# Two-brain states during collaborative drawing reflect leader–follower dynamics in intergenerational dyads

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**Keywords:** fNIRS, intergenerational, creative drawing, functional connectivity, brain states, collaboration, dyadic

## Highlights

- Two-brain states can characterise within- and between-brain connectivity.
- Seven two-brain states identified using data-driven approach.
- Intergenerational collaborative drawing linked to asymmetric connectivity.

## Acknowledgments

We thank the survey center operated by UZH Healthy Longevity Center, University of Zurich, for their assistance with recruitment of older adults from the Zurich community. We thank Tessa Portier and Medea Häuselmann for their assistance with data collection, and Linda Fanconi for scheduling sessions. We thank Filiz Kanele for proofreading.

## Author Contributions

LAN: Conceptualisation, Data curation, Formal analysis, Investigation, Validation, Visualisation, Writing – original draft, Writing – review & editing. RM: Supervision, Equipment donation, Conceptualisation, Data curation, Investigation, Visualisation, Writing – original draft, Writing – review & editing. ESC: Conceptualisation, Funding acquisition, Project administration, Writing – review & editing.

## Conflict of Interest

The authors declare no potential conflict of interest.

## Funding

Two Cortivision Photon Cap devices provided to RM through the Cortivision Pathfinder Program (grant number CPP-2023/09/01). Oil pastels provided to RM by Caran D'Ache (agreement number 712517). RM, LN, and ESC were supported by the Social Brain Sciences Lab at ETH Zurich.

**Abstract**

Engaging with others in social scenarios can result in the alignment of brain activity between individuals. Dyadic
(i.e., hyperscanning) studies typically estimate average region-specific levels of connectivity between brains (as
opposed to within brains) across a given task to quantify brain activity alignment. This approach assumes
symmetric interactions with equal and mutual adaptation from both dyad members, excluding asymmetric (e.g.,
leader–follower) contexts. Such approaches also obscure spatial dynamics (i.e., relationship between different
brain regions) and temporal dynamics during unfolding interactions. To overcome these challenges, we took a
data-driven approach to quantify within- and between-brain connectivity during collaborative drawing among
dyads. Specifically, we used sliding windows and Riemannian-geometry-based $k$-means clustering to identify
recurrent two-brain states while 61 dyads drew alone and together at 6 weekly timepoints. Thirty dyads comprised
young adults only (same generation) and 31 dyads comprised one older and one younger individual
(intergenerational). We identified 7 two-brain states, 3 of which were specific to real (not pseudo) dyads. One
two-brain state showed convincing evidence of sensitivity to collaboration context: During collaborative drawing,
low-to-medium between-brain connectivity and prominent within-brain connectivity in bilateral IFG in a single
dyad member arose for longer periods in intergenerational than same generation dyads. No two-brain state
showed evidence of longitudinal changes across sessions. These findings inform recent accounts of neural
dynamics that emphasise the complementary roles of within-brain and between-brain connectivity. Furthermore,
they suggest that state-based analyses can inform neural dynamics in a way not captured by traditional analysis
techniques.

**1 Introduction**

Human social interaction is an inherently dynamic and reciprocal process. Advances in wearable brain imaging
grant increasingly sophisticated insights into the neural underpinnings of rich, real-world interactions between
dyads and groups of people. To do so, studies typically quantify levels of interpersonal neural synchrony, by
estimating the level of connectivity between interacting individuals' brains. This approach is primarily suited to
understand symmetric interactions where both dyad members display the same underlying processes (e.g., mutual
adaptation). However, social interactions are often characterised by high asymmetry (e.g., in leader–follower
dynamics) and switching roles. To further understand the neural dynamics of social interactions, methods that
integrate within-brain and between-brain connectivity while preserving temporal information are needed. In this
study, we apply a state-based approach to functional near-infrared spectroscopy (fNIRS) data, recorded while
intergenerational and same generation dyads completed collaborative drawing tasks, to demonstrate the utility of
this method. In the following sections, we briefly describe interpersonal neural synchrony, current theoretical and
empirical stances on within-brain and between-brain connectivity, recent advances in state-based analyses for
dyadic neural data, before introducing the present study.

**1.1 Interpersonal alignment and interpersonal neural synchrony**

During social interactions, various forms of interpersonal alignment can arise between the interacting people (De
Felice et al., 2025; Hasson et al., 2012; Schilbach et al., 2013; Shamay-Tsoory et al., 2019). Interpersonal neural
alignment–the focus of this work–refers to the temporal synchronisation of patterns of brain activity between
individuals. Interpersonal alignment can also occur at the level of cognition (e.g., emotional contagion, alignment
in perceptions or beliefs), motor behaviours (e.g., matching body postures or movements), physiological signals

(e.g., heart rate or electrodermal activity), and endocrine (e.g. oxytocin) trajectories (Shamay-Tsoory et al., 2019).
Interpersonal alignment is theorised to be an adaptive mechanism that supports human health and wellbeing by
maintaining social cohesion (Bilek et al., 2022; Dikker et al., 2019, 2021; Hoehl et al., 2021).

Interpersonal neural alignment can be quantified using measures of interpersonal neural synchrony (INS), derived
from simultaneously recorded brain signals belonging to two or more interacting people. The acquisition of such
simultaneous recordings is commonly referred to as hyperscanning. Though hyperscanning can technically be
conducted with any brain imaging technique, mobile techniques such as functional near-infrared spectroscopy
(fNIRS), electroencephalography (EEG) are commonly used, as their mobility is optimal for naturalistic social
interactions involving body movement (Czeszumski et al., 2020; Hakim et al., 2023).

