

# <sup>1</sup> datashuttle: automated data management for experimental neuroscience

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## Software

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## <sup>9</sup> Summary

<sup>10</sup> Datashuttle is a Python package that facilitates data standardisation in neuroscience.  
<sup>11</sup> Experimental data are often stored using custom folder structures and naming conventions,  
<sup>12</sup> which hinders data sharing, reproducibility, and the development of community tools.  
<sup>13</sup> Datashuttle addresses this by providing user-friendly tools to create, validate, and transfer  
<sup>14</sup> standardised experimental data folders. The package can be used programmatically—integrated  
<sup>15</sup> into existing Python scripts for data acquisition—or via a graphical user interface.

## <sup>16</sup> Statement of Need

<sup>17</sup> The past decade has seen significant progress in the development of neuroscience data standards. Experimental datasets have become increasingly complex, with multiple modalities (e.g. behaviour, electrophysiology and imaging) often collected from a single subject. At its core, standardisation facilitates reproducibility by ensuring these complex datasets are well organised, accessible, machine-readable and sufficiently documented ([Martone, 2024](#)). This standardisation permits robust, automated project management including the transfer of experimental data between machines and validation of project contents. Detailed specifications covering folder, file and metadata naming and structural conventions are required to achieve this goal.

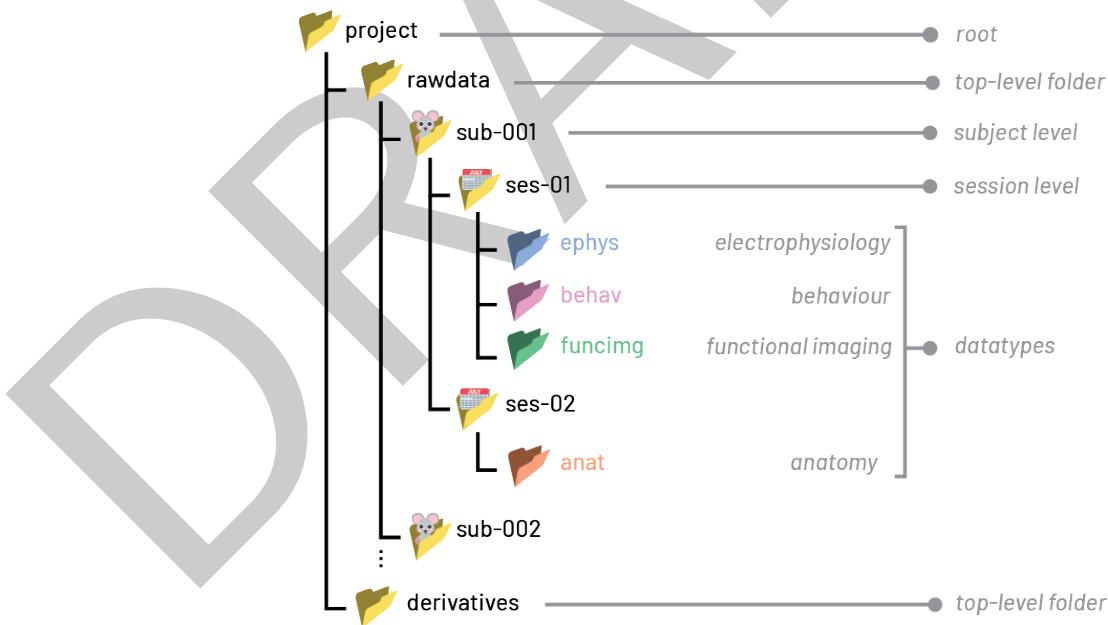
<sup>26</sup> Development and dissemination of comprehensive standards has been driven by community organisations such as the International Neuroinformatics Coordinating Facility (INCF) ([Abrams et al., 2022](#)). This includes adoption of the FAIR principles ([Abrams et al., 2022; Wilkinson et al., 2016](#)) ensuring data are Findable, Accessible, Interoperable and Reusable. Important standardisation initiatives include the Brain Imaging Dataset Structure (BIDS) ([Gorgolewski et al., 2016](#)), a file, folder and metadata standard widely used in neuroimaging, and the open file format Neurodata Without Borders ([Rübel et al., 2022](#)). These initiatives aim to achieve ‘full’ standardisation that enables automated analysis of machine-readable experimental datasets.

<sup>34</sup> There is currently a rich ecosystem of tooling for working with standardized data, although these tools typically require coding experience to use. BIDS ([Gorgolewski et al., 2017](#)) and NWB ([Rübel et al., 2022; Teeters et al., 2015](#)) each have rich software ecosystems. NWB provides tools for the reading, writing, editing and validation of NWB files ([Baker et al., 2025; Tritt et al., 2025](#)), alongside infrastructure for visualizing and sharing ([Magland et al., 2025](#)). The BIDS community have developed many packages for converting raw (mostly neuroimaging) data to BIDS format ([Gorgolewski et al., 2020](#)), as well as reading, writing and validating BIDS formatted folders, files and metadata ([Gorgolewski et al., 2020; Yarkoni et al., 2020](#)).

