BrainHack Marseille

Open collaboration in neuroscience

Open tools for Open science

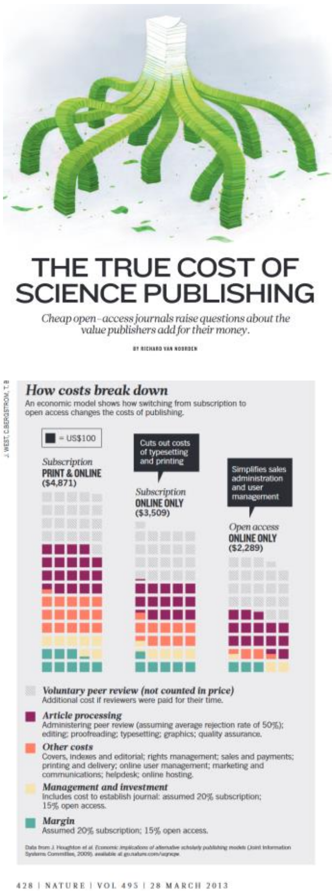
By Manuel Mercier, Simon Moré, Guillaume Auzias & Arnaud Le Troter

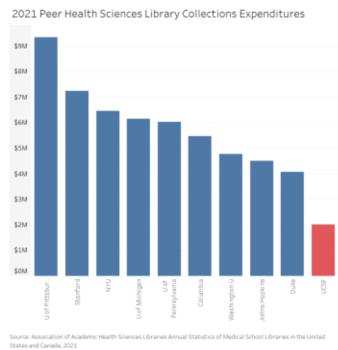
Why Open Science?

Scientific research is a common good:

- It is funded by the citizens
- Knowledge is (*should be*) a public resource

The irony of the publication system

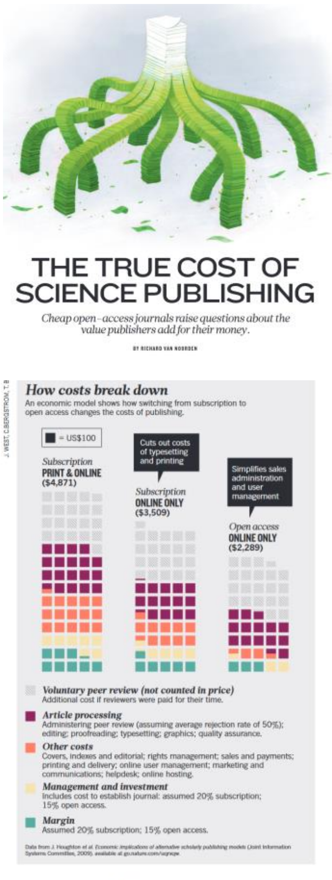


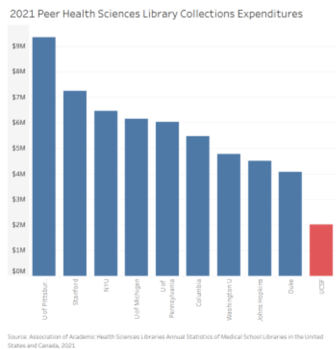


ELSEVIER

Net income :
£1.922 billion (2019)
Article Publishing Charge for open access:
$3450 (in Neuroimage, ed. Elsevier)

The irony of the publication system





Net income :
£1.922 billion (2019)
Article Publishing Charge for open access:
$3450 (in Neuroimage, ed. Elsevier)

ELSEVIER

- New formats and predatory journal

Crisis in science : replicability and reproducibility

Open access, freely available online

Essay

Why Most Published Research Findings Are False

John P. A. Ioannidis

Summary

There is increasing concern that most current published research findings are false. The probability that a research claim is true may depend on study power and bias, the number of other studies on the same question, and, importantly, the ratio of true to no relationships among the relationships probed in each scientific field. In this framework, a research finding is less likely to be true when the studies conducted in a field are smaller; when effect sizes are smaller; when there is a greater number and lesser preselection of tested relationships; where there is greater flexibility in designs, definitions, outcomes, and analytical modes; when there is greater financial and other interest and prejudice; and when more teams are involved in a scientific field in chase of statistical significance. Simulations show that for most study designs and settings, it is more likely for a research claim to be false than true. Moreover, for many current scientific fields, claimed research findings may often be simply accurate measures of the prevailing bias. In this essay, I discuss the implications of these problems for the conduct and interpretation of research.

Published research findings are sometimes refuted by subsequent evidence, with ensuing confusion and disappointment. Refutation and controversy is seen across the range of research designs, from clinical trials and traditional epidemiological studies [1–3] to the most modern molecular research [4,5]. There is increasing concern that in modern research, false findings may be the majority or even the vast majority of published research claims [6–8]. However, this should not be surprising. It can be proven that most claimed research findings are false. Here I will examine the key factors that influence this problem and some corollaries thereof.

The Essay section contains opinion pieces on topics of broad interest to a general medical audience.

Modeling the Framework for False Positive Findings

Several methodologists have pointed out [9–11] that the high rate of nonreplication (lack of confirmation) of research discoveries is a consequence of the convenient, yet ill-founded strategy of claiming conclusive research findings solely on the basis of a single study assessed by formal statistical significance, typically for a *p*-value less than 0.05. Research is not most appropriately represented and summarized by *p*-values, but, unfortunately, there is a widespread notion that medical research articles

It can be proven that most claimed research findings are false.

should be interpreted based only on *p*-values. Research findings are defined here as any relationship reaching formal statistical significance, e.g., effective interventions, informative predictors, risk factors, or associations. "Negative" research is also very useful. "Negative" is actually a misnomer, and the misinterpretation is widespread. However, here we will target relationships that investigators claim exist, rather than null findings.

As has been shown previously, the probability that a research finding is indeed true depends on the prior probability of it being true (before doing the study), the statistical power of the study, and the level of statistical significance [10,11]. Consider a 2×2 table in which research findings are compared against the gold standard of true relationships in a scientific field. In a research field both true and false hypotheses can be made about the presence of relationships. Let R be the ratio of the number of "true relationships" to "no relationships" among those tested in the field. R is characteristic of the field and can vary a lot depending on whether the field targets highly likely relationships or searches for only one or a few true relationships among thousands and millions of hypotheses that may be postulated. Let us also consider, for computational simplicity, circumscribed fields where either there is only one true relationship (among many that can be hypothesized) or the power is similar to find any of the several existing true relationships. The pre-study probability of a relationship being true is $R/(R+1)$. The probability of a study finding a true relationship reflects the power $1-\beta$ (one minus the Type II error rate). The probability of claiming a relationship when none truly exists reflects the Type I error rate, α. Assuming that c relationships are being probed in the field, the expected values of the 2×2 table are given in Table 1. After a research finding has been claimed based on achieving formal statistical significance, the post-study probability that it is true is the positive predictive value, PPV. The PPV is also the complementary probability of what Wacholder et al. have called the false positive report probability [10]. According to the 2×2 table, one gets $PPV = (1-\beta)R/(R - \beta R + \alpha)$. A research finding is thus

Citation: Ioannidis JPA (2005) Why most published research findings are false. PLoS Med 2(8): e124.

Abbreviation: PPV, positive predictive value

John P. A. Ioannidis is in the Department of Hygiene and Epidemiology, University of Ioannina School of Medicine, Ioannina, Greece, and Institute for Clinical Research and Health Policy Studies, Department of Medicine, Tufts-New England Medical Center, Tufts University School of Medicine, Boston, Massachusetts, United States of America. E-mail: jioannid@cc.uoi.gr

Competing Interests: The author has declared that no competing interests exist.

DOI: 10.1371/journal.pmed.0020124

Essay

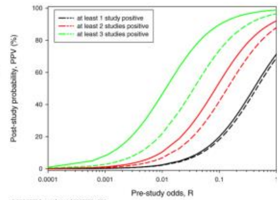
Most Published Research Findings Are False—But a Little Replication Goes a Long Way

Ramal Moonesinghe*, Muin J. Khoury, A. Cecile J. W. Janssens

We know there is a lot of lack of replication in research findings, most notably in the field of genetic associations [1–3]. For example, a survey of 600 positive associations between gene variants and common diseases showed that out of 166 reported associations studied three or more times, only six were replicated consistently [4]. Lack of replication results from a number of factors such as publication bias, selection bias, Type I errors, population stratification (the mixture of individuals from heterogeneous genetic backgrounds), and lack of statistical power [5].

In a recent article in *PLoS Medicine*, John Ioannidis quantified the theoretical basis for lack of replication by deriving the positive predictive value (PPV) of the truth of a research finding on the basis of a combination of factors. He showed elegantly that most claimed research findings are false [6]. One of his findings was that the more scientific teams involved in studying the subject, the less likely the research findings from individual studies are to be true. The rapid early succession of contradictory conclusions is called the "Proteus phenomenon" [7]. For several independent studies of equal power, Ioannidis showed that the probability of a research finding being true when one or more studies find statistically significant results declines with increasing number of studies.

As part of the scientific enterprise, we know that replication—the performance of another study statistically confirming the same hypothesis—is the cornerstone of science and replication of findings is very important before any causal inference can be drawn. While the importance of replication is also acknowledged by Ioannidis, he does not show how PPVs of research findings increase when more studies have



doi:10.1371/journal.pmed.0040028.g001

Figure 1. Probability of a True Relationship When At Least One, Two, or Three (Out of Ten) Studies Have Statistically Significant Results as a Function of the Pre-Study Odds of a True Relationship ($\alpha = 0.05$)

Dashed lines refer to power of 0.2 and solid lines to power of 0.8.

statistically significant results. In this essay, we demonstrate the value of replication by extending Ioannidis' analyses to calculation of the PPV when multiple studies show statistically significant results.

The probability that a study yields a statistically significant result depends on the nature of the underlying relationship. The probability is $1-\beta$ (one minus the Type II error rate) if the relationship is true, and α (Type I error rate) when the relationship is false, i.e., there is no relationship. Similarly, the probability that r out of n studies yield statistically significant results also depends on whether the underlying relationship is true or not. Let $B(p,r,n)$ denote the probability of obtaining at least r statistically significant results out of n independent and identical studies, with p being the

The Essay section contains opinion pieces on topics of broad interest to a general medical audience.

Funding: The authors received no specific funding for this article.

Competing Interests: The authors have declared that no competing interests exist.

Citation: Moonesinghe R, Khoury MJ, Janssens ACJW (2007) Most published research findings are false—But a little replication goes a long way. PLoS Med 4(2): e28. doi:10.1371/journal.pmed.0040028

Abbreviations: PPV, positive predictive value

Ramal Moonesinghe and Muin J. Khoury are at the National Office of Public Health Genomics, Coordinating Center for Health Promotion, Centers for Disease Control and Prevention, Atlanta, Georgia, United States of America. A. Cecile J. W. Janssens is in the Department of Public Health, Erasmus University Medical Center, Rotterdam, The Netherlands. The findings and conclusions in this report are those of the authors and do not necessarily represent the views of the Centers for Disease Control and Prevention or the Agency for Toxic Substances and Disease Registry.

*To whom correspondence should be addressed. E-mail: RMoonesinghe@CDC.gov

Crisis in science : replicability and reproducibility

Open access, freely available online

Essay

Why Most Published Research Findings Are False

John P. A. Ioannidis

Summary

There is increasing concern that most current published research findings are false. The probability that a research claim is true may depend on study power and bias, the number of other studies on the same question, and, importantly, the ratio of true to no relationships among the relationships probed in each scientific field. In this framework, a research finding is less likely to be true when the studies conducted in a field are smaller; when effect sizes are smaller; when there is a greater number and lesser preselection of tested relationships; where there is greater flexibility in designs, definitions, outcomes, and analytical modes; when there is greater financial and other interest and prejudice; and when more teams are involved in a scientific field in chase of statistical significance. Simulations show that for most study designs and settings, it is more likely for a research claim to be false than true. Moreover, for many current scientific fields, claimed research findings may often be simply accurate measures of the prevailing bias. In this essay, I discuss the implications of these problems for the conduct and interpretation of research.

Published research findings are sometimes refuted by subsequent evidence, with ensuing confusion and disappointment. Refutation and controversy is seen across the range of research designs, from clinical trials and traditional epidemiological studies [1–3] to the most modern molecular research [4,5]. There is increasing concern that in modern research, false findings may be the majority or even the vast majority of published research claims [6–8]. However, this should not be surprising. It can be proven that most claimed research findings are false. Here I will examine the key factors that influence this problem and some corollaries thereof.

The Essay section contains opinion pieces on topics of broad interest to a general medical audience.

Modeling the Framework for False Positive Findings

Several methodologists have pointed out [9–11] that the high rate of nonreplication (lack of confirmation) of research discoveries is a consequence of the convenient, yet ill-founded strategy of claiming conclusive research findings solely on the basis of a single study assessed by formal statistical significance, typically for a p-value less than 0.05. Research is not most appropriately represented and summarized by p-values, but, unfortunately, there is a widespread notion that medical research articles should be interpreted based only on p-values. Research findings are defined here as any relationship reaching formal statistical significance, e.g., effective interventions, informative predictors, risk factors, or associations. "Negative" research is also very useful. "Negative" is actually a misnomer, and the misinterpretation is widespread. However, here we will target relationships that investigators claim exist, rather than null findings.

It can be proven that most claimed research findings are false.

As has been shown previously, the probability that a research finding is indeed true depends on the prior probability of it being true (before doing the study), the statistical power of the study, and the level of statistical significance [10,11]. Consider a 2 × 2 table in which research findings are compared against the gold standard of true relationships in a scientific field. In a research field both true and false hypotheses can be made about the presence of relationships. Let R be the ratio of the number of "true relationships" to "no relationships" among those tested in the field. R is characteristic of the field and can vary a lot depending on whether the field targets highly likely relationships or searches for only one or a few true relationships among thousands and millions of hypotheses that may be postulated. Let us also consider, for computational simplicity, circumscribed fields where either there is only one true relationship (among many that can be hypothesized) or the power is similar to find any of the several existing true relationships. The pre-study probability of a relationship being true is $R/(R+1)$. The probability of a study finding a true relationship reflects the power $1 - \beta$ (one minus the Type II error rate). The probability of claiming a relationship when none truly exists reflects the Type I error rate, α. Assuming that c relationships are being probed in the field, the expected values of the 2 × 2 table are given in Table 1. After a research finding has been claimed based on achieving formal statistical significance, the post-study probability that it is true is the positive predictive value, PPV. The PPV is also the complementary probability of what Wacholder et al. have called the false positive report probability [10]. According to the 2 × 2 table, one gets $PPV = (1-\beta)R/(R - \beta R + \alpha)$. A research finding is thus

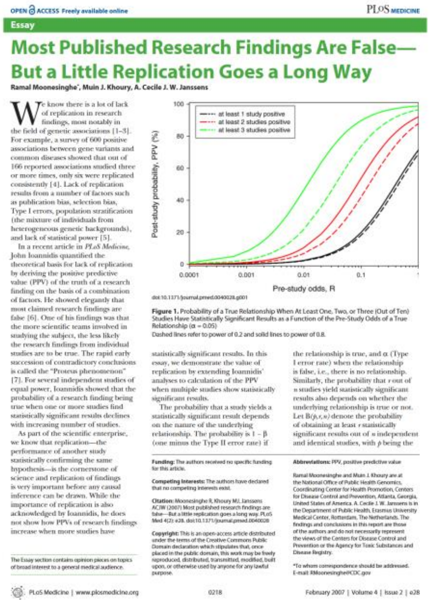
Citation: Ioannidis JPA (2005) Why most published research findings are false. PLoS Med 2(8): e124.

