication.

Additionally, results can be presented at conferences, which allows for an open discussion of reliability. However, environmental constraints to travel to (especially oversea) conferences must be considered and virtual or hybrid formats preferred[8,9]. While virtual conferences and video streaming are associated with their own carbon emissions, these are estimated at less than 10% of in-person meeting emissions[86,87]. Hence, the advantages of travelling to conferences and benefiting from face-to-face interactions and resources involved in these travels should be carefully weighed, for example by choosing one to two conferences a year maximum, or by travelling to conferences by train instead of aeroplane whenever possible[86,87].

During the past years, the sharing of data, materials, and analysis code has been advocated by politicians, funders, the scientific community, and scientific journals alike. Sharing of data and material does not only allow other researchers to reproduce the originally reported results but also allows other researchers to re-use these data for secondary analyses. To this end, this allows for the sustainable use of scarce resources (work hours, time, and funds) while at the same time facilitating the acceleration of cumulative scientific progress. This has been demonstrated impressively by the scientific advances achieved in part through open data during the COVID-19 pandemic[59]. While publicly sharing research data and materials has clear and indisputable advantages for society and science (and can allow estimating the validity of scientific measures[60] and data transformation methods[61] as well as help avoid statistical errors[62]) it can even benefit individual researchers' careers though new collaborations[63,64], despite some perceived barriers[65]. By keeping data to themselves, researchers support that these precious, often tax-funded data are lost for the broader scientific community and society as a whole[44,66,67]. On the other hand, data sharing can save billions of dollars by making sure that these data are preserved and reusable[68]. Of note, sharing data upon request has been shown to rarely result in actual sharing of data[69]. Therefore, sharing data publicly is important, with appropriate ethical and juridical considerations prior to data collection[70, 71].

Yet, these prospects can only be achieved when data and materials are shared in a way that allows other researchers to actually find, understand, and use them. To this end, the so-called FAIR (Findability, Accessibility, Interoperability, and Reuseability) principles[28] provide a guide on how to achieve this. To date, however, data sharing - in particular in cognitive and behavioural neuroscience - is still in its infancy and many publicly available datasets are not readily reusable due to the lack of clear community standards[72]. Despite enormous potential to foster sustainability of science, shared data and materials often run the risk of consuming additional resources and energy as we built a "digital data cemetery". Hence, (funded) large scale data sharing consortia and scientific infrastructure projects (e.g., ENIGMA[32,33], OpenNeuro[30,68]; or STRESS-EU[73], a database of human acute stress studies) are deeply needed to ensure that the enormous potential of sharing data and materials can live up to its prospects with respect to both sustainable use of scarce resources and scientific progress.

In addition to sharing data, every-day practices of interactions between researchers also require reconsideration. For instance, the exchange of materials between researchers including experimental files or any other kind of digital files should be preferably done through sharing of links to cloud storages rather than sending large email attachment files. In fact, sending large email attachments is a relatively unsustainable practice from a climate perspective[74] and should be avoided in common practice. As there is still a lack of awareness of the carbon footprint of large email attachments, pointing it out the next time we receive one of such is a simple way to make a small contribution.

Last but not least, open distribution of research findings and datasets enhances access and promotes further scientific inquiry. Proper data curation, including the use of platforms like data repositories and journals with open access policies, ensures that shared datasets are discoverable and usable[75]. This allows maximally exploiting a given data set after it has already consumed energy thus complementing its carbon footprint with an appropriate impact on scientific discovery.

Intersectional Approaches in Sustainability Research

In the context of scientific research on human behaviour and experience, the principles of diversity, equity, and inclusion (DEI) are crucial for ensuring comprehensive and sustainable research practices. Incorporating diverse perspectives from researchers of different backgrounds such as genders, races, or other identities is essential for advancing equitable research endeavours. Researchers' geopolitical contexts influence the identification and prioritisation of environmental issues, leading to a more nuanced understanding of global sustainability challenges[76]. Including minority groups in research fosters equity by integrating diverse cultural and experiential knowledge systems, as well as enriching research with broader perspectives[77]. Feminist perspectives offer critical insights into the interconnectedness of gender, environmental justice, and sustainability, advocating for transformative changes aligned with principles of social equity and environmental stewardship (for psychological science[78, 79]; for feminism and open science[80]). These intersectional approaches ensure that sustainability research is inclusive and capable of generating innovative, contextually relevant solutions that emphasise the importance of diverse voices in shaping sustainable practices[81].

Towards a More Sustainable Future in Neuroscientific Research

Neuroscientific research can have a particularly strong impact on the environment. With this position paper, we raise awareness for responsible scientific stewardship in times of the climate crisis. Although we are fully aware that researchers do not have the time or resources to immediately implement all of the changes suggested above, we provided a comprehensive guideline aimed to empower each individual researcher to conduct sustainable neuroscientific research by careful implementation of open science practices at each step of the research cycle. This enables researchers to freely pick which practices they can most effectively adopt right now or in the future. Furthermore, we discuss areas of potential tension between sustainability and open science practices, for example when prompting researchers to make all data openly and permanently available, and how this tension can be navigated sensitively to strike a balance that safeguards sustainable neuroscience for decades to come (see Figure 3 for our suggestion for sustainable neuroscience in the future).

