

Issues and recommendations from the OHBM COBIDAS MEEG committee for reproducible EEG and MEG research

Authors – copy
Published in Nature Neuroscience

<https://doi.org/10.1038/s41593-020-00709-0>

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Abstract

The Organization for Human Brain Mapping (OHBM) has been active in advocating for the instantiation of best practices in neuroimaging data acquisition, analysis, reporting, and sharing of both data and analysis code, to deal with issues in science related to reproducibility and replicability. Here we summarize recommendations for such practices in magnetoencephalographic (MEG) and electroencephalographic (EEG) research, recently developed by the OHBM neuroimaging community known by the abbreviated name of COBIDAS MEEG. We discuss rationale for the guidelines and their general content, which encompasses many topics under active discussion in the field. We highlight future opportunities and challenges to maximizing the sharing and exploitation of MEG and EEG data, and also how this 'living' set of guidelines will evolve to continually address new developments in neurophysiological assessment methods and multimodal integration of neurophysiological data with other data types.

Keywords

best practices; data acquisition; data analysis; data sharing; magnetoencephalography; electroencephalography; COBIDAS; Organization for Human Brain Mapping

3997 words, 3 figures, 2 boxes, 3 tables, 88 references

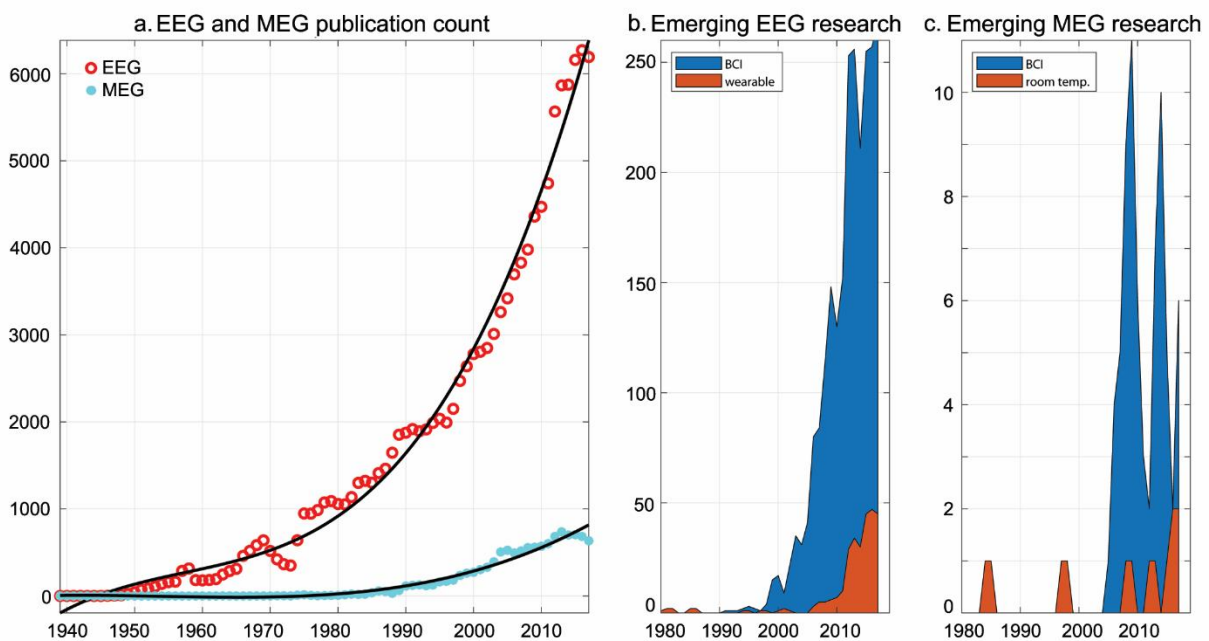
1 The OHBM COBIDAS MEEG report

2 The neuroimaging community, like many other scientific communities, is actively engaged
3 in open science practices designed to improve reproducibility and replicability¹ of scientific
4 findings. The Organization for Human Brain Mapping (OHBM), through Committees on
5 Best Practices in Data Analysis and Sharing (COBIDAS), promotes and distributes
6 commonly agreed practices formalizing their terminology, in consensus with other
7 organizations. OHBM has developed the COBIDAS reports^{2,3} to present best practices
8 for specific neuroimaging methods, propose a standardized scientific language for
9 reporting and promote effective sharing of data and methods. The reports are useful to
10 (i) those preparing manuscripts and grant proposals of their work, (ii) editors and
11 reviewers, (iii) neuroimaging educators; and (iv) those with expertise in a neuroimaging
12 technique who seek to become *au fait* with another.

13
14 In this Perspective, we focus on the COBIDAS MEEG report² highlighting some of the
15 main issues and ensuing recommendations generated by the committee. Our purpose is
16 to provide a better understanding of how some acquisition parameters, design, analysis
17 and reporting choices *can influence reproducibility*. Beyond these, many other issues
18 have also found their way in the recommendations (see boxes 1, 2 & tables 1, 2, 3). As
19 such, these recommendations represent the *minimal requirements* to be reported to
20 ensure reproducible MEEG studies, and for each recommendation full details can be
21 found in the COBIDAS report itself². At the same time, many of these seemingly basic
22 pieces of advice are contentious. A great deal of discussion has been spent on
23 terminology, and our proposal is a consensus that adopts and extends the terminology
24 used in the Brain Imaging Data Structure (BIDS <https://bids.neuroimaging.io/>) that
25 enables better data sharing (initially for MRI⁴ and now also for neurophysiological data
26 with MEG-BIDS⁵, EEG-BIDS⁶ and iEEG-BIDS⁷). It also follows nomenclatures of the
27 International Federation for Clinical Neurophysiology (IFCN <https://www.ifcn.info/>) current
28 clinical guidelines, thus integrating research and clinical practices. It is also clear to us
29 that there is no best analysis workflow (even if some general principles exist, e.g. Fig. 2)
30 or best statistical approach, only optimal solutions to a given problem - and *this is why*
31 *reporting context, acquisition and analysis details are so important*.