**1.2 Theoretical and empirical approaches to within-brain and between-brain connectivity**

Two main theoretical frameworks account for the emergence of INS, respectively termed common cognitive
processing and mutual prediction. *Common cognitive processing* posits that when two people interact, both people
perceive similar stimuli, causing both people's brains to respond in comparable ways at comparable time delays
(Burgess, 2013). This framework is limited to characterising symmetrical forms of interpersonal alignment, such
as shared attention or mutual coordination (Hamilton, 2021). Social interactions may however take many
additional forms (e.g., individual action where one person demonstrates something for another person to learn,
asymmetric adaptation, and turn-taking). Asymmetric social interactions may arise from different physical roles,
such as speaking and listening, teaching and learning, demonstrating and imitating, or different social roles, such
as pairings of clinicians and patients, parents and children, or even people of different generations or cultures.
Adapted for symmetric and asymmetrical interactions, the *mutual prediction* framework posits that people
continuously predict potential changes in their shared environments, including social information about each
other, and the interdependence of interacting people's predictions result in increased INS (Bilek et al., 2022;
Kingsbury et al., 2019; Wolpert et al., 2003).

A further strength of the mutual prediction framework is that it offers a theoretical basis for differentiating
between within-brain connectivity (i.e., functional connectivity) and between-brain connectivity (i.e., INS). The
distinction is particularly informative in asymmetric interactions. For example, in leader–follower settings, a
computational model shows greater within-brain connectivity in the leader than the follower (Heggli et al., 2019),
reflecting how the follower adapts to the leader unilaterally. By contrast, when two individuals adapt to each other
mutually, both show greater between-brain connectivity than within-brain connectivity (Heggli et al., 2019, 2021).
Evidence further suggests that within-brain and between-brain connectivity are associated with different
functional demands in the emergence of behavioural synchrony: Within-brain connectivity plays a role in the
early phases of initiating behavioural synchrony, whereas between-brain connectivity supports the maintenance of
synchronised behaviour once it is established (Marton-Alper et al., 2023).

Considered together, these findings highlight how the neural dynamics of interacting partners, just as the
dynamics within a single brain, are complex and oscillate between patterns of segregation and integration that are
shaped by the functional demands of the task (Heggli et al., 2019; Marton-Alper et al., 2023; Park & Friston,
2013; Shamay-Tsoory, 2022). In other words, the different dynamics (e.g., individual action, mutual or
asymmetric adaptation, and coordinated behaviour) shape both the strength and configuration of functional
connectivity within and between brains. A closer examination of these configurations, specifically taking spatial
and temporal information into account, can inform our understanding of social interactions.

### 1.3 Two-brain states as a tool for exploring interpersonal dynamics

When computing INS levels from two people's fNIRS signals (the technique employed in this study), researchers commonly use a signal processing method called wavelet transform coherence (WTC; see Hakim et al., 2023 for detailed review of INS metrics). WTC returns the local correlation between two signals for a given channel pair in a given time and frequency window (Gvirts et al., 2023). The extracted values are then typically averaged across the task duration. When applied to signals from two interacting individuals, WTC can be interpreted as an extension of conventional functional connectivity, operationalizing correlation-based dependency between neural timeseries, but across brains rather than within one brain (Hasson et al., 2012).

Averaging WTC values across an interaction between two individuals per region might however obscure the temporal dynamics of INS. Insights into the temporal dynamics of INS are especially relevant for tracking and interpreting INS in naturalistic settings where people build relationships across multiple sessions and where the interaction dynamics are not externally paced by a pre-specified experimental design. Temporal dynamics of INS can be preserved using approaches that quantify changes in INS at a biologically relevant timestep (e.g., seconds for haemodynamic fluctuations recorded with fNIRS).

The spatial dynamics of INS are also typically obscured via commonly used unidimensional metrics of INS (e.g., computing WTC between channel-pair, then conducting comparisons at the group level per channel pairing, which are then visualised to report as findings). This can be overcome by incorporating the spatial mapping of the INS values (e.g., as a matrix rather than a single value) into the analysis before conducting comparisons at the group level. Introducing the spatial dimension to dyad-level analysis can shed light on the configurations of functional connectivity within and between brains.

One way of conceptualising INS analyses that preserve temporal and spatial dynamics is to identify recurrent spatial patterns, i.e., *brain states*, in the brain signals recorded from interacting dyads. This can be achieved by extending the identification of brain states from within single brains to within and between dyads' brains, wherein both brains are considered components of a single integrated system (Shamay-Tsoory, 2022). Li and colleagues (2025) offer a recent proof of concept that this approach can be conducted in EEG data, by extending the concept of microstates, quasi-stable configurations of brain activity (Michel & Koenig, 2018), to joint analysis of dyadic neural data. Their analysis revealed that two-brain microstates differed between observer—actor paradigms and tasks with more symmetrical demands (Li et al., 2025). With this approach, Li and colleagues were able to examine concurrent patterns of brain activity but did not measure functional connectivity. Two-brain states of connectivity can be used to investigate how regions within and across brains are integrated or segregated over time.

