Investigating EEG Inter-brain Synchrony: Methods to gather Meaningful Evidence

Federico Cassioli[1] *, Nellia Bellaert[1], Matias Pulópulos Tripiana[2], Sarah Galdiolo[3], Mandy Rossignol[1], Clay B. Holroyd[4 §] Rudi De Raedt[2 §]

1. Department of Cognitive Psychology and Neuropsychology, University of Mons, Mons (Belgium)

2. Department of Experimental Clinical and Health Psychology, Ghent University (Belgium)

3. Department of Clinical Psychology, University of Mons, Mons (Belgium)

4. Department of Experimental Psychology, Ghent University (Belgium)

Author Note

***Corresponding author**
Correspondence concerning this article should be addressed to Federico Cassioli, (https://orcid.org/0000-0001-5623-2634), Department of Cognitive Psychology and Neuropsychology, University of Mons, Mons, 7000 (Belgium). Email: federico.cassioli@umons.ac.be

§Clay B. Holroyd and Rudi De Raedt share last authorships.

Funding
This work has been funded by the Research Foundations FWO and F.R.S.-FNRS under the Excellence of Science (EOS) program (EOS 40007528/ G0I2422N).

Declaration of interest
The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this article.

Data, materials, and code availability
The code used in this work related to signal processing and statistical analysis is available at (https://osf.io/ecbfg/?view_only=7b3fe35155e9496ba56fc4ca326bd553).

Acknowledgments
The authors would like to thank everyone from the EOS TRIAD team who contributed their time and ideas to this work during its development.

CRediT author contribution statement
Federico Cassioli: conceptualization, data curation, formal analysis, investigation, methodology, project administration, resources, software, validation, visualization, writing—original draft, writing—review and editing. **Nellia Bellaert**: conceptualization, formal analysis, methodology, software, visualization, writing—review and editing. **Matias Pulópulos Tripiana**: methodology, validation, writing—review and editing. **Sarah Galdiolo**: funding acquisition, resources, supervision, writing—review and editing. **Mandy Rossignol**: funding acquisition, resources, supervision, writing—review and editing. **Clay B. Holroyd**: conceptualization, methodology, supervision, validation, visualization, writing—review and editing. **Rudi De Raedt**: conceptualization, funding acquisition, methodology, supervision, writing—review and editing.

Abstract

Synchrony has been proposed as a relevant phenomenon for investigating social neurophysiological and psychological processes, with inter-brain synchrony, in particular, presumed to facilitate the functional integration of multiple brains. However, the lack of an accepted definition and a cohesive theoretical corpus that allows hypothesis-based approaches, often combined with inadequate empirical methods, weakens this area of research. To address this, we propose a rigorous definition of inter-brain synchrony and link various theoretical contributions to justify the existence of meaningful temporal alignment between different brain activities. This article outlines a set of methods to provide valid evidence supporting this neural mechanism. Our approach entails extracting instantaneous phase data from Hilbert-transformed EEG time series recorded from individuals under different experimental conditions that account for confounding factors such as shared attention, cognitive, and motor dependencies. We then describe multiple data analysis approaches, including circular statistics combined with permutation testing, and mutual information. Finally, we present an example of a potential application within the context of cooperation in nuclear families. We believe that, by employing such methods consistently, the concept of inter brain synchrony is falsifiable. Whether this phenomenon is empirically supported or not, it will contribute to advancing our understanding of the social brain.

Keywords: inter-brain synchrony, EEG, social interaction, methods, phase synchronization.

1. Introduction

1.1 A definition of inter-brain synchrony

Two entities, or independent oscillators, are said to be in a state of synchrony when adjustments in their rhythm converge to a common frequency as a result of interactions such as coupling, feedback, mutual interference, or communication (Gupta et al., 2018; Pikovsky et al., 2003). Ubiquitous in nature, synchronous patterns have been investigated across diverse fields (Hulthén et al., 2022; Provenzano & Baggio, 2021), driven by the meta-assumption that studying entities together over time can reveal significant information about the system they compose. This is because the behaviours of individual entities by themselves often do not fully represent the behaviour of the overall system. The uniqueness of synchrony lies not in the mere co-occurrence of the components' behaviours but in the extent of their dynamic adjustments to each other. Considering three dimensions—magnitude, time-lag, and the features under investigation—we propose to represent synchrony between two entities as a cuboid, as shown in Figure 1. Magnitude refers to the strength of the dynamical adjustment of the two entities; time-lag denotes the delay between a change in one entity and the corresponding change in the other; and the features are the measures used to investigate the synchronous relationship (e.g., synchrony in firefly flashing can be analysed in terms of flash duration, flash density, flash frequency, or flash intensity). In this work, we consider synchrony defined not as a stochastic, spurious, or merely concurrent-correlational phenomenon, but as a certain temporal and functional coordination between two entities in their happening and development. Thus, synchrony here reflects a peculiar state of interconnectedness in which different entities come together in a harmonious and integrated manner.

