Survey on Open Science Practices in Functional Neuroimaging

Christian Paret a,b,⁎, Nike Unverhau a, Franklin Feingold c, Russell A. Poldrack c, Madita Stirner a, Christian Schmahl a, Maurizio Sicorello a

a Department of Psychosomatic Medicine and Psychotherapy, Central Institute of Mental Health Mannheim, Medical Faculty Mannheim / Heidelberg University, Germany
b Sagol Brain Institute, Wolfson Institute for Advanced Imaging, Tel-Aviv Sourasky Medical Center and School of Psychological Sciences, Tel-Aviv University, Israel
c Department of Psychology, Stanford University, Stanford, CA

ARTICLE INFO

Keywords:
Data sharing
fMRI
Metascience
Neuroimaging
Open science
Preregistration
Research methods
Replication
Reproducibility
Robustness
Validity

ABSTRACT

Replicability and reproducibility of scientific findings is paramount for sustainable progress in neuroscience. Pre-registration of the hypotheses and methods of an empirical study before analysis, the sharing of primary research data, and compliance with data standards such as the Brain Imaging Data Structure (BIDS), are considered effective practices to secure progress and to substantiate quality of research. We investigated the current level of adoption of open science practices in neuroimaging and the difficulties that prevent researchers from using them.

Email invitations to participate in the survey were sent to addresses received through a PubMed search of human functional magnetic resonance imaging studies that were published between 2010 and 2020. 283 persons completed the questionnaire.

Although half of the participants were experienced with preregistration, the willingness to preregister studies in the future was modest. The majority of participants had experience with the sharing of primary neuroimaging data. Most of the participants were interested in implementing a standardized data structure such as BIDS in their labs. Based on demographic variables, we compared participants on seven subscales, which had been generated through factor analysis. Exploratory analyses found that experienced researchers at lower career level had higher fear of being transparent and researchers with residence in the EU had a higher need for data governance. Additionally, researchers at medical faculties as compared to other university faculties reported a more unsupportive supervisor with regards to open science practices and a higher need for data governance.

The results suggest growing adoption of open science practices but also highlight a number of important impediments.

1. Introduction

Neuroimaging, and in particular functional magnetic resonance imaging (fMRI), has contributed greatly to the generation and testing of neural models of brain function and dysfunction in mental disorders. Although the number of neuroimaging publications increases every year, a growing literature is shaking the ground, questioning the replicability of many reported findings (Botvinik-Nezer et al., 2020; Button et al., 2013; Eklund et al., 2016; Poldrack et al., 2017). Assessing validity requires researchers to be fully transparent about the a priori hypotheses underlying a study, the complete reporting of methods, and the availability of data to reproduce the findings. These conditions are often not met (Carp, 2012a; Guo et al., 2014). Open science practices can protect against such adversities, but they confront scientists with additional demands to learn and adopt new techniques. To accelerate the implementation of open science practices, it is necessary to better understand obstacles that prevent researchers from adopting these practices. While survey data are available on researchers’ preferences, barriers and fears related to data sharing in psychology (Houtkoop et al., 2018), open science practices besides data sharing have not been surveyed in the behavioral sciences, yet. Neuroimaging data is complex and hard to de-identify (Amico and Goñi, 2018; Bari et al., 2019; Finn et al., 2015; Valizadeh et al., 2018; Wachinger et al., 2015), confronting researchers in this field with intricate challenges to share data. We investigated the familiarity, adoption, experience, and obstacles concerning open science practices in neuroimaging research. We focused on three fundamental instruments of a reproducible science: Preregistration, data sharing, and current standards of formatting and structuring data as implemented with the Brain Imaging Data Structure (BIDS) (Gorgolewski et al., 2016). In a preregistration, authors provide an overview on the planned study and explain the a priori hypotheses along with the methods they plan to use to test the hypotheses.

⁎ Correspondence to: Christian Paret, Central Institute of Mental Health, J5, D-68159 Mannheim, Germany, Tel: +49-(0)-621-1703-4462
E-mail address: christian.paret@zi-mannheim.de (C. Paret).

https://doi.org/10.1016/j.neuroimage.2022.119306.
Received 18 December 2021; Received in revised form 3 May 2022; Accepted 10 May 2022
Available online 17 May 2022.
1053-8119/© 2022 The Author(s). Published by Elsevier Inc. This is an open access article under the CC BY license (http://creativecommons.org/licenses/by/4.0/)
(Nosek et al., 2018). The document is time-stamped and any changes made thereafter are documented for transparency. Preregistrations are instrumental to avoid confusion of a priori and a posteriori definition of hypotheses and analysis methods, which can easily lead to flawed interpretation of a p-value from a statistical result and can create overconfidence in findings (Gelman and Loken, 2014; Ioannidis, 2005; Munafò et al., 2017). In face of high flexibility in preprocessing and analysis methods (Botvinik-Nezer et al., 2020; Carp, 2012b), preregistration can dramatically enhance the transparency of a neuroimaging project. More than in basic science, it is mandatory to register clinical trials in a public registry before data acquisition, in order to publish in a renowned biomedical journal. In practice, leading clinical registries leave it at the discretion of the researcher as to how much detail they use to describe the analytic strategy for processing their neuroimaging data. One may register a neuroimaging endpoint in some way similar to “higher BOLD response in ROI (Region-of-Interest) X for the contrast of conditions A vs. B”. There are many possible analysis strategies to assess this endpoint; the search space for significant voxels could be extended to the whole-brain or reduced to a small volume defined by a ROI mask, the mask could be anatomically or functionally defined, and so on. For a confirmatory hypothesis test, the complete analysis plan should be defined a priori (Gentili et al., 2021; Poldrack et al., 2017), but this is hardly the case in clinical trials with neuroimaging endpoints.

A growing literature is providing tools and guidelines to facilitate reproducible neuroimaging findings and data sharing (Esteban et al., 2019; Gorgolewski et al., 2017; Laird, 2021; Nichols et al., 2017; Poldrack et al., 2017). Standards such as BIDS, which was introduced by Gorgolewski et al. (2016), present a well-documented scheme to structure data files in directories, provide agreed upon terminology for naming these files, and explain how metadata should be reported. The sharing of primary research data is critical for a reproducible science and can save resources, as existing data can be re-used and aggregated with other data sets for future research projects. Still, researchers often eschew data sharing, e.g. because of a lack of incentives, the fear of misuse, and legal issues such as data protection and privacy issues (Houtkoop et al., 2018; Sayogo and Pardo, 2013; Schmidt et al., 2016; Tenopir et al., 2011; White et al., 2020). In this respect, it is of interest how the General Data Protection Regulation (GDPR), which came into force in the European Union (EU) May, 2018, may affect the preference to share data among researchers. Hence, differences were explored between researchers who indicated residency inside vs. outside the EU. Moreover, the more complex the dataset, the more resources may be required to prepare a sharable dataset, thus taking up time that could be used to do new experiments (Poline et al., 2012). Where scientist practitioners must balance research and clinical work and where data are collected from vulnerable patient populations, the situation can be even more fraught. Therefore, we conducted exploratory analyses of differences between researchers who indicated an affiliation with a medical faculty vs. a different, non-medical faculty. Data and materials from this research are available online1 (Paret et al., 2022).