To identify brain states in fNIRS data, some studies used *a priori* definitions (Lu et al., 2022) or behavioural markers (Dai et al., 2024), though these constrain the space of possible states to those anticipated in advance. Focusing on fluctuations in functional connectivity (i.e., dynamic functional connectivity) in fNIRS data, Zhang & Zhu (2020) used a *k*-Means clustering analysis on Pearson correlation matrices of single-brain activity in time windows. They show that such an approach can be useful to reduce the complexity of high-dimensional connectivity data while respecting the spatial configuration and temporal dynamics by replicating previous results using other brain imaging techniques (Zhang & Zhu, 2020). Li and colleagues (2021) present a two-brain extension of this approach, clustering channel-pair WTC matrices derived from time windows in fNIRS data collected during a dyadic creative design task. This provides novel insights into the neural dynamics of social

interactions; however, their analysis focuses on inter-brain channel pairs. The full bandwidth of two-brain states
may include patterns that are characterised as much by the extent of within-brain connectivity as by the extent of
between-brain connectivity (Heggli et al., 2019; Marton-Alper et al., 2023). Integrating information on both is
therefore necessary to gain the full picture. Näher and colleagues (2024) further demonstrated that the usage of
additional measures of similarity between neural signals in tandem with Riemannian geometry-based approaches
that preserve the intrinsic structure of inter-channel relationships outperforms traditional models in classification
of brain states. These findings motivate an approach that applies Riemannian geometry-based clustering models to
within-brain and between-brain dynamic functional connectivity data, enabling the discovery of two-brain states
in a data-driven manner.

**1.4 Present study: Exploring intergenerational collaborative interactions using two-brain states**

This preregistered study (anonymised link) is a secondary analysis of an existing fNIRS hyperscanning dataset
(anonymised link). We applied two-brain state analysis approach to the dataset, which includes 732 individual
fNIRS recordings from 61 dyads who each attended 6 creative drawing sessions. Thirty of the dyads are same
generation dyads (young adults) and 31 are intergenerational (1 young adult with 1 older adult).

To gain insight into the symmetric and asymmetric interaction dynamics involved in intergenerational
collaborative drawing, we aimed to:

1. Identify two-brain states based on dynamic functional connectivity in fNIRS data acquired during
collaborative drawing.
2. Examine the extent to which collaborative vs. independent activity and same generation vs.
intergenerational interactions give rise to specific two-brain states.
3. Investigate the extent to which any identified two-brain states change across repeated encounters.

Analyses of combined single-brain states were also included in our preregistration and are presented in the
Supplementary Material.

**2 Methods**

**2.1 Transparency and openness**

This study consists of secondary analysis of the fNIRS data, from which initial analyses of INS levels during
same generation and intergenerational collaborative drawing are presented by [redacted for peer review]. Our pre-
registered data analysis plan as well as data and code can be found on the Open Science Framework (OSF;
anonymised link). We report how we determined our sample size, all data exclusions (if any), all manipulations,
and all measures in the study (Munafò et al., 2017).

**2.2 Participants**

We aimed to collect as many useable datasets as possible between December 2023 and June 2024. The final
sample consists of 122 participants. We assigned older adults ($n = 31$, age 70+ years) and younger adults ($n = 91$,
age 18–35 years) to same generation or intergenerational dyads. Same generation dyads ($n = 30$) consisted of only
younger adults (22.5 years [SD = 3.6]; 36 female, 24 male), intergenerational dyads ($n = 31$) consisted of one

older adult (76 years [SD = 4];18 female, 13 male) and one younger adult (24 years [SD = 4]; 19 female, 11 male,
1 other). All dyads began the study as strangers; they had never met prior to the first experimental session.

We recruited participants through [redacted for peer review] university recruitment pool, the [redacted for peer
review] University center, as well as local seniors' clubs and community organizations (e.g., choirs, theatre
groups, and orchestras), via social media and paper flyers. We included individuals who spoke German fluently
and did not report having any known psychological or neurological disorders (e.g., stroke, ADHD, depression)
when completing the screening questionnaire.

We obtained written informed consent from all participants. Ethical approval was obtained from the Ethics
Committee of the [redacted for peer review] (Ref: 2023-01073). The study was conducted according to the
Declaration of Helsinki.

**2.3 Procedure**

**Experimental sessions.** Each dyad attended six experimental sessions, spaced roughly one week apart. Upon
arrival, participants completed questionnaires, separated from one another by a felt partition wall for privacy. The
questionnaires measured loneliness levels (De Jong Gierveld & van Tilburg, 2006) and attitudes toward
individuals from their own and the other (older or younger) generation (Pittinsky et al., 2011). Participants
completed an empathy questionnaire at the first session only (Paulus, 2009). Next, fNIRS caps were placed on
participants' heads and images for 3D head models were acquired. Then, fNIRS sensors were positioned on caps
and fNIRS devices turned on, signal quality was optimised by additional hair clearing, and fNIRS recordings were
initiated.

At each session, dyads completed three 5-min blocks of drawing with oil pastels. First, dyads drew alone for 5
min on separate pieces of paper, separated from one another by a felt partition wall so they could not see each
other. Next, the partition wall was removed. Dyads received a piece of A3 art paper, on which to draw together for
5 min, twice. To ensure constant levels of conversation between drawing conditions (i.e., alone and together), we
instructed participants that they should not talk while drawing, and that they could talk as much as they desired
during the rest of the experimental session. We provided no instructions as to what or how to draw, allowing
participants and dyads maximal freedom to interact freely in a naturalistic environment.

Following the final drawing block, dyads then completed a short collaborative task that varied each week to
maintain motivation across sessions (e.g., speed-based tasks, a jigsaw puzzle, a divergent thinking task). The felt
wall was placed between participants, who then completed a measure of social closeness (Aron et al., 1992) and
wrote subjective comments on the experimental session. After the final session, the lead experimenter conducted a
semi-structured interview with each participant about their experience in the study.