32
33 The MEEG community has always been proactive in discussing good practices and
34 reporting, evidenced by the long history of published guidelines⁸⁻¹⁵. Some aspects of
35 these guidelines have remained current despite the rapidly changing developments in
36 MEEG hardware/software and methods. While the OHBM COBIDAS MEEG report
37 follows this tradition, it differs from previous guidelines in three important respects. First,
38 it has a focus on practices that specifically aid with reproducibility and data sharing.
39 Second, the COBIDAS MEEG report exists as a *living document* in the format of a
40 WordPress blog that invites feedback and comments
41 (<https://cobidasmeeq.wordpress.com/>), with version controlled preprint releases on the
42 Open Science Framework (<https://osf.io/a8dhx/>). We invite readers to refer to this
43 document² when preparing scientific material. There has been exponential growth in the
44 MEG and EEG literature in the 21st century (see Fig. 1a). A dynamic guideline is
45 important as there have been many updates of acquisition and analysis methods, and the
46 implementation of new technologies needs also to be integrated while keeping a coherent

47 set of recommendations. For instance, portable EEG devices, portable MEG devices
 48 operating at room temperature, and Brain Computer Interfaces (BCI) have not been
 49 considered as these are still emerging technologies (Fig. 1 b,c). Yet as these become
 50 more extensively used and available, experience will grow and best practices will need
 51 development. Additionally, COBIDAS MEEG has not considered invasive EEG (iEEG)
 52 recordings, despite their long history and recent renewed interest. In future, these might
 53 be integrated under a more general 'COBIDAS Neurophysiology' document. Third, the
 54 target population for the COBIDAS MEEG guidelines is considerably broader and larger
 55 than that served by previous guidelines, which traditionally were targeted to members of
 56 neurophysiological societies or interest groups concerned with one specific imaging
 57 modality (EEG or MEG), analytical method (ERP, spectrum, source, etc) or practice
 58 (research or clinic).
 59



60
 61 **Figure 1. Overview of the total number of MEEG publications with emerging research fields a.**
 62 *Number of EEG and MEG publications by year of publication. b. Emerging EEG research. Number of*
 63 *publications under the topics of Brain Computer Interface [BCI] and mobile/wearable EEG by year. c.*
 64 *Emerging MEG research. Number of publications by year for BCI and room temperature [Optically Pumped*
 65 *Magnetometer based] portable MEG. Source for literature searches: Medline.*
 66

67 Terminology and reporting recommendations

68 To promote reproducible experimentation, one must share a common language. Some
 69 terms are common across imaging modalities, but can have slightly different usages. The
 70 COBIDAS MEEG terminology for describing task parameters and data acquisition follows
 71 those of the COBIDAS MRI and Brain Imaging Data Structure (Box 1). Of particular
 72 interest to MEEG researchers, we recommend using 'run' rather than 'block', which are
 73 used interchangeably in MEEG, but clearly differ for PET or MRI. Also, we recommend

74 explicitly reporting the space in which data processing (i.e. statistical analyses and
75 modeling) is taking place: sensor vs. source. This is important as certain analytical
76 methods may not be suitable for use in sensor space. While other data spaces have been
77 reported in the literature, e.g. independent component space, these are only
78 mathematical subspaces of the more general categories mentioned here.

79

80 There is also a specific MEEG terminology to describe features in the data that does not
81 exist for MRI-based studies. Our recommendations (Box 2) are to follow conventions and
82 common nomenclature¹⁶, consistent with IFCN guidelines. We propose additional
83 considerations for reporting EEG results aimed at reducing confusion in the literature as
84 follows: (1) for reporting evoked data in sensor space, recording site(s) should be noted
85 (e.g., vertex N100), as response polarity can vary by either original or post-hoc scalp
86 reference electrode and underlying cortical folding; (2) latency windows used to quantify
87 event-related components should be explicitly mentioned. For reporting spontaneous or
88 resting-state MEEG data, in particular for spectral analyses, we advocate explicitly
89 reporting boundaries of different frequency bands. There is confusion in the literature
90 caused by inconsistencies in designating 'canonical' frequency bands^{14,17} (e.g., delta,
91 theta, alpha, beta, gamma). Here, we considered IFCN guidelines¹⁴ for delineating
92 canonical MEEG frequency bands, as these remain close to those originally proposed in
93 the late 1920s by Berger¹⁸, and in the 1930s by Walter¹⁹, as well as Jasper and
94 Andrews¹⁶, and align with the main clinical textbook in the field²⁰. That said, due to
95 inconsistencies across literatures, we made a slight adjustment to the transition between
96 alpha and beta ranges to guide results description for time-frequency analyses.

97

98

Session. A logical grouping of neuroimaging and behavioural data collected consistently across participants. A session includes the time involved in completing all experimental tasks. This begins when a participant enters the research environment and continues until he/she leaves. This would typically start with informed consent procedures, followed by participant preparation (i.e., electrode placement and impedance check for EEG; fiducial and other sensor placement for MEG). It would end when the electrodes are removed (for EEG) or the participant exits the MEG room, but could potentially also include a number of pre- or post-MEEG observations and measurements (e.g., anatomical MRI, additional behavioural or clinical testing, questionnaires), even on different days. Defining multiple sessions is appropriate when several identical or similar data acquisitions are planned and performed on all (or most) participants, often in the case of some intervention between sessions (e.g., training or therapeutics) or for longitudinal studies.

Run. An uninterrupted period of continuous data acquisition without operator involvement. Note that continuous data need not be saved continuously; in some paradigms, especially with long inter-trial intervals, only a segment of the data (before and after the stimulus of interest) are saved. In the MEEG literature, this is also sometimes referred to as a block. (Note the difference with the 'block' term in COBIDAS MRI, where multiple stimuli in one condition can be presented over a prolonged and continuous period of time.)

Event. An isolated occurrence of a presented stimulus, or a subject response recorded during a task. In addition to the identity of the events, it is essential to have exact timing information synchronized to the MEEG signals. For this, a digital trigger channel with specific marker values, or a text file with marker

values and timing information can be used. (This term has been defined here in a more narrow and explicit sense than that for COBIDAS MRI, mainly because of the specialized requirements surrounding the high temporal resolution acquisition of MEEG data.)