2. Methods

2.1. Participants

A PubMed search with the search term (“fMRI” OR “functional magnetic resonance imaging” OR “functional Magnetic Resonance Imaging”) AND (“2010/01/01”[Date - Publication] : “3000”[Date - Publication])2 and Filter: Humans was done to collect email addresses from corresponding authors of scientific articles published between 2010/01/01 and 2020/08/28. The “Humans” search filter was applied to exclude animal imaging work. The search results were exported to text files, which were further processed with an online app to remove duplicates and to extract email addresses (https://github.com/christianparet/Survey-on-Open-Science-Practices-in-Functional-Neuroimaging-Dataset-and-Materials). An email was sent to 14,690 addresses on 2020 Dec 1, with an invitation to participate, including a personalized link to the survey. If the recipients did not click the link or did not complete the survey after 14 days, they received a single reminder email. Figure 1 illustrates the recruitment approach. From 342 persons who clicked the invitation link, 82.75% completed the questionnaire and were included in analysis, corresponding to an overall response rate of 2.42 % and resulting in N = 283 participants to be-analyzed. It took participants 9.62 min on average (3.17; numbers reported in brackets are standard deviations) to arrive at the final slide of the questionnaire.

Participants were aged 43.89 years on average (9.74), dominantly male (66 %), mostly trained in psychology, and reported an average research experience of 16.58 years (8.49). Most were affiliated with a university and reported themselves in cognitive neuroscience. Half of the sample held a full or associate professorship or a comparable position (Figure 2). Participants from the European Union were overrepresented in the sample, while the USA and UK ranked second and third in number of participants (Figure 3, Table 1). A PubMed search with the search term (“fMRI” OR “functional magnetic resonance imaging” OR “functional Magnetic Resonance Imaging”) AND (“2010/01/01”[Date - Publication] : “3000”[Date - Publication])2 and Filter: Humans was done to collect email addresses from corresponding authors of scientific articles published between 2010/01/01 and 2020/08/28. The “Humans” search filter was applied to exclude animal imaging work. The search results were exported to text files, which were further processed with an online app to remove duplicates and to extract email addresses (https://github.com/christianparet/Survey-on-Open-Science-Practices-in-Functional-Neuroimaging-Dataset-and-Materials). An email was sent to 14,690 addresses on 2020 Dec 1, with an invitation to participate, including a personalized link to the survey. If the recipients did not click the link or did not complete the survey after 14 days, they received a single reminder email. Figure 1 illustrates the recruitment approach. From 342 persons who clicked the invitation link, 82.75% completed the questionnaire and were included in analysis, corresponding to an overall response rate of 2.42 % and resulting in N = 283 participants to be-analyzed. It took participants 9.62 min on average (3.17; numbers reported in brackets are standard deviations) to arrive at the final slide of the questionnaire.

Participants were aged 43.89 years on average (9.74), dominantly male (66 %), mostly trained in psychology, and reported an average research experience of 16.58 years (8.49). Most were affiliated with a university and reported themselves in cognitive neuroscience. Half of the sample held a full or associate professorship or a comparable position (Figure 2). Participants from the European Union were overrepresented in the sample, while the USA and UK ranked second and third in number of participants (Figure 3, Table 1).

Figure 1. Subject flow chart. Summary of recruitment approach and number of responses at each step.

1 https://github.com/christianparet/Survey-on-Open-Science-Practices-in-Functional-Neuroimaging-Dataset-and-Materials.

2 Practically, we did four searches, each covering a period of two or more years (i.e., 2010-2012, 2013-2014, 2015-2016, 2017-today), to limit the total number of exported entries per search.
2.2. Materials

The questionnaire was composed of five building blocks. Blocks 1-3 focused on three areas of open science practices: data structure, preregistration and data sharing. The fourth block asked about technical expertise with software and the fifth part assessed sociodemographic data. In the beginning of each block a brief introduction to the topic area with definitions for key terms was provided. One or more questions on the subjective experience with the topic followed. Further, it included one or more questions to assess the likelihood to adopt practices of this topic area in the future on a 5-point Likert scale (“extremely unlikely” - 1, “somewhat unlikely” - 2, “neither likely nor unlikely” - 3, “somewhat likely” - 4, “extremely likely” - 5). The items for the data structure block were created by the author team with the major goal to assess knowledge and usage of BIDS in the fMRI community. Barriers and fears of adopting preregistration and data sharing practices were assessed by asking for agreement with statements on a 7-point Likert scale (“strongly disagree” - 1, “disagree” - 2, “somewhat disagree” - 3, “neither agree nor disagree” - 4, “somewhat agree” - 5, “agree” - 6, “strongly agree” - 7). For the data sharing block we used items from a previously published study on data sharing in psychology (Houtkoop et al., 2018). Due to the broader scope of our survey and to reduce burden for participants, a selection of items and response options was drawn from Houtkoop et al. (2018) and used in our questionnaire. Furthermore, we restructured the item blocks from Houtkoop et al.’s survey. The items that Houtkoop et al. had grouped to a block on barriers related to data sharing were split up in one item block asking for preferred options to share data and in a second item block asking for a number of potential barriers. In the barriers-item block we merged these items with other items from Houtkoop et al.’s survey, which specifically assessed fear-related barriers of data sharing. The items on barriers for and fears of preregistration were inspired by the items on barriers for and fears of data sharing. For example, the preregistration item “preparing a preregistration is too time consuming for me” was based on the data sharing item “preparing data to make it suitable for online sharing is too time consuming for me”. Thus, several items from the preregistration block resembled items from the data sharing block which focused on comparable challenges such as lack of time, high complexity and lack of
training in open science practices. Other items asked specific questions about each topic area (for example, “I am afraid that my preregistered hypotheses may turn out false” from the preregistration block or “I am afraid that other researchers will discover errors in my data” from the data sharing block). The online questionnaire was implemented using SoSci Survey (Leiner, 2019).