The data analysed in this study consists of the fNIRS recordings during the three drawing blocks.

**fNIRS acquisition.** To record cortical hemodynamic activity during the drawing and collaborative tasks, we used
two Cortivision Photon Cap fNIRS systems with a sampling frequency of ~5 Hz. We positioned 26 optodes (16
sources emitting wavelengths of 760 and 850 nm, and 10 detectors) over four regions of interest (ROIs): the left
and right inferior frontal gyrus (IFG) and the left and right temporoparietal junction (TPJ). The optode montage is
visualised in Supplementary Figure 1. To synchronise the fNIRS recordings, we used PsychoPy (Peirce et al.,

2022) to write triggers marking the beginning of each drawing and the collaborative activity directly into the
recordings.

**Optode digitisation.** After the researcher placed the fNIRS cap on a participant's head and before securing the
optodes, the researcher recorded a 3D head scan using Structure Sensor Pro connected to an Apple iPad Pro.
Using MATLAB and the Fieldtrip toolbox (Oostenveld et al., 2011), we manually co-registered the head scan to
MNI space. We then used optode positions in MNI coordinates to calculate channel locations in MNI space, inter-
optode distances, and distances between channel locations and centres of regions of interest. We calculated these
distance measures to assess channel quality and positional stability across sessions.

**2.4 Data analysis**

**Missing data.** Though we endeavoured to include fNIRS recordings characterizing all combinations of
participants, sessions, and ROIs, some data were missing or excluded from the analysis due to technical issues
(e.g., signal interruptions caused by Bluetooth failure) or low data quality identified during the channel selection
process (described below). Data exclusions are detailed in Supplementary Table 1.

**fNIRS channel selection.** We retained one channel per ROI to the following criteria, to ensure the inclusion of
high-quality signals, as previously done by De Felice and colleagues (2024). Included channels showed visual
evidence of cardiac oscillation, inter-optode distance between 17 mm and 40 mm (Brigadoi & Cooper, 2015) and
scalp coupling indices (SCI) > 0.7 and <1. The SCI was calculated in *MNE-nirs* (Luke et al., 2021) by cross-
correlation between the signal at the two wavelengths between 0.7 and 1.35 Hz where cardiac oscillation is
expected (Pollonini et al., 2014). To select the best channel for a given participant, session and ROI, we used the
channel physically located closest to the centre of the region of interest when more than one channel survived the
inclusion criteria above.

**fNIRS preprocessing.** Using *MNE-python* (Gramfort et al., 2014)  and *MNE-nirs* (Luke et al., 2021), we first
resampled the raw optical intensity signals to 5 Hz. We converted signals to optical density and corrected Motion
artifacts using Temporal Derivative Distribution Repair (Fishburn et al., 2019) to remove extracerebral systemic
noise like cardiac, respiratory, baroreceptive, or sympathetic activity (Yücel et al., 2021), we conducted short
channel regression using the short channel with the highest SCI. We then converted signals to oxygenated and
deoxygenated haemoglobin concentration values using the modified Beer–Lambert law and an age-adjusted
partial pathlength factor (Garcia-Castro, n.d.; Scholkmann & Wolf, 2013). This age-adjustment is validated for
ages 0-70 years. We set the age parameter to 70 for participants >70 years. We filtered the signals using a band-
pass filter between 0.015 and 4 Hz. Next, we segmented signals for each channel into task blocks (i.e., drawing
alone, drawing together) and z-standardised segmented signals within channels.

**Pseudo dyads.** To validate whether the properties of identified brain states are specific to true interaction, we
compared real dyads with pseudo dyads, generated from all combinations of participants who did not interact as a
pair in the dataset. Pseudo dyads included same generation dyads of two younger adults and intergenerational
dyads, but no same generation dyads of two older adults.

**2.5 Identifying brain states and extracting brain-state timeseries**

We performed the following computations on the [redacted for peer review] high-performance computing cluster
at [redacted for peer review], using *scikit-learn* (Pedregosa et al., 2011), and *pyriemann* (Barachant et al., 2026).
The clustering pipeline consisted of five key components (Figure 1). First, we concatenated individuals' signals
into dyadic (two-brain) data frames to represent dyads (real and pseudo) as a unit. Second, we temporally
segmented the dyadic signals using a sliding window. Third, we estimated neural connectivity matrices mapping
within-brain and between-brain connectivity using four kernel functions (i.e., similarity metrics) on the
temporally segmented signals. Fourth, we identified brain states using a clustering algorithm. Fifth and finally, we
assigned each signal segment to its respective brain state, generating a time series of brain states.

**Concatenation.** Per dyad and task block, we concatenated the fNIRS signals (8-channel timeseries) concatenated
to create a 16-channel timeseries. Within dyads, concatenation order was fixed, such that the same dyad members'
signals are first in each concatenated time series. This is specifically relevant for intergenerational dyads, where
the younger dyad member's signals (channels 1-8 of joint timeseries) preceded the older dyad member's signals
(channels 9-16 of joint timeseries).

