

FMRIPrep: a robust preprocessing pipeline for functional MRI

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1 Preprocessing of functional MRI (fMRI) involves numerous steps to clean and standardize data
 2 before statistical analysis. Generally, researchers create *ad hoc* preprocessing workflows for
 3 each new dataset, building upon a large inventory of tools available for each step. The
 4 complexity of these workflows has snowballed with rapid advances in MR data acquisition and
 5 image processing techniques. We introduce *fMRIPrep*, an analysis-agnostic tool that
 6 addresses the challenge of robust and reproducible preprocessing for task-based and resting
 7 fMRI data. *fMRIPrep* automatically adapts a best-in-breed workflow to the idiosyncrasies of
 8 virtually any dataset, ensuring high-quality preprocessing with no manual intervention. By
 9 introducing visual assessment checkpoints into an iterative integration framework for
 10 software-testing, we show that *fMRIPrep* robustly produces high-quality results on a diverse
 11 fMRI data collection comprising participants from 54 different studies in the OpenfMRI
 12 repository. We review the distinctive features of *fMRIPrep* in a qualitative comparison to other
 13 preprocessing workflows. We demonstrate that *fMRIPrep* achieves higher spatial accuracy as
 14 it introduces less uncontrolled spatial smoothness than one commonly used preprocessing
 15 tool. *fMRIPrep* has the potential to transform fMRI research by equipping neuroscientists with
 16 a high-quality, robust, easy-to-use and transparent preprocessing workflow which can help
 17 ensure the validity of inference and the interpretability of their results.

18 Functional magnetic resonance imaging (fMRI) is a commonly used technique to map human brain
 19 activity¹. However, the blood-oxygen-level dependent (BOLD) signal measured by fMRI is typically
 20 mixed with many non-neural sources of variability². Preprocessing identifies the nuisance sources and
 21 reduces their effect on the data³. Other major preprocessing steps⁴ deal with particular imaging arti-
 22 facts and the anatomical location of signals. For instance, slice-timing⁵ correction (STC), head-motion
 23 correction (HMC), and susceptibility distortion correction (SDC) address particular artifacts; while co-
 24 registration, and spatial normalization are concerned with signal location (see Online Methods, sec.
 25 Preprocessing of fMRI in a nutshell, for a summary). Extracting a signal that is most faithful to the
 26 underlying neural activity is crucial to ensure the validity of inference and interpretability of results⁶.
 27 Faulty preprocessing may lead to the interpretation of noise patterns as signals of interest. For example,
 28 Power et al. demonstrated that unaccounted-for head-motion can generate spurious and systematic cor-
 29 relations in resting-state fMRI⁷, which would be interpreted as functional connectivity. An illustration
 30 of failed spatial normalization familiar to most researchers is finding significant activation outside of the

31 brain. Other preprocessing choices may result in the removal of signal originating from brain activity.
 32 The ongoing debate on the need for regressing out global signals^{2,8,9} reflects just such concerns. Thus,
 33 a primary goal of preprocessing is to reduce sources of Type I errors without inducing excessive Type II
 34 errors.

35 Workflows for preprocessing fMRI produce two broad classes of outputs: *preprocessed* data (as op-
 36 posed to *raw*, original data) and measurements of experimental *confounds* for use in later modeling.
 37 Preprocessed data generally include new fMRI time-series after the application of retrospective signal
 38 correction and filtering algorithms. In addition, these data are typically resampled onto a target space
 39 appropriate for analysis, such as a standardized anatomical reference. The *confounds* are additional
 40 time-series such as physiological recordings and estimated noise sources that are useful for analysis (e.g.
 41 they can be applied as nuisance regressors). Some commonly used confounds include: motion param-
 42 eters, framewise displacement (FD⁷), spatial standard deviation of the data after temporal differencing
 43 (DVARS⁷), global signals, etc. Preprocessing may include further steps for denoising and estimation
 44 of confounds. For instance, dimensionality reduction methods based on principal components analysis
 45 (PCA) or independent components analysis (ICA), such as component-based noise correction (*Comp-*
 46 *Cor*¹⁰) or automatic removal of motion artifacts (ICA-AROMA¹¹).

47 The neuroimaging community is well equipped with tools that implement the majority of the individ-
 48 ual steps of preprocessing described so far. These tools are readily available within software packages
 49 including AFNI¹², ANTs¹³, FreeSurfer¹⁴, FSL¹⁵, Nilearn¹⁶, or SPM¹⁷. Despite the wealth of accessible
 50 software and multiple attempts to outline best practices for preprocessing^{2,4,6,18}, the large variety of data
 51 acquisition protocols have led to the use of *ad hoc* pipelines customized for nearly every study; for exam-
 52 ple, Carp¹⁹ found 223 unique analysis workflows across 241 fMRI studies. Thus, current preprocessing
 53 workflows offer a poor trade-off between the quality of results and robust, consistent performance on
 54 datasets other than those that they were built for. Alternatively, researchers can adopt the acquisition
 55 protocols defined by large neuroimaging consortia like the Human Connectome Project (HCP²⁰) or the
 56 UK Biobank²¹, which then allows the use of their preprocessing pipelines^{22,23} developed for those stud-
 57 ies. Since these pipelines are optimized for particular data acquisition protocols, they are not applicable
 58 to datasets acquired using different protocols. In practice, the neuroimaging community lacks a prepro-
 59 cessing workflow that reliably provides high-quality and consistent results on arbitrary datasets.

60 Here we introduce *fMRIprep*, a preprocessing workflow for task-based and resting-state fMRI. *fMRI-*
 61 *Prep* is built around four driving principles: 1) **robustness** to the idiosyncrasies of the input dataset; 2)
 62 **quality** of preprocessing outcomes; 3) **transparency** to encourage the scrutiny of preprocessing results
 63 for quality, and to facilitate accurate communication of the methods; and 4) **ease-of-use** with the min-
 64 imization of manual intervention. *fMRIprep* is robust by virtue of a flexible, self-adapting architecture
 65 that combines tools from existing neuroimaging analysis packages. Tools for each processing operation
 66 are selected through an evidence-driven and community-informed optimization process. Here we also
 67 report a comprehensive evaluation of the workflow on a large and heterogeneous subsample of the
 68 OpenfMRI repository, to quantify robustness and quality of the results. This evaluation leverages the
 69 comprehensive visual reports generated by *fMRIprep*, which facilitate assessment and curation of the re-
 70 sults. These reports exemplify the “glass-box” philosophy with which the software was developed; rather
 71 than hiding a complex set of operations within a monolithic black box, *fMRIprep* exposes interim results
 72 at multiple steps to encourage active engagement by the scientist.

RESULTS

73 *fMRIprep* is a robust and convenient tool for researchers and clinicians to prepare both task-based
 74 and resting-state fMRI for analysis. Its outputs enable a broad range of applications, including within-
 75 subject analysis using functional localizers, voxel-based analysis, surface-based analysis, task-based
 76 group analysis, resting-state connectivity analysis, and many others. In the following, we describe the
 77 overall architecture, software engineering principles, and a comprehensive validation of the tool.