2.3. Data analysis

Statistics software R version 4.0.5 was used to analyze the data. To analyze individual differences, we defined subgroups based on demographic variables of interest: 1) Career level (full/associate professors vs. assistant professors or lower stage), 2) years of research experience, 3) European Union residency (EU resident vs. no EU resident) and 4) affiliation with medical faculty (university hospital/medical faculty vs. other faculty). Variables of interest for subgroup analysis were defined post hoc. T-tests were used to assess individual differences and Bayes Factor (BayesFactor Version 0.9.12-4.2, Morey et al., 2018) was determined to assess the relative evidence for the alternative hypothesis versus the null hypothesis (BF₁₀). We used the low information cauchy prior with a scale factor of 0.707, which is the default of the BayesFactor package that was used for this analysis and which has been suggested for psychological applications. Bayes Factors take values between p(Data|H1) and p(Data|H0), with the common minimum cutoff of 3 (or below ½) indicating claims of evidence in favour of one hypothesis over the other. To explore latent variables that may drive responses to items on both data sharing and preregistration, an exploratory factor analysis was performed using R package lavaan 0.6-7 and psych 2.0.12 (Rosseel, 2012). An exploratory structural equation model was chosen to leverage the advantages of exploratory factor analysis and confirmatory factor analysis (Marsh et al., 2014), allowing the evaluation of exploratory models with goodness of fit measures. In total, the 28 statements that related to barriers and fears of data sharing and preregistration, as well as preferences of how to share data, were used for the analyses. Each statement was rated on a Likert scale ranging from 1 (“strongly disagree”) to 7 (“strongly agree”). Factor analysis was performed using maximum likelihood estimation and oblique rotation (Ol vulin), allowing factors to correlate with each other. The number of factors was determined using parallel analysis. Items with factor loadings >0.4 were retained.

To investigate whether groups with different response patterns exist, we performed a data-driven cluster analysis on the seven factors received from exploratory structural equation modeling. The euclidean distance was used to construct the dissimilarity matrix and clustering performed using Ward’s method. The optimal number of clusters was chosen based on the elbow and the silhouette method using the factoextra package version 1.0.7 (Kassambara and Mundt, 2020). To explore whether any demographic variables could predict cluster belongingness, we performed a logistic regression with research experience, primary affiliation with medical faculty, EU residency, and career level as predictors. Model accuracy was calculated using the Caret package (Kuhn, 2008). The cluster analysis as well as regression analysis were not preregistered and were done post hoc.

We report all data exclusions, all manipulations and all measures in the study (Simmons et al., 2012). With the recruitment procedures we aimed to receive as many responses as possible and we did not set the target sample size a priori.

3. Results

3.1. Descriptive results

3.1.1. Preregistration is facing challenges

42.4% participants indicated they have never preregistered a study. Among the rest of participants, the most frequently used preregistration platform was the Open Science Framework (OSF, 32.5%), followed by ClinicalTrials.gov (25.1%), and AsPredicted (9.5%). 14.1% indicated they had submitted a registered report article type (Chambers et al., 2015) to a scientific journal (Figure 5a). About the same number of participants who said they had preregistered a study before indicated they were likely or extremely likely to preregister their next study online.
(55%), while 26% disagreed (Figure 5b). Participants who had previously preregistered a study were more inclined to say that they would preregister their next study online, indicated by a significant correlation ($X^2 = 64.444, df = 4, p<0.001$). Asked about potential barriers for preregistration, 64% agreed at least to some extent with the statement that their analyses were too complex to preregister. The statement “There is no sufficient reward for preregistration” reached the second rank (53%). 46% agreed that preparing a preregistration is too time-consuming for them and 41% agreed that they know too little about preregistration platforms or that they have never learned to preregister a project. 74% disagreed with the statement that they had never thought about preregistering a project (14% agreed). 10% indicated that their supervisor does not support preregistration. Asked about potential fears of preregistration, 49% agreed that they were afraid that their preregistered methods may turn out as suboptimal or inadequate. 23% agreed they were afraid that their preregistered hypotheses may turn out false. We also asked whether participants think that it is necessary to register studies with an explorative research question and 48% agreed (Figure 5c).

3.1.2. Sharing raw data is common practice for many

66% of all participants said they have shared neuroimaging raw data with other researchers outside their department before. Asked about the intention to share primary research data of their next neuroimaging paper in an online repository, 54% indicated they were likely or extremely likely to do this, while 25% were unlikely or extremely unlikely (Figure 6a). Asked whether they were not allowed to share primary neuroimaging data due to legal constraints, 64% disagreed at least to some extent, while 9% agreed (27% did neither agree nor disagree, Figure 6b). If participants did not disagree strongly with the above statement, i.e. they thought that they were not allowed to share primary neuroimaging research data, a follow up question was asked to investigate the reasons (N=210 saw the question). Most participants endorsed the statement that anonymity cannot be guaranteed if the data is shared (45.2% agreed at least somewhat). 41% indicated their consent forms state that data will not be shared. 29.5% responded that their institutional review board does not allow them to share data. 14.8% reported stakeholder interests prohibiting data from being shared and 6.7% said that a funder, advisor or supervisor does not allow them to share data (Figure 6c).

3.1.2. Europeans more hesitant to share raw data online in the future

To explore interindividual differences that may result from national data protection legislation, we compared participants who indicated their country of residence within the European Union (EU) vs. outside...
C. Paret, N. Unverhau, F. Feingold et al.  NeuroImage 257 (2022) 119306

3.1.3. Researchers appreciate data sharing agreements

To learn more about the preferred mode of data sharing, we let participants evaluate several options on how data can be shared with other researchers. Highest agreement was found for the option to share data under a data sharing agreement to be signed by the recipient (65%), directly followed by the option to share upon personal request and thereby bypassing a data repository (64%). With 58% agreement, sharing via a managed online repository with restricted access found high approval, too. The option to share via an online repository with unrestricted access was preferred by 35% of participants, while 45% expressed disagreement with this item. 17% preferred that researchers with reasonable interest can work with their data, but that this work needs to be done on the server of their home institution (63% disagreed). Finally, 6% agreed they preferred not to give away raw data to other researchers, whereas 81% disagreed (Figure 7a).

3.1.4. Lack of resources poses a high hurdle to data sharing

Asked about barriers for and fears of data sharing, 67% agreed at least somewhat that preparing data to make it suitable for online shar-
Figure 6. Data sharing: Descriptive results from questions asking for a) plan to share data of next neuroimaging paper, b) legal constraints permitting to share data, and c) reasons for not being allowed to share data.

ing is too time-consuming. The second leading statement “I lack funding to make data suitable for online sharing” received 61% agreement. 47% of participants agreed they are afraid of being scooped, i.e., that other researchers may publish results obtained from their data set before they can. 41% agreed they knew too little about suitable data repositories and 40% agreed they never learned to share their research data online. 38% endorsed the statement they are afraid not to get proper recognition for sharing data. The concern that data sets were too big (33%) or too complex (30%) to share were found on the following ranks. 25% expressed fears that other researchers could run alternative analyses on their data to rebut their own conclusions and 24% agreed they are afraid that other researchers will discover errors in their data. 11% agreed their supervisor does not support online data sharing. 11% agreed they have never thought about data sharing, whereas 81% disagreed (Figure 7b).