**Temporal segmentation and kernel matrix estimation.** Per dyad and task block, timeseries were segmented
using a sliding window (size = 15 s, shifted in an increment of 1 s). We selected five kernel functions to quantify
similarity between neural signals in a time window, which is returned as a kernel matrix. Specifically, we selected
a subset of the kernel function used by Näher and colleagues (2024), prioritising kernel functions with unique
properties. The selected kernel functions included covariance, correlation coefficient, Tyler's M-estimator-based
covariance, Ledoit–Wolf shrunk covariance, and the radial basis function kernel (further detailed in the
Supplementary Material). To ensure positive definiteness and numerical stability for clustering algorithms, we
applied additional kernel-level shrinkage to all resulting kernel matrices (Upton & Cook, 2014). As part of
hyperparameter tuning, the shrinkage parameter $\lambda$ was set to three different values; details of the tuning procedure
are provided below. For each shrinkage parameter, kernel function, and time window, we derived and shrunk
kernel matrices separately for oxygenated haemoglobin (HbO) and deoxygenated haemoglobin (HbR), and then
combined them into a block diagonal matrix (Näher et al., 2024). For readers interested in gaining familiarity with
kernel matrix estimation, we recommend perusing Shawe-Taylor and Cristianini (2004).

**Clustering procedure.** Based on a recent demonstration that Riemannian geometry-based models outperform
classical models in classification of fNIRS brain states (Näher et al., 2024), we applied a Riemannian geometry-
based *k*-means clustering algorithm to identify brain states during activities. Clusters were identified using data
from real dyads only. To determine which kernel function and shrinkage parameter to employ (i.e., via
hyperparameter tuning), we employed a brute-force grid search. We entered the combined block diagonal matrices
containing HbO and HbR connectivity into clustering and subsequent hyperparameter tuning. The hyperparameter
space is detailed in Supplementary Table 3. We determined the best combination of hyperparameters using the
Calinski-Harabasz index (CHI; Calinski & Harabasz, 1974), which favours coarser *k*-Means solutions with strong
global separation, and the Davies-Bouldin index (DBI; Davies & Bouldin, 1979), which favours finer *k*-Means
solutions that are locally well defined. The CHI indicated a three-cluster solution, while the DBI indicated a
seven-cluster solution. Further selected hyperparameters are reported in Supplementary Table 2. Here, we report
the seven-cluster solution favoured by DBI which was more detailed and therefore more informative for
subsequent analyses and interpretation; the three-cluster solution is reported in the Supplementary Material.

**Metrics of temporal dynamics of two-brain states extracted from brain-state timeseries.** After
hyperparameter tuning, we fit back the clustering with the best combination of hyperparameters into the data sets

to yield a time series of brain-state sequences. We estimated three metrics commonly used to describe state

sequence time series: occurrence, coverage, and duration. *Occurrence* refers to the number of times a state

occurred during the task. *Coverage* refers to the relative time a state is active as a ratio of the total time. *Duration*

is the mean duration a given state occurs consecutively and can thus be interpreted as a measure of a given state's

stability.

**Figure 1.** A) From left to right, a summary of the protocol followed at each session. B) The time series of fNIRS signals recorded from 2 dyad members were concatenated into a single dataframe. Coloured boxes represent discrete windows ($W_i$) for which kernel matrices were computed. Window length was 15 s and windows were shifted in increments of 1 s. C) Using 5 different kernel functions, kernel matrices were computed and shrunk per window for HbO and HbR separately. Per window, kernel function, and shrinkage parameter, the HbO and HbR matrices were combined into a block diagonal matrix. D) Using block diagonal matrices of real dyads only, a Riemannian-geometry-based k-Means identified recurrent brain states. Optimal hyperparameters (kernel function, shrinkage, number of clusters) were determined in a brute-force grid search. E) The identified states were then backfit onto time series of real and pseudo dyads, such that each window received a state label. F) The temporal dynamics of the two-brain states per real and pseudo dyad and per task were quantified using 3 metrics, namely occurrence, duration, and coverage. Group level statistical comparisons were conducted on these metrics.

**2.6 Statistical analyses**

The primary aim of this study was to explore the extent to which dyadic brain states differ between collaborative and independent drawing (drawing together vs. drawing alone). In addition, we explored the influence of dyad composition (intergenerational vs. same generation, hereafter called group). In addition to our pre-registered exploratory analyses of coverage, we also conducted non-preregistered exploratory analyses of occurrence and duration. We carried out the anlyses below using R and the R packages *emmeans* (Lenth, 2021), *lme4* (Bates et al., 2015), *lmtest* (Zeileis & Hothorn, 2002), *MASS* (Venables & Ripley, 2002), *purrr* (Wickham & Henry, 2026), and *tidyverse* (Wickham et al., 2019). We made graphics using the packages *ggplot2* (Wickham, 2016) and *viridis* (Garnier et al., 2023).

To establish whether each brain state was the result of true dyadic interactions or could also be observed when the signals of who did not interact were aligned, we contrasted real and pseudo dyads. We fit separate negative binomial models for each metric (n = 3; rationale described in Supplementary Material). The formula was the following: *metric ~ state * drawingTask * dyadType * group * session,* where drawingTask refers to drawing together or alone, dyadType refers to real and pseudo dyads, and group refers to same generation and intergeneration groups. We identified brain states showing significant differences between real and pseudo dyads using planned contrasts for each combination of task and group. In the case that any single combination (e.g., drawing alone and same generation group) differed significantly between real and pseudo dyads for a given brain state, we conducted further contrasts between task, group, and the interaction thereof, on that brain state. To account for multiple comparisons, *p*-values in contrast analyses were adjusted using the False Discovery Rate (FDR) procedure (Benjamini & Hochberg, 1995). The same process was repeated for the slope of each metric across sessions.

