

¹ SOVABIDS: EEG-to-BIDS conversion software focused ² on automation, reproducibility and interoperability

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Software

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¹⁵ Summary

¹⁶ Electroencephalography (EEG) data are used in many fields, from neuroscience to clinical
¹⁷ research, but it often comes in different formats and structures, making it hard to organize, share,
¹⁸ or compare across studies. SOVABIDS is an open-source tool that helps researchers convert
¹⁹ EEG data into the Brain Imaging Data Structure (BIDS) ([Gorgolewski et al., 2016](#)), a standard
²⁰ data structure that aligns with FAIR principles (Findability, Accessibility, Interoperability, and
²¹ reusability). Specifically, BIDS ensures data consistency and interoperability, making it easier
²² to analyze, share, and integrate EEG data across different tools, data repositories and research
²³ groups. Rather than manually renaming files or reorganizing folders, SOVABIDS allows users
²⁴ to define simple rules to automate the conversion ([Figure 1](#) illustrates this conversion process).
²⁵ The tool is designed to be flexible and user-friendly, supporting customization without requiring
²⁶ advanced programming skills. It can be used as a Python package or as a command-line tool,
²⁷ and includes [comprehensive documentation](#) with [tutorials](#) to help users get started. SOVABIDS
²⁸ also integrates with other tools, making it suitable for both small research projects and large
²⁹ collaborative studies.

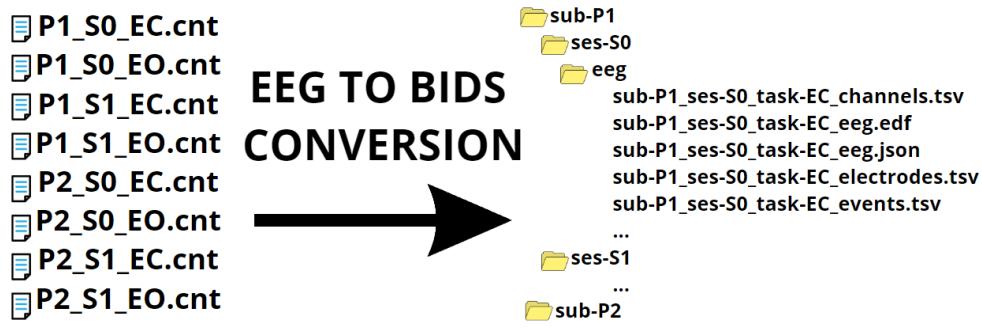


Figure 1: Illustration of the EEG to BIDS conversion. The left side shows raw EEG files with participant-specific naming conventions (for example, P1_S0_EC.cnt), where P1 and P2 represent participants, S0 and S1 indicate sessions, and EC (Eyes Closed) and EO (Eyes Open) refer to tasks. These raw files are converted into the BIDS format, shown on the right, where data are systematically organized into subject (sub-), session (ses-), and modality (eeg) folders. Each EEG recording is saved in standardized BIDS-compliant formats, including .edf for EEG signals and .tsv/.json for metadata.

30 Statement of need

31 Electroencephalography is a widely used neuroimaging technique that provides high temporal
 32 resolution for studying brain activity. Its applications span numerous fields, including cognitive
 33 neuroscience, clinical diagnostics, brain-computer interfaces, and neuroengineering. With the
 34 increasing volume and complexity of EEG data, ensuring reproducibility, standardization, and
 35 interoperability has become a growing priority in the field. The Brain Imaging Data Structure
 36 for EEG (EEG-BIDS) (Pernet et al., 2019) provides a consistent framework for organizing
 37 EEG datasets, facilitating data sharing (Markiewicz et al., 2021), large-scale collaborations,
 38 cross-study comparisons, and promoting FAIR data practices (Wilkinson et al., 2016) across a
 39 wide range of research applications from fundamental cognitive neuroscience to large-scale
 40 clinical neuroimaging.