Trial. A period of time that includes a sequence of one or more events with a prescribed order and timing, which is the basic, repeating element of an experiment. For example, a trial may consist of a cue followed after some time by a stimulus, followed by a response, followed by feedback. An *experimental condition* is a functional unit defined by the design and usually includes many trials of the same type. Critical events within trials are usually represented as time-stamps or “triggers” stored in the MEEG data file, or documented in a marker file.

Epoch. In the MEEG literature, the term *epoch* designates the outcome of a data segmentation process. Typically, epochs in event-related designs (for analysis of event-related potentials or event-related spectral perturbations) are time-locked to a particular event (such as a stimulus or a response). Epochs can also include an entire trial, made up of multiple events to suit the data analysis plan. (This terminology is not used in the COBIDAS MRI specification.)

Sensors. Sensors are the physical objects or transducers that are used to perform the analogue recording, i.e., EEG electrodes and MEG magnetometers/gradiometers. Sensors are connected to amplifiers, which not only amplify, but also filter the MEEG activity.

Channels. Channels refer to the digital signals that have been recorded by the amplifiers. It is thus important to distinguish them from sensors. A ‘bad channel’ refers to a channel that is producing a consistently artifactual or low-quality signal.

Fiducials. Fiducials are markers placed within a well-defined location, which are used to facilitate the localization and co-registration of sensors with other spatial data (e.g., the participant’s own anatomical MRI image, an anatomical MRI template or a spherical model). Some examples are vitamin-E markers, reflective disks, felt-tip marker dots placed on the face, or sometimes even the EEG electrodes themselves. Fiducials are typically placed at a known location relative to, or overlying, anatomical landmarks.

Anatomical landmarks. These are well-known, easily identifiable physical locations on the head (e.g., nasion at the bridge of the nose; inion at the bony protrusion on the midline occipital scalp) acknowledged to be of practical use in the field. Fiducials are typically placed at anatomical landmarks to aid localization of sensors relative to geometric data.

Sensor space. Sensor space refers to a representation of the MEEG data at the level of the original sensors, where each of the signals maps onto the spatial location of one of the sensors.

Source space. Source space refers to MEEG data reconstructed at the level of inferred neural sources that presumably gave rise to the measured signals (according to an assumed biophysical model). Each signal maps onto a spatial location that is readily interpretable in relation to the individual, or a template-based, brain anatomy.

Box 1. Specific MEEG terminology and definitions with respect to data acquisition.

Event-related response component vs deflection. For time domain MEEG data, “component” traditionally refers to a functional brain process that has a characteristic spatial distribution and canonical latency⁸. Because of this loaded meaning for the term “component”, the term “deflection” is a useful alternative.

Event-related response nomenclature. For EEG, event-related response components are named using a convention, where (EEG) response polarity and its *nominal* latency form the name (e.g., N100, N170, P300, N400, etc.), preferably adding the recording site. This was first published in the International Federation for Clinical Neurophysiology (IFCN) guidelines in 1983 (and updated in 1999), and advocated for reporting of clinical data¹¹, based on original nomenclature⁸. For MEG, the analogous components are referred to by two conventions: (1) an “m” added to the component name (e.g., N100m, N170m) or (2) referred to as M100, M170, etc.

Specialized MEEG event-related component nomenclature. Certain MEEG responses e.g. mismatch negativity (MMN), contingent negative variation (CNV), error-related negativity (ERN), among others, refer to specific responses elicited in particular types of paradigm, or to presumed mental states (e.g., error detection).

Other nomenclature. Early studies often refer to event-related components by successive EEG waveform deflections (e.g., P1, N1, P2, N2 etc.). However, this nomenclature is no longer recommended. That said, there is an established literature on some later ERP components such as P3a and P3b (also known as P300 or the late positive component (LPC) in the literature). In these cases, referring to their well-established names could be more appropriate (or adapted e.g., P300a, P300b), ideally citing the original article describing the component. In the auditory literature, brain-stem evoked responses were originally labelled, and today are still known, by Roman numerals I to VII.

Canonical MEEG frequency bands:

infra-slow:	< 0.1 Hz
delta:	0.1 to < 4 Hz;
theta:	4 to < 8 Hz;
alpha:	8 to < 13 Hz;
beta:	13 to 30 Hz;
gamma:	> 30 to 80 Hz.

Gamma band signals may occur at frequencies higher than 80 Hz²¹, but the majority of MEEG studies use the lower (original) values of the range, as above. For MEG the gamma band can extend out to 1 KHz²², so statistical analysis of gamma activity may identify *ranges of activity* within this very broad frequency band²³. Therefore, reporting specific values of frequencies of interest within the gamma band may be more useful.

Oscillation. This term is specific to a spectral peak within a frequency band of interest, and not a general increase in MEEG power within a canonical frequency band²⁴. The oscillation is defined by its peak frequency, bandwidth, and power.

Box 2. Specific MEEG terminology and definitions with respect to data analysis.

104 **Which essential data acquisition parameters and experimental design**
105 **attributes should always be reported?**

106 When investigators report scientific findings or share data, a surprising number of
107 important parameters are often omitted, hampering both reproducibility and replicability.
108 To overcome these omissions, the COBIDAS MEEG report² contains a substantial
109 Appendix of Tables listing desirable parameters to be reported. We do not discuss these
110 in detail here, however; Table 1 provides a selected list of important basic descriptors of
111 experimental paradigms, participants, and measured behaviors. We have specifically
112 highlighted these parameters in Table because many of these tend to be omitted the
113 most, either in already published manuscripts or in new manuscripts being submitted to
114 journals. Here we also touch on why their omission creates ongoing problems for
115 replications and for meta-analyses.

116
117 **Issue 1: Basic hardware/software and acquisition parameters.** Many published
118 papers omit basic data acquisition details: acquisition system type, number of sensors
119 and their spatial layout, acquisition type - continuous/epoched, sampling rate and
120 analogue filter bandwidth (low-pass and high-pass). The latter in particular is most often
121 omitted, yet during data acquisition *all* MEEG recording systems use filter circuitry
122 (potentially as defaults that are not always obvious to the user) which inherently limits
123 what is measured. Low-frequency artifacts due to respiration or skin conductance
124 responses can be present, and on the higher frequency end, other artifacts might be
125 aliased if they have not been filtered out (and therefore undersampled). Conversely,
126 effects of interest in the EEG might have inadvertently been filtered out by inappropriately
127 applied filter settings at data acquisition. There is no way to assess for these possibilities
128 if the filter characteristics have not been reported.