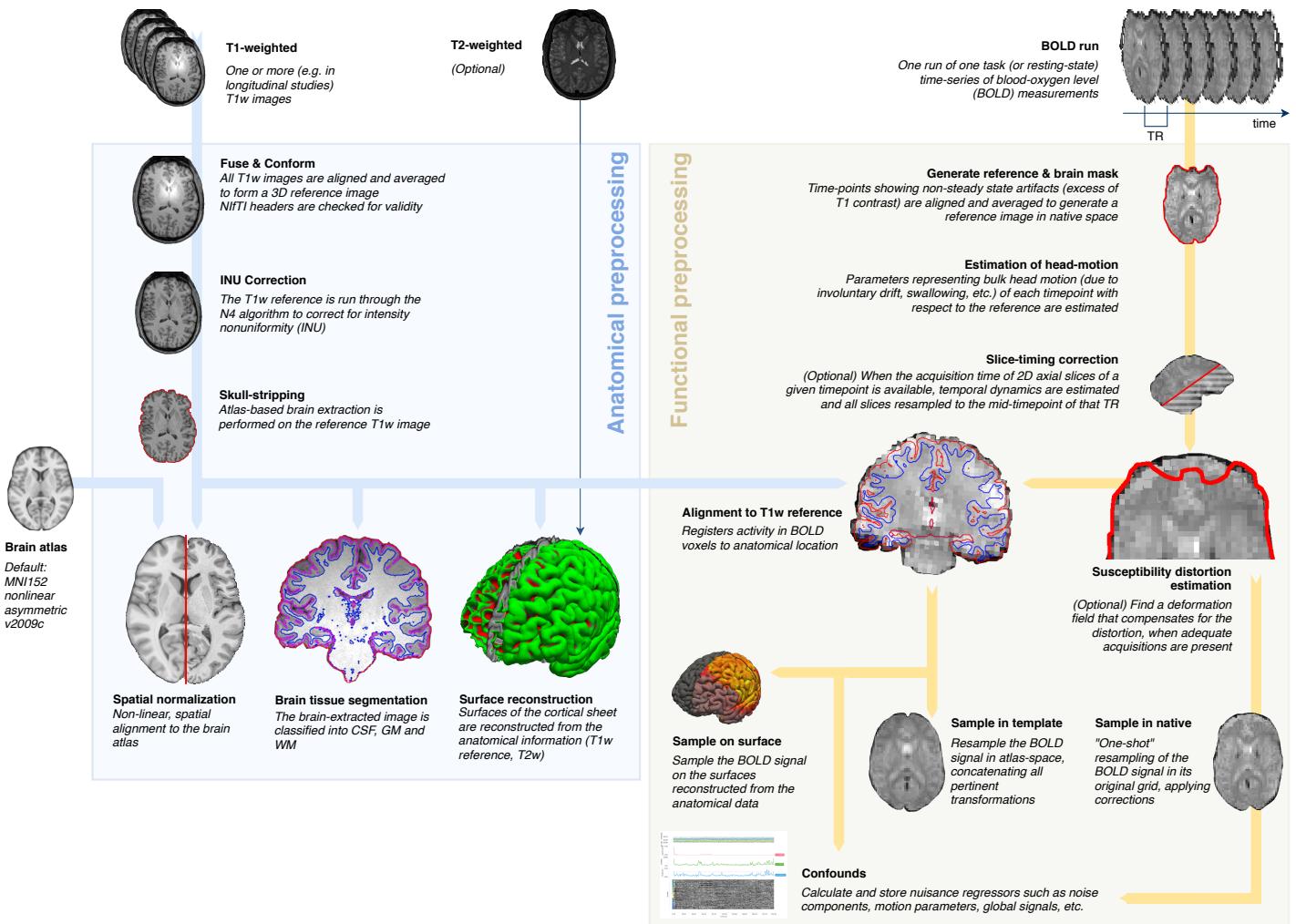


Figure 1. fMRIPrep is a fMRI preprocessing tool that adapts to the input dataset. Leveraging the Brain Imaging Data Structure (BIDS²⁴), the software self-adjusts automatically, configuring the optimal workflow for the given input dataset. Thus, no manual intervention is required to locate the required inputs (one T1-weighted image and one BOLD series), read acquisition parameters (such as the repetition time –TR– and the slice acquisition-times) or find additional acquisitions intended for specific preprocessing steps (like field maps and other alternatives for the estimation of the susceptibility distortion). Outputs are easy to navigate due to compliance with the BIDS Extension Proposal for derived data (see Online Methods, Figure S4).

78 A modular design allows for a flexible, adaptive workflow

79 The foundation of *fMRIPrep* is presented in *Figure 1*. The workflow is composed by sub-workflows
 80 that are dynamically assembled into different configurations depending on the input data. These building
 81 blocks combine tools from widely-used, open-source neuroimaging packages (see *Table 1* for a summary). *Nipype*²⁵ is used to stage the workflows and to deal with execution details (such as resource
 82 management). As presented in *Figure 1*, the workflow comprises two major blocks, separated into
 83 anatomical and functional MRI processing streams.

85 **Automatically understanding the input dataset.** The Brain Imaging Data Structure (BIDS²⁴) allows
 86 *fMRIPrep* to precisely identify the structure of the input data and gather all the available metadata (e.g.
 87 imaging parameters). *fMRIPrep* reliably adapts to dataset irregularities such as missing acquisitions or
 88 runs through a set of heuristics. For instance, if only one participant of a sample lacks field-mapping
 89 acquisitions, *fMRIPrep* will by-pass the correction step for that one participant.

Table 1. State-of-art neuroimaging offers a large catalog of readily available software tools. *fMRIPrep* integrates best-in-breed tools for each of the preprocessing tasks that its workflow covers.

Preprocessing task	<i>fMRIPrep</i> includes	Alternatives (not included within <i>fMRIPrep</i>)
Anatomical T1w brain-extraction	<code>antsBrainExtraction.sh</code> (ANTs)	<code>bet</code> (FSL), <code>3dSkullstrip</code> (AFNI), <code>MRTOOL</code> (SPM Plug-in)
Anatomical surface reconstruction	<code>recon-all</code> (FreeSurfer)	CIVET, BrainSuite, Computational Anatomy (SPM Plug-in)
Head-motion estimation (and correction)	<code>mcflirt</code> (FSL)	<code>3dvolreg</code> (AFNI), <code>spm_realign</code> (SPM), <code>cross_realign_4dfp</code> (4dfp), <code>antsBrainRegistration</code> (ANTs)
Susceptibility-derived distortion estimation (and unwarping)	<code>3dqwarp</code> (AFNI)	<code>fugue</code> and <code>topup</code> (FSL), FieldMap and HySCO (SPM Plug-ins)
Slice-timing correction	<code>3dTshift</code> (AFNI)	<code>slicetimer</code> (FSL), <code>spm_slice_timing</code> (SPM), <code>interp_4dfp</code> (4dfp)
Intra-subject registration	<code>bbregister</code> (FreeSurfer), <code>flirt</code> (FSL)	<code>3dvolreg</code> (AFNI), <code>antsRegistration</code> (ANTs), <code>Coregister</code> (SPM GUI)
Spatial normalization (inter-subject co-registration)	<code>antsRegistration</code> (ANTs)	<code>@auto_tlrc</code> (AFNI), <code>fnirt</code> (FSL), <code>Normalize</code> (SPM GUI)
Surface sampling	<code>mri_vol2surf</code> (FreeSurfer)	MNE, Nilearn
Subspace selection methods	<code>melodic</code> (FSL), ICA-AROMA	Nilearn, LMGS (SPM Plug-in)
Confounds	<i>in-house</i> implementation	TAPAS PhysIO (SPM Plug-in)
Steady-state detection	<i>in-house</i> implementation	<i>Ad hoc</i> implementations

90 Preprocessing anatomical images. The T1-weighted (T1w) image is corrected for intensity non-
91 uniformity (INU) using `N4BiasFieldCorrection`²⁶ (ANTs), and skull-stripped using `antsBrainExtrac-`
92 `tion.sh` (ANTs). Skull-stripping is performed through coregistration to a template, with two options
93 available: the OASIS template²⁷ (default) or the NKI template²⁸. Using visual inspection, we have found
94 that this approach outperforms other common approaches, which is consistent with previous reports²².
95 When several T1w volumes are found, the INU-corrected versions are first fused into a reference T1w
96 map of the subject with `mri_robust_template`²⁹ (FreeSurfer). Brain surfaces are reconstructed from
97 the subject's T1w reference (and T2-weighted images if available) using `recon-all`³⁰ (FreeSurfer). The
98 brain mask estimated previously is refined with a custom variation of a method (originally introduced in
99 `Mindboggle`³¹) to reconcile ANTs-derived and FreeSurfer-derived segmentations of the cortical gray matter
100 (GM). Both surface reconstruction and subsequent mask refinement are optional and can be disabled
101 to save run time when surface-based analysis is not needed. Spatial normalization to the ICBM 152
102 Nonlinear Asymmetrical template³² (version 2009c) is performed through nonlinear registration with
103 `antsRegistration`³³ (ANTs), using brain-extracted versions of both the T1w reference and the standard
104 template. ANTs was selected due to its superior performance in terms of volumetric group level over-
105 lap³⁴. Brain tissues –cerebrospinal fluid (CSF), white matter (WM) and GM– are segmented from the
106 reference, brain-extracted T1w using `fast`³⁵ (FSL).