41 The datasets generated in studies using electroencephalography are not only large and complex,
 42 but also vary widely due to the multitude of formats used by different hardware vendors. Thus,
 43 despite the advantages of BIDS, the conversion of EEG datasets to the BIDS standard can be
 44 challenging, especially for researchers who are not well-versed in technical data manipulation,
 45 and those from smaller or less well-resourced institutions. Researchers are thus obliged to
 46 wrestle with converting their data to BIDS following data acquisition. This process is prone to
 47 error if done manually, which poses particular problems for large studies. Software solutions
 48 are available to assist the conversion, but they require either basic programming skills (e.g.,
 49 MNE-BIDS (Appelhoff et al., 2019), data2bids in FieldTrip (Oostenveld et al., 2011) and
 50 EEG-BIDS in EEGLAB (Delorme & Makeig, 2004)), or detailed user input for each file being
 51 converted, again limiting practicality for large studies as happens in EEG2BIDS (Rogers et al.,
 52 2022).

53 SOVABIDS addresses this challenge by enabling reproducible semi-automatic and interoperable
 54 conversion of EEG datasets into the BIDS standard, even by non-technical users. This
 55 democratizes access to BIDS compliance, enabling more EEG data to be shared and analyzed
 56 within the broader scientific community. Moreover, SOVABIDS facilitates the development of
 57 user-friendly graphical frontends, which further enhances its accessibility to a wider audience,
 58 including those who may not be familiar with programming or data structuring concepts.
 59 SOVABIDS leverages established EEG analysis tools, in particular MNE (Gramfort et al., 2013)
 60 for reading EEG data formats and MNE-BIDS (Appelhoff et al., 2019) for BIDS compliant data
 61 saving. It also incorporates open-source best practices like automated testing and [streamlined documentation](#) that includes [usage examples](#), ensuring continuous enhancement, and facilitating

63 community usage and collaboration in maintaining and improving the software.

64 Research Impact Statement

65 SOVABIDS is currently available on the Neurodesk platform www.neurodesk.org (Renton et al.,
66 2024). It has been used in both academic research and published scientific studies, including a
67 Master's thesis on EEG-based Alzheimer's risk classification (Henao Isaza, 2023), a Bachelor's
68 thesis on web-based EEG processing tools (Zapata Saldarriaga, 2022), and a peer-reviewed
69 study focused on harmonizing EEG features across multiple recording sites (Jaramillo-Jimenez
70 et al., 2024).

71 Software Design

72 Developing an EEG-to-BIDS conversion tool requires balancing usability, automation,
73 reproducibility, and flexibility while ensuring compatibility with existing neuroimaging
74 tools. SOVABIDS was designed with these challenges in mind, prioritizing accessibility for
75 non-technical users, handling variations in EEG data structures, and enabling seamless
76 integration with other software. The following five design principles guided its development:

77 1. Adoption by non-technical users

78 To decrease the need of programming skills, the conversion uses human-readable and writable
79 YAML configuration files rather than a scripting language. This approach was inspired by
80 Bidscoin (Zwiers et al., 2022), a BIDS converter for MRI data. To maximise software adoption,
81 step-by-step guides for SOVABIDS are provided.

82 2. Automation that can accommodate outliers

83 The planned output of EEG experiments is usually multiple identically-organised data structures,
84 typically one for each participant. Nevertheless, in practice data organisation often varies
85 slightly between participants; for example, due to temporary technical issues, the data recorded
86 for some participants might be partial or have repeated segments. Like other conversion tools
87 such as Bidscoin (Zwiers et al., 2022) and HeuDiConv (Halchenko et al., 2023), we leverage
88 the generally similar data organisation across participants, but we extend this by allowing
89 for non-identical data structures. This is done by utilising two configuration files (which are
90 illustrated in Figure 2):

- 91 ▪ The [Rules File](#), which encodes the general conversion rules for a multiple-participant
92 EEG dataset.
- 93 ▪ The [Mappings File](#), which is derived from the Rules File, and holds specific conversion
94 rules for every individual participant.