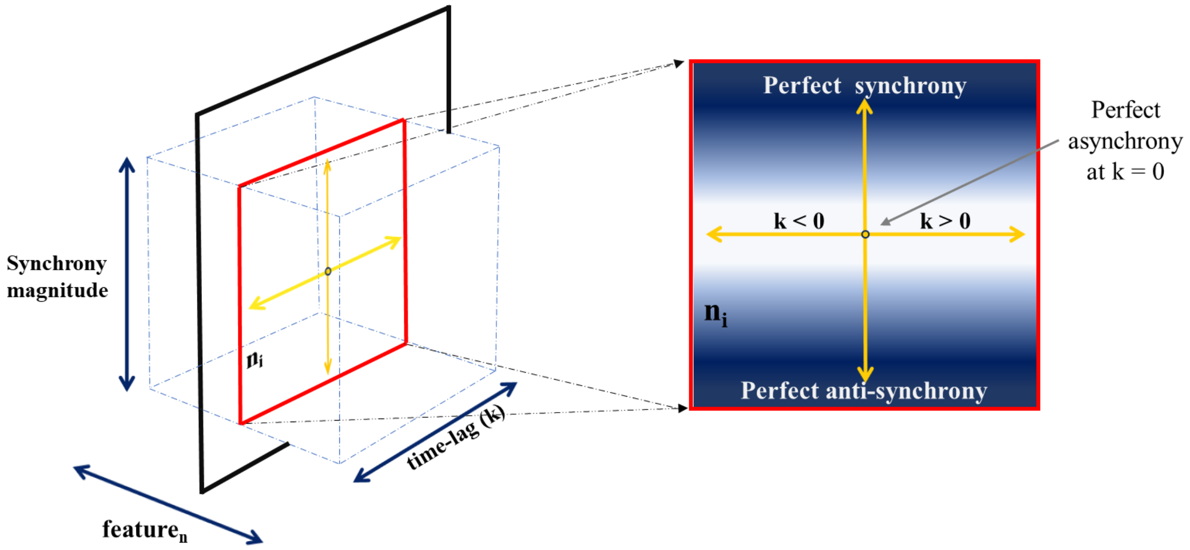

Figure 1. A geometrical representation of synchrony considering three dimensions: magnitude, time-lag (k), and the features (n) under investigation. Regarding magnitude, two entities(x,y) that are completely independent are in a state of perfect *asynchrony*. As the magnitude of synchrony increases, either positively (*synchrony*) or negatively (*anti-synchrony*), two states are approached respectively: perfect synchrony (i.e., for every increase in a feature of x, a feature in y also increases) and perfect anti-synchrony (i.e., for every increase in a feature x, a feature in y decreases). The second dimension is the time-lag between x and y, denoted as k, with an arbitrary sign based on the assigned reference (either x or y). Consequently, given a measured feature (n_i) in both x and y at a time lag k, we can think of all the states of synchrony represented by the surface of a quadrilateral where the origin (0, 0) is a state of perfect asynchrony at a zero-lag. The third dimension represents multiple independent feature$_n$ under consideration. While this model assumes the same random variable is examined across two different entities (or two different variables in the same

system), it can be adapted to represent dependencies between two different random variables. At a theoretical level, the volume of a cuboid captures all measurable synchrony states between x and y, at a time-lag bounded by [-k, k], and the features defined by features_n.

In recent years, social interactions and various forms of synchrony have garnered major attention in neuropsychology and neuroscience (Uhlhaas & Singer, 2006; Wheatley et al., 2024). Within interpersonal relationships, synchrony is believed to occur on a multi-modal level during social interaction, encompassing both physiological (e.g., cardiac) and behavioural (e.g., walking) processes (Coutinho et al., 2021; Delaherche et al., 2012; Ikeda et al., 2017). The continuous exchange of information in social contexts increases the complexity of these interactions, which result from decision-making processes involving mentalization and dynamic predictions (Kingsbury & Hong, 2020). Despite extensive review efforts (Atzil-Slonim et al., 2023; Birk et al., 2022; Hale et al., 2024; Zhao et al., 2024) that have thoroughly examined these modalities, their integration remains incompletely understood. Regardless of the modality through which synchrony manifests, it is evident that these patterns would be mediated by brain processes (Holroyd, 2022). Hence, researchers have increasingly directed their attention to a phenomenon known as inter-brain synchrony (IBS).

To the best of our knowledge, regardless of the vast body of research on the subject and the concerns previously raised (Burgess, 2013; Holroyd, 2022), no formal definition of IBS accompanied by an appropriate theoretical framework and neuroimaging methods has been proposed to explore or support IBS. Addressing these two gaps is crucial for developing a falsifiable and hypothesis-driven approach, particularly in the contexts of brain connectivity measures. Conversely, providing an explanation for the neuroanatomical and brain sources of IBS is beyond the scope of this study. As recommended by Leist and Hengstler (2018), the current paper is structured as follows: first, we describe the essential criteria for properly characterizing IBS, followed by our proposed formal definition. Next, we outline the current methodological tools for validly detecting IBS. Given the challenges highlighted in the recent literature, we propose a description of procedures and materials, including sampling, experimental procedures, signal processing, and statistical analysis. We then present an exemplary case of these methods in the context of a nuclear (i.e., triadic) family during cooperation. Finally, we discuss the necessary information researchers should share to enable replication and improve the comparability of IBS research. Further reflection is dedicated to robustness, accuracy, and quantification of uncertainty.

When measuring IBS, a sine qua non condition is that the phenomenon should not be explained by confounders such as neural entrainment, motor-induced or attention-enhanced neural *dependence*, as explained by Holroyd (2022). Hereafter, we will refer to this alignment as a statistical dependence, as we prefer to treat it with no assumptions on the distribution of the variables, or the nature of their relationship (e.g., nonmonotonic). In this sense, dependence implies a statistical association but does not necessarily imply causation. Controlling these confounding factors is essential to properly measure IBS. Specifically, neural entrainment refers to the share of dependence explained by common external sources (e.g., a visual flicker at a certain frequency). Motor-induced dependence accounts for the neural component resulting from the behaviour of one agent driving the neural activity of both individuals (e.g., eye-gaze). Another element could be due to an intentional motor alignment (e.g., imitation). Finally, attention-enhanced dependence is related to factors such as engagement and arousal, which could enhance neural entrainment and motor-induced dependence. Additionally, top-down processes due to shared memories or cultural factors could be also seen as part of this source of attention-enhanced dependence.