107 Preprocessing functional runs. For every BOLD run found in the dataset, a reference volume and its
108 skull-stripped version are generated using an in-house methodology (reported in Online Methods, sec.
109 Particular processing elements of *fMRIPrep*). Then, head-motion parameters (volume-to-reference trans-
110 form matrices, and corresponding rotation and translation parameters) are estimated using `mcflirt`³⁶
111 (FSL). Among several alternatives (see *Table 1*), `mcflirt` is used because its results are comparable
112 to other tools³⁷ and it stores the estimated parameters in a format that facilitates the composition of
113 spatial transforms to achieve one-step interpolation (see below). If slice timing information is available,
114 BOLD runs are (optionally) slice time corrected using `3dTshift` (AFNI¹²). When field map information is

available, or the experimental “fieldmap-less” correction is requested (see Highlights of *fMRIPrep* within the neuroimaging context), SDC is performed using the appropriate methods (see Online Methods, *Figure S3*). This is followed by co-registration to the corresponding T1w reference using boundary-based registration³⁸ with nine degrees of freedom (to minimize remaining distortions). If surface reconstruction is selected, *fMRIPrep* uses *bbregister* (FreeSurfer). Otherwise, the boundary based coregistration implemented in *flirt* (FSL) is applied. In our experience, *bbregister* yields the better results³⁸ due to the high resolution and the topological correctness of the GM/WM surfaces driving registration. To support a large variety of output spaces for the results (e.g. the native space of BOLD runs, the corresponding T1w, FreeSurfer’s *fsaverage* spaces, the atlas used as target in the spatial normalization step, etc.), the transformations between spaces can be combined. For example, to generate preprocessed BOLD runs in template space (e.g. MNI), the following transforms are concatenated: head-motion parameters, the warping to reverse susceptibility-distortions (if calculated), BOLD-to-T1w, and T1w-to-template mappings. The BOLD signal is also sampled onto the corresponding participant’s surfaces using *mri_volsurf* (FreeSurfer), when surface reconstruction is being performed. Thus, these sampled surfaces can easily be transformed onto different output spaces available by concatenating transforms calculated throughout *fMRIPrep* and internal mappings between spaces calculated with *recon-all*. The composition of transforms allows for a single-interpolation resampling of volumes using *antsApplyTransforms* (ANTs). Lanczos interpolation is applied to minimize the smoothing effects of linear or Gaussian kernels³⁹. Optionally, ICA-AROMA can be performed and corresponding “non-aggressively” denoised runs are then produced.

Extraction of nuisance time-series. *FMRIPrep* is analysis-agnostic and thus, it does not perform any temporal denoising. Nonetheless, it provides researchers with a diverse set of confound estimates that could be used for explicit nuisance regression or as part of higher-level models. This lends itself to decoupling preprocessing and behavioral modeling as well as evaluating robustness of final results across different denoising schemes. A set of physiological noise regressors are extracted for the purpose of performing component-based noise correction (*CompCor*¹⁰). Principal components are estimated after high-pass filtering the BOLD time-series (using a discrete cosine filter with 128s cut-off) for the two *CompCor* variants: temporal (*tCompCor*) and anatomical (*aCompCor*). Six *tCompCor* components are then calculated from the top 5% variable voxels within a mask covering the subcortical regions. Such subcortical mask is obtained by heavily eroding the brain mask, which ensures it does not include cortical GM regions. For *aCompCor*, six components are calculated within the intersection of the aforementioned mask and the union of CSF and WM masks calculated in T1w space, after their projection to the native space of each functional run (using the inverse BOLD-to-T1w transformation). Frame-wise displacement⁴⁰ is calculated for each functional run, using the implementation in Nipype. DVARS are also calculated using Nipype. Three global signals are extracted within the CSF, the WM, and the whole-brain masks using Nilearn¹⁶. If ICA-AROMA¹¹ is requested, the “aggressive” noise-regressors are collected and placed within the corresponding confounds files. In addition, a “non-aggressive” version of preprocessed data is also provided since this variant of ICA-AROMA denoising cannot be performed using only nuisance regressors.

154 **Visual reports ease quality control and maximize transparency**

155 Users can assess the quality of preprocessing with an individual report generated per participant.
 156 *Figure 2* shows an example of such reports and describes their structure. Reports contain dynamic
 157 and static mosaic views of images at different quality control points along the preprocessing pipeline.
 158 Many visual elements of the reports, as well as some of the figures in this manuscript are generated
 159 using Nilearn¹⁶. Only a web browser is required to open the reports on any platform, since they are
 160 written in hypertext markup language (HTML). HTML also enables the trivial integration within online
 161 neuroimaging services such as [OpenNeuro.org](https://openneuro.org), and maximizes shareability between peers. These reports
 162 effectively minimize the amount of time required for assessing the quality of the results. They also help
 163 understand the internals of processing by visually reporting the full provenance of data throughout the

164 workflow. As an additional transparency enhancement, reports are accompanied by a *citation boilerplate*
 165 (see Online Methods, *Box S1*) that follows the guidelines for reporting fMRI studies by Poldrack et
 166 al.⁴¹. Meant for its inclusion within the methodological section of papers using *fMRIPrep*, the boilerplate
 167 provides a literate description of the processing that includes software versions of all tools involved in
 168 the particular workflow and gives due credit to all authors of all of the individual pieces of software used
 169 within *fMRIPrep*.

170 Highlights of *fMRIPrep* within the neuroimaging context

171 *fMRIPrep* is not the first preprocessing pipeline for fMRI data. The most widely used neuroimaging
 172 packages generally provide workflows, such as afni_proc.py (AFNI) or feat (FSL). Other alternatives
 173 include C-PAC⁴² (configurable pipeline for the analysis of connectomes), HCP Pipelines or the Batch
 174 Editor of SPM. In this section, we highlight some additional features beyond robustness and quality that
 175 will likely incline scientists to find in *fMRIPrep* the best fit for their fMRI preprocessing needs.

176 **Analysis-agnostic:** *fMRIPrep* is meant to support all kinds of analysis. To some extent, all alternative
 177 workflows limit the possible analyses that can be performed on the preprocessed data. These limitations
 178 mostly derive from the coordinates space of the outputs and the regular (volume) vs. irregular (surface)
 179 sampling of the BOLD signal. For example, HCP Pipelines supports surface-based analyses on subject
 180 or template space. Conversely, afni_proc.py, C-PAC and feat are volume-based only. *fMRIPrep* allows
 181 a multiplicity of output spaces including subject-space and atlases for both volume-based and surface-
 182 based analyses. While *fMRIPrep* avoids including processing steps that may limit further analysis (e.g.
 183 spatial smoothing), other tools are designed to perform preprocessing that supports specific analysis
 184 pipelines. For instance, C-PAC performs several processing steps towards the connectivity analysis of
 185 resting-state fMRI.

186 **Susceptibility distortion correction (SDC) in the absence of field maps.** Many legacy and current
 187 human fMRI protocols lack the MR field maps necessary to perform standard methods for SDC. *fMRIPrep*
 188 adapts the “fieldmap-less” correction method for diffusion echo-planar imaging (EPI) images introduced
 189 by Wang et al.⁴³. They propose using the same-subject T1w reference as the *undistorted* target in a
 190 nonlinear registration scheme. To maximize the similarity between the T2* contrast of the EPI scan
 191 and the reference T1w, the intensities of the latter are inverted. To regularize the optimization of the
 192 deformation field only displacements along the phase-encoding (PE) direction are allowed, and the
 193 magnitude of the displacements is modulated using priors. To our knowledge, no other existing pipeline
 194 implements “fieldmap-less” SDC to the BOLD images.

195 ***fMRIPrep* is thoroughly documented, community-driven, and developed with high-standards of**
 196 **software engineering.** Preprocessing pipelines are generally well documented, however the extreme
 197 flexibility of *fMRIPrep* makes its proper documentation substantially more challenging. As for other large
 198 scientific software communities, *fMRIPrep* contributors pledge to keep the documentation thorough and
 199 updated along coding iterations. Packages also differ on the involvement of the community: while *fMRI-Prep*
 200 includes researchers in the decision making process and invites their suggestions and contributions,
 201 other packages have a more closed model where the feedback from users is more limited (e.g. a mailing
 202 list). In contrast to other pipelines, *fMRIPrep* is community-driven. This paradigm allows the fast adop-
 203 tion of cutting-edge advances on fMRI preprocessing. For example, while *fMRIPrep* initially performed
 204 STC before HMC, we adapted the tool to the recent recommendations of Power et al.¹⁸ upon a user’s
 205 request*. This model has allowed the user base to grow rapidly and enabled substantial third-party con-
 206 tributions to be included in the software, such as the support for processing datasets without anatomical
 207 information. The open-source nature of *fMRIPrep* has permitted frequent code reviews that are effective
 208 in enhancing the software’s quality and reliability⁴⁴. Finally, *fMRIPrep* undergoes continuous integration
 209 testing (see Online Methods, *Figure S5*), a technique that has recently been proposed as a mean to
 210 ensure reproducibility of analyses in computational sciences^{45,46}.