42 ezBIDs (Levitas et al., 2024) provides a web-based GUI for conversion and sharing of  
 43 BIDS datasets, though it is focused on neuroimaging rather than neuroscience more generally.  
 44 Further, DataLad (Halchenko et al., 2021) is a software for the version control and transfer  
 45 of large datasets, often used within the BIDS community for distributing neuroimaging data.  
 46 While highly valuable, these tools generally require coding experience, raw data conversion and  
 47 good understanding of the underlying data scheme to use, with functionality distributed over  
 48 multiple packages.

49 The adoption of data standards in systems neuroscience is not yet widespread (Klingner et al.,  
 50 2023). This is due in part to the inherent, and necessary, complexity required to achieve full  
 51 standardisation (Pierré et al., 2024) and lack of tools to automate the full management of  
 52 standardised projects without requiring coding experience. Further, not all systems neuroscience  
 53 methods have a corresponding data specification (e.g. fibre photometry). Researchers often  
 54 default to custom folder structures in lieu of full standardisation, leading to inconsistencies  
 55 both across and within laboratories.

56 Datashuttle aims to bridge the gap between ‘no standardisation’ and full standardisation by  
 57 implementing a simple specification called ‘NeuroBlueprint’ (Ziminski et al., 2025) (Figure 1).  
 58 NeuroBlueprint mandates only folder naming and structure conventions, while recommending  
 59 file and metadata-naming schemes. It is designed to be easy to adopt, meaning it is suitable for  
 60 the busy data-acquisition stages of a project in which applying full standardisation is often too  
 61 onerous. The structure and format are heavily inspired by BIDS, in order to reduce redundancy  
 62 across specifications and facilitate later transition to this more comprehensive schema. This  
 63 means that while NeuroBlueprint is not sufficiently standardised to ensure data are FAIR, it  
 64 provides an easy-to-use starting point that requires relatively little effort to adopt.



**Figure 1:** The NeuroBlueprint specification. Raw data (i.e. as collected from acquisition machines) are organised hierarchically by subject, session, and datatype. Subject and session names consist of key-value pairs. Only the sub- and ses-keys are required and others are optional. Acquired data are placed in the datatype folder, with valid datatype names defined in the specification. Derived data are stored in the top-level derivatives folder, and while not mandated, it is advised to organise these similar to the rawdata directory.

65 Datashuttle automates the creation, validation and transfer of experimental folders in  
 66 NeuroBlueprint standard. It is designed to drop into existing scripted or manual data-acquisition

67 pipelines, ensuring standardisation at the point of data collection. Datashuttle offers flexible  
 68 data transfer capabilities that make standardisation practical and convenient, rather than an  
 69 added burden. With minimal dependencies and no lock-in, it provides a lightweight, adaptable  
 70 solution for managing neuroscience project workflows.

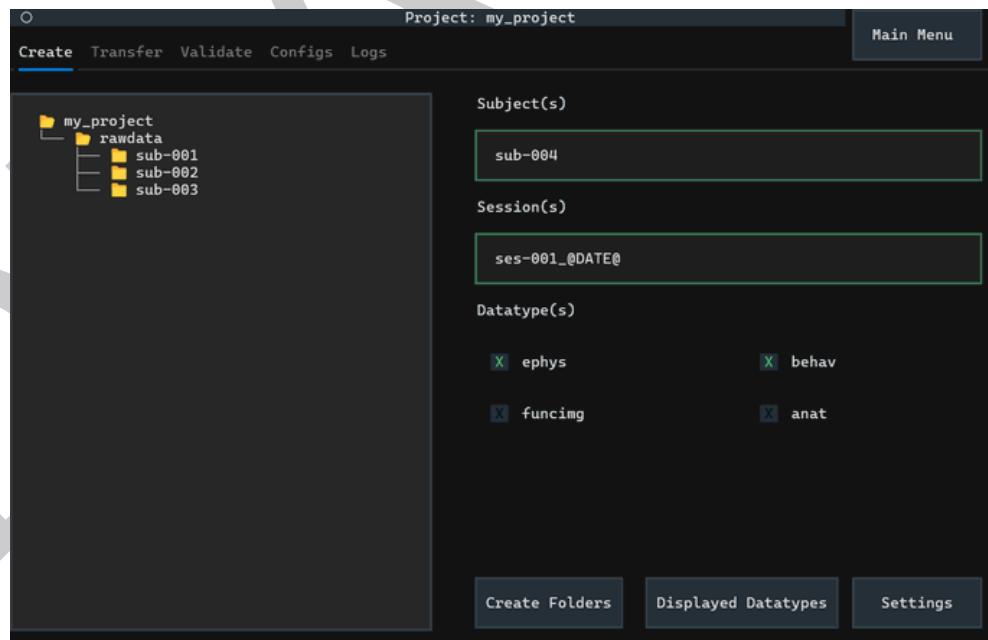
## 71 Features

72 Datashuttle can be installed via the package manager conda. While pip installation is supported,  
 73 the non-Python dependency RClone (used to manage data transfers) must be installed separately.  
 74 The cross-platform terminal user interface (TUI) is built with Textual ([McGugan, 2021](#)) and  
 75 can be used in the system terminal.