129
130 **Issue 2: EEG reference electrodes, impedances.** A key aspect of EEG is that
131 measurements are differential voltages relative to a reference electrode. A ground
132 electrode serves as a way to reduce non-common mode signals in the EEG e.g. line noise
133 or electrical stimulation artifacts. The reference and ground electrode locations must
134 therefore always be reported.

135
136 Note that physically linked earlobe/mastoid electrodes during acquisition are not
137 recommended as they are not a neutral reference, can introduce distortions in the data,
138 and make modelling intractable²⁵. This cannot be corrected with subsequent re-
139 referencing or data analysis. Recording quality should also be homogenous across the
140 scalp, and therefore the impedance measurement procedure and impedance values, for
141 passive EEG electrode systems, should be reported. (For active electrode systems this
142 may not always be possible). Optimal electrode impedances vary relative to an amplifier's
143 input impedance, and to a lesser extent with electrode type (passive or active) and
144 ambient noise level. A statement on acceptable electrode impedances (e.g.
145 manufacturer's recommendation) for the specific setup, as well as actual values (on
146 average, or an upper bound) and the time(s) when impedances were measured during
147 the experiment (e.g., start, middle, end) should be provided. Reporting these procedures
148 allows a reader to make a judgment on the quality of the data.

149

150 **Issue 3: Statistical power.** When null hypothesis testing is the statistical method used,
 151 reporting on *a priori* statistical power is recommended as a good practice. The probability
 152 that a study detects an effect *when there is an effect* is, however, a difficult problem in the
 153 context of EEG and MEG because it depends on the complex balance between number
 154 of trials and participants, itself a function of the experimental design (within versus
 155 between participants²⁶), on chosen statistical method, and on the MEEG features of
 156 interest, including their locations, orientations and distance from sensors²⁷. We
 157 recommend defining the main data feature(s) of interest and then estimating the minimal
 158 effect size to determine power. A minimal effect size is the smallest effect relevant for a
 159 given hypothesis. Effect size should be determined using estimates from independent
 160 data, existing literature, and/or pilot data. The latter should not be part of the final sample.
 161 If no electrophysiological data are available, behavioural data can be used as a minimal
 162 estimate of required sample size. In any cases, be aware that errors in calculating effect
 163 size and statistical power can occur from small sample sizes (i.e. pilot data²⁸). Since (i)
 164 effect sizes of many neural effects (as measured with MEEG studies) are often smaller
 165 than that of behavioural reaction time effects, and (ii) some trials/epochs are rejected due
 166 to artifacts, thus diminishing the number of trials/epochs available for statistical analyses,
 167 this imposes lower bounds on how many trials and participants are needed²⁹ to achieve
 168 high statistical power. Therefore, more events and participants than has traditionally been
 169 common practice are more often required than not.
 170
 171

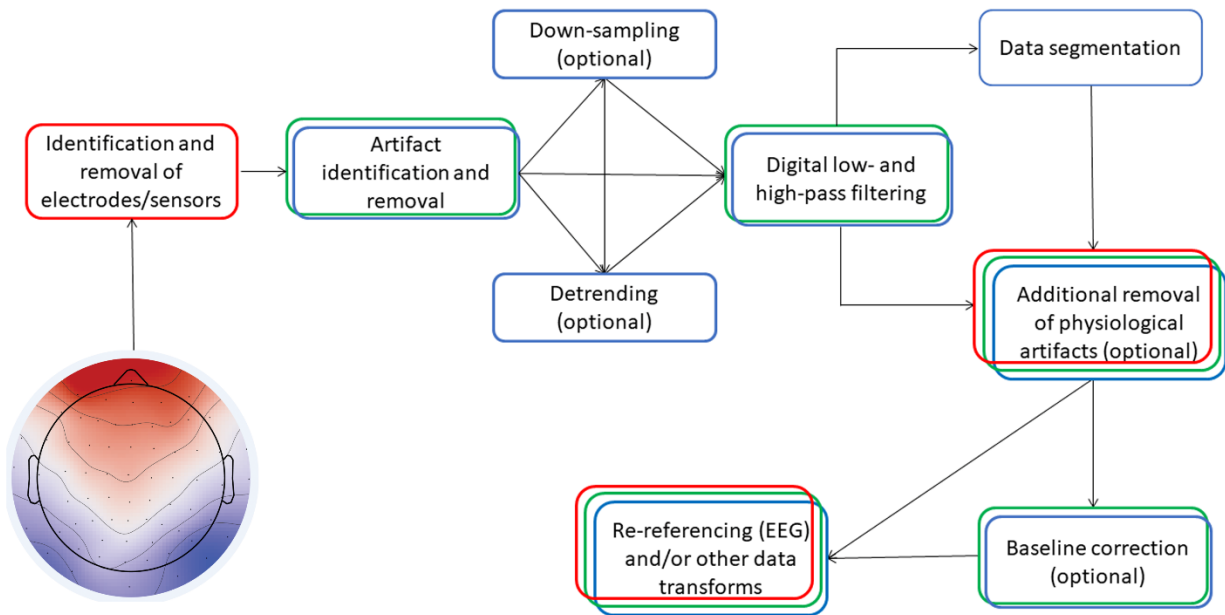
Experimental attribute	Reporting	Supplementary materials
Participant selection	<ul style="list-style-type: none"> - population - recruitment - sampling strategy - demographics - medications - consent 	Individual demographics and questionnaires
Experimental set-up	<ul style="list-style-type: none"> - recording environment - seated or lying down - anaesthetic agent if any, with dosage and administration method 	
Experimental task information	<ul style="list-style-type: none"> - Instructions - number of runs and sessions - stimuli origin and properties - software (type, version and operating system) and hardware used for stimulus presentation - conditions and stimuli order and timing - how task-relevant events are determined 	scripts and stimuli
Task-free recordings	<ul style="list-style-type: none"> - eyes open vs closed 	