Beyond controlling for confounders, the following considerations should be contemplated. First, IBS should not exhibit task or environment specificity (i.e., IBS, hypothesized as a mechanism of social interaction, should be observable across a range of tasks, though the extent of this generalizability is still unknown) and should not be explained by shared behavioural cues. Secondly, IBS, when measured with correlational techniques without experimental manipulation, is not directly observable; instead, it should manifest as a difference in explained neural dependence relative to a reference condition, reflecting the extent of social adjustment. Third, since synchrony results from interaction rather than mere co-occurrence, randomness and spurious correlations must be statistically ruled out. Moreover, even if evidence supports IBS, it should not be considered a social cognitive mechanism per se but should be tested as a predictor of social interaction outcomes and as a potential causal mechanism demonstrated through measurable changes, limiting reliance on untestable cognitive assumptions. Fourth, any type of synchrony, requires "energy" transmission across a medium (i.e., the wooden table subject to mechanical vibrations for the two pendulums of Huygens). For IBS, the medium should (and must) consist of sensory channels that allow information flows between interacting individuals. It is worth noting that if zero-lag synchrony is assumed possible, it should be induced by complex (and non-linear) intra-brain synchronizations that occurs simultaneously across individuals, based on previously exchanged information. Also, IBS should not merely reflect simple coupling or basic information exchange between interacting individuals during a specific task (e.g., turn-taking during a conversation could induce dependence at very low frequencies; Nguyen et al., 2023). Lastly, epistemologically, the assumptions underlying the definition of general synchrony and IBS influence the choice of synchrony estimator. Such estimators may only capture partial information or distort it, and the interdependence between signals might not be fully represented if the analysis focuses on a certain dimension (e.g., phase vs. amplitude dependence) or if the physical properties of the signal do not match the synchrony of interest for the selected time window (i.e., when the rate of change in the chosen metric does not reflect the actual physical phenomenon). This could lead to false positives (e.g., using an inflating estimator such as phase-locking value, e.g., Burgess, 2013) or false negatives (e.g., missing synchrony by focusing on irrelevant frequencies, leading to wrongfully equating absence of evidence with evidence of absence).

Considering the conditions described above, IBS, at a certain time lag and frequency, can be defined as neural dependence, in terms of the information one signal provides about another, between the signals of interacting individuals, accounting for the putative neural mechanism that promotes social interactions through the functional integration of multiple brains, and which cannot be explained by neural entrainment, motor-induced dependence, attention-enhanced dependence, or randomness. A graphical representation of IBS is depicted in Figure 2.

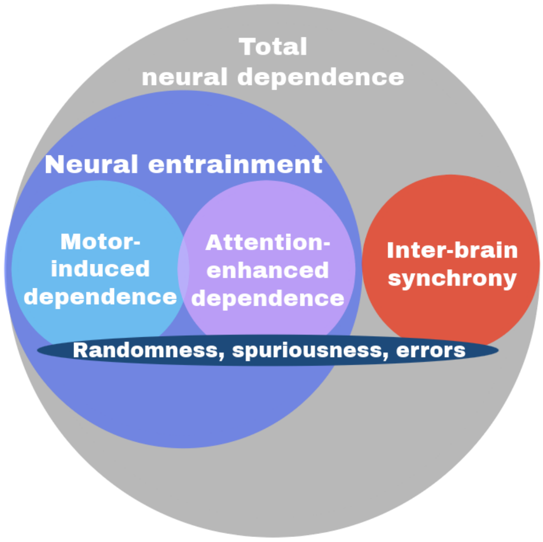

Figure 2. A Venn diagram illustrating the concept of *inter-brain synchrony* (IBS). IBS is conceptualized as the difference between the total neural dependence between signals of interacting individuals and that derived from confounders. Randomness, spuriousness and errors are factors that transversally impact all the components ranging from measurement or error-inflating techniques. Total neural dependence is potentially not completely explained by the considered factors as their computation brings in some assumptions (e.g., a linear or circular dependency or approaches such as mutual information, see Fernandes & Gloor, 2010), making hazardous to equating the total theoretical dependency to the other dimensions. IBS is represented by the red area.

1.2 Theoretical perspectives and current state-of-art on inter-brain synchrony

With this strict definition of IBS, we can now propose a theoretical foundation and develop appropriate methods to test this phenomenon.

The Relational Neuroscience framework suggests that IBS might occur in various social contexts or processes (e.g., social learning, co-regulation, cooperation) and across different interaction partners (De Felice et al., 2024). Similarly, focusing on affiliative bonds, the biobehavioral model of mutual influences in the formation of affiliative bonds (Feldman, 2012) emphasizes biobehavioral synchrony, which encompasses behavioral, genetic, hormonal, brain, mental, and autonomic components, as mechanisms for co-regulation between attachment partners. This synchrony would significantly impact the development throughout childhood and adolescence. According to this model, individuals within a system affect each other's physiology through processes such as social synchrony during the formation of affiliative bonds. A related perspective, the multi-brain framework for social interaction, directly addresses neural synchrony. It conceptualizes social exchange as an interaction between two or more neural systems, coupled through sensory inputs and behaviour (Kingsbury & Hong, 2020), a definition that aligns with the concept of generalized synchrony discussed earlier.