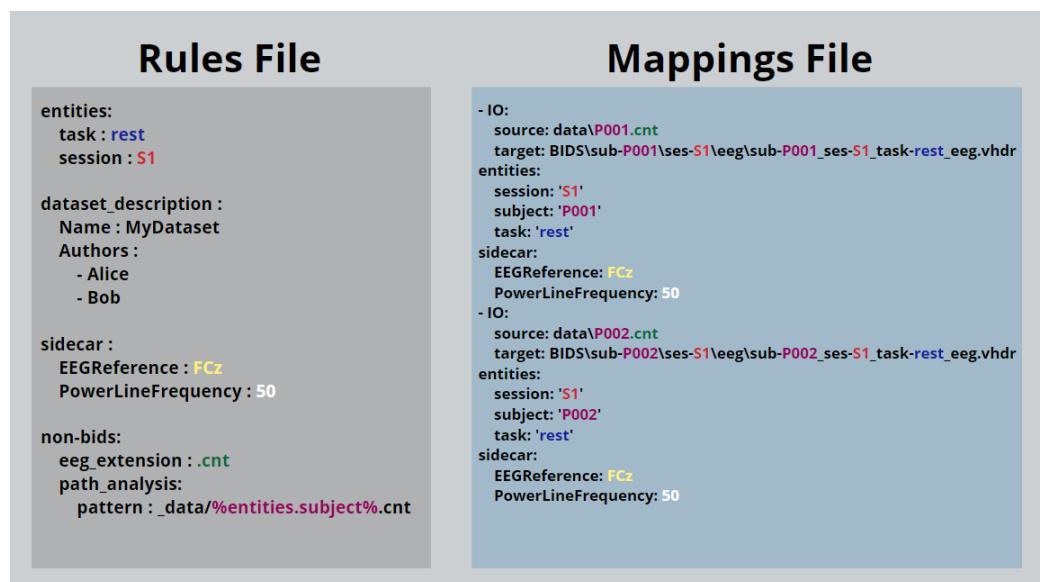


Figure 2: From a Rules File, a mapping for each file in the dataset can be generated and saved in the Mappings File. The colors illustrate how the information in both files is related.

95 In addition, the user can derive the initial Rules File from a community or institutional
 96 template, further decreasing manual input. For more fine-tuning of special cases, a user-
 97 supervised adjustment loop can be set up through SOVABIDS' interoperable API (Application
 98 Programming Interface) to connect with an external graphical user interface (GUI), allowing
 99 for fast manual inputs when a fully automated generation is not possible.

100 To support increased automation, SOVABIDS implements heuristics that take advantage of
 101 common file path patterns found in EEG research. Unlike tools that rely on strict prefix-based
 102 identification, such as the “–sub-prefix” and “–ses-prefix” options in Bidscoin ([Zwiers et al., 2022](#)) and Bidsme ([Belyi et al., 2023](#)), SOVABIDS enables flexible metadata extraction
 103 directly from file paths. It can extract not only subject and session information, but also other
 104 BIDS-relevant properties, including task labels. This flexibility is supported through multiple
 105 approaches:

- 106 ▪ Regular expressions, for advanced users who require precise control.
- 107 ▪ Placeholder-based templates, which offer an intuitive way to define rules (as shown in
 the “path_analysis” section of [Figure 2](#)).
- 108 ▪ Paired source-target examples, designed for users without experience in regular expressions
 or placeholders.

112 3. Reproducible conversion

113 All the parameters needed to fully replicate the conversion are saved in the configuration files
 114 along with provenance information. This allows the user to evaluate, correct and repeat the
 115 conversion in case the BIDS-organised dataset has an invalid structure (as detected using a
 116 BIDS validator) or incorrect content (usually discovered during the analysis stage).

117 4. Interoperability

118 To increase maintainability, SOVABIDS does not include a graphical user interface, but its API
 119 allows interoperability with other applications, primarily GUI front ends (desktop or web-based).
 120 We used a remote procedure call (RPC) protocol, as its action-oriented design naturally fits the
 121 process-driven nature of data conversion workflows. Additionally, interoperability is enhanced
 122 through the YAML-based configuration files, which allow users to define conversion rules in a

123 structured, human-readable format. This enables seamless integration with the many tools
 124 that support it without sacrificing the ease of managing the configuration files. To demonstrate
 125 the usability of the API, a [basic GUI was developed in Flask](#).

126 5. Broad support of formats

127 SOVABIDS is designed to convert EEG datasets into the BIDS standard while accommodating
 128 diverse data formats. Since it relies on MNE-Python for reading electrophysiology files, any
 129 EEG format supported by MNE can be processed and converted. As of now, however, the
 130 software has been specifically tested with BrainVision (.vhdr) and Neuroscan (.cnt) files only.