3.1.5. High interest in using BIDS
72% of respondents indicated that they had heard about BIDS before. 35% said that they had used BIDS in the past and have been working with it for 2.27 (1.78) years on average. The vast majority, 91%, find it likely or extremely likely that they are going to use BIDS in the future (Figure 8a). Participants who said that they have not used BIDS before were asked to report the reason. Most indicated they had not heard about BIDS before (41.5%), they had no time to implement it in the lab (36.1%), or to learn more about it (28.4%). 12.6% agreed they were lacking technical expertise to get BIDS conversion running, 10.9% said they were currently implementing it, and 6% said they were using a different data structure format than BIDS. 5.5% deemed BIDS not relevant for their lab (Figure 8b). Those preferring to operate software via graphical user interface (GUI) used BIDS significantly less often as com-
pared participants who prefer to interact via command interface, $X^2(1) = 18.72, p < 0.001$. Those who indicated that they had used BIDS before were then asked about experience with BIDS-compatible software: 32% participants experienced with BIDS used custom code to convert raw neuroimaging data into the BIDS format, while 16% indicated that they have not used any conversion software (Figure 8c). Several participants confirmed they have been using software that can operate on BIDS formatted data sets such as fMRIPrep (Esteban et al., 2019) (44%), MRIQC (Esteban et al., 2017) (23%), OpenNeuro (Markiewicz et al., 2021) (18%) and other tools (<10%) (Figure 8d) Table 1.

Figure 7. Data sharing: Descriptive results from questions addressing a) preferred options of data sharing and b) barriers for and fears of data sharing.
Figure 8. Descriptive results from questions addressing BIDS. A) Intention of using BIDS in the future. B) N = 183 participants have not used BIDS before and were asked why. Participants could check one or more response options. Bars show the percentage of responses per option. C) N = 101 participants have used BIDS before and were asked what conversion software they had used. Participants could check one or more response options. Bars show the percentage of responses per option. C) N = 101 participants have used BIDS before and were asked what BIDS compatible software they had used. Participants could check one or more response options. Bars show the percentage of responses per option.

Table 1
Sociodemographic information about the surveyed sample.

| Personal Data          | Sample (N = 283) |
|------------------------|------------------|
| Age (years)            | 43.89 ± 9.74     |
| Country of Residence   |                  |
| In the EU              | 161 (57)         |
| Outside the EU         | 122 (43)         |
| Research Experience    | 17.58 ± 8.49     |

3.2. Group differences on latent variables

3.2.1. Factors underlying barriers, fears, and preferences of preregistration and data sharing

We explored whether the answers of our participants could be reduced to a smaller set of interpretable latent variables. Bartlett’s test confirmed that the items correlated sufficiently, $X^2(378) = 3135.5, p < 0.001$, to explore the structure with factor analytic methods. The KMO test indicated overall acceptable Measure of Sample Adequacy (MSA = 0.81). On item level, the MSA suggested the inadequacy of the item “It is necessary to register studies with an explorative research question” (MSA = 0.46). We excluded the item, due to the low MSA and as it
does not name a barrier or fear as the rest of the items. While parallel analysis recommended the eight-factor solution, we decided to choose a seven-factor model, as it already provided good model fit (Table 2): The Comparative Fit Index (CFI) reached 0.937 (cut off >0.9) while the Root Mean Square Error of Approximation (RMSEA) was below the cut-off of 0.05 (RMSEA = 0.042). The seven factors resulting from this analysis included: fear of being transparent, lack of experience with and appeal of preregistration, complexity of own research, need for data governance, unsupportive supervisor, lack of experience with data sharing, and lack of resources for data sharing.

The eight-factor solution as compared to the seven-factor solution was mainly characterized by a split of factor “Lack of experience with and appeal of preregistration” in two factors characterized by items addressing the prior experience (“I have never learned to preregister a project”, “I have never thought about preregistering a project”, “I know too little about suitable preregistration platforms”) and the appeal of preregistration (“Preparing a preregistration is too time consuming for me”, “There is no sufficient reward for preregistration”). One item that loaded on factor “Complexity of own research” in the seven-factor solution changed to the factor characterized by items addressing the appeal of preregistration (“The analyses I do are too complex to preregister”) of the eight-factor solution. The item “I am afraid that my preregistered hypotheses may turn out false”, which belonged to the factor “Fear of being transparent” in the seven-factor model, did not anymore exceed the threshold of loading 0.4 on any of the factors in the eight-factor model. Taken together, the eight-factor vs. seven-factor model further differentiated preregistration related statements and limited the scope of factor “Complexity of own research” from the seven-factor solution to the complexity (and size) of one’s data set for sharing.

We used the results from factor analysis to build seven subscales from our questionnaire. For each participant we calculated subscale scores by averaging the item scores assigned to each factor. The subscale scores were further used to explore individual differences, comparing participants based on demographic variables. The Bonferroni corrected results as well as results from analysis of Bayes Factors of all performed comparisons can be found in Table 3. For the factor “Fear of being transparent” we found that people with a lower career level were significantly more fearful than people with a higher career level. For “need for data governance”, people having their primary affiliation with a medical faculty showed significantly higher scores than people having their primary affiliation with a psychological or other faculty. Respondents residing in the EU had a higher need for data governance than non-EU respondents. Lastly, people affiliated with a medical faculty scored higher on “unsupportive supervisor”, as did respondents with a lower career level compared to respondents with a higher career level.

### 3.2.2. Distinct open science profiles

We explored whether there are groups of participants with distinct profiles, according to scores achieved on the subscales, which might serve as potential target groups for future actions on open science practices. The suggested optimal number of clusters was two, which was supported by the highest Dunn Index for the two-cluster solution (0.155), compared to the three- and four-cluster solutions (Figure 9a). As visible in the profile plot (Figure 9b), cluster 1 consists of researchers with less experience with open science practices, more complex datasets, and more concerns regarding data sharing and preregistration, as well as a less supportive supervisor and fewer resources for data sharing. Cluster 2 was composed of researchers who were more experienced with open science practices and who saw overall less barriers and had lower fears.