To explain the relationship between informational input and neural phenomena during social interaction, the Interactive Alignment Theory (Pickering & Garrod, 2004), as cited in Schoot et al. (2016), builds on Friston & Frith's (2015) work. Schoot et al. (2016) argue that such interaction involves a non-static inference about others, where individuals continuously update their beliefs about the world and sample sensory information to minimize predictive errors. In this context, IBS could be operationalized as a measure of alignment, or statistical dependence, in the signals of two interacting individuals. Its magnitude should be inversely proportional to the social prediction error, defined as the difference between the expected and actual outcome during interactions with others, achieved through mutual prediction (de Bruin & Michael, 2021). For example, a speaker and a listener aligned at a syntactic level should show a neural coupling, or dependence, in cortical areas associated with that cognitive process. De Bruin & Michael (2021) noted that a previous study (Stephens et al., 2010) could not disentangle neural coupling from specific communicative signals and did not account for the dynamic nature of interactions, which contradicts Friston & Frith's theory (2015). This highlights two important considerations: first, IBS should be tested in real social interactions where the social unit shares a goal and intentionality, and where the situation requires the continuous alignment of the agents' generative models. Second, IBS should be disentangled from potential confounders, as we argued earlier. By integrating the multi-brain and Relational Neuroscience frameworks, with the Interactive Alignment Theory and the biobehavioural synchrony model, we can hypothesize the existence of IBS in interacting individuals engaged in tasks that require the dynamic alignment of their internal models to facilitate information exchange.

Despite attempts to formulate valid methods to address similar aims (Tamburro et al., 2023), we believe that the issues we highlighted above were never properly considered in neuroimaging testing, leading to biased evidence. For example, a meta-analysis (Réveillé et al., 2024) on electroencephalographic (EEG) hyperscanning (i.e., the term often employed for the conjoint neuroimaging data acquisition) found moderate associations between IBS and situation characteristics at an individual, team, and organizational level ($g = 0.66$, 95% CI [0.50–0.81], $n = 22$, $k = 78$, $p < 0.001$) and between IBS and affective and behavioural team processes ($r = .45$, 95% CI [.29-.59], $n = 9$, $k = 24$, $p < 0.001$), as well as a small correlation between IBS and team performance ($r = 0.16$, 95% CI [0.02–0.29], $n = 14$, $k = 41$, $p = 0.024$). Instead, a meta-analysis on functional near-infrared spectroscopy (fNIRS) studies (Czeszumski et al., 2022) compared cooperative and non-cooperative conditions, finding a large effect size ($g = 1.98$, 95% CI [1.47, 2.49], $n = 21$, $z = 7.68$, $p < 0.001$). However, it is highly probable that these results are inflated due to the lack of the considerations we proposed. Among these are the lack of a definition and operationalization of IBS, the absence of controls for all confounders, and the use of statistical approaches that do not fit the nature of the data.

Only recently has the testing of the causal role of inter-brain dynamics with non-invasive brain stimulation (NIBS) begun. These protocols involve manipulating neural patterns in multiple individuals, using transcranial alternating current stimulation (tACS) on dyads. Novembre et al. (2017) showed that in phase stimulation at 20 Hz, localized at the motor cortex (i.e., anode placed over C3 and cathode over PZ, according to the International 10/20 system; Homan et al., 1987) increased their ability to synchronize tapping. This supports the fact that dyads exposed to in-phase stimulation during a preparatory period might have enhanced action coordination compared to baseline, a pattern not found in surrogate data. Such approaches are valuable, with recent propositions to refine such designs (Semertzidis et al., 2024). However, the mechanisms by which neural oscillations couple and maintain such states at an interindividual level remain poorly understood, with many temporal, spatial, and frequencies asymmetries within and between dyads (Takeuchi, 2024). So far, in most experimental designs, the definition of synchrony often remains unexplicit, and stimulation-induced IBS is still an unverified assumption, and brain-to-brain phase coupling during real-life interaction has not been measured. In a recent study (Lu et al., 2023), behavioral coordination was investigated in three independent groups respectively undergoing tACS (20hz, in-phase), transcranial direct current stimulation (tDCS), and a sham condition while measuring oxyhemoglobin through fNIRS. The anode was placed at FC6, and four cathodes were placed at F6, FT8, C6, and FC4 to cover the right inferior frontal gyrus. In their task, although it does not meet the criteria mentioned earlier, the dyads were instructed to press buttons as synchronously as possible after a signal. IBS, computed as oxyhemoglobin cross-correlation at the prefrontal cortex (Fpz), was maintained after stimulation, only in the tACS group. Interestingly, linear correlations were found between IBS and coordination performance metrics of the dyads (i.e., the difference or sum of response times), with significant correlations for the tACS group (r = -.437, p = .048) and tDCS group (r = -476, p = .029), supporting the conjecture that IBS could facilitate information exchange and positively impact social interaction outcomes, such as lower response times. No significant correlation was reported for the sham group. However, as these correlations were found only in one task block where no IBS significant differences were observed, further studies are needed. This also raises questions about whether fNIRS captures IBS, given its limited temporal resolution.

Besides the promising reported studies in the literature, more evidence is still required (Carollo & Esposito, 2024). A critical question remains, are there proper methods to measure IBS with neuroimaging techniques? To address this question, we focus on EEG data for our use case, as suggested in Grootjans et al., (2024). EEG may strike the best balance between temporal resolution, necessary for investigating the granularity of temporal alignment, and ecological validity, allowing participants to interact with some movement and communication, unlike other techniques (Tsoi et al., 2022). Another reason for focusing on EEG brain oscillations lies in our definition of IBS that stresses the time-based adjustment phenomenon, with less emphasis on its specific brain sources. However, our proposed methods can be conceptually adapted, with necessary adjustments, to other time series data that offer different informational advantages (Tsoi et al., 2022). Building on earlier advocacy (Newman et al., 2024; Pérez & Davis, 2023; Redcay & Schilbach, 2019) and the ideas outlined previously, the aim of this methods paper is to describe analytically the necessary methods for gathering meaningful evidence for IBS using EEG data from individuals interacting together and to improve inter-brain methodologies. If further confirmed, given the strong relationship between health and social interactions, the understanding of synchrony as a medium for inter-individual interactions provides valuable information on the underlying precursors of the social brain (Chen et al., 2018).