131 Software Architecture

132 The software architecture of [SOVABIDS](#) is designed to streamline the process of converting
 133 EEG datasets to the BIDS format. As depicted in [Figure 3](#), the system is built around two
 134 core modules that work in tandem to simplify this complex task:

- 135 ▪ Rules Module: At the heart of SOVABIDS, the Rules Module is where the logic of
 136 conversion is enacted. Users define specific rules in the 'Rules File', which the module
 137 applies to target EEG files, extracting and compiling conversion parameters into a
 138 'Mappings File'. This 'Mappings File' becomes the blueprint for the subsequent data
 139 transformation process, ensuring that the individualized nuances of each EEG file are
 140 accounted for. These nuances can be introduced through manual editing or through the
 141 interoperation with GUIs by leveraging the RPC API.
- 142 ▪ Conversion Module: Acting upon the 'Mappings File', this module is responsible for
 143 the hands-on task of converting raw EEG data into the BIDS format. It's a crucial
 144 step that translates the preparatory work done by the Rules Module into a structured
 145 dataset aligned with the stringent requirements of the BIDS standard, allowing for better
 146 interoperability and reproducibility of research.

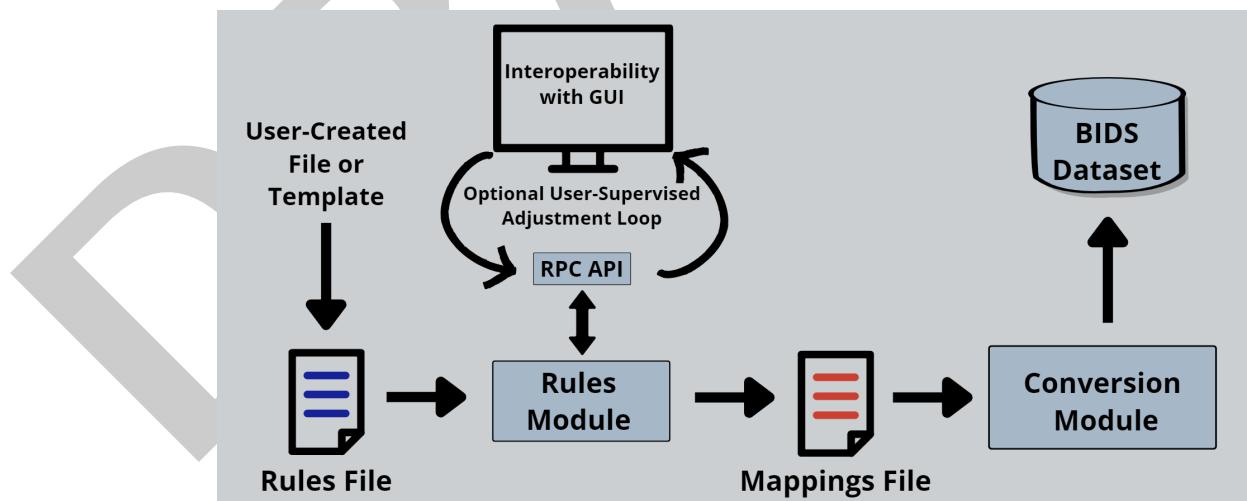


Figure 3: The architecture of SOVABIDS. The conversion process starts with a user-defined Rules File, which encodes general conversion rules (represented in blue inside the Rules File). The Rules Module processes these rules to generate a Mappings File, which contains specific configurations for all EEG files (each red line in the Mappings File represents the configuration of a different EEG file). The Conversion Module then applies these configurations to produce a BIDS-compliant dataset. Interoperability is enabled via an RPC API, allowing integration with external tools, including graphical user interfaces for optional user-supervised adjustments.

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155 of Queensland.

156 AI Usage Disclosure

157 The primary architecture and core functionality of this software were completed prior to
158 December 2023. Generative AI tools were not used in the conceptual design, methodological
159 decisions, or scientific development of the project.
160 After March 2025, limited use of generative AI tools was made for maintenance and supporting
161 tasks. The tools used were ChatGPT Codex (o4-mini) and ChatGPT (GPT-4.1).
162 AI assistance was used for: - Updating and improving GitHub Actions continuous integration
163 workflows - Enhancing and clarifying documentation - Assisting in the implementation of a
164 utility function for generating random 1/f signals - Minor code refactoring and formatting
165 improvements - Minor improvements on the paper
166 All AI-assisted outputs were carefully reviewed, edited, tested, and validated by the authors.
167 All core design decisions and scientific judgments were made by the human authors.

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