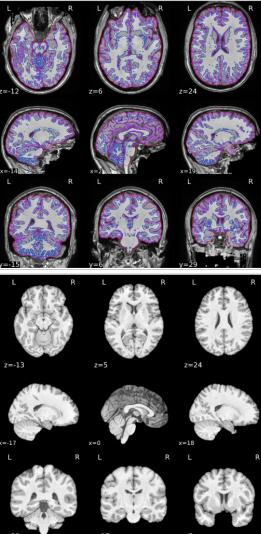
*<https://neurostars.org/t/obtaining-movement-estimates-before-slice-time-correction/1007>

Summary

Reports start with an overview of the dataset, as identified using BIDS.



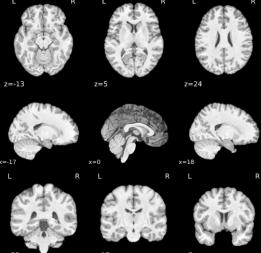
T1-weighted reference, brain mask, intensity inhomogeneity and brain tissue segmentation panel. A static mosaic allows the assessment of these four crucial steps of pre-processing anatomical images.



Anatomical processing

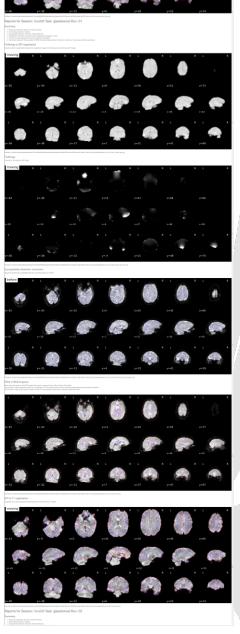
Several panels allow for quality control of the anatomical workflow. Brain tissue segmentation, spatial normalization and surface reconstruction (if requested) can be inspected using these visualization panels.

Spatial normalization. A dynamic mosaic that transitions between the target atlas space and the T1w-reference aligned into that space allows checking the accuracy of this image registration process.

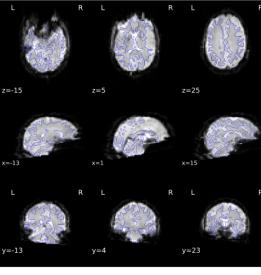


Fieldmaps processing

When the dataset contains any of the supported alternatives to estimate the deformation map corresponding to susceptibility distortions, these panels help assess these images were correctly processed.



Susceptibility distortion correction. If fieldmap information was found or the "fieldmap-less" correction is requested, the step is assessed with a dynamic mosaic that transitions between the unwarped ("after") and original ("before"). Contours of the white-matter are also presented as anatomical cue.



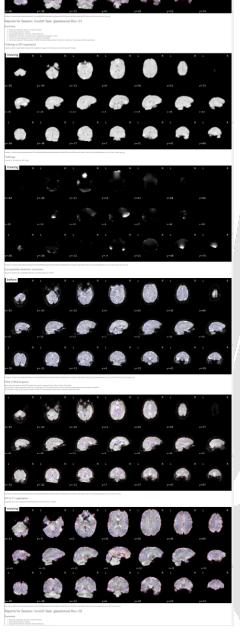
Functional processing

Each BOLD run across the different tasks and sessions will be presented at different quality control points.

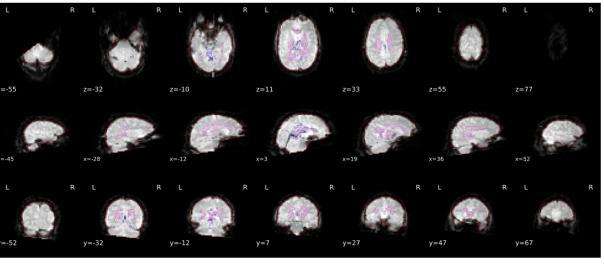
First, when fieldmaps were found, some mosaics will show the alignment of those maps to the BOLD reference. The block ends with a dynamic plot showing how images are unwarped.

The report also shows processing in native BOLD space plotting the brain mask calculated from the functional MR signal and the regions-of-interest (ROIs) where the CompCor confounds are calculated.

Finally, the alignment between same-subject T1-weighted and that specific BOLD run is presented.



BOLD mask and CompCor ROIs. The final BOLD signal is presented, with contours representing the outline of the brain mask, and two regions-of-interest (ROIs) where CompCor confounds are estimated.



Errors

fMRIprep is explicit about errors, and any problems encountered along the processing will be listed at the end of the report, with collapsible panels containing the specific detail of each error.

Alignment of BOLD and the T1w reference. The correct alignment to the anatomical reference is assessed with a dynamic mosaic that renders the reconstructed surfaces over the BOLD reference.

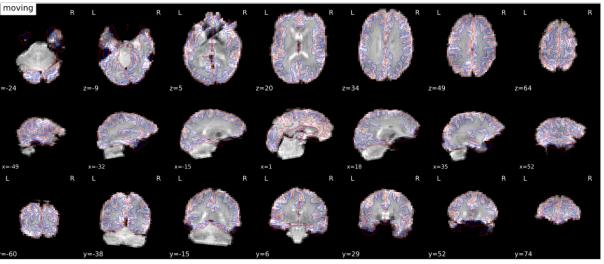


Figure 2. Anatomy of the visual reports generated by fMRIprep. The visual reports ease quality control of the results and help understand the preprocessing flow.

211 Ensuring reproducibility with hard versioning and containers. For enhanced reproducibility, *fMRI-Prep*
 212 fully supports execution via the Docker (<https://docker.com>) and Singularity⁴⁷ container platforms.
 213 Container images are generated and uploaded to a public repository for each new version of *fMRIPrep*.
 214 This helps address the widespread lack of reporting of specific software versions and the large variabil-
 215 ity of software versions, which threaten the reproducibility of fMRI analyses¹⁹. These containers are
 216 released with a fixed set of software versions for *fMRIPrep* and all its dependencies, maximizing run-
 217 to-run reproducibility in an easy way. Except for C-PAC, alternative pipelines do not provide official
 218 support for containers. The adoption of the BIDS-Apps⁴⁵ container model makes *fMRIPrep* amenable to
 219 a multiplicity of infrastructures and platforms: PC, high-performance computing (HPC), Cloud, etc.

220 ***fMRIPrep* yields high-quality results on a diverse set of input data**

221 *Figure 3* presents the validation framework that we applied to iteratively maximize the robustness
 222 of the tool and validate the quality of the results. The validation framework implements a testing plan
 223 elaborated prior the release of the version 1.0 of the software (see Online Methods, sec. Evaluation of
 224 *fMRIPrep*). The plan is divided in two validation phases in which different data samples and validation
 225 procedures are applied. *Table 2* describes the data samples used on each phase and emphasizes how
 226 these data are collected from a large number of different, unrelated studies. In Phase I, we ran *fMRIPrep*
 227 on a manually selected sample of participants that are potentially challenging to the tool's robustness,
 228 exercising the adaptiveness to the input data. Phase II focused on the visual assessment of the quality of
 229 preprocessing results on a large and heterogeneous sample.

230 **Validation Phase I – Fault-discovery testing.** We tested *fMRIPrep* on a set of 30 datasets from [OpenfMRI](#)
 231 (see *Table 2*). Included participants were manually selected for their low quality as visually assessed by
 232 two experts using MRIQC¹⁰⁵ (the assessment protocol is further described in in Online Methods, sec.
 233 Evaluation of *fMRIPrep*). Data showing substandard quality are known to likely degrade the outcomes
 234 of image processing¹⁰⁵, and therefore they are helpful to test software reliability. Phase I concluded with
 235 the release of *fMRIPrep* version 1.0 on December 6, 2017.

236 **Validation Phase II – Quality assurance and reliability testing.** We extended the evaluation data
 237 up to 54 datasets from OpenfMRI (see *Table 2*). Participants were selected randomly as described in
 238 Online Methods, sec. Evaluation of *fMRIPrep*. Validation Phase II integrated a protocol for the screening
 239 of results into the software testing (*Figure 3*). As shown in *Figure 4*, this effectively contributed to
 240 substantive improvements on the quality of results. Three raters (authors CJM, KJG and OE) evaluated
 241 the 213 visual reports at six quality control points throughout the pipeline, and also assigned an overall
 242 score to each participant. Their ratings are made available with the corresponding reports for scrutiny.
 243 The scoring scale has three levels: 1 (“poor”), 2 (“acceptable”) and 3 (“excellent”). A special rating of 0
 244 (“unusable”) is assigned to critical failures that hamper any further processing beyond the quality control
 245 checkpoint. After Phase II, 50 datasets out of the total 54 were rated above the “acceptable” average
 246 quality level. The remaining 4 datasets were all above the “poor” level and in or nearby the “acceptable”
 247 rating. *Figure 4* illustrates the quality of results, while Online Methods, *Figure S6* shows the individual
 248 evolution of every dataset at each of the seven quality control points. Phase II concluded with the release
 249 of *fMRIPrep* version 1.0.8 on February 22, 2018.