Abbreviation: PPV, positive predictive value

John P. A. Ioannidis is in the Department of Hygiene and Epidemiology, University of Ioannina School of Medicine, Ioannina, Greece, and Institute for Clinical Research and Health Policy Studies, Department of Medicine, Tufts-New England Medical Center, Tufts University School of Medicine, Boston, Massachusetts, United States of America. E-mail: jioannid@cc.uoi.gr

Competing Interests: The author has declared that no competing interests exist.

DOI: 10.1371/journal.pmed.0020124



OPEN ACCESS Freely available online PLoS MEDICINE

Essay

Most Published Research Findings Are False—But a Little Replication Goes a Long Way

Ramal Moonesinghe*, Muin J. Khoury, A. Cecile J. W. Janssens

We know there is a lot of lack of replication in research findings, most notably in the field of genetic associations [1–3]. For example, a survey of 600 positive associations between gene variants and common diseases showed that out of 166 reported associations studied three or more times, only six were replicated consistently [4]. Lack of replication results from a number of factors such as publication bias, selection bias, Type I errors, population stratification (the mixture of individuals from heterogeneous genetic backgrounds), and lack of statistical power [5].

In a recent article in *PLoS Medicine*, John Ioannidis quantified the theoretical basis for lack of replication by deriving the positive predictive value (PPV) of the truth of a research finding on the basis of a combination of factors. He showed elegantly that most claimed research findings are false [6]. One of his findings was that the more scientific teams involved in studying the subject, the less likely the research findings from individual studies are to be true. The rapid early succession of contradictory conclusions is called the "Proteus phenomenon" [7]. For several independent studies of equal power, Ioannidis showed that the probability of a research finding being true when one or more studies find statistically significant results declines with increasing number of studies.

As part of the scientific enterprise, we know that replication—the performance of another study statistically confirming the same hypothesis—is the cornerstone of science and replication of findings is very important before any causal inference can be drawn. While the importance of replication is also acknowledged by Ioannidis, he does not show how PPVs of research findings increase when more studies have statistically significant results. In this essay, we demonstrate the value of replication by extending Ioannidis' analyses to calculation of the PPV when multiple studies show statistically significant results.

The probability that a study yields a statistically significant result depends on the nature of the underlying relationship. The probability is $1 - \beta$ (one minus the Type II error rate) if the relationship is true, and α (Type I error rate) when the relationship is false, i.e., there is no relationship. Similarly, the probability that r out of n studies yield statistically significant results also depends on whether the underlying relationship is true or not. Let $B(p,r,n)$ denote the probability of obtaining at least r statistically significant results out of n independent and identical studies, with p being the

doi:10.1371/journal.pmed.0040028.g001

Figure 1. Probability of a True Relationship When At Least One, Two, or Three (Out of Ten) Studies Have Statistically Significant Results as a Function of the Pre-Study Odds of a True Relationship ($\alpha = 0.05$)

Dashed lines refer to power of 0.2 and solid lines to power of 0.8.

The Essay section contains opinion pieces on topics of broad interest to a general medical audience.

Funding: The authors received no specific funding for this article.

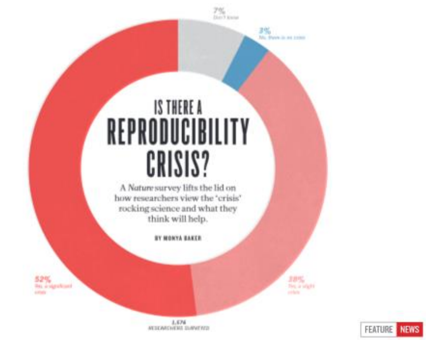
Competing Interests: The authors have declared that no competing interests exist.

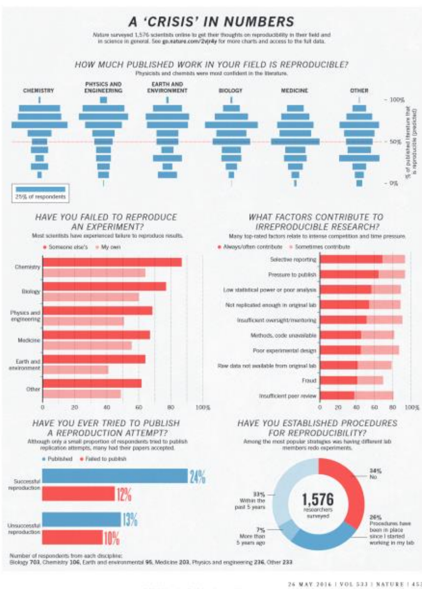
Citation: Moonesinghe R, Khoury MJ, Janssens ACJW (2007) Most published research findings are false—But a little replication goes a long way. PLoS Med 4(2): e28. doi:10.1371/journal.pmed.0040028

Abbreviations: PPV, positive predictive value

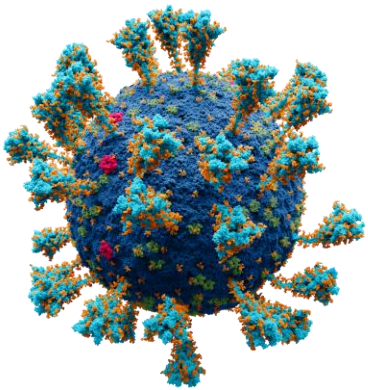
Ramal Moonesinghe and Muin J. Khoury are at the National Office of Public Health Genomics, Coordinating Center for Health Promotion, Centers for Disease Control and Prevention, Atlanta, Georgia, United States of America. A. Cecile J. W. Janssens is in the Department of Public Health, Erasmus University Medical Center, Rotterdam, The Netherlands. The findings and conclusions in this report are those of the authors and do not necessarily represent the views of the Centers for Disease Control and Prevention or the Agency for Toxic Substances and Disease Registry.

* To whom correspondence should be addressed. E-mail: RMoonesinghe@CDC.gov



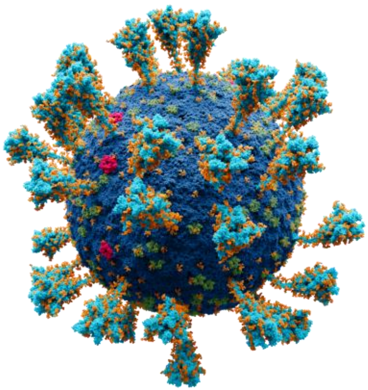


Crisis with science : the critical link with society



Plantu (France) - Cartooning for Peace

Crisis with science : the critical link with society



Plantu (France) - Cartooning for Peace

DISINFODEMIC

Deciphering **COVID-19** disinformation

Policy brief 1

Authors: Julie Posetti and Kalina Bontcheva

Nine key themes of the disinfodemic

This research has identified nine key themes present in content associated with the disinfodemic. These themes frequently feature racism and xenophobia.

1. Origins and spread of the coronavirus/COVID-19 disease
While scientists first identified cases of novel coronavirus (the virus that causes the disease COVID-19) connected to an animal market in the Chinese city of Wuhan, there are many conspiracy theories that blame other actors and causes. These extend from blaming the 5G network through to chemical weapons manufacturers. Using a label like "Chinese virus" instead of neutral terminology inflates location into an adjective, in an historical echo of early pandemics that gave a biased meaning to a noun.

2. False and misleading statistics
Often connected to the reported incidence of the disease and mortality rates.

3. Economic impacts.
This theme includes spreading false information about the economic and health impacts of the pandemic, suggestions that social isolation is not economically justified, and even claims that COVID-19 is overall creating jobs.

4. Discrediting of journalists and credible news outlets.
This is a theme often associated with political disinformation, with unsupported accusations that certain news outlets are themselves peddling in disinformation. This behaviour includes abuse levelled at journalists publicly, but it is also used by less visible disinformation campaigns to undermine trust in verified news produced in the public interest. Attacks on journalists in the time of COVID-19 have been associated with crackdowns on critical coverage of political actors and states.

5. Medical science: symptoms, diagnosis and treatment.
This theme includes dangerous disinformation about immunity, prevention, treatments and cures. For example, myriad 'sticky' memes claim that drinking or gargling cow urine, hot water, or salt water could prevent the infection reaching lungs. They cannot.

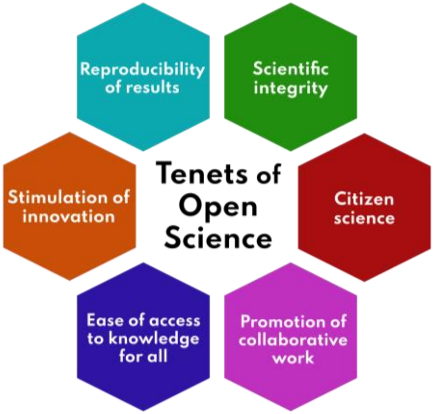
6. Impacts on society and the environment
This theme in the disinfodemic ranges from panic buying triggers and false information about lockdowns, through to the supposed re-emergence of dolphins in Venetian canals.

7. Politicisation
One-sided and positively-framed information is presented in an effort to negate the significance of facts that are inconvenient for certain actors in power. Other disinformation designed to mislead for political advantage includes: equating COVID-19 with flu; making baseless claims about the likely length of the pandemic; and assertions about the (un)availability of medical testing and equipment.

8. Content driven by fraudulent financial gain
This includes scams designed to steal people's private data.

9. Celebrity-focused disinformation
This theme includes false stories about actors being diagnosed with COVID-19.

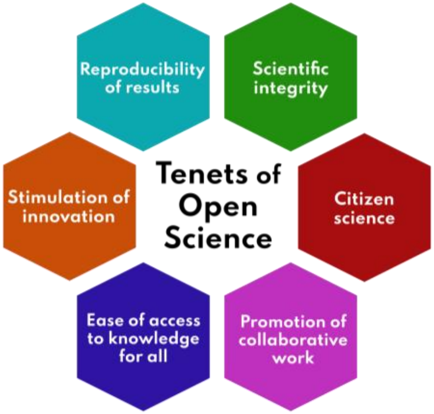
Crisis response : Open Science and good practices



PLUS:
Better citation rates for open access articles and research data

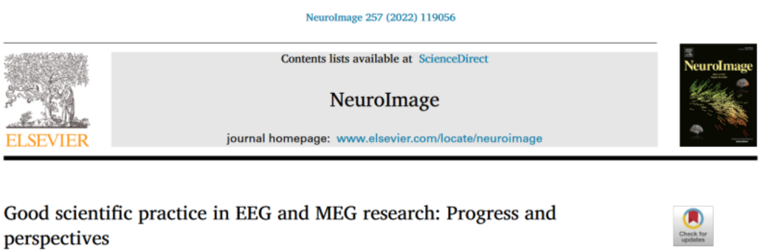
Open data, **open** source software and **open** source hardware all are critical to enabling reproducibility in the sense of validation of the original data analysis.

Crisis response : Open Science and good practices



Open data, **open** source software and **open** source hardware all are critical to enabling reproducibility in the sense of validation of the original data analysis.

! **PLUS:**
Better citation rates for open access articles and research data

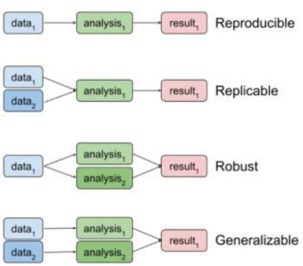

NeuroImage 257 (2022) 119056

Contents lists available at ScienceDirect

NeuroImage

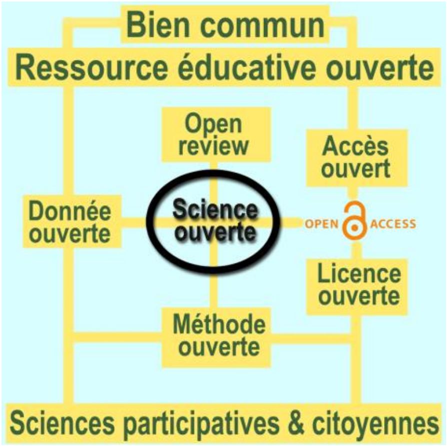
journal homepage: www.elsevier.com/locate/neuroimage

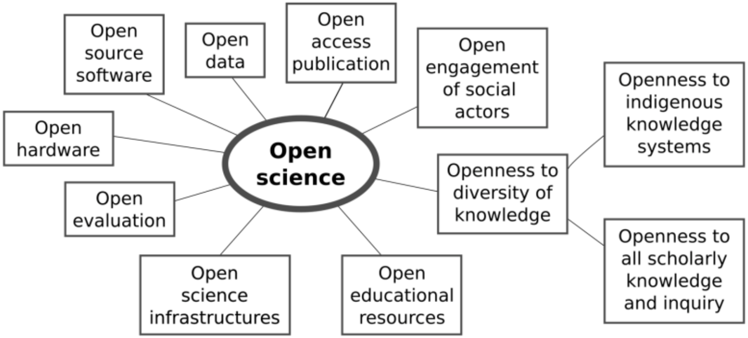
Good scientific practice in EEG and MEG research: Progress and perspectives