**3 Results**

First, we identified the two-brain states during creative drawing, based on the combined HbO and HbR block diagonal matrices. We set qualitative thresholds based on the distributions of connectivity values to describe the strength of connections: high >= 0.3, medium >= 0.25, low >= 0.2, very low < 0.2. We identified seven two-brain states, which are labelled with letters from A to G, are visualised in Figure 2. States A, B, and C correspond to relatively low, medium, and high connectivity within and between brains, respectively (i.e., A = low, B = low to medium, C = high). States D and E correspond to low-to-medium connectivity between brains and medium-to-high connectivity within only one dyad member's brain (D for first and E for second dyad member). States F and G correspond to low-to-medium connectivity between brains and prominent within-brain connectivity specifically between bilateral IFG in only one dyad member (F for first and G for second dyad member).

**Figure 2.** Seven two-brain states identified using Riemannian geometry-based clustering of dynamic functional connectivity matrices. Matrices show similarities in the HbO signals between ROIs belonging to each dyad member (distinguished by 1 and 2). States A-B show low, medium, and high connectivity within and between brains, respectively. States D-E show low-to-medium connectivity between brains and high connectivity within only one dyad member's brain. States F-G show low-to-medium connectivity between brains and prominent within-brain connectivity, specifically between bilateral IFG in only one dyad member. The pairs of brains with purple lines show the strength of the within and between-brain connectivity; lighter purple = lower connectivity, darker purple = greater connectivity. Connectivity matrices for HbR signal show high levels of similarity to these matrices and are visualised in Supplementary Figure 2.

For each brain-state and metric (occurrence, coverage, duration) and brain-state (A–G) we first assessed the extent to which the metric differs between real and pseudo dyads. Next, using planned contrasts, we evaluated the extent to which dyadic brain states differ between collaborative and independent drawing, intergenerational and same generation dyads, and the interaction between these contexts.

### 3.1 Occurrence (n windows in which a brain state occurs)

**Real vs. pseudo dyads.** We observed differences between real and pseudo dyads for state B (Intergenerational group, drawing together: $z = -3.29$, $p_{adj} = .014$) and state D (Intergenerational group, drawing alone: $z = 3.39$, $p_{adj} = .014$). States A, C, E, F and G did not differ significantly between real and pseudo dyads for any drawing condition or group (Supplementary Tables 4 and 5).

**States B and D.** Likelihood ratio tests showed main effects of state and task ($p < .05$; Supplementary Table 6). Contrast analyses revealed no statistically significant differences in any states between tasks or groups after FDR correction. There were a trend towards lower occurrence of state D in drawing alone compared to drawing together, but only in intergenerational dyads ($z = -2.62$, $p_{adj} = .053$), and a trend towards lower occurrence of state D in intergenerational dyads compared to same generation dyads, but only for drawing alone ($z = -2.72$, $p_{adj} = .053$; Figure 3; Supplementary Table 7).

### 3.2 Coverage (proportion of time a state is active)

**Real vs. pseudo dyads.** We observed differences between real and pseudo dyads for state B (Intergenerational group, drawing together: $z = -2.98$, $p_{adj} = .027$),  state D (Intergenerational group, drawing alone: $z = 3.18$, $p_{adj} = .020$), and state G (Intergenerational group, drawing together: $z = -3.30$, $p_{adj} = .020$). We observed a trending difference for state F (Intergenerational group, drawing together: $z = 2.68$, $p_{adj} = .052$). States A, C, and E did not differ significantly between real and pseudo dyads for any drawing condition or group (Supplementary Tables 8 and 9). No further analyses were conducted for state F.

**States B, D, G.**  Likelihood ratio tests showed a main effect of state, as well as interaction effects for state and group, and task and group ($p < .05$; Supplementary Table 10). Contrast analyses revealed no statistically significant differences in any states between tasks or groups after FDR correction. There were trends towards higher coverage of state D during drawing together than alone, but only for intergenerational dyads ($z = 2.41$, $p_{adj} = .095$), as well as towards lower coverage of state D ($z = -2.90$, $p_{adj} = .067$) and higher coverage of state G ($z = -2.30$, $p_{adj} = .097$) in the intergenerational group compared to the same generation group, but only while drawing alone (Figure 3; Supplementary Table 11).

### 3.3 Duration (mean n consecutive windows where state occurs)

**Real vs. pseudo dyads.** We observed a difference between real and pseudo dyads for state G (Intergenerational group, drawing together: $z = -4.51$, $p_{adj} < .001$). States A–F did not differ significantly between real and pseudo dyads for any drawing condition or group (Supplementary Tables 12 and 13).

**State G.** Likelihood ratio tests showed a significant effect of group ($p < .05$; Supplementary Table 14). Contrast analyses revealed a significant difference while drawing together, where intergenerational dyads showed significantly longer durations than same generation dyads ($z = 3.59$, $p_{adj} = .002$; Figure 3; Supplementary Table 15).

### 3.4 Longitudinal changes in two-brain states

We examined the differences in the slopes of occurrence, coverage, and duration of the two-brain states across sessions between real dyads and pseudo dyads. There were no significant differences in occurrence, duration or coverage after FDR correction (Supplementary Tables 16–18), therefore, we did not conduct any further analyses.

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**Figure 3.** Per metric, the two-brain states that differed significantly between real and pseudo dyads. Planned contrasts showed no
significant difference between task, group, or task*group interactions for occurrence or coverage. For duration, a significant difference
between groups was observed for drawing together. As in Figure 2, the pairs of brains with purple lines show the strength of the within and
between-brain connectivity for each state; lighter purple = lower connectivity, darker purple = greater connectivity.