250 ***fMRIPrep* improves spatial precision through reduced smoothing**

251 We investigate whether the focus on robustness against data irregularity comes at a cost in quality
 252 of the preprocessing outcomes by comparing it to the commonly used FSL *feat* workflow. Using all
 253 the scans of the “stopsignal” task in DS000030 (N=257 participants) from [OpenfMRI](#), we ran *fMRIPrep*
 254 and a standard *feat* workflow. We chose *feat* because DS000030 had successfully been preprocessed
 255 and analyzed with FSL tools previously⁵⁵. Smoothing is intentionally excluded from both preprocessing
 256 routes with the aim to apply it early within a common (identical) analysis workflow. We calculated
 257 standard deviation maps in MNI space¹⁰⁶ for the temporal average map of the “stopsignal” task derived
 258 from preprocessing with both alternatives. Visual inspection of these variability maps (*Figure 5*) reveals

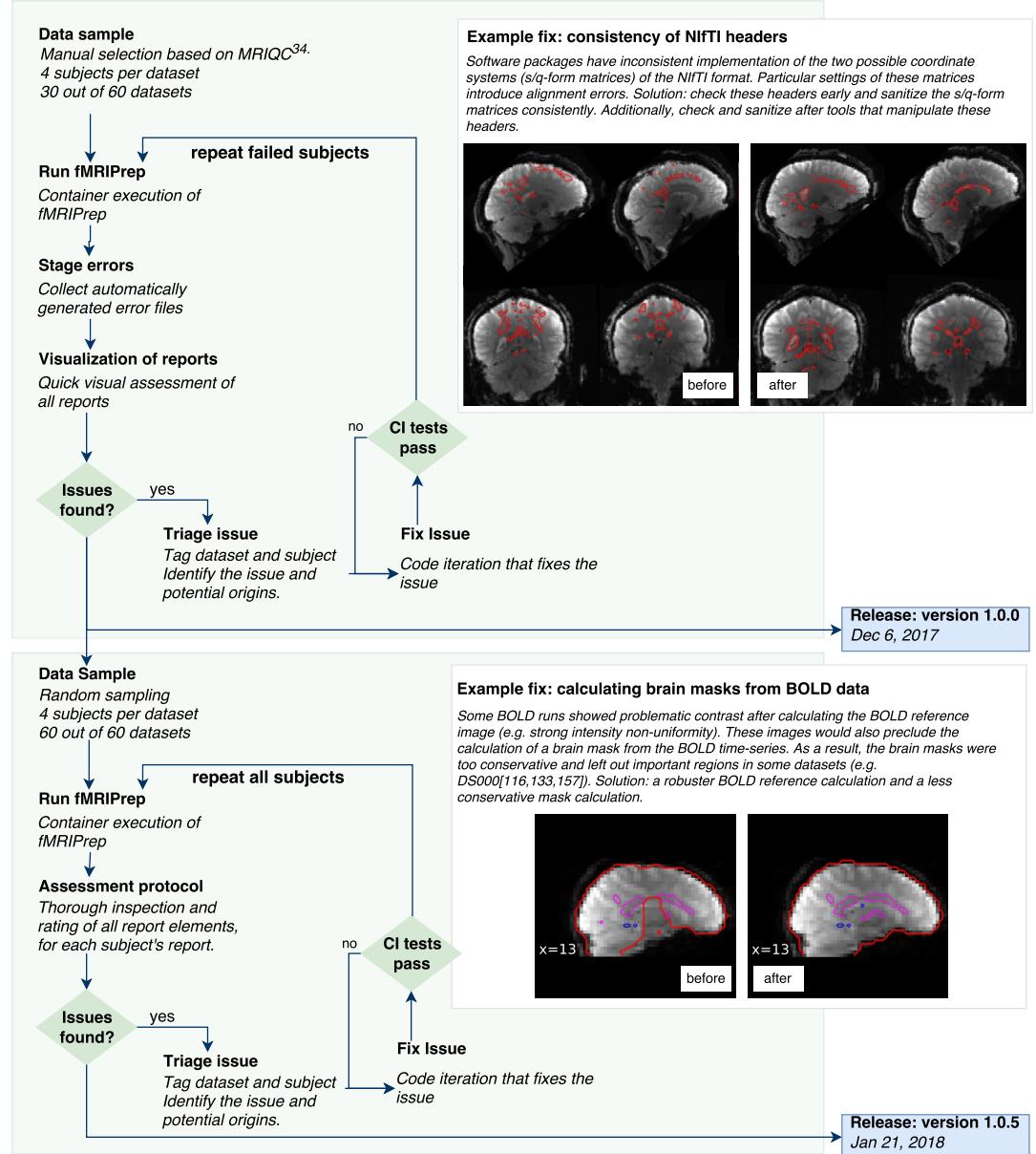


Figure 3. Combining visual assessment within the software testing flow. We complement well-established techniques for software integration testing with manual assessment of the outputs. The evaluation framework is designed with two subsequent testing phases. Phase I focuses on fault-discovery and visual reports are used to better understand the issues found. The top box (Example fix 1) shows an example of defect identified and solved during this testing cycle. After addressing a total of 21 issues affecting 7 datasets, and the release of *fMRIPrep* version 1.0.0, the next testing stage is initiated. Phase II focuses on increasing the overall quality of results as evaluated visually by experts. Following an inspection protocol, reports from 213 participants belonging to 58 different studies were individually assessed. We found 12 additional issues affecting 11 datasets that have been addressed with the release of *fMRIPrep* version 1.0.3 on January 3, 2018. The bottom box (Example fix 2) illustrates one of these issues, which produced errors in the brain extraction process from BOLD data.

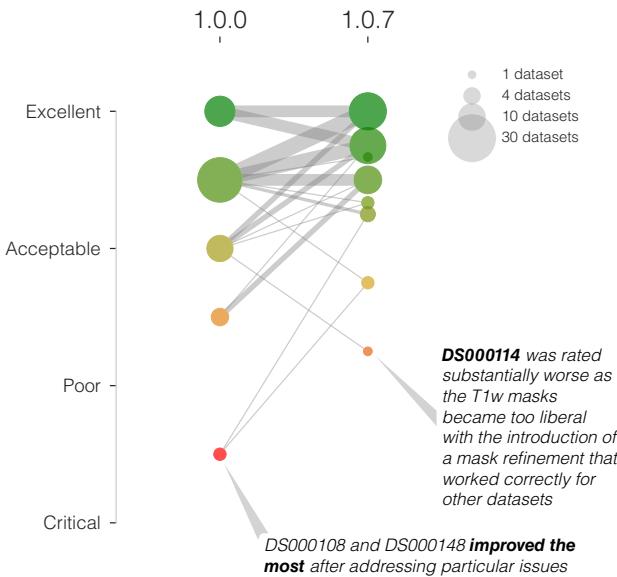


Figure 4. Integrating visual assessment into the software testing framework effectively increases the quality of results. In an early assessment of quality using *fMRIprep* version 1.0.0, the overall rating of two datasets was below the “poor” category and four below the “acceptable” level (left column of colored circles). After addressing some outstanding issues detected by the early assessment, the overall quality of processing is substantially improved (right column of circles), and no datasets are below the “poor” quality level. Only two datasets are rated below the “acceptable” level in the second assessment (using *fMRIprep* version 1.0.7).

259 a higher anatomical accuracy of *fMRIprep* over *feat*, likely reflecting the combined effects of a more
260 precise spatial normalization scheme and the application of “fieldmap-less” SDC. *fMRIprep* outcomes
261 are particularly better aligned with the underlying anatomy in regions typically warped by susceptibility
262 distortions such as the orbitofrontal lobe, as demonstrated by close-ups in Online Methods, *Figure S7*.

We also compared preprocessing done with *fMRIPrep* and FSL’s *feat* in two common fMRI analyses. First, we performed within subject statistical analysis using *feat* –the same tool provides preprocessing and first-level analysis– on both sets of preprocessed data. Second, we perform a group statistical analysis using ordinary least squares (OLS) mixed modeling (*flame*¹⁰⁷, FSL). In both experiments, we applied identical analysis workflows and settings to both preprocessing alternatives. Using AFNI’s 3dFWHMx, we estimated the smoothness of data right after preprocessing (unsmoothed), and after an initial smoothing step of 5.0mm (full-width half-minimum, FWHM) of the common analysis workflow. As visually suggested by *Figure 5*, we indeed found that *feat* produces smoother data (*Figure 6A*). Although pre-processed data were resampled to an isotropic voxel size of 2.0×2.0×2.0 [mm], the smoothness estimation (before the prescribed smoothing step) for *fMRIPrep* was below 4.0mm, very close to the original resolution of 3.0×3.0×4.0 [mm] of these data. The first-level analysis showed that the thresholded activation count maps for the go vs. successful stop contrast in the “stopsignal” task were very similar (*Figure 6B*). It can be seen that the results from both pipelines identified activation in the same regions. However, since data preprocessed with *feat* are smoother, the results from *fMRIPrep* are more local and better aligned with the cortical sheet.