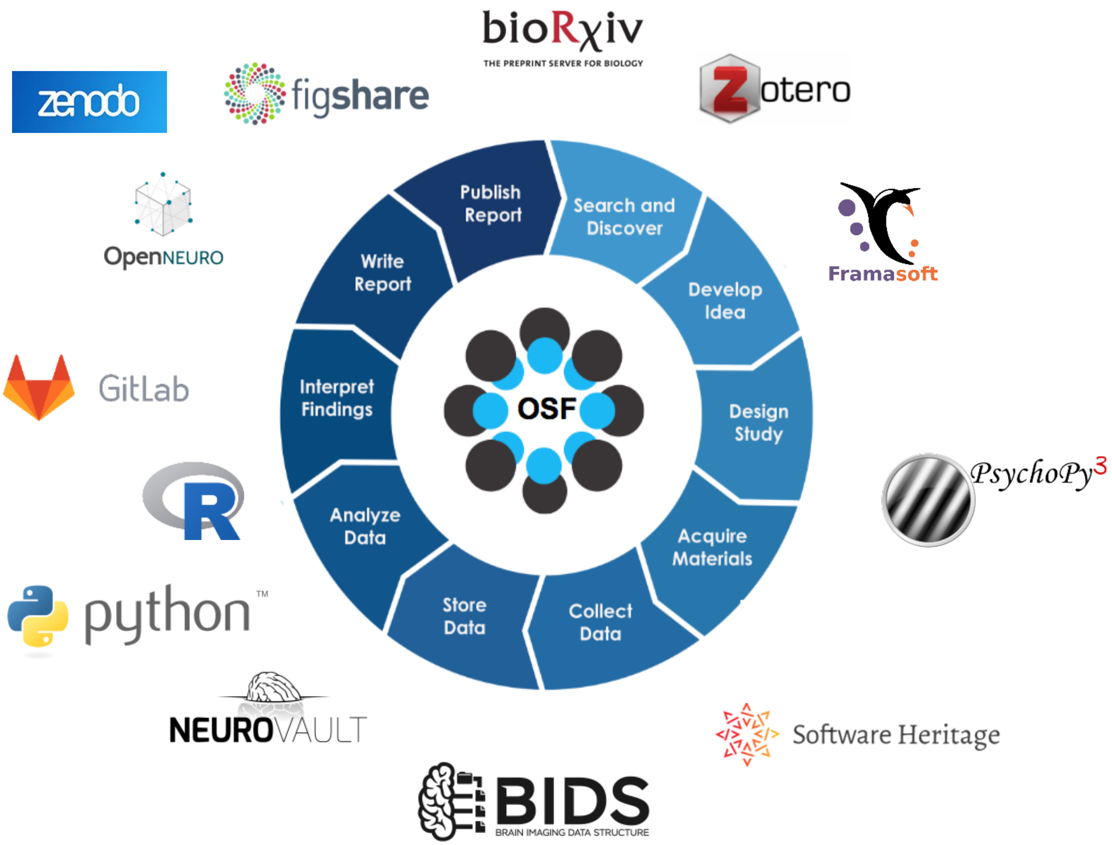
Niso et al., 2022

Open tools for Open Science





Research life cycle & Open tools



Open Science: a good research practice

FAIR Principles | Implementation Networks | News | Events | Resources | About GO FAIR

FAIR Principles

In 2016, the '**FAIR Guiding Principles for scientific data management and stewardship'** were published in *Scientific Data*. The authors intended to provide guidelines to improve the **F**indability, **A**ccessibility, **I**nteroperability, and **R**euse of digital assets. The principles emphasise machine-actionability (i.e., the capacity of computational systems to find, access, interoperate, and reuse data with none or minimal human intervention) because humans increasingly rely on computational support to deal with data as a result of the increase in volume, complexity, and creation speed of data.

A practical "how to" guidance to go FAIR can be found in the **Three-point FAIRification Framework**.

Open Science: aftermaths

Advices about good practices :

- Early makes it easy
- Take a step back
- Leverage on quality
- Impact on citations
- etc …

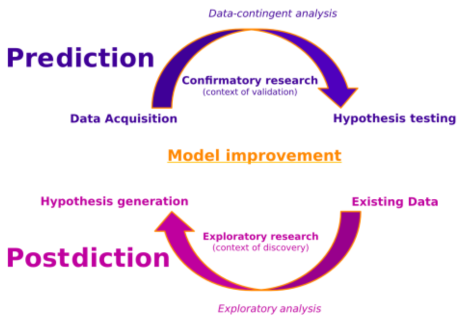
Open Science: aftermaths

Advices about good practices :

- Early makes it easy
- Take a step back
- Leverage on quality
- Impact on citations
- etc …

Open Science and Open Tools foster:

- dissemination
- implementation / applied research
- distinction between pre/post-diction



BrainHack Marseille

Open collaboration in neuroscience

Open tools for Open science

By Manuel Mercier, Simon Moré, Guillaume Auzias & Arnaud Le Troter

once upon a time « Open »

1989 : GNU General Public License **(GPL)** : free and open-source software

1991 : Arxiv : archive ouverte et pré-publication (physique, maths)

2001-2003 : OpenAccess, Creative Commons

2004 : OKF : Open Knowledge Association (Cambridge) :

« where does my money go »

2007 : CKAN : Comprehensive Knowledge Archive Network (OKF) :

datasharing

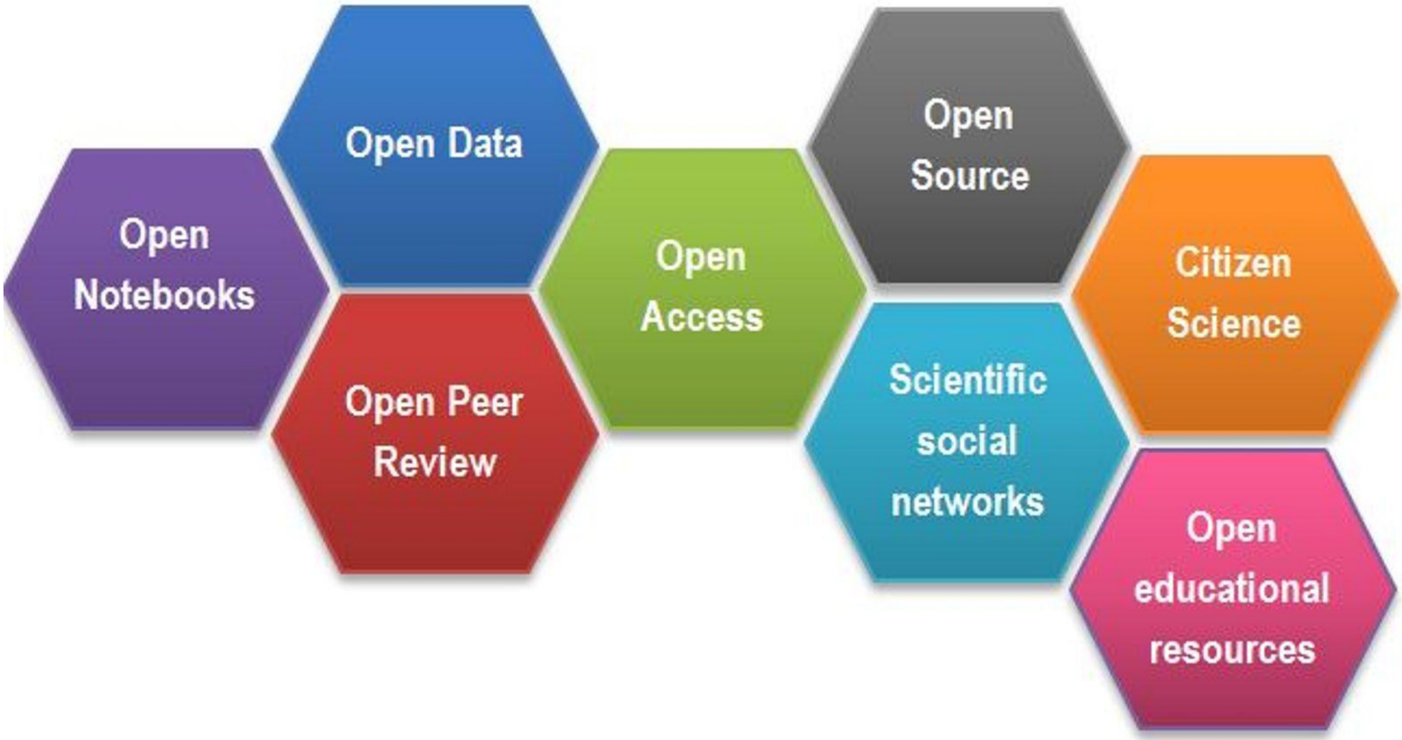
2012 : Sci-Hub

2018 : Plan S Coalition S

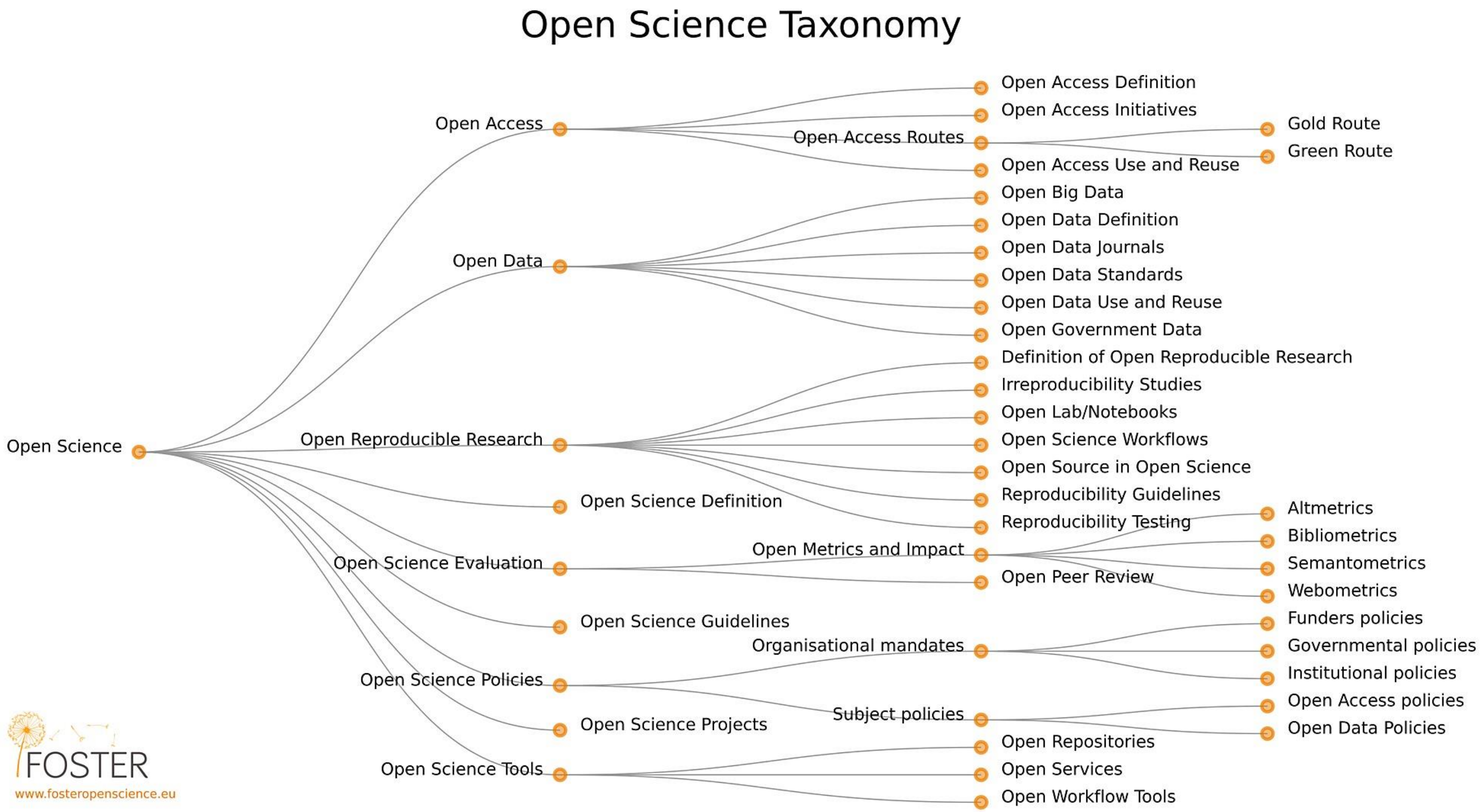
national plans (2018 & 2021 in France)

What is OpenScience ?

unhindered dissemination of research publications and data

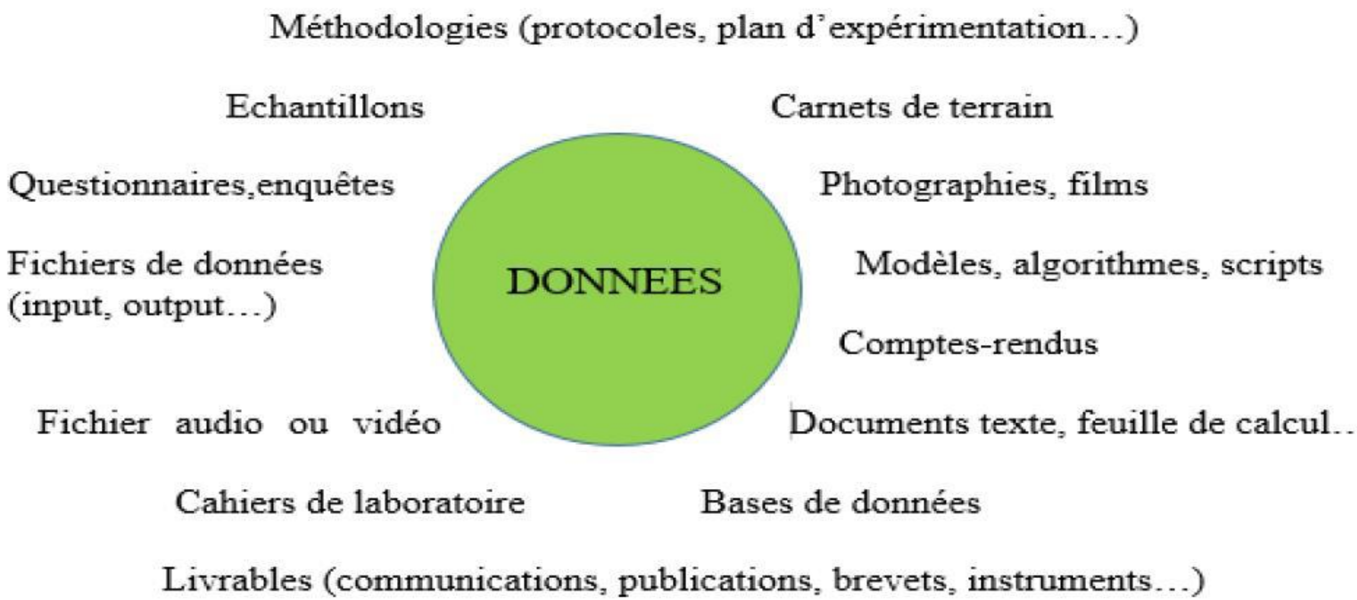


What is OpenScience ?