2. Methods to investigate IBS

2.1 Sampling for IBS

In hyperscanning research, the combination of unknown effects and limited sample sizes represents a methodological challenge (Andrea et al., 2022). This concern is further amplified by the need to exclude multiple confounders and by arbitrary decisions made by researchers, which can hinder the gathering of replicable evidence (Zimmermann et al., 2023). When considering sampling procedures, two factors must be addressed: the appropriate number of data points and the overall sample size, specifically in terms of participant dyads or social systems.

Determining the required sample size for testing inter- or intra-group differences can be achieved using standard power analysis techniques. For instance, to estimate the minimum sample size in terms of dyads, needed to detect a medium standardized mean difference (d = .4) in a dependent samples t-test, assuming standard error rates (α = .05; 1- β = .9) and that all assumptions are met, the required sample size is estimated to be n=55. The biological sex of the participants should be considered when assembling the dyads, either by testing only same-sex dyads or social units, or by ensuring similar group sizes for combinatorial balance.

Conversely, there are no established guidelines or analyses for determining the sample size, in terms of data points, needed to reliably detect IBS. For this reason, researchers investigating inter-brain dependence should start by defining a model of connectivity that accurately represents IBS. They should then select appropriate models or statistical tests that align with their hypotheses, followed by the applications of Monte Carlo simulations to inform their experimental conditions and sampling specifics.

For exemplary purposes, we propose to operationalize IBS as a shared and independent source equally projected onto the distinct signals of two participants. This represents one of the many specific hypotheses regarding the operationalization of IBS. In this context, our focus is determining the required sample size to test for a significant bivariate relationship between the instantaneous phases of their time series. As we will show in the Statistical section (2.5), validly detecting this relationship is achieved using the adjusted circular correlation coefficient (Zimmermann et al., 2023), which forms the basic building block of our analysis plan. For these reasons, we performed a set of Monte Carlo simulations using the "ft_connectivitysimulation" function from the FieldTrip toolbox (version fieldtrip-20240704) on MATLAB (R2022b; The MathWorks, Natick, USA), executed on Microsoft Windows 11 (version 23h2). These simulations generated EEG time series data, with a specified connectivity structure. Although phase data are often modelled using von Mises distributions, the circular equivalent of a Gaussian, we used simulation-based analysis to avoid additional assumptions about the nature of the data (Chakraborty & Wong, 2023). The aim was to evaluate the minimum sample size required for each experimental condition to detect various IBS magnitudes between two EEG signals, given fixed type 1 and type 2 error rates (α = .01; 1-β = .9). We adhered to standard reporting practices for simulation studies (Siepe et al., 2023) and for functional connectivity simulations (Bastos & Schoffelen, 2016). The code is provided in the supplementary material. For the simulations, we assumed a generative model consisting of a linear mixture with two independent sources (x, y), representing two brain signals from two individuals (e.g., two electrodes placed on the prefrontal cortex on a mother and a father). IBS is theoretically conceptualized here as a shared signal projected equally into each source, with a certain unknown magnitude, similar to the approach in Zimmermann et al. (2023). To maintain a simplified structure, we did not implement any delay matrix. This model (Figure 2a) can simulate, for example, two brain signals within the theta frequency (here considered as 4-8 Hz), with varying magnitudes of instantaneous IBS. We introduced variance to each source post-linear mixing to simulate white noise (.5 standard deviation in the parameter 'cfg.absnoise'). As explained in the signal processing section (2.4), the bandpassed trials (4-8 Hz) were concatenated and the instantaneous phase was extracted via the Hilbert transform.

To test the relationships between phases, we employed the adjusted circular correlation coefficient (Equation 2), which tests the null hypothesis of no circular relationship between two time series with biased mean direction. Further details are reported in the statistical analysis section (2.5). The null hypothesis is rejected if the significance of the $CCor_{adj}$ is less than or equal α. Our performance measures were the powers of the test per conditions where the true effect is manipulated across different sample sizes, estimated by 'P(Test rejectsH_0)'. We varied the sample size from 1 to 60 seconds of artifact-free data at a sampling rate of 256 Hz (256 data points per epoch). Thus, we examined effective data ranges between 256-15360 data points, in steps of 256 data points, performing 10.000 simulations per step to ensure stability and reduce the Monte Carlo Standard Error (MCSE). Given the limited knowledge of the real effect size of IBS, we evaluated seven different scenarios for IBS magnitude: absence of IBS and six incremental degrees of magnitude (in the parameter cfg.mix, respectively: no IBS = 0, then IBS = .6; .7.; .8; .9; 1; 1.5) which can account for small to medium effects. The chosen range corresponds to an effective clean recorded data, which is realistic in ecological terms, to which a total percentage of 20%, approximating at 70 seconds, has to be added for data removal due to artifacts, noise, and other reasons (non-necessarily overlapping between participants). The results, which we believe provide a robust estimate for adequately powered IBS detection, are presented in Figure 2b. According to the analysis, an optimal time window of analysis is in the order of 55 seconds, assuming a modest IBS magnitude (with a parameter set at cfg.mix=.7). No missing values were observed. For each scenario and sample size, we computed the MCSE. Across all simulations, the highest observed MCSE was $MCSE_{max} = .005$.