To investigate the implications of either pipeline on the group analysis use-case, we run the same OLS modeling on two disjoint subsets of randomly selected subjects. We calculate several metrics of spatial agreement on the resulting maps of (uncorrected) p -statistical values, and also after binarizing these maps with a threshold chosen to control for the false discovery rate at 5%. The overlap of statistical maps, as well as Pearson's correlation, were tightly related to the smoothing of the input data. In Online Methods, sec. Comparison to FSL feat we report the group-level analysis in full. We ran two variants of

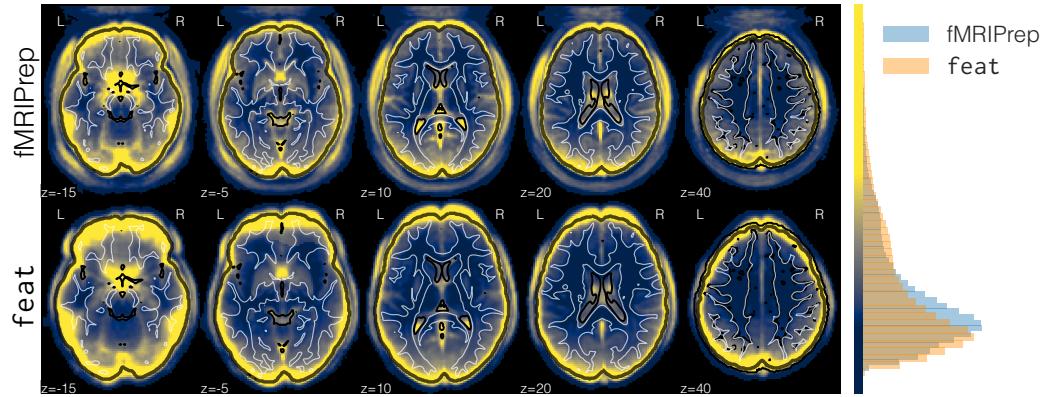


Figure 5. Maps of between-subjects variability of the averaged BOLD time-series resampled into MNI space. We preprocessed DS000030 ($N=257$) with fMRIprep and FSL feat. This figure shows greater between-subject variability of the averaged BOLD series obtained with feat, in MNI space. The top box of the panel shows these maps at different axial planes of the image grid, with reference contours from the MNI atlas. The map summarizing feat-derived results displays greater variability outside the brain mask delineated with the black contour. This effect is generally associated with a lower performance of spatial normalization¹⁰⁶. The histogram at the right side plots the normalized frequency of variability (arbitrary units) for both maps, within the brain mask. The distribution corresponding to FSL feat shows a heavier tail. See Online Methods, *Figure S7* for close-ups into regions affected by susceptibility-derived distortions.

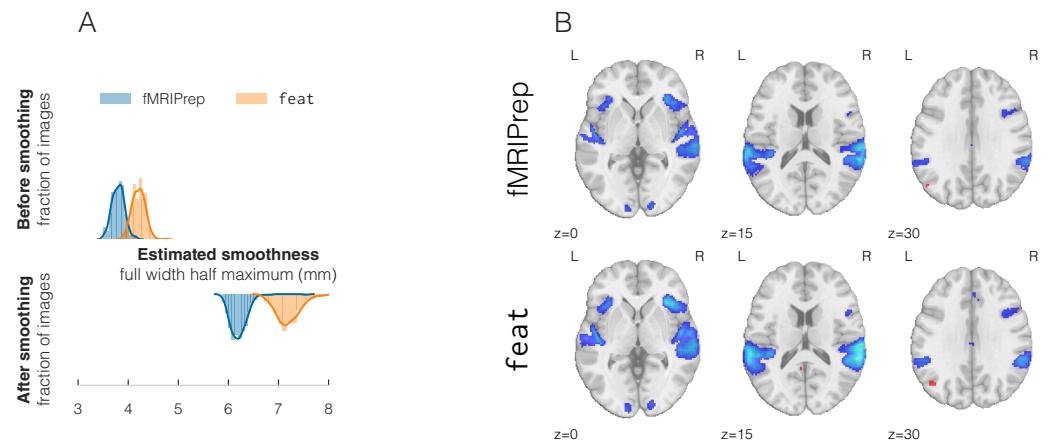


Figure 6. A | Estimating the spatial smoothness of data before and after the initial smoothing step of the analysis workflow confirmed that results of preprocessing with feat are intrinsically smoother. Therefore, fMRIprep allows the researcher for a finer control over the smoothness of their analysis. B | Thresholded activation count maps for the go vs. successful stop contrast in the “stopsignal” task after preprocessing using either fMRIprep or FSL’s feat, with identical single subject statistical modeling. Both tools obtained similar activation maps, with fMRIprep results being slightly better aligned with the underlying anatomy.

285 the analysis: with a prescribed smoothing of 5.0mm FWHM, and without smoothing step. These results
 286 showed that, at the group-level analysis, *fMRIPrep* and *feat* perform equivalently.

DISCUSSION

287 *fMRIPrep* is a fMRI preprocessing workflow developed to excel at four aspects of scientific software:
 288 *robustness* to data idiosyncrasies, high *quality* and consistency of results, maximal *transparency* in the
 289 assessment of results and subsequent communication, and *ease-of-use*. We describe how using the Brain
 290 Imaging Data Structure (BIDS²⁴) along with a flexible design allows the workflow to self-adapt to the
 291 idiosyncrasy of inputs (sec. A modular design allows for a flexible, adaptive workflow). The workflow
 292 (briefly summarized in *Figure 1*) integrates state-of-art tools from widely used neuroimaging software
 293 packages at each preprocessing step (see *Table 1*). Some other relevant facets of *fMRIPrep* and how
 294 they relate to existing alternative pipelines are presented in sec. Highlights of *fMRIPrep* within the neu-
 295 roimaging context. To note some, the analysis-agnostic nature of the tool, or the uniqueness of the
 296 “fieldmap-less” SDC method. We highlight that *fMRIPrep* is developed with the best software engineer-
 297 ing principles, which are fundamental to ensure software reliability. The pipeline is easy to use for
 298 researchers and clinicians without extensive computer engineering experience, and produces compre-
 299 hensive visual reports (*Figure 2*). These automated reports exemplify the “glass-box” principle, which
 300 requires that software allows scientists to understand how it works internally. This is in contrast to
 301 typical “black-box” applications that perform valuable services without providing a way to understand
 302 how the tool has transformed their data into the desired output. These reports maximize transparency
 303 by allowing scientists to critically inspect and better understand the underlying mechanisms of their
 304 preprocessing.

305 We demonstrate the robustness of *fMRIPrep* on a data collection from datasets associated with differ-
 306 ent studies (*Table 2*), representing the variety of input data in the field (sec. *fMRIPrep* yields high-quality
 307 results on a diverse set of input data). We then interrogate the quality of those results with the individual
 308 inspection of the corresponding visual reports by experts (sec. Visual reports ease quality control and
 309 maximize transparency and the corresponding summary in *Figure 4*). A comparison to FSL’s *feat* (sec.
 310 *fMRIPrep* improves spatial precision through reduced smoothing) demonstrates that *fMRIPrep* achieves
 311 higher spatial accuracy and introduces less uncontrolled smoothness (*Figures 5, 6*). Group *p*-statistical
 312 maps only differed on their smoothness (sharper for the case of *fMRIPrep*). The fact that first-level and
 313 second-level analyses resulted in small differences between *fMRIPrep* and our *ad hoc* implementation of
 314 a *feat*-based workflow indicates that the individual preprocessing steps perform similarly when they are
 315 fine-tuned to the input data. That justifies the need for *fMRIPrep*, which autonomously adapts the work-
 316 flow to the data without error-prone manual intervention. To a limited extent, that also mitigates some
 317 concerns and theoretical risks arisen from the analytical degrees-of-freedom¹⁹ available to researchers.
 318 *fMRIPrep* stands out amongst pipelines because it automates the adaptation to the input dataset without
 319 compromising the quality of results.