	- if eyes open, fixation point or not	
Behavioural measures	<ul style="list-style-type: none"> - nature of the response - acquisition device (product name, model, manufacturer, recording parameters) - interface with MEEG data and calibration procedures - errors and outliers handling - statistical analyses 	Individual response logs with scripts for behavioural data analysis

172 **Table 1. Recommendations for basic experimental attributes to include in an article, along with**
173 **suggested supplementary materials for increasing reproducibility.**

174 **Critical considerations for MEEG data pre-processing**

175 We define data preprocessing as any manipulation and transformation of the data.
176 Preprocessing order influences both the qualitative (e.g. SNR) and quantitative (e.g.
177 deflection and spectral amplitudes) properties of the data, and thus impacts directly the
178 replicability (Table 2). As parameter and algorithm complexity grow for MEEG data
179 analysis, providing details about all computations is mandatory as minor changes can
180 lead to large differences³⁰ in analysed output. Figure 2 outlines one of the more typical
181 workflows, or sequence of preprocessing steps; specific recommendations for each step
182 are available in the COBIDAS report (<https://cobidasmeeq.wordpress.com/>). For specific
183 analyses, or due to specific data characteristics, the processing order can vary, but the
184 order should be clearly justified and described in detail in accordance with our
185 recommendations.
186



187
 188 **Figure 2. Standard MEEG preprocessing steps.** Each step affects the data in the space (red), time (blue)
 189 and/or frequency (green) domains. Deviations from the proposed order are possible given the experimental
 190 set-up and/or MEEG feature(s) investigated but should be justified.

191

192

Step	Parameters	Impact
Sensor removal	<ul style="list-style-type: none"> - detection method and criteria - interpolation parameters if performed at this stage (e.g., trilinear, spline (+ order)) 	For low density coverage and/or clusters of sensors, in sensor space effects can be missed on the scalp; in source space, source locations and effects can be spurious
Artifact removal	<ul style="list-style-type: none"> - method used and the range of parameters (e.g., EEG data with a range larger than 75 microV) - for signal/noise separation methods (linear projection, spatial filtering techniques such as ICA³¹⁻³³) describe the algorithm and parameters used, report the number of ICs that were obtained, how non-brain IC were identified and how back-projection was performed. 	Can change or mask effects, create spurious effects
Physiological artifact removal	<ul style="list-style-type: none"> - types of features in the MEEG signal identified using which criteria 	

	<ul style="list-style-type: none"> - how many (and where relative to event onset) segments were removed - MEG specific: if signal-space projection methods (SSP³⁴) are used, report “empty room” measurements to estimate the topographic properties of the sensor noise and project it out from recordings containing brain activity. Related tools with a similar purpose include signal space separation methods and their temporally extended variants^{35,36} that rely on the geometric separation of brain activity from noise signals in MEG data 	
Downsampling	- method used (e.g. decimation, low-pass filter)	Affects the precision of time locked effect and can alter or remove spectral changes
Detrending	- detrending performed and the algorithm order (e.g., linear 1st order, piecewise, etc)	May affect connectivity metrics and statistical results
Filtering	<ul style="list-style-type: none"> - type of filter, cut-off frequency, filter order (or length), roll-off or transition bandwidth, passband ripple and stopband attenuation, filter delay and causality, direction of computation (one-pass forward/reverse, or two-pass forward and reverse) - for low pass, consider sampling rate setting, at least 2 to 2.5 times above the intended low pass cut off frequency (Nyquist-Shannon sampling theorem + filter roll-off) 	Consequences for estimating time-courses and phases ^{37,38}
Segmentation	specify the length of segments	Affects connectivity values especially considering sensor vs source space ³⁹
Baseline correction	<ul style="list-style-type: none"> - assure equal baselines between conditions/groups - method used (absolute, relative, decibel, regression) 	Affects signal to noise ratio, statistical type 1 error and power ^{40,41}

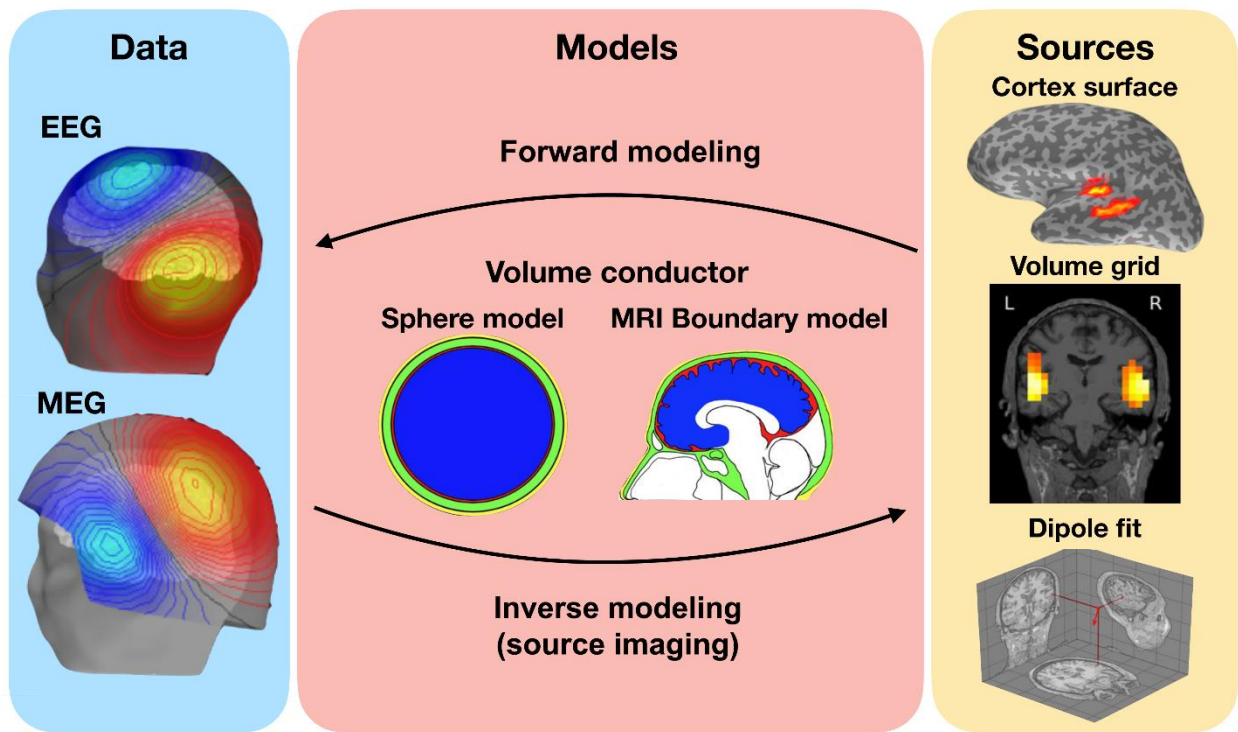
Re-referencing	<ul style="list-style-type: none"> - method used (subtracting the values of another channel or weighted sum of channels) - interpolation parameters if performed at this stage (e.g., trilinear, spline (+ order)) - for reference-free method (eg CSD) the software and parameter settings (interpolation method at the channel level and algorithm of the transform) must be specified. 	Changes raw effect size values and statistical results
Normalization (for multivariate analyses)	<ul style="list-style-type: none"> - describe if performed or not - if performed, indicate the type: univariate normalization or for all channels together, i.e. multivariate normalization (or whitening). - if multivariate normalization, specify the covariance estimation procedure. 	Affects source modelling and decoding performance ^{42,43} .
Spectral transformation	<ul style="list-style-type: none"> - data acquisition rate must be at least twice (Nyquist theorem) the highest frequency of interest in the analyzed data - an adequate pre-stimulus baseline should be specified for evoked MEEG data i.e. the baseline duration should be equal to at least three cycles of the lowest frequency to be examined⁴⁴. - details on the transformation algorithm and associated parameters. - the required frequency resolution is defined as the minimum frequency interval that two distinct underlying oscillatory components need to have in order to be dissociated in the analysis^{45,46}. 	Affects the precision of results