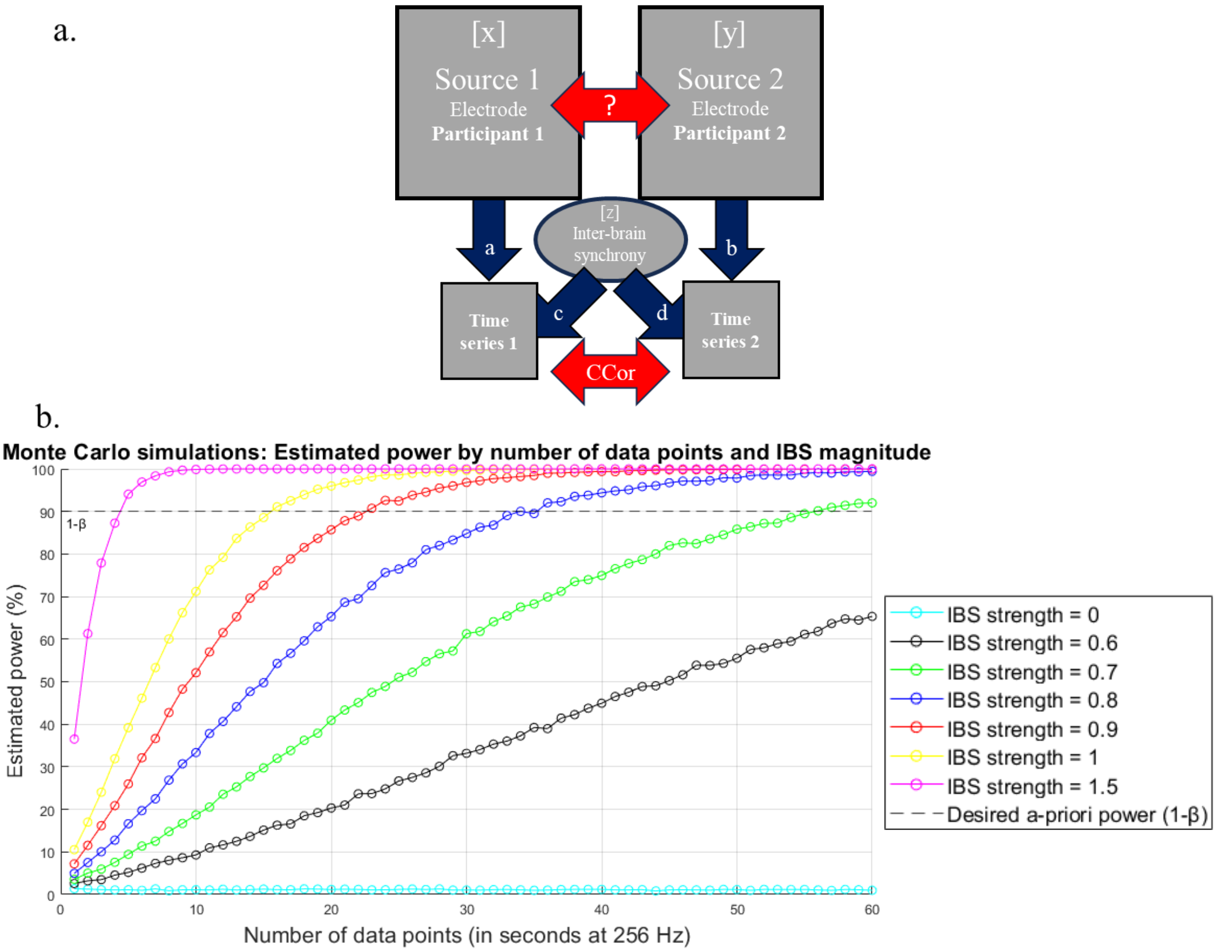

Figure 2. **a.** The model used for simulations in FieldTrip to conduct Monte Carlo simulations. The model generates two time series (time series 1 and time series 2, assumed to be from two participants, Participant 1 and Participant 2), from three unobserved components: source 1 (x), source 2 (y), and IBS (z). Respectively, x and y represent two separated direct sources (the arrows a and b) for the time series 1 and 2. The sources could be representing two electrodes placed on the cortexes of two participants, one corresponding to source x and the other to source y. IBS (z) represents a common source for the generated time series (the arrows c and d, here assumed c = d). The strength of the connectivity (denoted by '?') is manipulated in the form of seven different magnitudes and estimated, after data analysis, with the adjusted circular correlational coefficient ($CCor_{adj}$). **b.** Power analysis was conducted through Monte Carlo simulations with varying IBS magnitudes, maintaining 1-

β=.9 and α=.01 On the x-axis the sample size needed, in terms of seconds of data acquisition at a sampling rate of 256 Hz. The y-axis represents the power, as P(Test rejectsH0).

2.2 Experimental tasks to measure IBS

At a general level, the task used to measure IBS should preserve ecological validity to capture natural social processes (Babiloni & Astolfi, 2014) while avoiding excessive trial repetition, yet remaining sufficiently standardized to minimize inter- and intra-individual differences. It should also ensure sufficient statistical power to detect small but significant differences in dependencies. A baseline should be recorded at the beginning of the session. Moreover, given the speculated association between neural synchrony and social behaviours, the task should involve performance that is replicable alone and with others, involving multiple participants (>1) and incorporating social decision-making and shared intentionality, with limited to no learning effect. In addition, the task chosen by the researcher to investigate IBS should consist of three pseudorandomized blocks presented consecutively: a block with individual performance (*alone condition*), one involving the real-time observation of another social unit's performance of the same task (*observation condition*), and one where IBS is hypothesized by the researcher (*experimental condition*). As discussed in prior work (Holroyd, 2022; Zamm et al., 2024), including individual performance and observation of real performance serves as conditions to control for confounders. Condition characteristics should be established using a data-driven approach, such as the Monte Carlo simulations outlined in the previous section, ensuring that the selected task generates a sufficient amount of clean and usable data (e.g., in our specific case, within a 70-second range per condition).