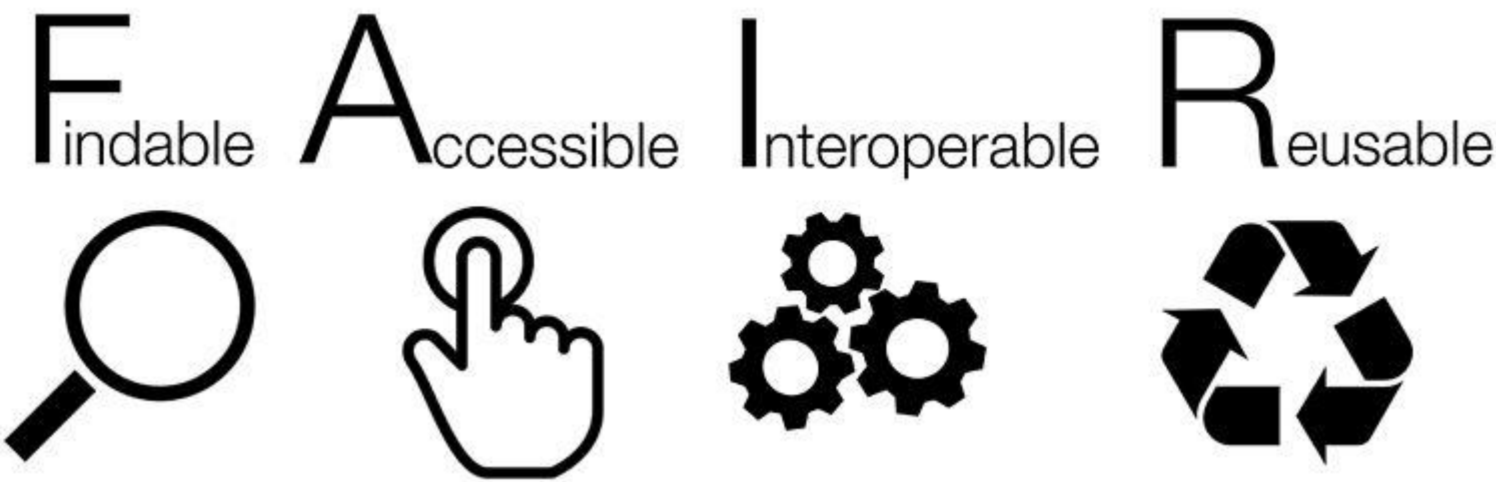
FOSTER
www.fosteropenscience.eu

What is data?



negative results

FAIR principles



F : Findable

Findability

Resource and its metadata are easy to find by both, humans and computer systems. Basic machine readable descriptive metadata allows the discovery of interesting data sets and services.

- **F1**. Resource is uploaded to a public repository.
- **F2**. Metadata are assigned a globally unique and persistent identifier.

A : Accessible

Findability

Resource and its metadata are easy to find by both, humans and computer systems. Basic machine readable descriptive metadata allows the discovery of interesting data sets and services.

- **F1**. Resource is uploaded to a public repository.
- **F2**. Metadata are assigned a globally unique and persistent identifier.

Accessibility

Resource and metadata are stored for the long term such that they can be easily accessed and downloaded or locally used by humans and ideally also machines using standard communication protocols.

- **A1**. Resource is accessible for download or manipulation by humans and is ideally also machine readable.
- **A2**. Publications and data repositories have contingency plans to assure that metadata remain accessible, even when the resource or the repository are no longer available.

I : Interoperable

Findability

Resource and its metadata are easy to find by both, humans and computer systems. Basic machine readable descriptive metadata allows the discovery of interesting data sets and services.

- **F1**. Resource is uploaded to a public repository.
- **F2**. Metadata are assigned a globally unique and persistent identifier.

Accessibility

Resource and metadata are stored for the long term such that they can be easily accessed and downloaded or locally used by humans and ideally also machines using standard communication protocols.

- **A1**. Resource is accessible for download or manipulation by humans and is ideally also machine readable.
- **A2**. Publications and data repositories have contingency plans to assure that metadata remain accessible, even when the resource or the repository are no longer available.

Interoperability

Metadata should be ready to be exchanged, interpreted and combined in a (semi)automated way with other data sets by humans as well as computer systems.

- **I1**. Resource is uploaded to a repository that is interoperable with other platforms.
- **I2**. Repository meta- data schema maps to or implements the CG Core metadata schema.
- **I3**. Metadata use standard vocabularies and/or ontologies.

R : Reusable

Findability

Resource and its metadata are easy to find by both, humans and computer systems. Basic machine readable descriptive metadata allows the discovery of interesting data sets and services.

- **F1**. Resource is uploaded to a public repository.
- **F2**. Metadata are assigned a globally unique and persistent identifier.

Accessibility

Resource and metadata are stored for the long term such that they can be easily accessed and downloaded or locally used by humans and ideally also machines using standard communication protocols.

- **A1**. Resource is accessible for download or manipulation by humans and is ideally also machine readable.
- **A2**. Publications and data repositories have contingency plans to assure that metadata remain accessible, even when the resource or the repository are no longer available.

Interoperability

Metadata should be ready to be exchanged, interpreted and combined in a (semi)automated way with other data sets by humans as well as computer systems.

- **I1**. Resource is uploaded to a repository that is interoperable with other platforms.
- **I2**. Repository meta- data schema maps to or implements the CG Core metadata schema.
- **I3**. Metadata use standard vocabularies and/or ontologies.

Reusability

Data and metadata are sufficiently well-described to allow data to be reused in future research, allowing for integration with other compatible data sources. Proper citation must be facilitated, and the conditions under which the data can be used should be clear to machines and humans.

- **R1.** Metadata are released with a clear and accessible usage license.
- **R2.** Metadata about data and datasets are richly described with a plurality of accurate and relevant attributes.

BrainHack Marseille

Open collaboration in neuroscience

Open tools for Open science

By Manuel Mercier, Simon Moré, Guillaume Auzias & Arnaud Le Troter

WHY and HOW to share your neuroimaging data ?

Read the journal **guidelines** regarding **data sharing**

Repositories dedicated for Neuroimaging data

Main steps to publish of dataset on the OpenNeuro plateform:

- steps for upload a MRI dataset
    - check Bids compliance (https://bids.neuroimaging.io)
    - push OK button ;-)

- understand what happens after your first upload
    - create a first version from the draft
    - Rights about your dataset (License changes)
    - Follow your dataset activity (download and DOI)

- Dataset management
    - client web application (user-friendly)
    - upgrade your dataset making snapshots (versioning when you add or remove data)
    - possibility to deploy your own openNeuro server (only for advanced users)

*journal **guidelines** regarding **data sharing***

Wiley's Data Sharing Policies

Wiley is committed to a more open research landscape, facilitating faster and more effective research discovery by enabling reproducibility and verification of data, methodology and reporting standards. We encourage authors of articles published in our journals to share their research data including, but not limited to: raw data, processed data, software, algorithms, protocols, methods, materials.

Refer to the table below to understand the various standardized data sharing policy categories:

	Data availability statement is published[1]	**Data has been shared**[2]	**Data has been peer reviewed**[3]	**Example Wiley journals**
Encourages Data Sharing	Optional	Optional	Optional	
Expects Data Sharing	Required	Optional	Optional	British Journal of Social Psychology
Mandates Data Sharing	Required	Required	Optional	Ecology and Evolution
Mandates Data Sharing and Peer Reviews Data	Required	Required	Required	Geoscience Data Journal American Journal of Political Science

https://authorservices.wiley.com/author-resources/Journal-Authors/open-access/data-sharing-citation/data-sharing-policy.html

[1] A data availability statement confirms the **presence or absence of shared data.**

[2] Links to data in data availability statements are checked to ensure they link to the data that the authors intended.
If data have been shared in a **data repository**, the data availability statement includes **a permanent link to the data**. Shared data is also cited.

[3] Quality and/or replicability of linked data are peer reviewed. Depending on the journal, this may be to **peer review the quality of the data** by ensuring that the results in the paper and the data in the repository align (for example, sample sizes and variables match), or it may be to **peer review the replicability of the data** to ensure that the claims presented in the journal article are **valid and can be reproduced**.

protocols, r

Refer to the table below to understand the various standardized data sharing policy categories.

Levels of availability: – → +

Levels of requirements: – → +

	Data availability statement is published[1]	Data has been shared[2]	Data has been peer reviewed[3]	Example Wiley journals
Encourages Data Sharing	Optional	Optional	Optional	
Expects Data Sharing	Required	Optional	Optional	British Journal of Social Psychology
Mandates Data Sharing	Required	Required	Optional	Ecology and Evolution
Mandates Data Sharing and Peer Reviews Data	Required	Required	Required	Geoscience Data Journal American Journal of Political Science

In the pass

In the era of openscience

https://authorservices.wiley.com/author-resources/Journal-Authors/open-access/data-sharing-citation/data-sharing-policy.html *journal **guidelines** regarding **data sharing***

nature portfolio

nature > nature portfolio > editorial policies > reporting standards and availability of data, materials, code and protocols

Editorial policies
- Authorship
- Competing interests
- Research Ethics
- Press and embargo policies
- Self archiving and license to publish

Reporting standards and availability of data, materials, code and protocols

An inherent principle of publication is that others should be able to replicate and build upon

Neuroscience

These data repositories all accept human-derived data (NeuroMorpho.org and G-Node also accept data from other organisms). Please note that human-subject data submitted to OpenfMRI must be de-identified.

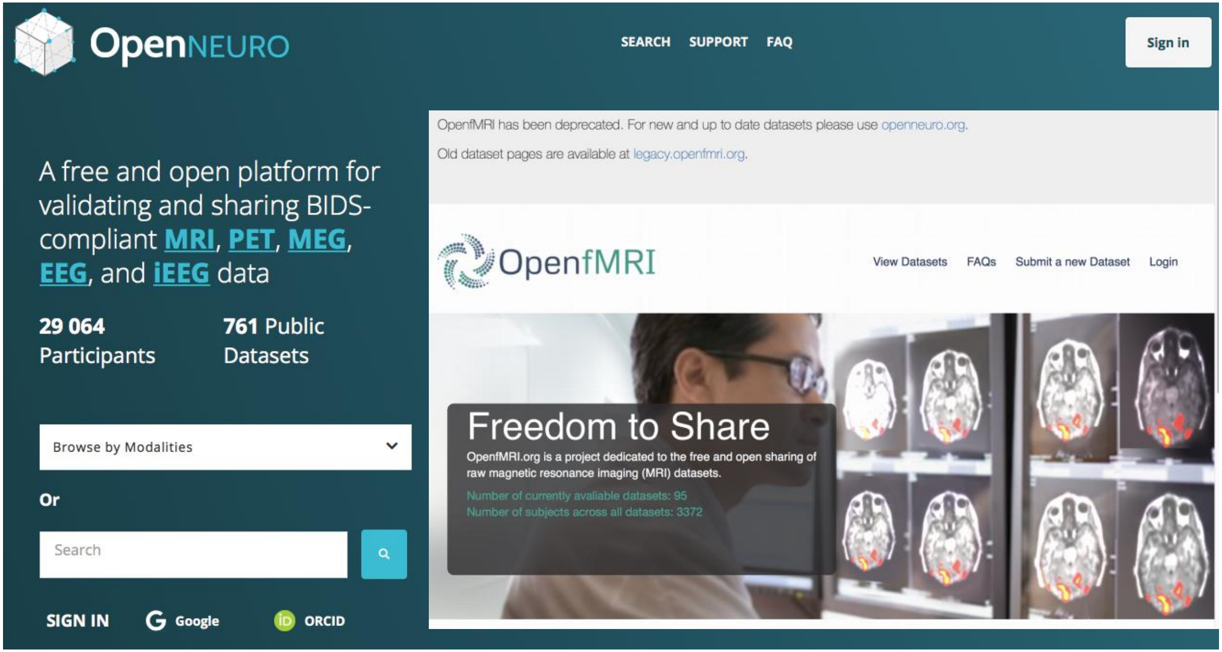
NeuroMorpho.org	view FAIRsharing entry
OpenNeuro (formerly OpenfMRI)	view FAIRsharing entry
G-Node	view FAIRsharing entry
Neuroimaging Informatics Tools and Resources Collaboratory (NITRC)	view FAIRsharing entry
EBRAINS	view FAIRsharing entry

Availability of data

Data availability: All published manuscripts reporting original research in Nature Portfolio journals must include a data availability statement. The data availability statement must make the conditions of access to the "minimum dataset" that are necessary to interpret, verify and extend the research in the article, transparent to readers. This minimum dataset may be provided through deposition in public community/discipline-specific repositories, custom proprietary repositories for certain types of datasets, or general repositories like Figshare, Zenodo and Dryad. Providing large datasets in supplementary information is strongly discouraged and the preferred approach is to make data available in repositories. *Scientific Data*, a Nature Portfolio journal, maintains a list of approved and recommended data repositories to support researchers seeking suitable repositories for their data. Please refer to our authorship policy for information about authors' responsibilities for preserving and making available data, code and materials upon publication. Authors are responsible for obtaining all necessary permissions and ensuring compliance with local regulatory requirements for data sharing.