193 **Table 2. Overview of data preprocessing steps, parameters that should be reported and their impact**
194 **on reproducibility.**
195

196 **Source modelling:** Source modelling and reconstruction is a major processing pipeline
197 step prior to statistical analyses and/or modeling that must be reported fully (Fig. 3).
198 Neural source reconstruction aims at explaining the spatio-temporal pattern of observed
199 sensor space MEEG data in terms of the underlying neuronal generators. This is known
200 as solving the *inverse problem*, which has no unique solution (i.e. it is mathematically ill-
201 posed). Models used to solve this problem are thus constrained by various assumptions,
202 two important ones being the volume conduction model of the head and the source model
203 itself. Since both affect result accuracy and reliability⁴⁷⁻⁴⁹, details on the forward model
204 (head model, numerical method (boundary/finite element), and conductivity), source
205 model (distributed/ focal) and the source localization method with parameters used (e.g.,

206 the regularization parameter) must be reported along with the used (versioned) software
 207 for a complete and reproducible report. Information on reconstruction quality is also
 208 crucial. For both MEG and EEG, since there are multiple methods to estimate sources,
 209 the expected accuracy, errors and robustness (as described in the literature) of the
 210 chosen method should, at minimum, be described. Resampling techniques can also be
 211 used to provide further information (bias, spatial confidence intervals, etc) on the
 212 reconstruction performed with the data at hand. The source reconstruction of low-density
 213 (below 128 channels) datasets should be fully justified and interpreted with caution, given
 214 that the number of sensors impact localization accuracy⁴⁹⁻⁵¹ and estimation of
 215 connectivity⁵². Different source modelling methods can be advantageous for particular
 216 applications, so reporting the rationale for choosing a source model is also important.

217



218

219 **Figure 3. Illustration of source modelling approaches.** To find active neural sources, a forward model
 220 must first be used to determine the scalp distribution of the EEG potential or MEG magnetic field for a (set
 221 of) known source(s). These models vary according to how sources are defined (either on the cortical surface
 222 or on a volumetric grid) and the volume conduction model, which simulates effects on the tissues in the
 223 head on propagation of activity to MEEG sensors (spherical head model vs. MRI derived models - here
 224 showing bone (green), cerebrospinal fluid (red), gray and white matter (blue) tissues). Information from the
 225 forward model is then inverted to attribute active sources to the measured MEEG signals.

226

227 **Critical considerations for MEEG data processing**

228 We define data processing as mathematical procedures that *do not change* the data, i.e.
229 statistical analysis and statistical modeling. There are many valid methods to analyse
230 MEEG data. The chosen method should best answer the posed scientific question⁵³ and
231 a rationale for its use should always be provided. Here we briefly examine some of the
232 main data processing issues discussed in the COBIDAS MEEG report².

233

234 **ROI-based analyses:** Selecting specific channels or source-level Regions-Of-Interest
235 (ROI) based on grand average differences between conditions/groups and then
236 performing statistical tests on these has at times been seen in the MEEG literature. This,
237 however, creates estimation biases (i.e. “double-dipping”)^{54,55}, irrespective of whether
238 one works in sensor or source space. ROI analyses in time, frequency or space (peak
239 analysis, window average, etc) while legitimate, should be justified *a priori* based on prior
240 literature or independent data or statistical contrasts.

241 **Mass univariate statistical modelling:** More recently, analyses tend to be performed at
242 the participant and group levels, using a hierarchical or mixed model approach for the
243 whole data volume (3D source space), and/or the spatio-temporal sensor space^{56,57}.
244 These types of analyses (and those that follow in the subsequent sections below) have
245 become more common and have not typically been addressed in previous guidelines.
246 Compared to tomographic methods, MEEG can have missing data (e.g., bad channels,
247 or transient intervals with artifacts), so reporting on how missing data have been treated
248 is crucial. Results must be corrected for multiple testing/comparisons (e.g., full brain
249 analyses or multiple feature/component maxima), but both *a priori* and *a posteriori*
250 thresholds⁵⁸ cannot adequately control the Type 1 family-wise error and should be
251 avoided⁵⁹. Special attention must also be given to data smoothness when using random
252 field theory⁶⁰. This is in contrast to *a posteriori* thresholds using null distributions
253 (bootstrap and permutations), which control well for family-wise Type 1 error rate^{61,62}.