To find out whether cluster-belongingness could be explained by demographic variables, we conducted a regression analysis. Overall the explanatory power of our regression model was marginally better than chance, $\chi^2(4) = 10.09, p = 0.039$, (Table 4) with an out-of-sample accuracy of 59.9%, based on 10-fold cross-validation. The combined effect of all variables had explanatory power, but no single variable was a significant contributor.

### 4. Discussion

Preregistration of research questions, hypotheses and the analysis plan as well as data sharing were proposed to improve the replicability, robustness and reproducibility (Munafò et al., 2017; Nosek et al., 2021). This survey aimed to shed light on the experience with and attitude towards open science practices in human neuroimaging, namely with regards to preregistration, data sharing and data standards. We reached out to researchers who had published as corresponding authors using human fMRI in the past. The resulting sample was mainly composed of researchers who were advanced in their careers. It can be assumed that most participants of this survey were heading their own labs and that they oversaw and exerted influence in their field of research.

The interest in preregistration was modest. About one half of participants had preregistered a study before, with OSF as the most commonly used platform. There was no indication of a trend towards more widespread use of preregistration in the future. Still, two thirds had at least thought about preregistering their research. It should be noted that we did not explicitly ask for experience with the preregistration of neuroimaging studies. The results therefore may represent experience with preregistration practices in general, including behavioral studies that did not involve neuroimaging. Besides the barriers and fears that we had asked for, some participants shared a critical perspective on the role of preregistration as a technique to promote the quality of science (Table 5, cf. Gelman and Loken, 2014; Szollosi et al., 2020). This view stands against advocates of preregistration who see no alternative to prevent hindsight bias and overconfidence in research findings (Nosek et al., 2018, 2019). Best practice guidelines explaining when and how to preregister neuroimaging research, which is often exploratory and complex, have not been established, yet, although new templates such as the Psychological Research Preregistration-Quantitative template (Preregistration Task Force, 2020) and an OSF template (Beyer et al., 2021) were made available, which is an important step in this direction. Furthermore, this survey demonstrated the rising awareness for the importance of data sharing in the neuroimaging community. Most participants had thought about online data sharing before. Data sharing mechanisms with access governance were clearly preferred (c.f. Cheah et al., 2015), while one third of participants also preferred sharing with unrestricted access. At large, the results are in line with the findings from Houtkoop et al. (2018) who surveyed psychologists about their views on data sharing practices. Although comparisons between their results and ours remain descriptive and are somewhat limited because of differences in methods, we observed some differences regarding data protection concerns: Compared to psychologists, neuroimaging researchers more frequently reported that their institutional review boards prohibited data sharing (30% vs. 5%), that they were constrained by lacking explicit consent from subjects to share data (41% vs. 28%), and that anonymity cannot be guaranteed (45% vs. 16%). Future research may try to answer the question, why researchers believe that their institutional review board does not allow them to share data, and why they are using consent forms saying that data will not be shared. As was brought up by one of the reviewers, a consent form may include such restriction intentionally if the researcher hopes that it improves the rate of participation, or unintentionally when the researcher merely follows institutional or supervisory recommendation without much consideration. While the former is a conscious choice based on assumption to be tested, the latter is rather due to ignorance. Lastly, while one third of respondents were using BIDS in current neuroimaging projects, we observed a strong interest to adopt BIDS in the future. While 35% of the full sample had practical experience with the conversion of data to BIDS (i.e., they said that they had converted one or more datasets), 25% indicated experience in working with BIDS datasets (“What BIDS-compatible software, if any, have you used before?”). The distinction between the generation and the consumption of BIDS datasets is important, because BIDS adds an extra set of requirements for data producers. On the other hand, BIDS is a simplification for data consumers. The questionnaire did
Table 2
Results with factor loadings from Exploratory Structural Equation Modeling.

| Factor 1                          | Factor 2                          | Factor 3                          | Factor 4                          | Factor 5                          | Factor 6                          | Factor 7                          |
|----------------------------------|-----------------------------------|-----------------------------------|-----------------------------------|-----------------------------------|-----------------------------------|-----------------------------------|
| Fear of being transparent        | Lack of experience with and appeal of pre-registration | Complexity of own research        | Need for data governance          | Unsupportive of supervisor        | Lack of experience with data sharing | Lack of resources for data sharing |

**How much do you agree on statements regarding possible options of sharing primary research data?**

- I prefer to share via an online repository with unrestricted open access 0.65
- I prefer to share upon personal request 0.52
- I prefer to share under a data sharing agreement to be signed by the recipient 0.78
- Researchers with reasonable interest can work with my raw data on the server of my institution 0.47
- I prefer to share via a managed online repository with restricted access 0.47
- I prefer not to give other researchers access to my raw data 0.58
- I am afraid that other researchers will discover errors in my data 0.85
- I am afraid that other researchers will perform alternative analyses on my data and argue that my conclusions are invalid 0.88
- My data set is too complex to share 0.86
- My data set is too big to share 0.8
- My boss does not support online data sharing 0.83
- I have never thought about sharing my research data online 0.45
- I know too little about suitable repositories 0.63
- I have never learned to share my research data online 0.59
- Preparing data to make it suitable for online sharing is too time consuming for me 0.58
- I lack funding to make data suitable for online sharing 0.52
- I am afraid that I will not get proper recognition for sharing my data 0.8
- I am afraid of being scooped: that other researchers may publish results from my data set before I can 0.8

**Possible barriers for and fears of data sharing**

- I am afraid that other researchers will discover errors in my data 0.44
- I am afraid that my preregistered hypotheses may turn out false 0.41
- Preparing a preregistration is too time consuming for me 0.49
- I have never learned to preregister a project 0.60
- There is not sufficient reward for preregistration 0.42
- I have never thought about preregistering a project 0.51
- I know too little about suitable preregistration platforms 0.74
- The analyses I do are too complex to preregister 0.41
- My boss does not support preregistration 0.77

* Items with factor loadings <0.4 were removed
Table 3
Results of significance testing for the demographic variables “Research experience”, “EU residency”, “Primary affiliation” and “Career level”. Results are significant at a corrected p<0.0017 using Bonferroni correction.