On this page
- Reporting requirements
- Availability of data
- Availability of materials
- Availability and peer review of computer code and algorithm

https://www.nature.com/nature-portfolio/editorial-policies/reporting-standards#availability-of-data https://elifesciences.org/articles/71774

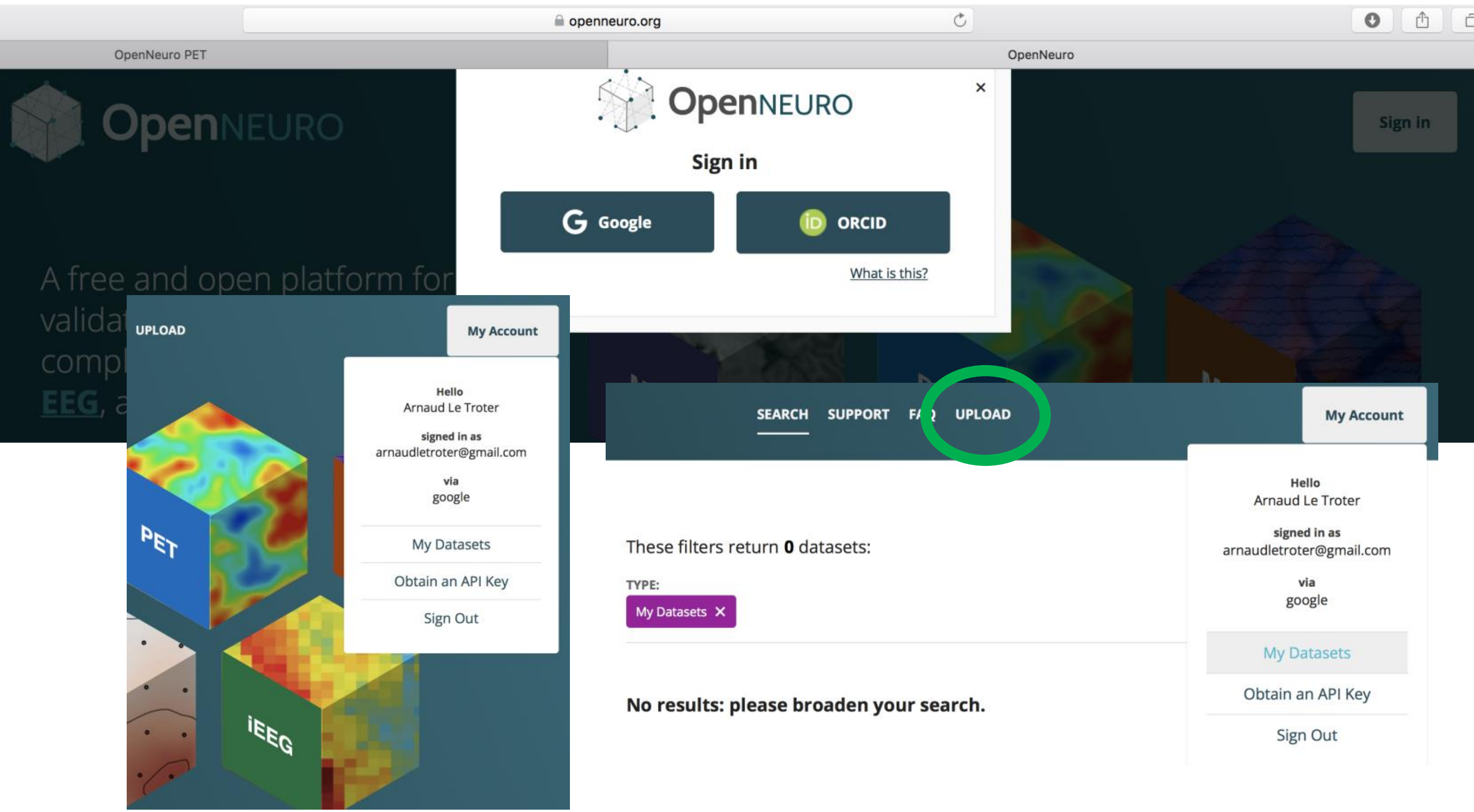


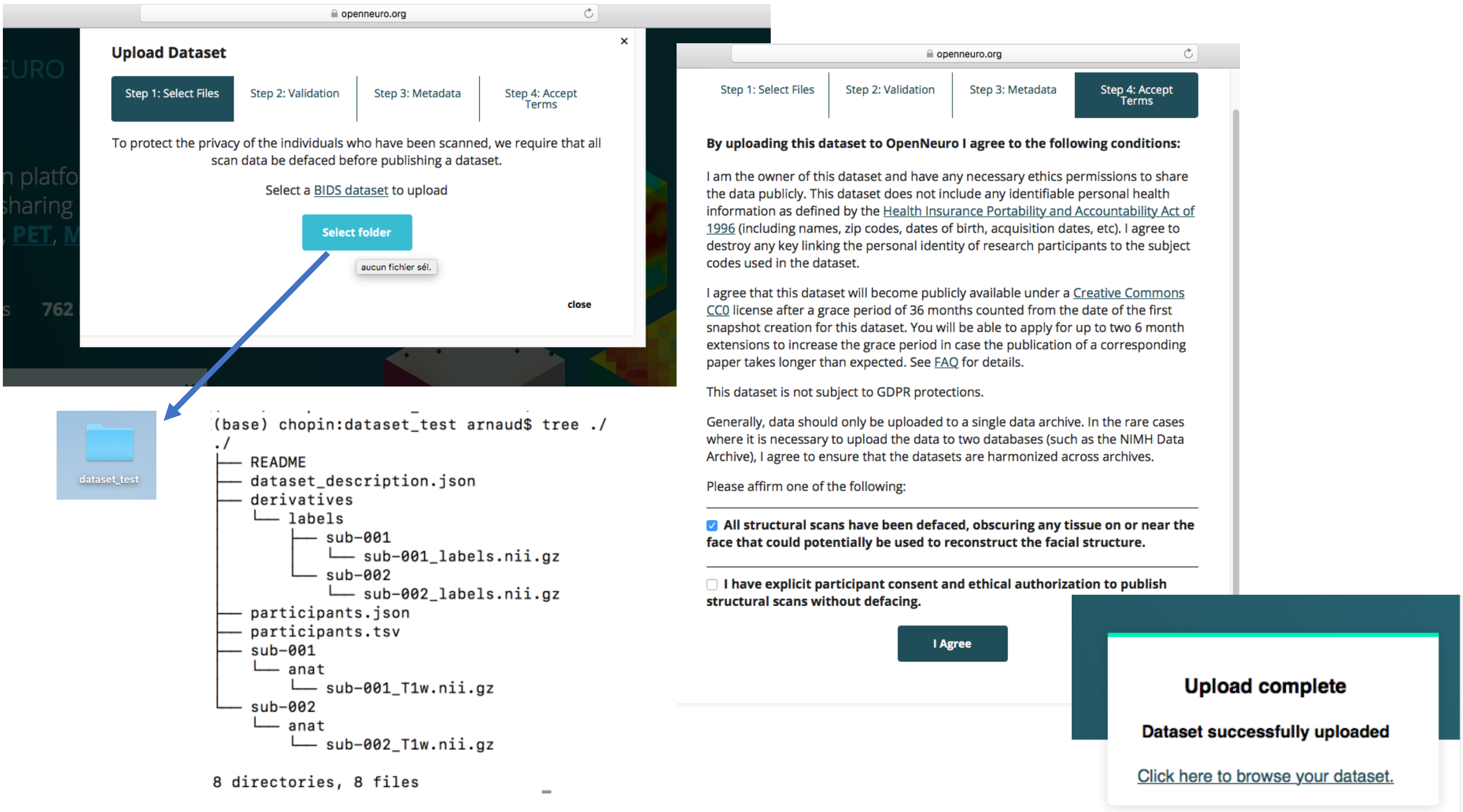
https://openneuro.org https://docs.openneuro.org/user_guide.html

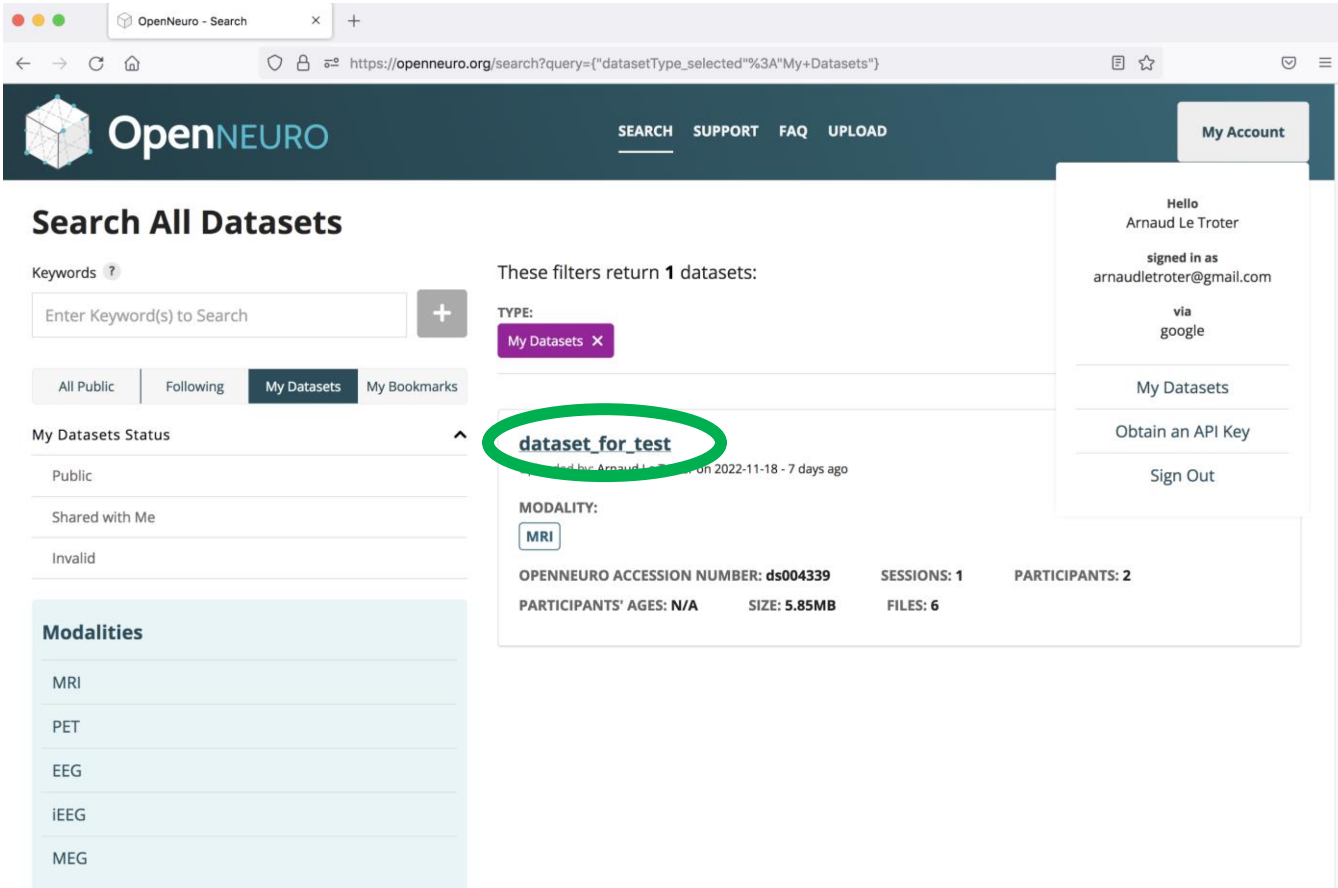
to freely store and share Brain Imaging Data Structure (BIDS) datasets.

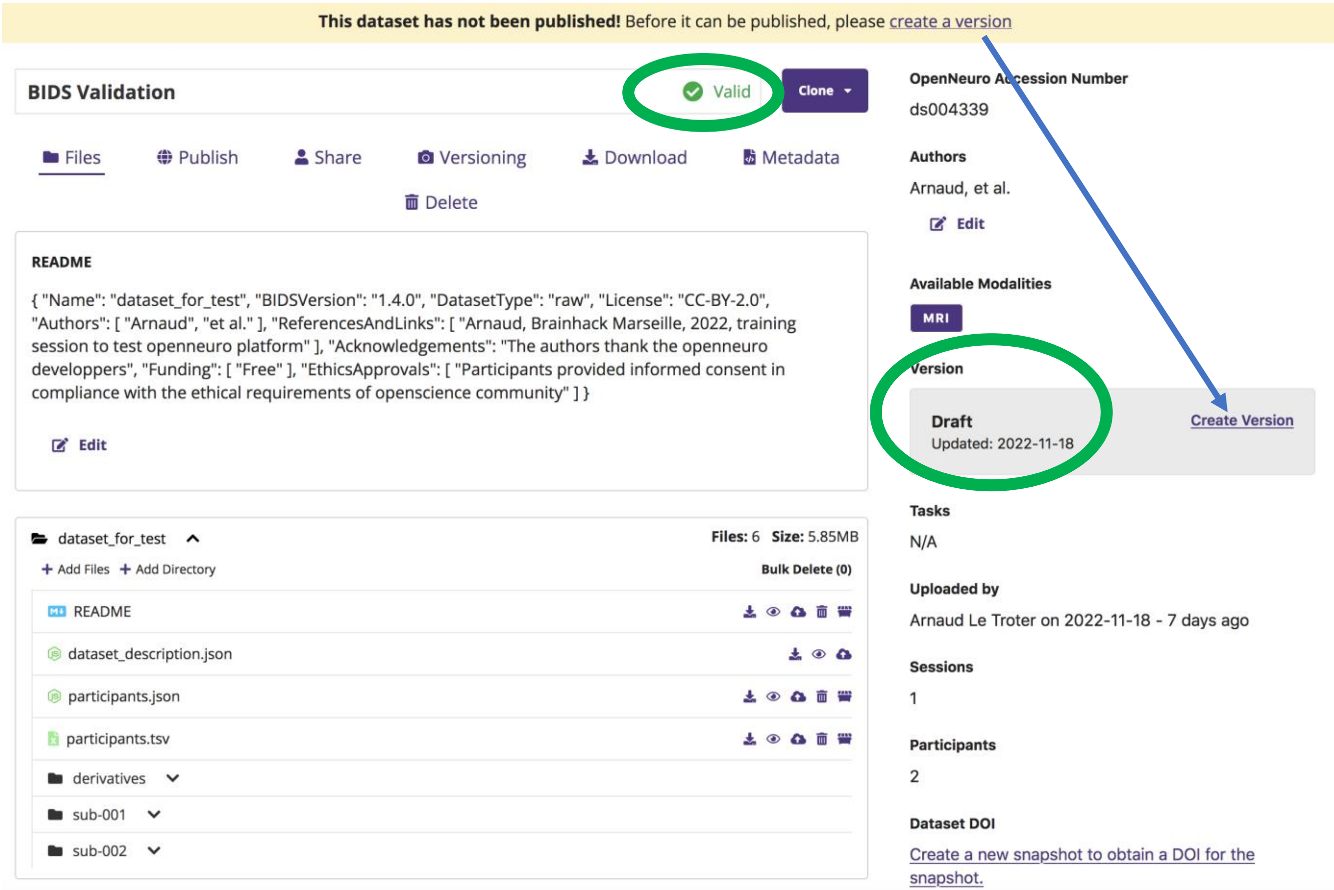
How do we proceed for a publication of a dataset on the OpenNeuro plateform