76 The typical workflow begins with researchers creating standardised folders at the start of  
 77 each experimental session. Data generated during acquisition (e.g. from cameras, behaviour-  
 78 monitoring devices or electrophysiology probes) are saved into the created folders. Real-time  
 79 validation features ensure that common errors such as duplicate subject or session IDs are  
 80 caught immediately. At the end of the experimental session, data are transferred to the  
 81 laboratory's central storage. Transfers can be made to a remote server either via a mounted  
 82 drive or SSH, while cloud services such as Google Drive and AWS S3 Buckets are also supported.

## 83 Folder Creation

84 NeuroBlueprint-formatted folder trees can be created for a given subject, session and datatype  
 85 (e.g. 'behav' for behaviour), with online validation to reduce the likelihood of errors in user  
 86 input ([Figure 2](#)).



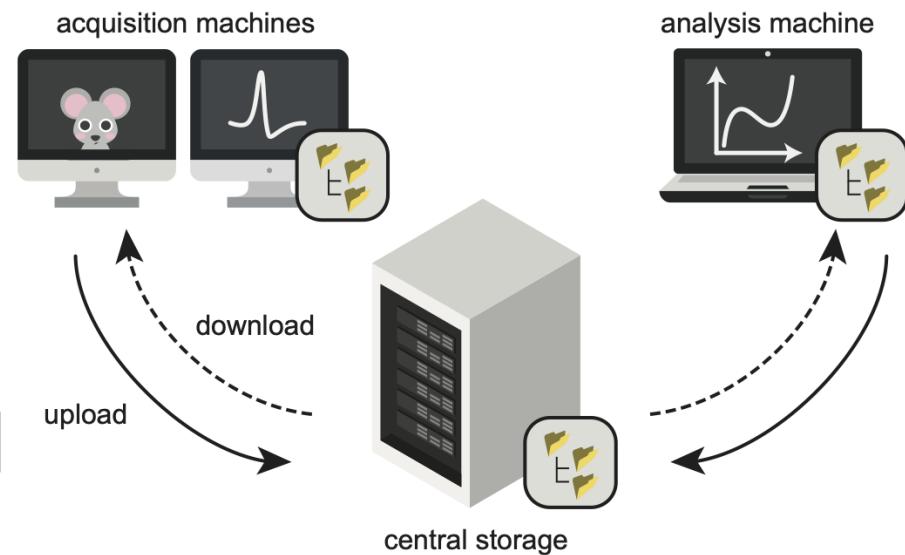
**Figure 2:** The Create Folders screen. Subject, session and datatype folders can be created through this interface. The text input border provides real-time validation results, while tags such as @DATE@ can be used to auto-format the system date. The current project is displayed on the left-hand directory tree, which can be used to copy file-paths and open the operating filesystem.

## 87 Validation

88 Validation catches issues such as duplicate subject or session IDs, inconsistent number of leading  
 89 zeros, bad key-value pair formatting and other common typographical errors. Validation can be  
 90 performed on an entire project, listing any formatting errors that are discovered. Additionally,  
 91 real-time validation during folder creation ensures no non-NeuroBlueprint format folders can  
 92 be made. Custom extensions to the validation can be added, with subject and session names  
 93 validated against user-defined regular expression templates.

## 94 Data Transfer

95 Datashuttle uses the open source tool RClone ([Craig-Wood, 2014](#)) to perform data transfers.  
 96 Experimental data can be ‘uploaded’ (from the local machine to central storage) or ‘downloaded’  
 97 (from the central storage to the local machine) ([Figure 3](#)). A benefit of standardisation is  
 98 machine-readable folder names—meaning it is simple to select arbitrary subsets of data for  
 99 transfer e.g. only the first five subjects.



**Figure 3:** Data transfers in datashuttle. A typical workflow involves transferring data from an acquisition machine to a central laboratory storage. Later, the entire dataset or subsets of it (e.g. only electrophysiology data) may be downloaded to an analysis machine for processing.

## 100 Logging

101 In order to track full provenance of the project, datashuttle operations are logged to file with  
 102 fancylog ([Ziminski & Tyson, 2025](#)). Logs can be accessed directly from disk or displayed in  
 103 the TUI.

## 104 Future Directions

105 Datashuttle will continue to evolve alongside the NeuroBlueprint specification, implementing  
 106 upcoming extensions as they emerge. While Datashuttle does not currently support a metadata  
 107 standard, this will be a key focus for future development to enable improved validation and  
 108 automation.

109 Currently, NeuroBlueprint is designed for experiments in which subjects go through the  
110 experimental procedures individually. However multi-animal experiments investigating social  
111 behaviours, in which animals interact during experimental sessions, are a growing area of  
112 neuroscience research. Future updates to both NeuroBlueprint and datashuttle will aim to  
113 support this use case.

## 114 Availability

115 Datashuttle's source code is available at <https://github.com/neuroinformatics-unit/datashuttle>  
116 and documentation published at <https://datashuttle.neuroinformatics.dev>.

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