| Research experience          | <16 years experience | >16 years experience | t-test results |
|------------------------------|----------------------|----------------------|----------------|
| (n=145) mean                 | (n=138) mean         | t                  | df | p   | BF<sub>10</sub> |
| Fear of being transparent    | 3.49                 | 3.19                | 1.89 | 278.83 | 0.06 | 0.72 |
| Lack of experience with + appeal of preregistration | 3.65 | 3.81 | -1.04 | 277.28 | 0.30 | 0.22 |
| Complexity of own research   | 3.43                 | 3.76                | -2.02 | 280.29 | 0.04 | 0.90 |
| Need for data governance     | 4.06                 | 4.26                | -1.30 | 281.00 | 0.19 | 0.29 |
| Unsupportive supervisor      | 2.74                 | 2.30                | 2.53 | 280.90 | 0.012 | 2.67 |
| Lack of experience with data sharing | 3.29 | 3.08 | 1.17 | 280.02 | 0.24 | 0.25 |
| Lack of resources for data sharing | 4.41 | 4.84 | -2.40 | 280.85 | 0.016 | 1.98 |

| Primary affiliation          | …with university hospital/medical faculty | …with psychological or other faculty | t-test results |
|------------------------------|-------------------------------------------|-------------------------------------|----------------|
| (n=139) mean                 | (n=144) mean                             | t                  | df | p   | BF<sub>10</sub> |
| Fear of being transparent    | 3.46                                     | 3.23                | 1.29 | 244.90 | 0.20 | 0.31 |
| Lack of experience with + appeal of preregistration | 3.85 | 3.60 | 1.56 | 244.80 | 0.12 | 0.44 |
| Complexity of own research   | 3.65                                     | 3.58                | 0.40 | 242.92 | 0.69 | 0.15 |
| Need for data governance     | 4.78                                     | 3.81                | 4.21 | 234.14 | *<0.001 | 496.00 |
| Unsupportive supervisor      | 2.87                                     | 2.15                | 4.04 | 230.99 | *<0.001 | 264.04 |
| Lack of experience with data sharing | 3.37 | 2.99 | 2.05 | 242.60 | 0.0415 | 1.01 |
| Lack of resources for data sharing | 4.81 | 4.46 | 1.80 | 243.35 | 0.07 | 0.64 |

| EU residency                 | Yes | No | t-test results |
|------------------------------|-----|----|----------------|
| (n=161) mean                 | (n=122) mean | t | df | p   | BF<sub>10</sub> |
| Fear of being transparent    | 3.38 | 3.31 | 0.43 | 267.13 | 0.67 | 0.14 |
| Lack of experience with + appeal of preregistration | 3.66 | 3.81 | -0.89 | 243.20 | 0.37 | 0.20 |
| Complexity of own research   | 3.57 | 3.63 | -0.38 | 267.10 | 0.70 | 0.14 |
| Need for data governance     | 4.36 | 3.89 | 3.09 | 250.66 | *<0.001 | 12.65 |
| Unsupportive supervisor      | 2.70 | 2.42 | 1.07 | 272.81 | 0.28 | 0.22 |
| Lack of experience with data sharing | 3.25 | 3.09 | 0.91 | 260.46 | 0.36 | 0.20 |
| Lack of resources for data sharing | 4.56 | 4.69 | -0.72 | 245.63 | 0.47 | 0.17 |

| Career level                 | Full/Associate Professor | Other | t-test results |
|------------------------------|--------------------------|-------|----------------|
| (n=123) mean                 | (n=124) mean             | t     | df | p   | BF<sub>10</sub> |
| Fear of being transparent    | 3.02                     | 3.66 | -4.23 | 280.16 | *<0.001 | 545.9 |
| Lack of experience with + appeal of preregistration | 3.60 | 3.84 | -1.56 | 280.87 | 0.12 | 0.42 |
| Complexity of own research   | 3.59                     | 3.59 | -0.03 | 272.55 | 0.98 | 0.13 |
| Need for data governance     | 4.22                     | 4.10 | 0.79 | 279.79 | 0.43 | 0.18 |
| Unsupportive supervisor      | 2.22                     | 2.83 | 3.56 | 276.69 | *<0.001 | 47.45 |
| Lack of experience with data sharing | 2.97 | 3.39 | 2.39 | 281.00 | 0.017 | 1.93 |
| Lack of resources for data sharing | 4.73 | 4.51 | 1.24 | 279.37 | 0.22 | 0.27 |

Table 4
Results from logistic regression with Cluster as the dependent variable and the demographic variables “research experience”, “career level”, “EU residency” and “affiliation with medical faculty” as predictors.

| Variable                        | Estimate     | Std. Error | z-value | p-value | 95% CI            |
|---------------------------------|--------------|------------|---------|---------|-------------------|
| (Intercept)                     | -0.329       | 0.330      | -0.996  | 0.319   | [-0.682 0.318]    |
| Research experience             | 0.113        | 0.312      | 0.361   | 0.718   | [-0.504 0.723]    |
| Career level                    | -0.570       | 0.312      | -1.830  | 0.067   | [-1.188 0.038]    |
| EU residency                    | 0.082        | 0.267      | 0.306   | 0.759   | [-0.444 0.605]    |
| Affiliation with medical faculty | 0.498        | 0.264      | 1.884   | 0.059   | [-0.018 1.019]    |
not further differentiate these two sorts of usage when asking why participants did not use BIDS, and whether they were going to use BIDS in the future. In that sense, the motivation of respondents to use/not use BIDS remains unclear. A substantial proportion of participants had not yet heard about BIDS. The major bottleneck for adopting BIDS appears to be limited time. This finding may reflect the expectation that introducing a new data standard to the lab would cost a lot of resources. Such apprehension is understandable in the face of limited resources that are available for research in the public domain. The availability of software that is easier to operate, e.g. to convert data into BIDS via GUI instead of command line interface, may facilitate the implementation of the data standard in more labs with less experience in programming (c.f. Table 5).

Fears and barriers in the way of adopting open science practices may be governed by a few underlying dimensions. If the latter were known, further research could investigate how these factors are shaped by current research practices, whether they relate to certain parameters (e.g. demographic variables), and whether they are amenable to targeted intervention. In a first approach to this question, we identified seven factors driving the responses to this survey. An exploratory analysis of these factors revealed some interesting differences between sub-groups of participants: experienced researchers at lower career level expressed higher fears of being transparent as compared to those at higher career level. Furthermore, a higher need for data governance was expressed by researchers at medical faculties as well as researchers residing within the EU, aligning with higher agreement among EU residents that they were
Table 5
In the end of the survey, the participants were given the opportunity to write a free-text comment to the authors of the survey. 45 (17%) of the participants took advantage of this option. The table lists a selection of these comments that bring up aspects that were not properly covered by the survey questions, or that give constructive feedback on the questionnaire itself. Comments have been shortened or reworded at the discretion of the author (CP) to make them more concise.