In the *alone* condition, each participant should be completely isolated to prevent any information transfer between subjects. Participants perform the selected task individually, following its specific set of rules. In this setup, all inputs should be delivered equally and simultaneously to participants, but separately to each individual (e.g., stimuli appearing on personal and separate monitors). Once participants complete their trial, they signal this in a way that does not influence the trials of others (e.g., by pressing a button). This condition is designed to isolate exogenous factors that are task- and environment-specific (e.g., the sensorial data from the stimuli), as well as any motor activity that may induce neural entrainment.

In the *observation condition*, the participants are together, observing a group of confederates, composed of an equal number of individuals (i.e., two if the research focuses on dyads), performing the selected task. The confederates engage in natural social interactions, using verbal and non-verbal communication. The biological sex of the confederates either matches that of the participants or alternates to maintain balance. Participants are instructed to attentively observe how the task is carried out by the social unit and are allowed to discuss the process verbally. This condition is designed to control for the neural entrainment and attention-enhanced components (e.g., influence of physical co-presence).

In the *experimental condition,* the social behavior that the researcher hypthesizes to be associated with IBS should be elicited in participants. It is essential to ensure that all participants engage in the task under equivalent conditions (e.g., at equal distances and with similar ease of intervention). Moreover, the task should closely mimic a real social situation when executed jointly and incorporate dynamic alignment to facilitate information exchange, as theory suggests. For instance, based on the available literature (Czeszumski et al., 2022), there is evidence linking cooperative behaviours and IBS. Therefore, cooperation could serve as a proposed experimental condition, as illustrated in our exemplary paradigm in Section 3. Moreover, multiple (but not excessive) trials should be conducted for each condition, with stimuli randomized for each condition and order, without repetition. As conjectured earlier and based on our definition of IBS, IBS should be observable during the experimental condition (e.g., during social cooperation), exhibited as statistical divergence not just from the baseline but also from the two other conditions (alone, observation).

Although necessary, these procedures are not sufficient to fully exclude the confounders we highlighted earlier in Section 1.1. As suggested by Holroyd (2022), attention levels to the stimuli typically predict the degree of interindividual neural alignment, which does not fall under our definition of IBS. In the experimental condition, attention levels are likely to be enhanced compared to the alone or observation condition due to the inherent characteristics of this setting. This implies that we cannot confidently rule out the possibility that attention-enhanced dependence influences our condition comparisons, highlighting inherent limitations in correlational approaches. A potential solution is to collect additional data on physiological arousal to account for this factor. Such measurement should be compatible with the EEG and minimise disruption to ecological validity. Only by establishing significant differences—through the procedures described in the following paragraphs—between the experimental condition and the other two conditions, while excluding the influence of attention-enhanced dependence, can we conclude that we are measuring a phenomenon likely independent of the assessed confounders and associated with the ongoing social processes among the tested participants.

2.3 Other data

In the previous section, we emphasized the necessity of three conditions, to compare the condition where IBS is expected to manifest (experimental condition) with two control conditions that account for components of neural entrainment (alone, observation). We further highlighted that these procedures must be accompanied by the collection of additional data accounting for confounding factors, particularly attention-enhanced dependence. For this reason, it is essential to include a standard measure of physiological arousal (e.g., heart rate, pupillometry-based measures, skin conductance, e.g., Bach et al., 2010; Pulopulos et al., 2021).

Post-trial perceived difficulty and anxiety, perceived levels of engagement, should be gathered using visual analogue scales. The task trials can be video recorded, as utilizing videorecording and behavioural coding approaches could help quantify the social behaviours that contribute most to IBS and provide further insight into the relationship between IBS and behaviour. Additionally, other confounding variables that may influence IBS should be considered. For example, assessing intimacy and closeness, empathy levels, anxiety (state and trait), emotion regulation, mental health and executive functioning/self-regulation could be relevant. Task-specific variables should also be measured.

2.4 EEG signal processing for IBS: it is not just a phase

Each subject should be equipped with a set of EEG scalp electrodes, according to the 10-20 system, to sufficiently map the areas of interest (e.g., frontal, central, temporal, parietal, and occipital). The analysis should focus on specific regions of interest (ROIs) derived from a priori hypotheses. These ROIs are expected to be activated in response to the nature of the task, while other areas may be investigated with appropriate precautions. For instance, a researcher examining IBS during cooperative behavior (i.e., the experimental condition is a cooperative condition) should particularly consider the prefrontal cortex (PFC) and temporoparietal regions, as suggested by the meta-analysis conducted by Czeszumski et al. (2022).

Aside the specifics of each EEG system, we recommend delay testing and suggest rotating the EEG equipment to counterbalance any hardware errors, thus mitigating potential data acquisition biases. Regarding the choice of an hyperscanning setup, Barraza et al. (2019) offer a comprehensive description of EEG systems from different manufacturers. For each condition, the time windows of interest for the EEG analysis are the performance time of the fastest participant for the alone trials, and the actual trial time for the observation and experimental trials. Epoching should be defined based on a data-oriented approach, as shown earlier. The data cleaning and preparation fall outside the scope of this article. However, general recommendations include down sampling if necessary, filtering (0.5 Hz high-pass filter and 30 Hz low-pass filter), removing noise channels, referencing, epoching/segmentation, rejecting epoch through visual inspection; performing independent component analysis (ICA), and removing ICA components to eliminate nonbrain artifacts (e.g., eye blinks, heartbeats) and electrical noise. Finite impulse Response (FIR) filters are often the safest option for avoiding phase distortion and ensuring accurate computation of synchrony measures. The common frequencies of interest, delta (.5-4 Hz), theta (4-8Hz), alpha (8-12Hz) and beta (13-30 Hz, or further divided into beta1, 14-20 Hz and beta2, 20-30 Hz), can be tested separately with a priori hypothesis or exploratively. Conversely, there are several reasons suggesting that detecting IBS within the gamma band (>30 Hz) is improbable, including potential contamination by electromyographic activity and the gamma band's faster dynamics compared to the slow dynamics of behaviour (Holroyd, 2022).