254 **Multivariate statistical inference:** Multivariate statistical tests (e.g. MANOVA, Linear
255 Discriminant Analysis) are typically performed in space or time/frequency, thus also
256 leading to a multiple comparisons problem that needs to be properly addressed. The
257 problem of not correcting adequately for multiple comparisons remains a common
258 omission for such data analyses.

259

260 **Multivariate pattern classification:** Decoding approaches should strive to minimise bias
261 and unrealistically high classification rates, commonly referred to as “overfitting”. To avoid
262 overfitting, a nested cross-validation procedure should be used, where independent
263 subsets of the data are used to estimate the parameters, fit the classification model, and
264 estimate performance metrics. It is also important to justify data-split choice, as some
265 approaches can give biased estimates (e.g. leave-one-out on correlated data⁶³).

266

267 **Connectivity:** The term “connectivity” is an umbrella term often used to refer to multiple
268 methods, which may create some confusion in the literature^{64,65}. In the MEEG context, it
269 generally refers to analyses that aim to detect *coupling* between two or more channels or
270 sources. We recommend explicitly referring to functional (correlational) or effective

271 (causal) connectivity⁶⁶ and to describe the specific method used (e.g. effective Granger
 272 connectivity, partial coherence, dynamic causal modelling (DCM), etc). Table 3 outlines
 273 different approaches in connectivity analyses and lists important variables to report. With
 274 respect to the *computed metrics*⁶⁷, it is essential to report all parameters since they have
 275 a major effect on analytic outputs^{49,52}. Statistical dependence measures in either sensor
 276 or source space should be specified (e.g., correlation, phase coupling, amplitude
 277 coupling, spectral coherence, entropy, DCM, Granger causality), as well as analysis
 278 assumptions (e.g., linear versus unspecified; directional versus non-directional). For
 279 cross-frequency coupling (CFC)-based analyses, coupling type⁶⁸ should be explicitly
 280 noted. CFC occurs when activity at lower frequencies modulates higher frequency
 281 amplitude, phase or frequency. Since even one type of CFC can be extracted using
 282 multiple methods^{69–71}, analysis methods and all associated parameters, such as filtering,
 283 must also be specified in detail.

284
 285 Connectivity from MEG or EEG can be obtained from *sensor or source space measures*⁷²,
 286 and many discussions on the validity or utility of those measures exist. Our view is that
 287 while statistical metrics of dependency can be calculated at channel level (which can be
 288 useful for e.g. biomarking), these are not measures of neural connectivity^{67,73} and
 289 therefore cannot be used for causal inference⁷⁴. Neural connectivity can only be obtained
 290 after biophysical modeling (assuming it is accurate enough), considering volume
 291 conduction (e.g. spatial leakage of source signals⁷⁶) and spurious connections due to
 292 unobserved common sources.

293

Specifications	Parameters
Connectivity analysis	specify type: effective [causal] or functional [correlational] specify exact method used
Network estimation approaches	approach: data driven [e.g. ICA, time frequency analysis based] or anatomical/model driven? native space vs. template space? ^{75,76} If data driven, specify methods & parameters [e.g. time-frequency decomposition method] if anatomically driven, specify parcellation approach & parameters graph theoretical measures: motivation of metrics ⁷⁷ , specify if directed/undirected network, define nodes/edges, specify thresholding criteria
Consideration on computing metrics	consider effects of epoch length ³⁹ for dynamic connectivity measures describe all temporal parameters ⁷⁸ (e.g. window size, overlap, wavelet frequency and scale) for spectral coherence/synchrony measures: specify exact formulation (or reference), any subtraction or normalisation with respect to an experimental condition or mathematical criterion, is the measure debiased? for partial coherence and multiple coherence measures: describe all variables, specify exact variables used, and whether data are partialised, marginalised, conditioned, or orthogonalized for DCM ⁷⁹ specify model type (event-related potential, canonical

	<p>microcircuit); describe full space of considered functional architectures; connectivity matrices present/modulated (forward, backward, lateral, if intrinsic); vector of between-trial effects, the number of modes, the temporal window modelled, and the priors on source locations; statistical approach: at the level of models or the family of models (Fixed- or Random-effects, FFX or RFX); connectivity parameters (Frequentist versus Bayesian, Bayesian Model Averaging (BMA) over all models or conditioned on the winning family/model</p>
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Table 3. Necessary parameters to report in MEEG connectivity modeling to ensure reproduction of the method used.

294
295

296 **Results reporting and display items**

297 The COBIDAS MEEG report² discusses results reporting and figures in considerable
298 detail. In what follows we highlight some of the more common problematic aspects, where
299 even previously published neurophysiological studies have omitted important data
300 characteristics.

301
302 **Issue 1: Figures.** In figures depicting neurophysiological waveforms, we advocate the
303 inclusion of variability measures (e.g., confidence intervals) and clearly annotated scales
304 for all displayed data attributes. Moreover, since MEEG activity is characterized by its
305 topography, it is recommended that waveforms/spectra of the full set of channels are
306 shown (either in the main document or in supplementary materials).

307
308 **Issue 2: Using frequency band names across the lifespan.** Considerable ambiguities
309 and confusion exist in the spontaneous/resting-state MEEG literature due to inconsistent
310 use of terminology, and not assessing a particular cortical rhythm’s reactivity¹⁶. The well-
311 known posterior alpha rhythm characteristically occurs following eye closure and
312 diminishes greatly on eye opening. Importantly, during the lifespan posterior alpha
313 changes peak frequency: in infants (3-4 months of age) a reactive posterior rhythm first
314 appears at ~4 Hz, increasing to ~6 Hz at 12 months of age and to ~8 Hz at 36 months,
315 reaching adult frequencies of ~10 Hz by 6-12 years⁸⁰, and slowing again with normal
316 ageing²⁰. Specifying the *frequency and distribution of the activity* and noting its reactivity
317 is therefore important when studying aging. To reduce confusion, terms such as “baby
318 alpha” should be avoided, as central/rolandic (“mu”) rhythms (see COBIDAS MEEG
319 report for other issues related to mu rhythms) can develop in infants *before* the posterior
320 reactive rhythm that ultimately becomes fully-fledged “alpha” is seen. Currently, it is
321 difficult to perform meta-analyses because of the variability of use of various frequency
322 band names in the literature.