| Comments on further barriers in the way of open science |
|--------------------------------------------------------|
| General                                                |
| • Not forwarding career of aspiring PI                 |
| • Engineer would be needed for implementation          |
| BIDS                                                  |
| • Some format aspects such as tsv make BIDS inconvenient to use |
| • Journals require posting of primary data in idiosyncratic format, not in BIDS |
| • No MATLAB based option to convert to BIDS available |
| Preregistration                                        |
| • Difficulties getting preregistered report on longitudinal data accepted because first wave already collected |
| • Pre-registered analyses are often outdated once the study is complete |
| • Research questions that we address are always against the limits of what current analysis tools are capable of doing; questions mostly require fine-tuning methods, developing new approaches, bringing in other tools, etc. |
| • Preregistration constrains the creativity that is at the basis of progress in science |
| • Preregistration leads to terrible papers, where too much text is spent on explaining the preregistered content and the justifications for deviating from them |
| • Realistic standards for evaluating conformity to the preregistration missing |
| • Pre-registration is only meaningful for purely confirmatory studies. Purely confirmatory studies are only meaningful when there is a strong hypothesis and the goal of the confirmatory study is to confirm this hypothesis. |
| • The benefits of pre-registration have not been thoroughly demonstrated in order to merit its adoption |
| Data sharing                                           |
| • Data protection regulations from host institution incompatible with sharing |
| • Money to store and manage data repositories missing after grant terminates |
| • Neuroimaging data are intellectual property, rights of researchers acquiring data need to be protected |
| • No canonical interpretation of the laws/regulations available |
| • Practical guides on how to share clinical data online missing |
| • Whether the data will be used by anyone at all, and how long a given repository will last is unknown. |
| Comments expressing further fears of open science:     |
| • I could lose my job because not complying with host institutions data protection regulation |
| • My worries about not being able to publish every last ounce of results from my data are very high. |
| • I unfortunately think that the open science movement has the capacity to really disadvantage jr researchers in comparison to well-established labs |
| • Transparency is nice, but we seem to be willing to sacrifice part of our creativity through forced standardization |
| • My greatest fear is giving away your research ideas with preregistration |
| Feedback on the questionnaire:                         |
| • Don’t think this survey captured my opinions very accurately. I am a strong supporter of Open Science, but have a number of concerns about data sharing and the potential for abuse |
| • A question was lacking about lack of confidence in how to interpret the judicial bases for data sharing |
| • In the survey it was a bit unclear if data sharing refers to neuroimaging data only or in general |
| • Many researchers will not reply, let alone reply honestly |
| • I think that analyses for individual papers can be presupposed, but it would be hard to pre-specify analyses for large studies. I understood that you are referring to pre-registration of the entire large study, which I said I do not do |
| • There was insufficient opportunities to comment on the role of journals (static, laminated publications etc) in effectively prohibiting open science practices. Open science may obviate the need for journals. |
| • The question at the bottom of the page asking for legal issues yes/no was difficult to answer, because we have these issues for old data (not considering data sharing) but we always take care of these now in new projects (including data sharing). |
| • Many of your questions are difficult to answer / ambiguous since there are different hurdles to share data from healthy participants and patients |
| Other:                                                 |
| Pre-registration provides a way of claiming precedence for an idea, even if the results don’t bear out the findings |

not allowed to share imaging data and lower agreement to share primary data from their next neuroimaging study online. Research with patients in general is subject to strict juridical regulations for data protection. The GDPR has increased data protection requirements recently and poses significant challenges to researchers across Europe to reconcile data protection regulations with the sharing of human data (Clarke et al., 2019; Pelouquin et al., 2020; Suman and Pierce, 2018). Comparisons of EU vs. non-EU participants should be taken with some caution as we did not actively match the groups based on demographic characteristics, although we did not observe significant differences in demographic variables (t-values < 1.657, p-values > 0.098). Researchers at medical faculties as compared to other faculties also had higher chances to have a supervisor they perceived as less supportive with regards to reproducibility practices. Professors naturally scored low on this.

We explored the existence of distinct subgroups which differed in their profiles on open science-related fears and barriers. If such subgroups were identified, and generalized to a larger research community, this could inform how more targeted interventions, teaching programs, and policies can be developed. Cluster analysis revealed two groups that were either characterized by generally higher or generally lower fears and barriers. To take concerns of the high fears/barriers group seriously, the community should e.g. work out detailed guidelines to reconcile preregistration with challenges brought along by complex imaging projects and dominantly explorative research. The need for data governance could be addressed by stricter access requirements such as more restrictive licenses or Data Use Agreements (DUAs). Another way can be ensuring the data reuser properly cites the original data submitter. These can be done by the data-sharing platform. Further instruments to respond to the many barriers and fears of data sharing have been described elsewhere (Houtkoop et al., 2018). Among the factors distinguishing the high and low fears/barriers groups was the complexity of one’s research, which is usually less under the researcher’s voluntary control than other factors. This highlights the importance to support researchers with accessible resources, tools, and software, for example, preregistration templates specifically designed for fMRI (Beyer et al., 2021). Explorative regression analysis showed that a model including all demographic variables we had used to predict belongingness to the two clusters barely exceeded chance level (p = .039) and the out-of-sample accuracy was relatively low. None of the individual variables that were tested significantly contributed to prediction. Future research is necessary to confirm our findings and to explore more variables that may aid the prediction.
4.1. Limitations

Robust replication of our findings is necessary, in particular regarding the results from exploratory analyses of group differences. Conclusions from this survey are limited by the low response rate to the survey invitation (2.4%), which was below the rates reported in previous investigations (4% (Schmidt et al., 2016), 5% (Houtkoop et al., 2018), 9% (Tenopir et al., 2011)). Studies like ours that remove incomplete responses tend to find lower response rates. In addition, unlike previous studies, we did not recruit via our professional networks. While the latter is an effective strategy to increase responses, it may have the drawback of inflating the proportion of participants sharing a certain perspective on the topic (although the recruitment strategy we used does not protect against that bias). Clearly, researchers would only take the effort to participate when they shared a basic interest in the topic. The cluster analysis showed that about half of the sample reported less experience with and training in open science techniques as well as higher fears thereof, and we found that about 41% did not know BIDS before. Although it is hard to rule out sampling or response bias and the sample may not be representative, these numbers evidence reasonable variance in familiarity and attitude towards open science practices, which is necessary to receive meaningful results. We also note that some existing clusters can be underrepresented in our study, especially when they only make up a very small minority in the neuroimaging community or have a systematically lower propensity to respond to our survey. The recruitment strategy emphasized on researchers working with fMRI and investigating humans, generalization to researchers working with other neuroimaging modalities and other species is therefore limited. BIDS was initially introduced for human fMRI, therefore the results from this sample are easier to interpret as compared to a more heterogeneous sample of researchers working with different modalities, for whom the data standard became available later or which were not yet covered by BIDS at the time of this survey taking place. As the sample is mainly composed of advanced career level researchers, conclusions cannot be generalized to very early career researchers. Also, it should be noted that the questionnaire we had used is not a validated instrument. The Open Scholarship Survey (Beaudry et al., 2021), for instance, which has been designed for the investigation of similar research questions as ours, was not yet available when this project was started. Thus, the factor analytic results need to be interpreted in the context of this survey. The selection of items for this questionnaire was driven by the research interest of the authors, review of the existing literature on data sharing as well as practical considerations, i.e., to limit the effort of participants to complete the survey. We focused on barriers and fears, and did not interrogate beliefs about the benefits of open science (e.g. that open science practices can increase the quality and impact of one’s research output). Also, we did not assess objective measures such as the number of preregistered studies or the number of shared data sets, information that could be used for validation. Some aspects of open science were not touched by the survey such as sharing of materials and code. Thus, the results cover certain aspects of open science practices while others are not illuminated. Notwithstanding, it would be useful for the community to address questions around other practices in a similar manner. Finally, a few ambiguities in the questions where discovered by the participants who had shared their feedback with us (c.f. Table 5).