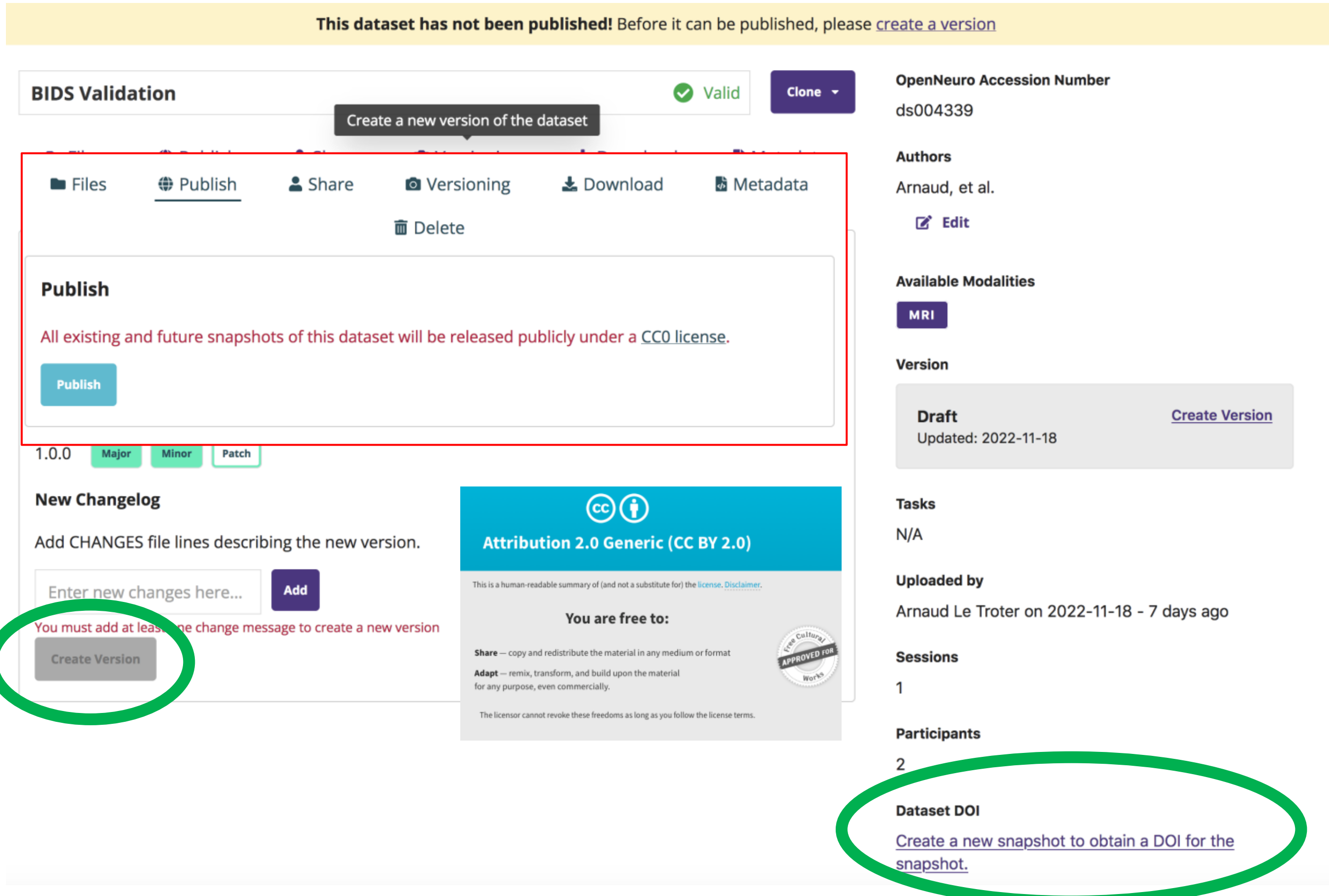
https://docs.openneuro.org/user_guide.html

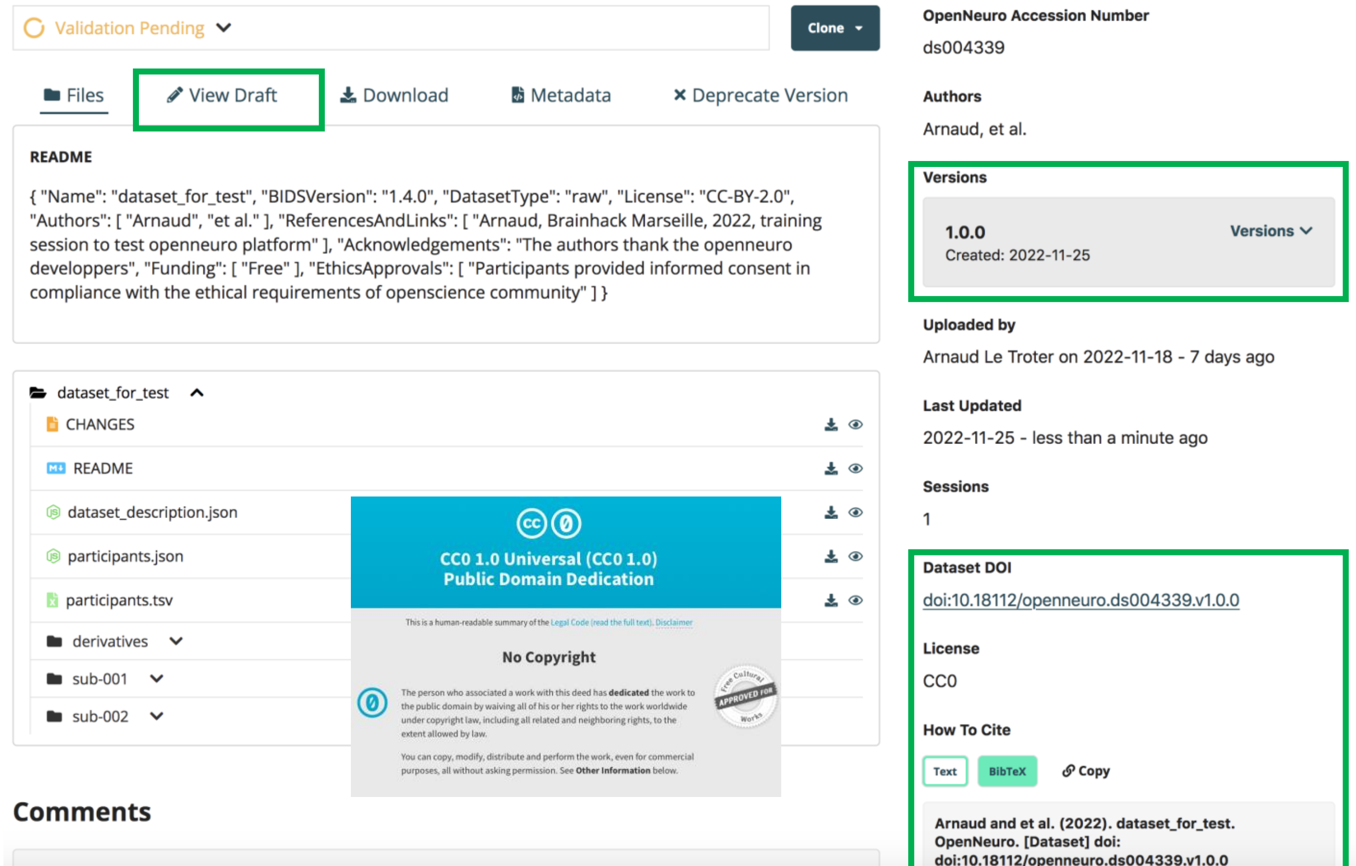

openneuro.org
OpenNeuro PET
OpenNeuro
OpenNEURO
Sign in
Google
ORCID
What is this?
Sign in
A free and open platform for
UPLOAD
My Account
Hello
Arnaud Le Troter
signed in as
arnaudletroter@gmail.com
via
google
My Datasets
Obtain an API Key
Sign Out
PET
iEEG
SEARCH
SUPPORT
UPLOAD
My Account
These filters return 0 datasets:
TYPE:
My Datasets
No results: please broaden your search.
Hello
Arnaud Le Troter
signed in as
arnaudletroter@gmail.com
via
google
My Datasets
Obtain an API Key
Sign Out

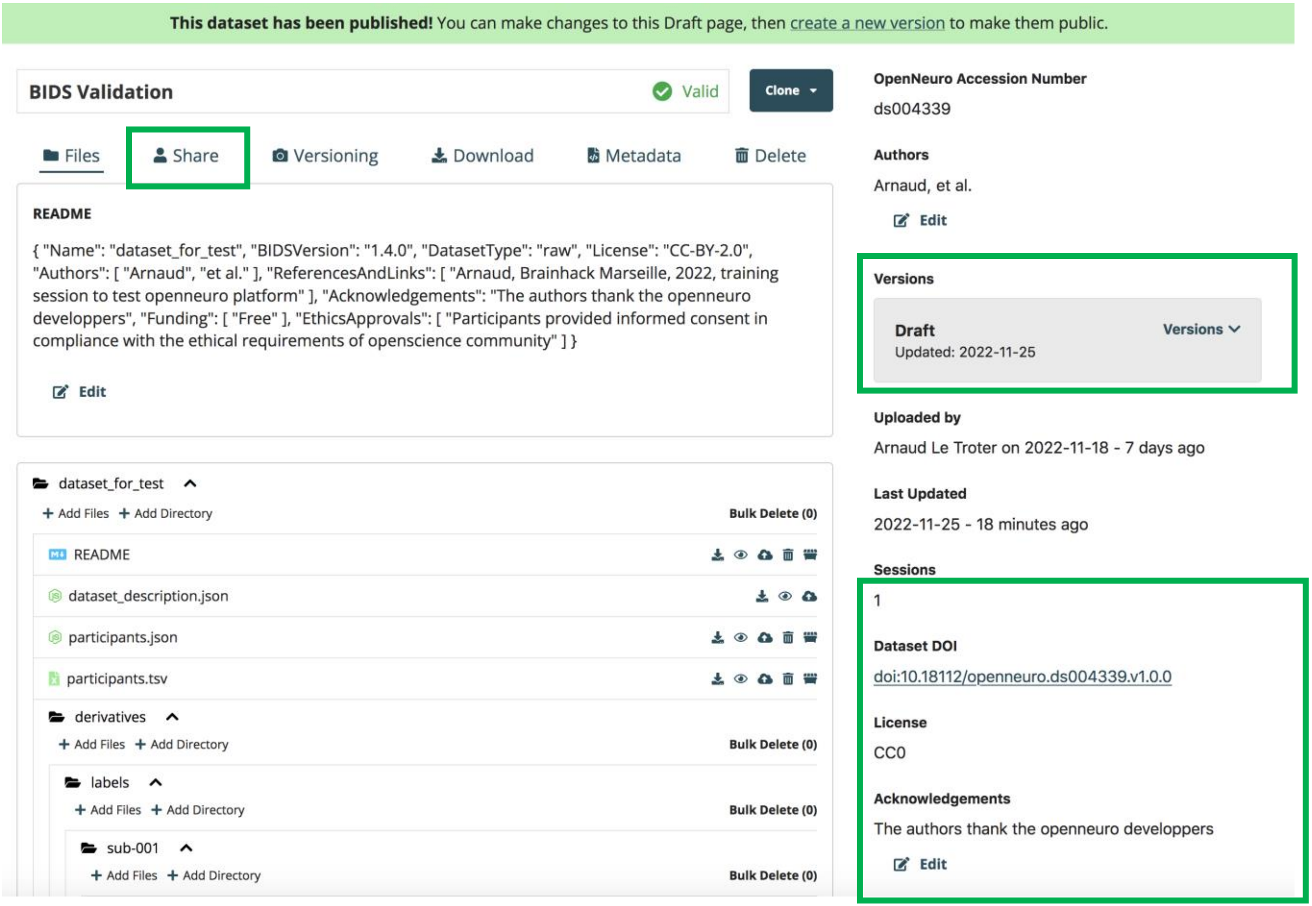

openneuro.org
Upload Dataset
Step 1: Select Files
Step 2: Validation
Step 3: Metadata
Step 4: Accept Terms
To protect the privacy of the individuals who have been scanned, we require that all scan data be defaced before publishing a dataset.
Select a BIDS dataset to upload
Select folder
aucun fichier sél.
close
dataset_test
(base) chopin:dataset_test arnaud$ tree ./
./
├── README
├── dataset_description.json
├── derivatives
│   └── labels
│   ├── sub-001
│   │   └── sub-001_labels.nii.gz
│   └── sub-002
│   └── sub-002_labels.nii.gz
├── participants.json
├── participants.tsv
├── sub-001
│   └── anat
│   └── sub-001_T1w.nii.gz
└── sub-002
    └── anat
        └── sub-002_T1w.nii.gz
8 directories, 8 files
openneuro.org
Step 1: Select Files
Step 2: Validation
Step 3: Metadata
Step 4: Accept Terms
By uploading this dataset to OpenNeuro I agree to the following conditions:
I am the owner of this dataset and have any necessary ethics permissions to share the data publicly. This dataset does not include any identifiable personal health information as defined by the Health Insurance Portability and Accountability Act of 1996 (including names, zip codes, dates of birth, acquisition dates, etc). I agree to destroy any key linking the personal identity of research participants to the subject codes used in the dataset.
I agree that this dataset will become publicly available under a Creative Commons CC0 license after a grace period of 36 months counted from the date of the first snapshot creation for this dataset. You will be able to apply for up to two 6 month extensions to increase the grace period in case the publication of a corresponding paper takes longer than expected. See FAQ for details.
This dataset is not subject to GDPR protections.
Generally, data should only be uploaded to a single data archive. In the rare cases where it is necessary to upload the data to two databases (such as the NIMH Data Archive), I agree to ensure that the datasets are harmonized across archives.
Please affirm one of the following:
All structural scans have been defaced, obscuring any tissue on or near the face that could potentially be used to reconstruct the facial structure.
I have explicit participant consent and ethical authorization to publish structural scans without defacing.
I Agree
Upload complete
Dataset successfully uploaded
Click here to browse your dataset.