320 One limitation of this work is the use of visual (the reports) and semi-visual (e.g. *Figure 5* and
 321 *Figure 6*) assessments for the quality of preprocessing outcomes. Although some frameworks have been
 322 proposed for the quantitative evaluation of preprocessing on task-based (such as NPAIRS¹⁰⁸) and resting-
 323 state¹⁰⁹ fMRI, they impose a set of assumptions on the test data and the workflow being assessed that
 324 severely limit their suitability. The modular design of *fMRIPrep* defines an interface to each processing
 325 step, which will permit the programmatic evaluation of the many possible combinations of software
 326 tools and processing steps. That will also enable the use of quantitative testing frameworks to pursue
 327 the minimization of Type I errors without the cost of increasing Type II errors.

328 The range of possible applications for *fMRIPrep* also presents some boundaries. For instance, very
 329 narrow field-of-view (FoV) images oftentimes do not contain enough information for standard image
 330 registration methods to work correctly. Reduced FoV datasets from [OpenfMRI](#) were excluded from the
 331 evaluation since they are not yet fully supported by *fMRIPrep*. Extending *fMRIPrep*’s support for these par-
 332 ticular images is already a future line of the development roadmap. *fMRIPrep* may also under-perform
 333 for particular populations (e.g. infants) or when brains show nonstandard structures, such as tumors,

334 resected regions or lesions. Nonetheless, *fMRIPrep*'s architecture makes it straightforward to extend the
 335 tool to support specific populations or new species by providing appropriate atlases of those brains. This
 336 future line of work would be particularly interesting in order to adapt the workflow to data collected
 337 from rodents and nonhuman primates. By contrast, *fMRIPrep* performed robustly on data from a simul-
 338 taneous MRI/electrocorticography (ECoG) study, which is extremely challenging to analyze due to the
 339 massive BOLD signal drop-out near the implanted cortical electrodes (see Online Methods, *Figure S10*).

340 Approximately 80% of the analysis pipelines investigated by Carp¹⁹ were implemented using either
 341 AFNI¹², FSL¹⁵, or SPM¹⁷. *Ad hoc* pipelines adapt the basic workflows provided by these tools to the
 342 particular dataset at hand. Although workflow frameworks like Nipype¹¹⁰ ease the integration of tools
 343 from different packages, these pipelines are typically restricted to just one of these alternatives (AFNI,
 344 FSL or SPM). Otherwise, scientists can adopt the acquisition protocols and associated preprocessing
 345 software of large consortia like the Human Connectome Project (HCP) or the UK Biobank. This option
 346 allows scientists to shortcut the intricacies of preprocessing by applying a “black-box” that has been
 347 validated on similar data by a third party. The *off-the-shelf* applicability of these workflows is contravened
 348 by important limitations on the experimental design. Therefore, researchers typically opt to recode
 349 their custom preprocessing workflows with nearly every new study¹⁹. That practice entails a “pipeline
 350 debt”, which requires the investment on proper software engineering to ensure an acceptable correctness
 351 and stability of the results (e.g. continuous integration testing) and reproducibility (e.g. versioning,
 352 packaging, containerization, etc.). A trivial example of this risk would be the leakage of *magic numbers*
 353 that are hard-coded in the source (e.g. a crucial imaging parameter that inadvertently changed from one
 354 study to the next one). Until *fMRIPrep*, an analysis-agnostic approach that builds upon existing software
 355 instruments and optimizes preprocessing for robustness to data idiosyncrasies, quality of outcomes, ease-
 356 of-use, and transparency, was lacking.

357 The rapid increase in volume and diversity of available data, as well as the evolution of more so-
 358 phisticated techniques for processing and analysis, presents an opportunity for significantly advancing
 359 research in neuroscience. However, the influx of new data, new analysis methods, and new modeling
 360 strategies represents a risk as well as an opportunity. The inferential promises of big data, and the
 361 sophisticated analysis tools that can leverage it, incentivize researchers to progressively build on more
 362 complex analysis pipelines that rely on more complex and more obscure models of the data to pro-
 363 duce interpretable results. This way of moving forward risks producing a future generation of cognitive
 364 neuroscientists who have become experts in using sophisticated computational methods, but have little
 365 to no working knowledge of the biological processes underlying brain's function¹¹¹. It also obscures
 366 important steps in the inductive process mediating between experimental measurements and reported
 367 findings. Easy-to-use, *off-the-shelf* tools that function as black boxes –providing scientists with limited
 368 insight into how the tool functions, and developed primarily behind closed doors– may only exacerbate
 369 this problem. *fMRIPrep* offers a novel “glass-box” approach for the development, maintenance and use
 370 of computational tools that mitigates these risks. By standardizing preprocessing, *fMRIPrep* allows re-
 371 searchers to focus their attention and expertise on the inferentially significant stages of data production,
 372 analysis and interpretation. Additionally, *fMRIPrep* mitigates concerns about black-box processing by
 373 being thoroughly documented, producing reports and visualizations at critical quality control points in
 374 the workflow, and being developed according to the best practices of open source engineering. These
 375 features of *fMRIPrep* make it possible for researchers to learn how the tool works, develop an under-
 376 standing of each step in the workflow, and even reconstruct the preprocessing pipeline from first principles.
 377 *fMRIPrep* aims to better equip fMRI practitioners to perform reliable, reproducible, statistical analyses
 378 with a high-standard, consistent, and adaptive preprocessing instrument.

CONCLUSION

379 Despite efforts to achieve high-quality preprocessing of idiosyncratic fMRI datasets, doing so reliably
 380 has remained an open problem. *fMRIPrep* is an analysis-agnostic, preprocessing workflow that yields
 381 consistent results across a wide range of input datasets. *fMRIPrep* is built on top of the best neuroimaging
 382 tools selected from various software packages. These tools are integrated into workflows that can be

383 dynamically combined to compose a full preprocessing workflow adapted to the input data. The optimal
 384 workflow for the input dataset is constructed at runtime, blending a set of heuristics with the Brain
 385 Imaging Data Structure (BIDS) to read the inputs. *fMRIprep* excels in four design goals: robustness,
 386 high-quality of results, transparency and ease-of-use. To validate and demonstrate these features, we
 387 integrate the individual screening of preprocessing results with continuous integration techniques of
 388 software testing. The process is aided by comprehensive, portable reports that inform the scientist about
 389 the workflow, ease the quality control of results and maximize the shareability of research outcomes.
 390 We highlight the aspects that justify the development of *fMRIprep* with respect to currently available
 391 preprocessing workflows. We quantitatively demonstrate that *fMRIprep* does not introduce uncontrolled
 392 smoothing as compared to one alternative software. *fMRIprep* aims to better equip fMRI practitioners
 393 to perform reliable, reproducible statistical analyses with a high-standard, transparent, and verifiable
 394 instrument.

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Table 2. Data from OpenfMRI used in evaluation. S: number of sessions; T: number of tasks; R: number of BOLD runs; Modalities: number of runs for each modality, per subject (FM indicates acquisitions for susceptibility distortion correction); Part. IDs (phase): participant identifiers included in testing phase; N: total of unique participants; TR: repetition time; #TR: length of time-series (volumes); Resolution: voxel size of BOLD series.