4.2. Conclusions

Limited time and insufficient education about tools to structure and share data were reported as the major barriers for adopting open science practices. Although half of the participants were experienced with preregistration, the willingness to preregister studies in the future was restrained, and some participants expressed a critical view on preregistration. Neuroimaging researchers are open to data sharing and most have experience with sharing primary research data. Concerns regarding the protection of the privacy of participants from neuroimaging experiments and missing sections in consent forms to enable data sharing (cf. Bannier et al., 2021) make researchers hesitant to share neuroimaging data. Measures to reinforce data sharing, to educate researchers how to prepare consent forms enabling data sharing, and to inform about existing infrastructure and mechanisms of data protection may increase the willingness to share primary neuroimaging data. Analyses of individual differences suggest that some groups of researchers may benefit more from certain measures to facilitate the usage of open science techniques: (1) Experienced researchers before tenure may benefit from measures reducing fears of being transparent. (2) Researchers in the EU may benefit from measures to satisfy the need for data governance. (3) Researchers at medical faculties would also benefit from measures to satisfy the need for data governance. In addition, researchers at medical faculties would benefit from measures aiming to create an environment that is more supportive of open science practices.

Declaration of competing interest

The authors declare no conflicts of interest.

Credit authorship contribution statement

Christian Paret: Conceptualization, Methodology, Data curation, Supervision, Project administration, Writing – original draft. Nike Unverhau: Software, Formal analysis, Data curation, Writing – review & editing. Franklin Feinhold: Methodology, Writing – review & editing. Russell A. Poldrack: Methodology, Writing – review & editing. Madita Stirner: Software, Formal analysis, Data curation. Christian Schmah: Methodology, Writing – review & editing. Maurizio Sicorello: Investigation, Project administration, Writing – review & editing.

Acknowledgement

Thanks are due to Gordon Feld for critical reading of an earlier version of this manuscript. We are thankful to our colleagues from the Department for Psychosomatic Medicine and Psychotherapy, CIMH, for their feedback on the questionnaire during development. Open access publication of this work was funded by the CIMH publication fund for young scientists.

References

Amico, E., Goñi, J., 2018. The quest for identifiability in human functional connectomes. Sci Rep 8, 8254. doi:10.1038/s41598-018-25089-1.
Bannier, E., Barker, G., Borghesani, V., Broeckx, N., Clement, P., Emblem, K.E., Ghosh, S., Glerean, E., Gorgolewski, K.J., Hava, M., Halchenko, Y.O., Herholz, P., Hespel, A., Hiemis, S., Hsu, Y., Hsu, C.-P., Huijser, D., de la Iglesia Vayá, M., Jancaulek, R., Kat-saros, V.K., Kieseler, M.-L., Maumet, C., Moreau, C.A., Mutsaerts, H.J., Oostenveld, R., Ozturk-Işık, E., Pascual Leone Espinosa, N., Pellman, J., Pernet, C.R., Pizziini, F.B., Tribulic, A.S., Toussaint, P.-J., Visconti di Oleggio Castello, M., Wang, F., Wang, C., Zhu, H., 2021. The Open Brain Consent: Informing neuroresearch participants and obtaining consent to share brain imaging data. Human Brain Mapping 42, 1945-1951. doi:10.1002/hbm.25351.
Barri, S., Amico, E., Vike, N., Talavágo, T.M., Goñi, J., 2019. Uncovering multi-site identifiability based on resting-state functional connectomes. NeuroImage 202, 115967. doi:10.1016/j.neuroimage.2019.06.045.
Beaudry, J.L., Chen, D.T., Cook, B.G., Errington, T.M., Fortunato, L., Given, L., Hahn, K., Ihle, M., Mellor, D.T., Nosteck, B.A., Pfeiffer, N., Reedy, M., Soderberg, C.K., 2021. The Open Scholarship Survey (OSS) [WWW Document]. URL: https://doi.org/10.17605/OSF.IO/NBB3N (accessed 9.28.21).
Beyer, F., Flannery, J., Gau, R., Janssen, L., Scharre, L., Hartmann, H., Nilsonne, G., Martin, S., Khalil, A., Lipp, I., Puhlmann, L., Heinrichs, H., Mohamed, A., Herholz, P., Sicorello, M., Panagoulas, E., 2021. A fMRI preregistration template. PsychArchives doi:10.23668/psycharchives.5121.
Bajracharya, A., Bakst, L., Ball, S., Barbieri, M., Bault, N., Beaton, D., Beintner, J., Benoit, R.G., Berkers, K.M.W.J., Bhunji, J.P., Biwal, B.B., Bobadilla-Suarez, S., Bortolini, T., Bottenhorn, K.L., Bowring, A., Braem, S., Brooks, H.R., Brunder, E.G., Calderon, C.B., Camilleri, J.A., Castrellon, J.J., Cecchetti, L., Cestlick, E.C., Cole, Z.J., Collignon, O., Cox, R.W., Cunningham, W.A., Czeczoch, S., Dadi, K., Davis, C.P., Luca, A.D., Delgado, M.R., Demirerio, L., Dennisson, J.B., Di, X., Dickie, E.W., Dobryakova, E., Donnell, C.L., Doktar, J., Duncan, N.W., Durme, J., Eed, A., Eickhoff, S.B., Erhart, A., Fontanesi, L., Fricke, G.M., Fu, S., Galván, A., Gau, R., Genon, S., Glattard, T., Glerean, E., Goeman, J.J., Golowin, S.A.E., González-García, C., Gorgolewski, K.J., Grady, C.L., Green,