OpenNeuro - Search
https://openneuro.org/search?query={"datasetType_selected"%3A"My+Datasets"}
OpenNEURO
SEARCH
SUPPORT
FAQ
UPLOAD
My Account
Hello
Arnaud Le Troter
signed in as
arnaudletroter@gmail.com
via
google
My Datasets
Obtain an API Key
Sign Out
Search All Datasets
Keywords
Enter Keyword(s) to Search
All Public
Following
My Datasets
My Bookmarks
My Datasets Status
Public
Shared with Me
Invalid
Modalities
MRI
PET
EEG
iEEG
MEG
These filters return 1 datasets:
TYPE:
My Datasets
dataset_for_test
on 2022-11-18 - 7 days ago
MODALITY:
MRI
OPENNEURO ACCESSION NUMBER: ds004339
SESSIONS: 1
PARTICIPANTS: 2
PARTICIPANTS' AGES: N/A
SIZE: 5.85MB
FILES: 6

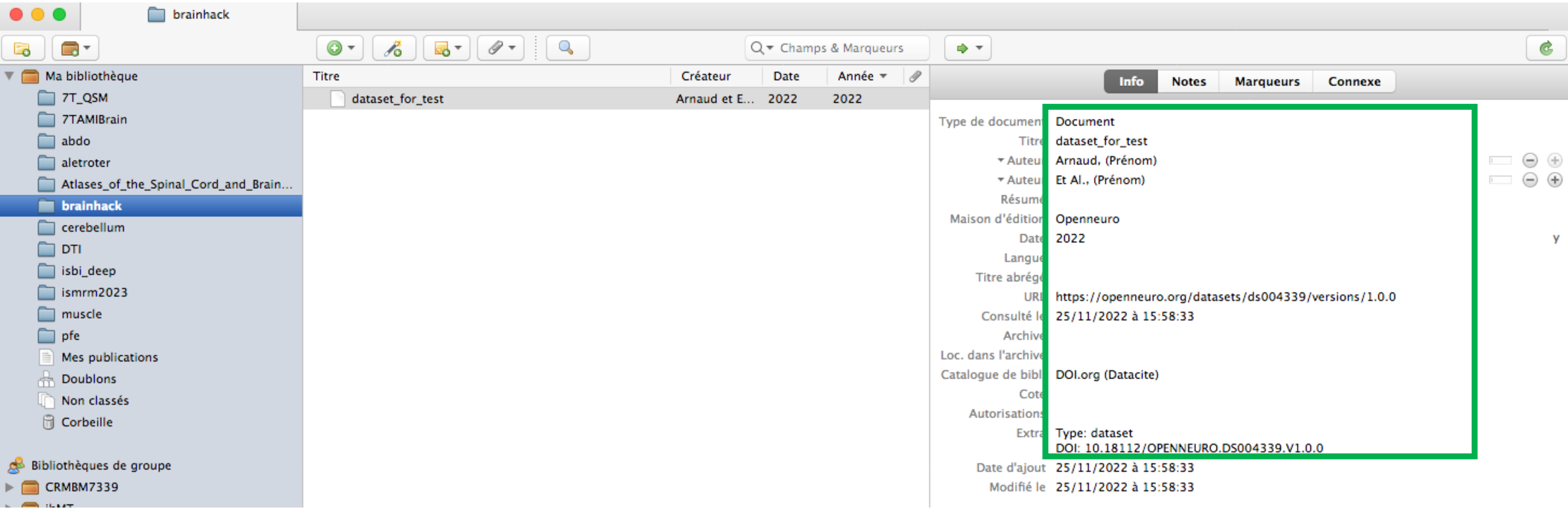

This dataset has not been published! Before it can be published, please create a version
BIDS Validation
Valid
Clone
Files
Publish
Share
Versioning
Download
Metadata
Delete
README
{ "Name": "dataset_for_test", "BIDSVersion": "1.4.0", "DatasetType": "raw", "License": "CC-BY-2.0", "Authors": ["Arnaud", "et al."], "ReferencesAndLinks": ["Arnaud, Brainhack Marseille, 2022, training session to test openneuro platform"], "Acknowledgements": "The authors thank the openneuro developpers", "Funding": ["Free"], "EthicsApprovals": ["Participants provided informed consent in compliance with the ethical requirements of openscience community"] }
Edit
dataset_for_test
Files: 6 Size: 5.85MB
Add Files
Add Directory
Bulk Delete (0)
README
dataset_description.json
participants.json
participants.tsv
derivatives
sub-001
sub-002
OpenNeuro Accession Number
ds004339
Authors
Arnaud, et al.
Edit
Available Modalities
MRI
Version
Draft
Updated: 2022-11-18
Create Version
Tasks
N/A
Uploaded by
Arnaud Le Troter on 2022-11-18 - 7 days ago
Sessions
1
Participants
2
Dataset DOI
Create a new snapshot to obtain a DOI for the snapshot.


This dataset has not been published! Before it can be published, please create a version
BIDS Validation
Valid
Clone
Create a new version of the dataset
Files
Publish
Share
Versioning
Download
Metadata
Delete
Publish
All existing and future snapshots of this dataset will be released publicly under a CC0 license.
Publish
1.0.0
Major
Minor
Patch
New Changelog
Add CHANGES file lines describing the new version.
Enter new changes here...
Add
You must add at least one change message to create a new version
Create Version
Attribution 2.0 Generic (CC BY 2.0)
This is a human-readable summary of (and not a substitute for) the license. Disclaimer.
You are free to:
Share — copy and redistribute the material in any medium or format
Adapt — remix, transform, and build upon the material
for any purpose, even commercially.
The licensor cannot revoke these freedoms as long as you follow the license terms.
OpenNeuro Accession Number
ds004339
Authors
Arnaud, et al.
Edit
Available Modalities
MRI
Version
Draft
Updated: 2022-11-18
Create Version
Tasks
N/A
Uploaded by
Arnaud Le Troter on 2022-11-18 - 7 days ago
Sessions
1
Participants
2
Dataset DOI
Create a new snapshot to obtain a DOI for the snapshot.


Validation Pending
Clone
Files
View Draft
Download
Metadata
Deprecate Version
README
{ "Name": "dataset_for_test", "BIDSVersion": "1.4.0", "DatasetType": "raw", "License": "CC-BY-2.0", "Authors": ["Arnaud", "et al."], "ReferencesAndLinks": ["Arnaud, Brainhack Marseille, 2022, training session to test openneuro platform"], "Acknowledgements": "The authors thank the openneuro developpers", "Funding": ["Free"], "EthicsApprovals": ["Participants provided informed consent in compliance with the ethical requirements of openscience community"] }
dataset_for_test
CHANGES
README
dataset_description.json
participants.json
participants.tsv
derivatives
sub-001
sub-002
Comments
CC0 1.0 Universal (CC0 1.0)
Public Domain Dedication
This is a human-readable summary of the Legal Code (read the full text). Disclaimer
No Copyright
The person who associated a work with this deed has dedicated the work to the public domain by waiving all of his or her rights to the work worldwide under copyright law, including all related and neighboring rights, to the extent allowed by law.
You can copy, modify, distribute and perform the work, even for commercial purposes, all without asking permission. See Other Information below.
APPROVED FOR Free Cultural Works
OpenNeuro Accession Number
ds004339
Authors
Arnaud, et al.
Versions
1.0.0
Created: 2022-11-25
Versions
Uploaded by
Arnaud Le Troter on 2022-11-18 - 7 days ago
Last Updated
2022-11-25 - less than a minute ago
Sessions
1
Dataset DOI
doi:10.18112/openneuro.ds004339.v1.0.0
License
CC0
How To Cite
Text
BibTeX
Copy
Arnaud and et al. (2022). dataset_for_test. OpenNeuro. [Dataset] doi: doi:10.18112/openneuro.ds004339.v1.0.0

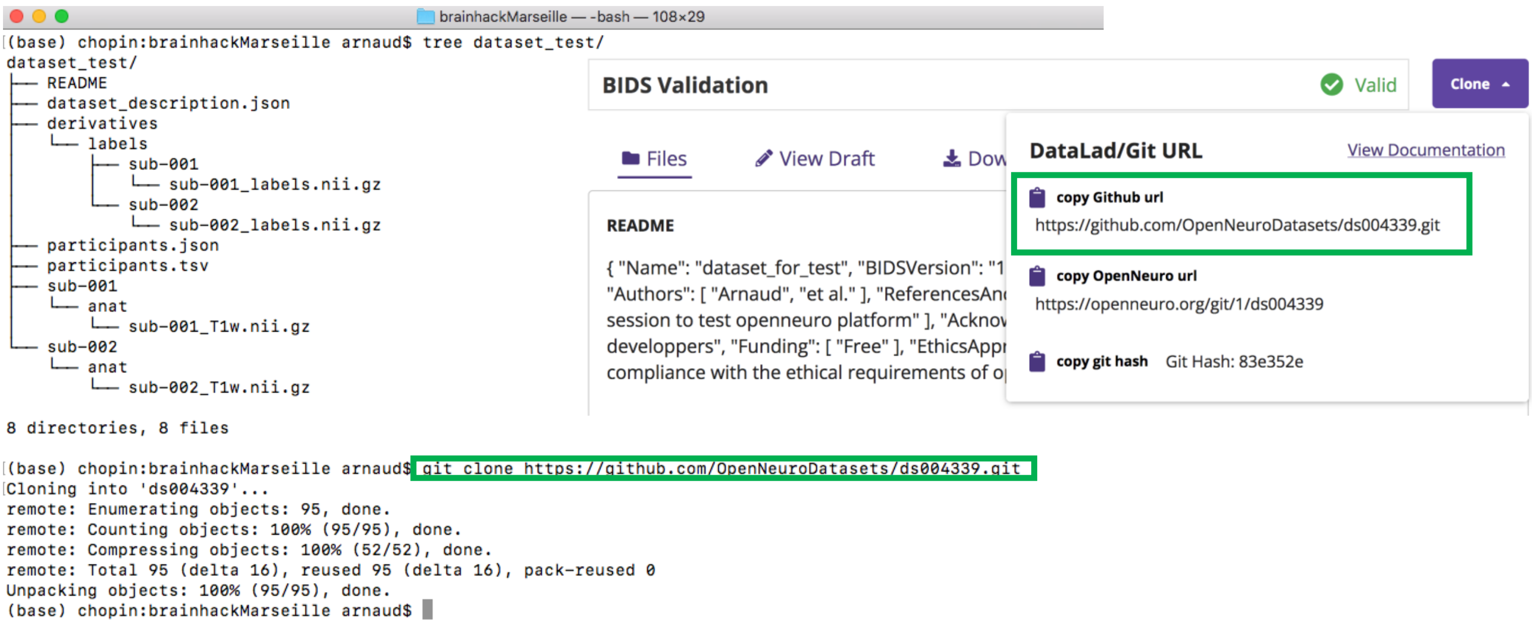

This dataset has been published! You can make changes to this Draft page, then create a new version to make them public.
BIDS Validation
Valid
Clone
Files
Share
Versioning
Download
Metadata
Delete
README
{ "Name": "dataset_for_test", "BIDSVersion": "1.4.0", "DatasetType": "raw", "License": "CC-BY-2.0", "Authors": ["Arnaud", "et al."], "ReferencesAndLinks": ["Arnaud, Brainhack Marseille, 2022, training session to test openneuro platform"], "Acknowledgements": "The authors thank the openneuro developpers", "Funding": ["Free"], "EthicsApprovals": ["Participants provided informed consent in compliance with the ethical requirements of openscience community"] }
Edit
dataset_for_test
+ Add Files + Add Directory
Bulk Delete (0)
README
dataset_description.json
participants.json
participants.tsv
derivatives
+ Add Files + Add Directory
Bulk Delete (0)
labels
+ Add Files + Add Directory
Bulk Delete (0)
sub-001
+ Add Files + Add Directory
Bulk Delete (0)
OpenNeuro Accession Number
ds004339
Authors
Arnaud, et al.
Edit
Versions
Draft
Updated: 2022-11-25
Versions
Uploaded by
Arnaud Le Troter on 2022-11-18 - 7 days ago
Last Updated
2022-11-25 - 18 minutes ago
Sessions
1
Dataset DOI
doi:10.18112/openneuro.ds004339.v1.0.0
License
CC0
Acknowledgements
The authors thank the openneuro developpers
Edit

zotero



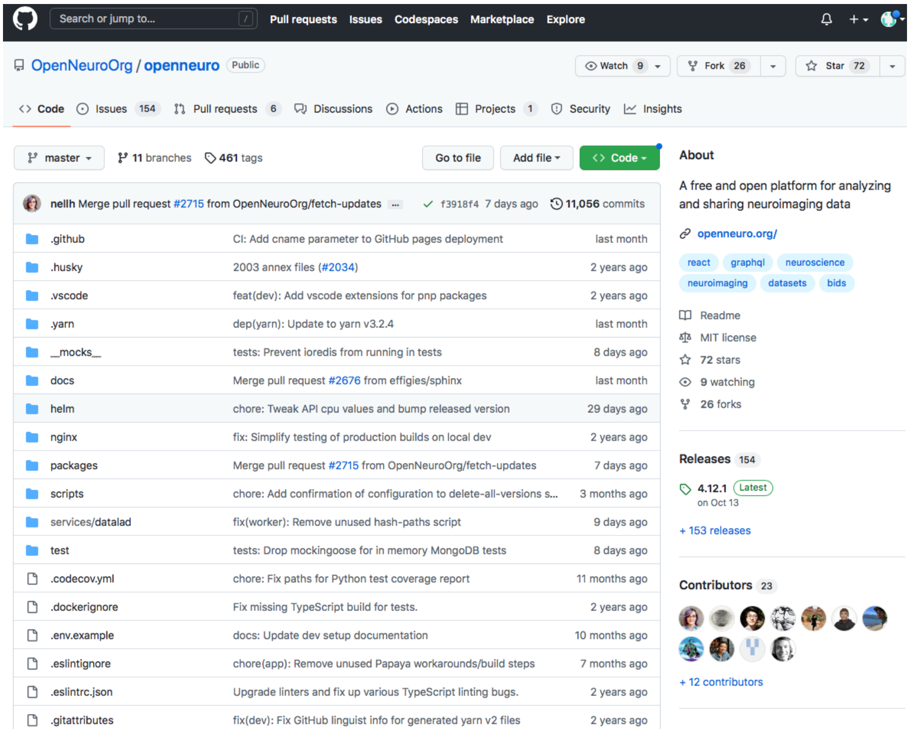
brainhack
Champs & Marqueurs
Ma bibliothèque
7T_QSM
7TAMIBrain
abdo
aletroter
Atlases_of_the_Spinal_Cord_and_Brain...
brainhack
cerebellum
DTI
isbi_deep
ismrm2023
muscle
pfe
Mes publications
Doublons
Non classés
Corbeille
Bibliothèques de groupe
CRMBM7339
Titre
Créateur
Date
Année
dataset_for_test
Arnaud et E...
2022
2022
Info
Notes
Marqueurs
Connexe
Type de document
Document
Titre
dataset_for_test
Auteur
Arnaud, (Prénom)
Auteur
Et Al., (Prénom)
Résumé
Maison d'édition
Openneuro
Date
2022
Langue
Titre abrégé
URL
https://openneuro.org/datasets/ds004339/versions/1.0.0
Consulté le
25/11/2022 à 15:58:33
Archive
Loc. dans l'archive
Catalogue de bibl
DOI.org (Datacite)
Cote
Autorisations
Extra
Type: dataset
DOI: 10.18112/OPENNEURO.DS004339.V1.0.0
Date d'ajout
25/11/2022 à 15:58:33
Modifié le
25/11/2022 à 15:58:33

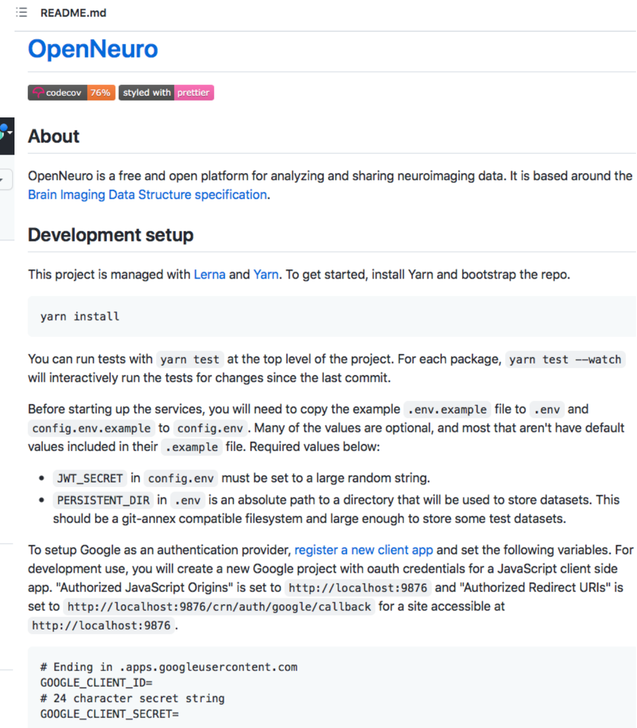
Clone your own dataset !