323
324 **Issue 3: Underspecifying results of statistical analyses.** For group or experimental
325 condition differences, the test statistic (e.g., F-values, t-values, Bayes Factors) must be
326 displayed. Reporting model assumptions (e.g. in linear models this includes Gaussianity
327 of residuals) and effect size (e.g., Cohen’s d, percentage difference and/or raw
328 magnitude) are also encouraged. It is also good practice to report the explained model
329 variance and data fit (both R-squared and RMSE), as well as parameters deriving from
330 the model(s) (e.g., weight estimates, maximum statistical values). For predictive models,

331 decoding accuracy (classification), R-squared or RMSE (regression) are the measures of
332 choice, but chance level should be included⁸¹. The area under a ROC curve can also be
333 used when doing binary classification. Whichever method is used, each (expected) effect
334 should be reported, *significant or not*, allowing readers to evaluate the dataset. This
335 permits comparison with similar studies, facilitates informed power analyses for planning
336 future studies, and will enable developments of a quantitative, more reproducible, view of
337 brain dynamics⁸².

338
339 For mass-univariate and multivariate analyses, statistical maps of the space tested are
340 usually displayed, with corresponding waveforms and topographic maps. While statistical
341 significance matters, providing only thresholded maps limits reproducibility. We
342 recommend displaying thresholded maps in manuscripts (with description of thresholding
343 method), while providing raw maps for all channels and time/frequency frames in
344 supplementary materials (ideally as a data matrix in a repository and not just a figure). To
345 allow the reader to evaluate observed effects, both the time course of the model
346 parameters and underlying data should be made available. Consideration should be given
347 to what figures should appear in the main manuscript versus those appearing in the
348 Supplementary Materials section.

349 **The evolution of COBIDAS, data sharing and future neuroimaging** 350 **studies**

351 The current COBIDAS MEEG recommendations correspond to best practices in 2019.
352 Reporting data using these criteria should improve the generation of reproducible and
353 replicable findings. As MEEG analysis pipelines become increasingly more complex,
354 more methodological details will likely need to be reported, challenging current views on
355 good writing practice and journal policies. In anticipation of, and to facilitate, this process
356 COBIDAS MEEG is a 'living' document (<https://cobidasmeeq.wordpress.com/>), that will
357 have periodic updates to include best practices for new methods as they become more
358 established.

359
360 We also encourage the MEEG community to share raw and derived data using BIDS,
361 together with data processing scripts⁸³. Sharing of data and scripts fosters reproducibility
362 and script re-usage encourages replicability across laboratories, promoting benefits to
363 research training and education. A huge challenge to MEEG replicability is the large data
364 space and variety of methods. Sharing of derived MEEG data (similar to fMRI data where
365 statistical maps are shared) would allow direct comparisons, replications and
366 aggregations of results across studies (e.g., meta-analysis). In an era of electronic
367 publishing, sharing derived data is straightforward (e.g. grand average ERPs between
368 two conditions consist of a file of a few kilobytes that can be added as supplementary
369 material or posted in a data repository).

370
371 Sharing original data is not always feasible since participant consent is required and
372 issues of confidentiality may be a particular concern for clinical samples. Datasets with
373 *whole head* anatomical MRI data can be similarly problematic, as head models cannot be
374 reconstructed if T1-weighted images are defaced or skull stripped. Even without structural

375 MRI, functional imaging data, including MEEG⁸⁴, could be indirectly identifiable.
376 Confidentiality is currently a world-wide discussion point, with cross-continental data-
377 sharing initiatives posing some challenges. We strongly encourage seeking ethical
378 clearance from participants regarding data sharing *before* commencing any study (see
379 open brain consent form examples (<https://open-brain-consent.readthedocs.io/>) for easy
380 to follow templates).

381
382 Exciting technical developments in MEEG (Fig. 1) will require updating of the COBIDAS
383 report to include best, modern, practices for these new methods, in particular for machine
384 learning algorithms that will likely play an increasingly prominent role in years to come^{85,86}.
385 Similarly, new generation room temperature MEG measurement sensors (or optically
386 pumped magnetometers) are emerging, allowing previously unavailable flexible
387 configurations of MEG sensor arrays^{87,88}. As we also progress towards “putting the brain
388 back into the body”, multimodal integration of MEEG data with other technologies such
389 as the simultaneous recording of movements or autonomic nervous responses, will create
390 new challenges in best practices, as cognitive and systems neuroscience moves out of
391 the laboratory, to more ecologically valid scenarios, and “into the wild”.

392 **Conclusions**

393 The first COBIDAS MEEG report was completed with prolonged and extensive
394 collaboration and consultation within the neuroimaging community. We aimed to compile
395 best practices for data gathering, analysis and sharing, to improve scientific reproducibility
396 and replicability. These guidelines were constructed not only for preparation of
397 manuscripts and grants, but also for scientists serving in editing and review roles, as well
398 as for education and research training of future scientists. Like the COBIDAS MRI report,
399 we see the COBIDAS MEEG report as a living document - designed to keep pace with
400 ever-changing scientific and methodological developments in the field. OHBM will
401 continue its efforts in defining best practices for brain imaging and welcomes all to
402 participate and contribute to this endeavour.

403 **Authorship**

404 CP and AP chaired the committee, planned the overall structure of the COBIDAS
405 document and this manuscript, each author contributed to entire sections of the COBIDAS
406 document used for this manuscript, all authors contributed and reviewed this manuscript.

407 **Acknowledgement**

408 The Committee thanks the hundreds of OHBM members who provided feedback on the
409 early version of the report and on the website. Thank you to Tom Nichols, Chair, OHBM
410 COBIDAS MRI for his insightful comments on an earlier draft of this Perspective.

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