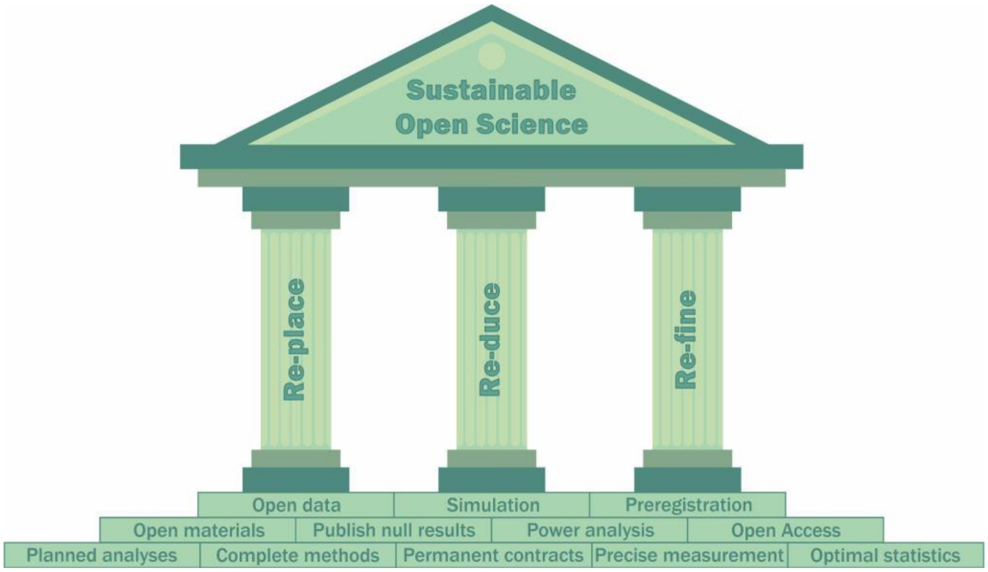

Figure 3. *The three pillars of sustainable open science: Sustainable open science rests on the three pillars, the 3 R's (Re-place, Re-duce, and Re-fine). In animal research, the 3 Rs are regarded as a relevant step to minimise animal cruelty thereby improving the cost-benefit-ratio of such work. Here, they enable minimising the environmental footprint of a research program likewise improving the cost-benefit-ratio. For example, replacing a new study with a simulation or a reanalysis of existing data, reducing the amount of compute needed by running only preregistered analyses, and refining experiments by optimising measurement precision are just a few of the open science practices that contribute to an open, robust, and transparent science based on sustainability.*

In order to make neuroscience more sustainable, we suggest focussing on reusing available open data whenever possible, refining methods to make them more sustainable and reducing carbon emission of testing by precisely determining sample sizes and optimising research protocols. To achieve these goals bit by bit, sustainability aspects and how to reduce a project's carbon footprint should already be included in teaching and training activities, e.g., how to save resources by coding more computationally efficiently or how to optimise data acquisition. Thereby equipping new generations of scientists for more sustainable practices. At the same time, we call for incentivising sustainable research efforts instead of rewarding the production of more and more unreliable research in ever increasing piles of unread papers, which will slowly but surely lead to more and more uptake of sustainable practices. This call applies to the institutions and governments that form the framework the researchers work in, as this responsibility cannot lie with the individual.

Efforts towards more sustainable research practices are urgently needed on multiple levels. This can, however, only be achieved when individual researchers, institutions, funders, and policy-makers work together and implement changes from bottom-up as well as from top-down. Only in this way can we change the focus of the scientific system from unsustainable and biased science to a more robust, informative and sustainable approach (e.g., DORA initiative[82,83]) to impact the current incentive structure in a positive way. Finally, no research exists without funding. Thus, a change in funding criteria is especially important, i.e., by considering the ecological impact of new data collection in neuroscientific fields, by supporting data reuse, and by fostering replication projects, in particular in the face of the current climate crisis. Considerations of sustainability need to be added to the criteria for funding after an adaptation period and should be explicitly reported on in grant applications. Further, this new awareness needs to be supported by funders, institutions and criteria for PhD theses supervision (e.g., by reducing the number of publications necessary for cumulative dissertations) and hiring procedures (e.g., when evaluating the track record of an applicant). Relatedly, there need to be structures in place that follow-up on promises made in grant proposals regarding data sharing and open science practices.

In conclusion, neuroscience urgently needs to consider sustainable practice given the high energy consumption and carbon footprint of many standard methods like fMRI and animal testing. Our proposed framework including the pillars <u>re-place</u> (open data and simulations), <u>re-duce</u> (tests using power analysis and planned analyses), and <u>re-fine</u> (precise measurements and optimal statistics) may help researchers take important steps in this direction at their own pace. We urge researchers to embrace these terms and fill them with life. Crucially, it is not important to attempt squaring the circle and immediately becoming a fully sustainable scientist, but taking first steps matters now.

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