Install your own openneuro repository platform

https://github.com/OpenNeuroOrg/openneuro





Tested on ubuntu 20

Data sharing is essential in the era of openscience

this way:

- offers readers the opportunity to better evaluate your work
- gives a better visibility to your works
- increases the opportunity of new studies derivated from your works
- provides a **better reproducibility** of results for others works (next talk)

OpenNeuro is a very nice platform to secure share your imaging data

and let's all contribute more and more to open science using this tools !

Thanks to openneuro developpers ;-)

BrainHack Marseille

Open collaboration in neuroscience

Open tools for Open science

By Manuel Mercier, Simon Moré, Guillaume Auzias & Arnaud Le Troter

Reproducible science: introducing open resources to grasp the problem and implement solutions

Guillaume Auzias

Open resources

- https://github.com/ohbm/hackathon2019/blob/master/Tutorial_Resources.md#open-science
- https://www.pathlms.com/ohbm/courses
- https://neurohackademy.org/neurohack_year/2022/
- https://textbook.nipraxis.org/intro.html
- https://www.nipreps.org/qc-book/welcome.html

roadmap

- The problem

- Solutions you can start implementing today!

ANALYSIS

The problem

NeuroImage 212 (2020) 116601

Contents lists available at ScienceDirect

NeuroImage

journal homepage: www.elsevier.com/locate/neuroimage

ELSEVIER

The empirical replicability of task-based fMRI as a function of sample size

Han Bossier[a,*], Sanne P. Roels[a], Ruth Seurinck[a], Tobias Banaschewski[b], Gareth J. Barker[c], Arun L.W. Bokde[d], Erin Burke Quinlan[e], Sylvane Desrivières[e], Herta Flor[f,g], Antoine Grigis[h], Hugh Garavan[i], Penny Gowland[j], Andreas Heinz[k], Bernd Ittermann[l], Jean-Luc Martinot[m], Eric Artiges[n], Frauke Nees[b,f], Dimitri Papadopoulos Orfanos[h], Luise Poustka[o], Juliane H. Fröhner Dipl-Psych[p], Michael N. Smolka[p], Henrik Walter[k], Robert Whelan[q], Gunter Schumann[e], Beatrijs Moerkerke[a], IMAGEN Consortium

ANALYSIS

Power failure: why small sample size undermines the reliability of neuroscience

Katherine S. Button[1,2], John P. A. Ioannidis[3], Claire Mokrysz[1], Brian A. Nosek[4], Jonathan Flint[5], Emma S. J. Robinson[6] and Marcus R. Munafò[1]

REVIEW

Experimenting with reproducibility: a case study of robustness in bioinformatics

Yang-Min Kim[1,2,3,4,*], Jean-Baptiste Poline[5,6] and Guillaume Dumas[1,2,3,4]

ARTICLE

DOI: 10.1038/s41467-018-07619-7 OPEN

Why rankings of biomedical image analysis competitions should be interpreted with care

Lena Maier-Hein et al.[#]

Article

Variability in the analysis of a single neuroimaging dataset by many teams

https://doi.org/10.1038/s41586-020-2314-9

Received: 14 November 2019

Accepted: 7 April 2020

Published online: 20 May 2020

Check for updates

A list of authors and affiliations appears in the online version of the paper.

Data analysis workflows in many scientific domains have become increasingly complex and flexible. Here we assess the effect of this flexibility on the results of functional magnetic resonance imaging by asking 70 independent teams to analyse the same dataset, testing the same 9 ex-ante hypotheses[1]. The flexibility of analytical approaches is exemplified by the fact that no two teams chose identical workflows to analyse the data. This flexibility resulted in sizeable variation in the results of hypothesis tests, even for teams whose statistical maps were highly correlated at

Article

Reproducible brain-wide association studies require thousands of individuals

https://doi.org/10.1038/s41586-022-04492-9

Received: 19 May 2021

Accepted: 31 January 2022

Published online: 16 March 2022

Open access

Check for updates

Scott Marek[1,30]✉, Brenden Tervo-Clemmens[2,3,30]✉, Finnegan J. Calabro[4,5], David F. Montez[6], Benjamin P. Kay[6], Alexander S. Hatoum[1], Meghan Rose Donohue[1], William Foran[4], Ryland L. Miller[1,6], Timothy J. Hendrickson[7], Stephen M. Malone[8], Sridhar Kandala[1], Eric Feczko[9,10], Oscar Miranda-Dominguez[9,10], Alice M. Graham[11], Eric A. Earl[9,11], Anders J. Perrone[9,11], Michaela Cordova[11], Olivia Doyle[11], Lucille A. Moore[11], Gregory M. Conan[9,11], Johnny Uriarte[11], Kathy Snider[11], Benjamin J. Lynch[9,12], James C. Wilgenbusch[9,12], Thomas Pengo[7], Angela Tam[13,14,15,16], Jianzhong Chen[13,14,15,16], Dillan J. Newbold[6], Annie Zheng[6], Nicole A. Seider[6], Andrew N. Van[6,17], Athanasia Metoki[6], Roselyne J. Chauvin[6], Timothy O. Laumann[1], Deanna J. Greene[18], Steven E. Petersen[6,17,19,20,21], Hugh Garavan[22], Wesley K. Thompson[23], Thomas E. Nichols[24], B. T. Thomas Yeo[13,14,15,16,25,26], Deanna M. Barch[1,21], Beatriz Luna[3,4], Damien A. Fair[9,10,27,31]✉ & Nico U. F. Dosenbach[6,17,19,28,29,31]✉

frontiers in NEUROSCIENCE

OPINION ARTICLE
published: 09 September 2013
doi: 10.3389/fnins.2013.00162

Instrumentation bias in the use and evaluation of scientific software: recommendations for reproducible practices in the computational sciences

Nicholas J. Tustison[1], Hans J. Johnson[2], Torsten Rohlfing[3], Arno Klein[4], Satrajit S. Ghosh[5], Luis Ibanez[6] and Brian B. Avants[7]*

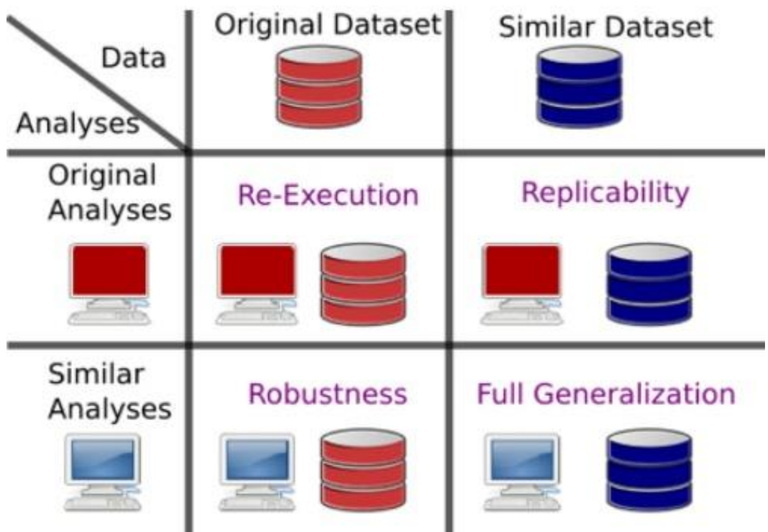
frontiers in Neuroinformatics

PERSPECTIVE
published: 07 February 2019
doi: 10.3389/fninf.2019.00001

Check for updates

Everything Matters: The ReproNim Perspective on Reproducible Neuroimaging

David N. Kennedy[1], Sanu A. Abraham[2], Julianna F. Bates[1], Albert Crowley[3], Satrajit Ghosh[2], Tom Gillespie[4], Mathias Goncalves[2], Jeffrey S. Grethe[4], Yaroslav O. Halchenko[5], Michael Hanke[6], Christian Haselgrove[1], Steven M. Hodge[1], Dorota Jarecka[2], Jakub Kaczmarzyk[2], David B. Keator[7], Kyle Meyer[5], Maryann E. Martone[4], Smruti Padhy[2], Jean-Baptiste Poline[8], Nina Preuss[3], Troy Sincomb[4] and Matt Travers[3]*



https://neurohackademy.org/neurohack_year/2022/

Monday

9:00am
Welcome to NeuroHackademy
Ariel Rokem
Noah Benson

9:30am
Icebreaker

10:30am
Reproducibility in fMRI: What is the problem?
Russell Poldrack

12:00pm
Lunch

1:30pm
What if all the data in the world were instantly accessible?
Satra Ghosh

3:00pm
Coffee Break

3:30pm
Neural decoding in the wild
Bing Brunton

5:00pm
Welcome reception

Tuesday

9:00am
Introduction to Python: the Basics
Noah Benson

9:00am
Data management in Python/Pandas
Ariel Rokem

10:00am
Coffee break

10:30am
Meta-analysis and reproducibility
Angela Laird

12:00pm
Lunch

1:30pm
Git from Scratch
Noah Benson

1:30pm
Collaboration patterns with Git
Ariel Rokem

3:00pm
Coffee Break

3:30pm
Docker
Noah Benson

5:00pm
Poster session

Wednesday

9:00am
Data visualization in Python
Ariel Rokem

9:00am
Introduction to Python: Control Flow
Noah Benson

10:00am
Coffee break

10:30am
Responsible data governance for neuroscience: the need for FAIR-C
Damian Eke

12:00pm
Lunch

1:30pm
Measuring and analyzing human functional brain networks
Caterina Gratton

3:00pm
Coffee Break

3:30pm
Hands on meta-analysis / NIMARE
Taylor Salo

3:30pm
Introduction to machine learning / scikit learn
Ariel Rokem

Thursday

9:00am
Parallelization with Python/Dask
Ariel Rokem

9:00am
Introduction to Python: NumPy
Noah Benson

10:00am
Coffee break

10:30am
BIDS-iEEG in practice to map electrical stimulation driven connectivity
Dora Hermes

12:00pm
Lunch

1:30pm
Data management for neuroimaging with datalad
Adina Wagner

3:00pm
Coffee Break

3:30pm
Cloud computing
Naomi Alterman

3:30pm
Deep learning
Noah Benson

Friday

9:00am
Processing intracranial data with MNE-python
Liberty Hamilton

10:00am
Coffee break

10:30am
The issues with statistics that will make your work irreproducible – and what we should do about it
JB Poline

12:00pm
Lunch

1:30pm
Data showcase
Melanie Ganz
Kendrick Kay
Adam Richie-Halford
Noah Benson

3:00pm
Coffee Break

3:30pm
Review session 1
Noah Benson

3:30pm
Review session 2
Ariel Rokem

The Solution (concept)

Neuron

CellPress

Volume 109, Issue 11, 2 June 2021, Pages 1769-1775

NeuroView

Brainhack: Developing a culture of open, inclusive, community-driven neuroscience

Rémi Gau [1, 76], Stephanie Noble [2, 76], Katja Heuer [3, 4, 76], Katherine L. Bottenhorn [5, 76], Isil P. Bilgin [6, 7, 76], Yu-Fang Yang [8, 76], Julia M. Huntenburg [9, 76], Johanna M.M. Bayer [10, 11, 76], Richard A.I. Bethlehem [12, 13, 76], Shawn A. Rhoads [14], Christoph Vogelbacher [15], Valentina Borghesani [16], Elizabeth Levitis [17, 18], Hao-Ting Wang [19, 20, 21], Sofie Van Den Bossche [22], Xenia Kobeleva [23, 24], Jon Haitz Legarreta [25], Samuel Guay [26], Selim Melvin Atay [27], Gael P. Varoquaux [28, 29] …Xi-Nian Zuo

https://textbook.nipraxis.org/intro.html

An example of solution to implement today

Practice and theory of brain imaging

Search this book...

Practice and theory of brain imaging

This is a hands-on course teaching the principles of functional MRI (fMRI) data analysis. We will teach you how to work with data and code to get a deeper understanding of how fMRI methods work, how they can fail, how to fix them, and how to develop new methods. We will cover the basic concepts in neuroimaging analysis, and how they relate to the wider world of statistics, engineering and computer science. At the same time we will teach you techniques of data analysis that will make your work easier to organize, understand, explain and share. Using this techniques will give you great benefits for collaborating with others, and for making your work reproducible.

At the end of the course we expect you to be able to analyze fMRI data using Python and to track and share your work with version control using git.

Please see the syllabus for a more detailed list of subjects we will cover.

Next
The problem and the plan

Open Science and Open Tools

Your turn to play !

BrainHack
Open collaboration in neuroscience
Marseille