**4 Discussion**

In this study, we implemented an approach to characterise shared patterns of neural activity during a type of
naturalistic social interaction that captures richer spatial and temporal information than traditional approaches.
Specifically, we identified seven distinct two-brain states, three of which were unique to real dyads, as opposed to
pseudo dyads. Of these three two-brain states, only one (G) differed significantly in duration between same and
intergenerational dyads, and only while dyads drew together. The increased duration of state G, which involved
medium-to-low between-brain connectivity and within-brain bilateral IFG connectivity for one dyad member,

likely reflects an intergenerational collaboration pattern, where the older person leads and the younger person follows. No significant longitudinal changes in the temporal dynamics of any two-brain states were observed across the six drawing sessions. We explore the implications of these findings below.

**4.1 Symmetrical within- and between-brain connectivity may reflect common cognitive processing**

The first group of states A-C shows symmetrical patterns of connectivity (Figure 2). These states show low, medium, and high connectivity within and between brains, respectively. From a theoretical perspective, this pattern could reflect common cognitive processing, i.e., that both dyad members' brains are responding similarly to the same stimulus (Burgess, 2013). Taking this perspective, the different strengths (low, medium, and high) of connectivity may reflect the degree to which the dyad members perceive the same stimuli differently. However, only state B differed between real and pseudo dyads, specifically occurring less often for real than pseudo dyads when intergenerational dyads drew together, and did not differ significantly from other group/task combinations. In other words, none of the identified symmetrical two-brain states of varying strengths were specific to a group or task in real dyads. This is perhaps not so surprising, as the open-ended nature of the creative task, drawing alone or together in silence, is unlikely to result in both dyad members perceiving the same stimuli the same way at the same time, as might happen if both individuals view the same visual stimuli or complete a clearly structured task (Finn et al., 2020; Li et al., 2021). Moving away from common cognitive processing, an alternative explanation for fleeting symmetrical two-brain states may be that they reflect transitions between less symmetrical two-brain states (Hendrikse et al., 2025; Mayo & Gordon, 2020; Roche et al., 2025).

**4.2 Asymmetric connectivity patterns during independent activity unlikely to reflect leader-follower dynamics**

States D and E feature low-to-medium connectivity overall, with prominent within-brain connectivity in one dyad member (Figure 2). State D, but not E, differed in occurrence and coverage between real and pseudo dyads. This emerged specifically for same generation dyads when drawing alone. As same generation dyad members are virtually indistinguishable, the relevance of the arbitrarily assigned first dyad member showing greater within-brain connectivity is not immediately clear. Our planned contrasts revealed trending differences between conditions for intergenerational dyads only, consistent with visual inspection (Figure 2) and descriptive statistics showing that state D is least represented when intergenerational dyads draw alone. In intergenerational dyads, state D indicates heightened within-brain connectivity in the younger dyad member.

We tentatively propose that the increased within-brain connectivity in a single dyad member might reflect reduced monitoring of the social environment (including the other dyad member) and/or heightened self-monitoring (Heggli et al., 2019). For example, intergenerational dyads draw alone may show less state D (relative to intergenerational dyads drawing together or same generation drawing in either condition), if the older dyad member engaged in heightened monitoring of the environment (i.e., the art at hand) and reduced monitoring of their behaviour relative to the younger dyad member. This aligns with existing findings that contralateral functional connectivity between IFG and TPJ is associated with higher-order social cognition, such as divergent thinking involved in creative drawing (Huang et al., 2024), regulating socially induced emotions (Grecucci et al., 2013), and controlling actions under averted gaze (Zillekens et al., 2019). Though the design of the present study is not sufficient to disentangle these potential mechanisms, future studies could incorporate additional measures to do so. These could include a measure of absorption in drawing, such as Rheinberg and colleagues' Short Flow Scale (Engeser & Rheinberg, 2008; Rheinberg et al., 2023), which has items that capture absorption as well as

social ease or worry during the drawing activity. The influence of direct and averted gaze could be captured using eye-tracking.

### 4.3 Asymmetric connectivity patterns during intergenerational collaboration highlight leader-follower dynamics

States F and G feature low-to-medium connectivity between brains and prominent within-brain connectivity between the bilateral IFG of one dyad member. State G, but not F, differed between real and pseudo dyads, specifically for intergenerational dyads drawing together. Here, the older dyad member shows marked within brain connectivity. This pattern aligns with the asymmetric connectivity patterns characteristic of leader–follower dynamics described by Heggli and colleagues (2019, 2021) and actor–observer dynamics observed using EEG by Li and colleagues (2025). In line with these findings, we propose that the longer mean duration of state G for intergenerational dyads, as compared to same generation dyads, reflect sustained leader–follower collaboration. Indeed, the intergenerational dyads' drawings were rated more collaborative than same generation dyads based on the coherence of the motifs and the use of space (reference redacted for peer review). The heightened within-brain connectivity for the older dyad members indicates that they are the leader (Heggli et al., 2019), and that the younger dyad members adapted to the older dyad members. This adaptation facilitated coordination for extended periods of time across the 5-minute drawing tasks, as evidenced by the longer durations of state G.