DS000XXX	Scanner	S	T	R	Modalities	Part. IDs (Phase I)	Part. IDs (Phase II)	N	TR	#TR	Resolution
001 ⁴⁸	SIEMENS	1	1	21	1 T1w, 3 BOLD	02, 03, 09, 15	01, 02, 07, 08	7	2.0	6300	3.12x3.12x4.00
002 ⁴⁹	SIEMENS	1	3	48	1 T1w, 6 BOLD	01, 11, 14, 15	02, 03, 04, 10	8	2.0	9510	3.12x3.12x5.00
003 ⁵⁰	SIEMENS	1	1	6	1 T1w, 1 BOLD	03, 07, 09, 11	02, 09, 10, 11	6	2.0	956	3.12x3.12x4.00
005 ⁵¹	SIEMENS	1	1	21	1 T1w, 3 BOLD	01, 03, 06, 14	01, 04, 05, 15	7	2.0	5040	3.12x3.12x4.00
007 ⁵²	SIEMENS	1	3	46	1 T1w, 5 BOLD	09, 11, 18, 20	03, 04, 08, 12	8	2.0	8205	3.12x3.12x4.00
008 ⁵³	SIEMENS	1	2	38	1 T1w, 5 BOLD	04, 09, 12, 14	10, 12, 13, 15	7	2.0	6808	3.12x3.12x4.39
009	SIEMENS	1	4	48	1 T1w, 6 BOLD	01, 03, 09, 10	17, 18, 21, 23	8	2.0	10528	3.00x3.00x4.00
011 ⁵⁴	SIEMENS	1	4	41	1 T1w, 5 BOLD	01, 03, 06, 08	03, 09, 11, 14	7	2.0	8041	3.12x3.12x5.00
017	SIEMENS	2	2	48	4 T1w, 9 BOLD	2, 4, 7, 8	2, 5, 7, 8	5	2.0	8736	3.12x3.12x4.00
030 ^{55,56}	SIEMENS	1	8	30	1 T1w, 7 BOLD		10[440,638,668,855]	4	2.2	6254	3.00x3.00x4.00
031 ⁵⁷	SIEMENS	107	9	191	29 T1w, 18 T2w, 46 FM, 191 BOLD		01	1	1.2	79017	2.55x2.55x2.54
051 ⁵⁸	SIEMENS	1	1	54	2 T1w, 7 BOLD	03, 04, 05, 13	02, 04, 06, 09	7	2.0	10800	3.12x3.12x6.00
052 ⁵⁹	SIEMENS	1	2	28	2 T1w, 4 BOLD	06, 08, 12, 14	05, 10, 12, 13	7	2.0	6300	3.12x3.12x6.00
053	SIEMENS	1	3	32	1 T1w, 8 BOLD		002, 003, 005, 006	4	1.2	10712	2.40x2.40x2.40
101	SIEMENS	1	1	16	1 T1w, 2 BOLD	06, 08, 16, 19	05, 11, 17, 20	8	2.0	2416	3.00x3.00x4.00
102 ⁶⁰⁻⁶²	SIEMENS	1	1	16	1 T1w, 2 BOLD	05, 19, 22, 23	08, 10, 16, 20	8	2.0	2336	3.00x3.00x4.00
105 ^{63,64}	GE	1	1	71	1 T1w, 11 BOLD	1, 2, 3, 6	1, 4, 5, 6	6	2.5	8591	3.50x3.75x3.75
107 ⁶⁵	SIEMENS	1	1	14	1 T1w, 2 BOLD	02, 05, 20, 29	05, 36, 39, 47	7	3.0	2315	3.00x3.00x3.00
108 ⁶⁶	GE	1	1	41	1 T1w, 5 BOLD	01, 03, 07, 17	03, 10, 24, 26	7	2.0	7860	3.44x3.44x4.50
109 ⁶⁷	SIEMENS	1	1	12	1 T1w, 2 BOLD	02, 10, 39, 47	02, 11, 15, 39	6	2.0	2148	3.00x3.00x3.54
110 ⁶⁸	GE	1	1	80	1 T1w, 10 BOLD	07, 09, 17, 18	01, 02, 03, 06	8	2.0	14880	3.44x3.44x4.01
114 ⁶⁹	GE	2	5	70	2 T1w, 10 BOLD	01, 05, 07, 08	02, 03, 04, 07	7	5.0	10626	4.00x4.00x4.00
115 ^{70,71}	SIEMENS	1	3	24	1 T1w, 3 BOLD	31, 68, 77, 78	04, 33, 67, 79	8	2.5	3288	4.00x4.00x4.00
116 ⁷²⁻⁷⁵	PHILIPS	1	2	36	1 T1w, 6 BOLD	02, 08, 10, 15	08, 12, 15, 17	6	2.0	6120	3.00x3.00x4.00
119 ⁷⁶	SIEMENS	1	1	31	1 T1w, 3 BOLD	10, 51, 59, 74	11, 26, 56, 58	8	1.5	7564	3.12x3.12x4.00
120 ⁷⁷	SIEMENS	1	1	11	1 T1w, 2 BOLD		04, 05, 08, 24	4	1.5	2376	3.12x3.12x4.00
121 ⁷⁸	SIEMENS	1	1	28	1 T1w, 4 BOLD	01, 04, 05, 20	01, 18, 22, 26	7	1.5	5656	3.12x3.12x4.00
133 ⁷⁹	PHILIPS	2	1	24	2 T1w, 6 BOLD		06, 21, 22, 23	4	N/A	3480	4.00x4.00x4.00
140 ⁸⁰	PHILIPS	1	1	36	1 T1w, 9 BOLD		05, 27, 32, 33	4	2.0	7380	2.80x2.80x3.00
148	GE	1	1	12	1 T1w, 1 T2w, 3 BOLD		09, 26, 28, 33	4	1.8	3162	3.00x3.00x3.00
157 ⁸¹	PHILIPS	1	1	4	1 T1w, 1 BOLD		04, 21, 23, 28	4	1.6	1485	4.00x4.00x3.99
158 ⁸²	SIEMENS	1	1	4	1 T1w, 1 BOLD		064, 081, 122, 149	4	2.0	1240	3.00x3.00x3.30
164 ⁸³	SIEMENS	1	1	4	1 T1w, 1 BOLD		006, 012, 019, 027	4	1.5	1480	3.50x3.50x3.50
168 ⁸⁴	SIEMENS	1	1	4	1 T1w, 1 BOLD		08, 27, 30, 49	4	2.5	2112	3.00x3.00x3.00
170 ⁸⁵⁻⁸⁷	GE	1	4	48	1 T1w, 12 BOLD		1700, 1708, 1710, 1713	4	3.0	2160	3.44x3.44x3.40
171 ⁸⁸	SIEMENS	1	2	20	1 T1w, 5 BOLD		control0[4,8,14], mdd03	4	3.0	2066	2.90x2.90x3.00
177 ⁸⁹	SIEMENS	1	1	4	1 T1w, 1 BOLD		04, 07, 10, 11	4	3.0	920	3.00x3.00x3.00
200 ⁹⁰	SIEMENS	1	1	4	1 T1w, 1 BOLD		2004, 2011, 2012, 2014	4	2.5	480	3.28x3.28x4.29
205 ⁹¹	SIEMENS	1	2	12	1 T1w, 3 BOLD		01, 05, 06, 07	4	2.2	4103	3.00x3.00x3.00
208 ⁹²	SIEMENS	1	1	4	1 T1w, 1 BOLD		27, 45, 56, 69	4	2.5	1200	3.44x3.44x3.00
212 ^{93,94}	SIEMENS	1	2	40	1 T1w, 10 BOLD		07, 13, 20, 29	4	3.0	5808	3.12x3.12x4.00
213 ⁹⁵	SIEMENS	1	1	4	1 T1w, 1 BOLD		06, 10, 12, 13	4	2.0	1120	3.00x3.00x3.99
214 ⁹⁶	SIEMENS	1	1	4	1 T1w, 1 BOLD		EESSO[06,31,33,34]	4	1.6	1364	3.44x3.44x5.00
216 ⁹⁷	GE	1	1	16	1 T1w, 4 BOLD (ME)		01, 02, 03, 04	4	3.5	2688	3.00x3.00x3.00
218 ⁹⁸	PHILIPS	1	1	12	1 T1w, 3 BOLD		02, 07, 12, 17	4	1.5	6709	2.88x3.00x2.88
219 ⁹⁸	PHILIPS	1	1	14	1 T1w, 3 BOLD		04, 09, 10, 12	4	1.5	7807	2.88x3.00x2.88
220 ⁹⁹	PHILIPS, SIEMENS	3	1	12	3 T1w, 3 BOLD		tbi[03,05,06,10]	4	N/A	1728	3.00x3.00x4.00
221	SIEMENS	2	1	15	1 MP2RAGE, 9 FM, 3 BOLD		010[016,064,125,251]	4	2.5	9855	2.30x2.30x2.30
224 ¹⁰⁰	SIEMENS	12	6	399	4 T1w, 4 T2w, 10 FM, 79 BOLD	MSC[05,06,08,09]	MSC[05,08,09,10]	5	2.2	88528	4.00x4.00x4.00
228	SIEMENS	1	1	4	1 T1w, 1 BOLD		pixar[001,017,103,132]	4	2.0	672	3.06x3.06x3.29
229 ¹⁰¹	SIEMENS	1	1	12	1 T1w, 3 BOLD		02, 05, 07, 10	4	2.0	4680	3.44x3.44x3.00
231 ¹⁰²	SIEMENS	1	1	12	1 T1w, 3 BOLD		01, 02, 03, 09	4	2.0	4548	2.02x2.02x2.00
233 ¹⁰³	PHILIPS	1	2	80	2 T1w, 10 BOLD	rid0000[12,24,36,41]	rid0000[01,17,31,32]	8	2.0	15680	3.00x3.00x3.00
237 ¹⁰⁴	SIEMENS	1	1	41	1 T1w, 5 BOLD	03, 08, 11, 12	01, 03, 04, 06	7	1.0	19844	3.00x3.00x3.00
243 ¹⁰⁴	SIEMENS	1	1	13	1 T1w, 1 BOLD	012, 032, 042, 071	023, 066, 089, 094	8	2.5	2884	4.00x4.00x4.00
Total				2176		120	202	304		551769	