The opposite pattern, indicative of the older dyad member adapting to the younger leader (i.e., state F), did differ significantly between pseudo and real dyads in terms of coverage, showing that this state is also unique to real interaction. Yet, because the coverage of state F did not differ significantly between drawing tasks or groups, this state where younger dyad members lead and older dyad members follow is not informative as to the dynamics of intergenerational collaboration.

The asymmetrical pattern of within-brain connectivity involves prominently elevated connectivity between the bilateral IFG. The bilateral IFG are involved in language processing (Bulut, 2022), inhibitory control (Hampshire et al., 2010), attention reorientation (Frank & Sabatinelli, 2012), and social cognition (Diveica et al., 2021; Tso et al., 2018). Across these functions, unilateral left IFG activation is more common than unilateral right IFG activation (Jackson, 2021; Krieger-Redwood et al., 2015), though healthy older adults tend to show greater right IFG activation (Hoffman & Morcom, 2018). In the silent drawing task, explicit speech processing can be excluded as a possible mechanism for the observed connectivity between the bilateral IFG. Though implicit speech processing cannot be excluded, inhibitory control and/or attention reorientation seem to be more viable contributors. To establish the provenance of the bilateral IFG connectivity, addition measures of behaviour (such as kinematics of turn-taking behaviour or gaze-tracking) may be useful to gain deeper insights into the pattern of within-brain connectivity observed in state G.

The strong effect of G in the intergenerational group might be additionally related to this finding. Building on these results, it seems reasonable to assume that states F and G reflect some semantic or inhibitory processes related to the task demands. Both inhibition of spontaneous impulses and semantic reasoning about the process or output can be speculated to be involved in drawing collaboratively.

### 4.4 Methodological considerations

Recently, there have been calls for developing data analysis techniques specific to fNIRS (Näher et al., 2024; Shin et al., 2024), as the scientific edge that fMRI and EEG approaches currently have over fNIRS might be partly due to the fact that a much richer and more mature range of methodologies specifically designed for the output of these methods already exists while fNIRS data still have yet to be fully exploited (Näher et al., 2024). The two-brain state analysis presented in this paper moves beyond averaging INS across tasks to a more holistic view that illuminates the temporal and spatial structure of two-brain dynamics, capturing the heterogeneity and asymmetry inherent in naturalistic interactions. The approach further extends previous approaches for characterizing two-brain states in fNIRS data (Li et al., 2021) as it integrates information on within-brain and between-brain connectivity and it goes beyond recently presented techniques for EEG data (Li et al., 2025), since it can capture between-brain connectivity in addition to observing two interacting brains in parallel.

It should be noted that a state-based analysis is one way of summarising continuous, high-dimensional data that captures the dominant structure and relative differences. Further research will show whether the states generalise across individuals and studies. Importantly, dynamic functional connectivity often displays a poor signal-to-noise ratio and hence low reliability (Laumann et al., 2024). Future analyses could investigate further kernel functions (Wang et al., 2015), different window sizes, as well as additional regions of interest. Moreover, Näher and colleagues (2024) present analyses based on the super kernel matrix method where hyperparameter tuning happens separately for both chromophores which has been shown to lead to better classification results and might also be beneficial in clustering. Finally, a more flexible procedure could involve clustering on the dyad-level first and then identifying which states that replicate across dyads and relate to the behavioural structure of the experiment (Zhang & Zhu, 2020).

**5 Conclusion**

This study demonstrates that two-brain states can be identified in fNIRS hyperscanning signals collected in a naturalistic setting, such as a collaborative drawing task. We identified seven distinct two-brain states that arise during social interactions, three of which are specific to real interactions. Of these, six showed no clear evidence, and at most trends, for differing temporal dynamics per dyad composition or drawing condition. A single two-brain state (featuring low-to-medium connectivity between brains and prominent within-brain connectivity bilateral IFG of one dyad member) was observed for longer periods in intergenerational dyads than same generation dyads, during collaborative drawing. None of the identified two-brain states showed evidence of longitudinal changes. These findings substantiate the claim that asymmetric neural dynamics play a role during social interaction and depend on alternating patterns of within-brain and between-brain connectivity (Marton-Alper et al., 2023; Shamay-Tsoory et al., 2019). Although not all identified brain states showed meaningful relationships with the collaboration context, these findings also suggest that approaches that preserve spatial and temporal information can be useful in characterising the neural dynamics in naturalistic social interaction, supporting their utility for future work.

**Glossary**

*Brain state* – A recurrent spatial pattern of brain activity.
*Common cognitive processing* – The theory that similar perception of stimuli causes interacting people's brains to
respond in comparable ways at comparable time delays to the stimuli.
*Coverage* – A brain state metric that indexes prevalence; the proportion of all windows in which a given state is
identified.
*Duration* – A brain state metric that indexes state stability; the mean number of consecutive windows in which a
given brain state is identified.
*Hyperparameter tuning* – Selection of appropriate values for model parameters that are not learned from the data
itself (e.g., shrinkage parameter or number of clusters) by evaluating model performance across a range of values
(the hyperparameter space) and choosing the one that best meets a predefined criterion
*Hyperscanning* – Simultaneous recording of brain activity from two or more people while they interact.
*Kernel function* – A (mathematical) function that quantifies similarity between two observations in a feature space
without explicitly computing their coordinates in that space
*Kernel matrix* – A square matrix containing kernel function values for all pairs of observations, quantifying their
mutual similarities
*Mutual prediction* – The theory that people continuously predict potential changes in their shared environments,
including social information about each other.
*Occurrence* – A brain state metric that indexes frequency; the number of windows in which a given state is
identified.

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