The focus of analysis should be on the instantaneous phase of the signals. Phase is defined as a portion of a cycle that a point within a waveform has completed in relation to a reference or a "zero" position (e.g., $\varphi = 2\pi * (t - t0) / T$) and is generally expressed as an angle in radians. Phase information is particularly well-suited for the estimation of inter-brain measures for several reasons (Burgess, 2013; Holroyd, 2022; Zimmermann et al., 2023). Phase changes occur on a timescale that aligns well with brain dynamics, on the order of milliseconds, and are specifically related to the timing of neuronal activity rather than the raw amount of firing neurons or spatial information of a neuronal population, which is, for example, better reflected in power measures. In our case, phase information is also more reliable since amplitude-based measures can be influenced by factors such as skull impedance and motor artefacts (Mezeiová & Paluš, 2012). Moreover, phase synchronization exactly matches our definition of IBS and our need for establishing a phase entrainment in terms of a temporal dependency in individuals engaging in an interaction together, while the amplitudes of phase-synchronized systems can potentially remain uncorrelated (Rosenblum et al., 1996).

The standard approach to quantify phase synchronization involves determining the instantaneous phase value, $\phi(t)$. Two common methods for this are the Hilbert transform applied to the filtered signal and the complex wavelet transform, yielding essentially equivalent results (Le Van Quyen et al., 2001). In this work, we have selected the Hilbert transform (Oppenheim, 1999) which converts a real signal, $s(t)$, into a complex-valued analytic signal, $z(t)$, by combining it with its Hilbert transform, $\hat{s}(t)$. From this complex signal, the instantaneous phase is extracted, $\phi(t) = \arg(z(t))$, with its derivative representing the instantaneous frequency. The instantaneous phase ranges from 0 to 2π and represents the phase angle's variation over one cycle. After extracting the time series of instantaneous phases (e.g., $\phi(t)$, $\varphi(t)$) for the frequencies of interest, across the different experimental conditions, epochs, and participants, these epochs can be treated separately depending on the assumptions taken. Subsequently, we will model these epochs to evaluate their degree of synchrony.

2.5 Statistical analysis

This paragraph assumes two phase time series treated as detailed in Section 2.4, for specific frequencies (e.g., theta) under the experimental conditions (i.e., alone, observation, and experimental/cooperation), with the aim of determining their statistical dependence. The distribution of a phase is inherently circular, suggesting the employment of circular statistical approaches (Mardia & Jupp, 2000). To analyse instantaneous phase statistically, we will briefly present two approaches: the first approach utilizes an adjusted version of CCorr, which is currently recommended for studying phase alignment, while a second approach based on mutual information (MI), where time-lags between time series and controlling for other variables is possible. Both CCorr and MI are considered more robust measures for detecting IBS compared to commonly used methods in IBS research, such as the Pearson correlation coefficient, coherence, phase-locking value, partial directed coherence, and phase-locking index (Burgess, 2013). To estimate the phase entrainment of neural time series, the CCorr (Fisher & Lee, 1983) has been proposed and subsequently verified to be less susceptible to spurious relations in the context of IBS (Burgess, 2013). As shown in (1), given two vectors x = $\phi(t)$ and y = $\varphi(t)$, with their mean directions ϕ, φ, CCor is the product-moment correlation between the sine components of these phase angles. CCorr has several notable properties: it is symmetric ($\text{CCorr}_{x,y} = \text{CCorr}_{y,x}$), bounded within the range [-1, 1], and tests the null hypothesis H_0 of significant independence between the circular variables x and y ($\text{CCorr}_{x,y} = 0$).

$$CCor\ (x,y) = \frac{\sum_{i=1}^{n} \sin\ (\phi\text{i}-\phi)\sin\ (\varphi\text{i}-\varphi)}{\sqrt{(\sum_{i=1}^{n} sin^2(\phi\text{i}-\phi))(\sum_{i=1}^{n} sin^2(\varphi\text{i}-\varphi))}} \quad (1)$$

Moreover, it was argued by Zimmermann et al. (2023) that while phase information is theoretically independent of amplitude, in practice, estimated phases can be influenced by various factors (van Diepen & Mazaheri, 2018) and the mean directions are often arbitrary. Consequently, a modified version of the CCorr has been proposed to better accommodate the nuances of EEG data (Zimmermann et al., 2023). In this modification, the numerator of (1) is replaced by ($R_{\text{x-y}} - R_{\text{x+y}}$) where R (x ±y) = $|e^{i(1\pm y)}|$, hence defining by equation (2)

$$CCor_{adj}\ (x,y) = \frac{(R_{\text{x-y}} - R_{\text{x+y}})}{\sqrt{(\sum_{i=1}^{n} sin^2(\phi\text{i}-\phi))(\sum_{i=1}^{n} sin^2(\varphi\text{i}-\varphi))}} \quad (2)$$

Based on Equation (2), a set of CCor_{adj} scores are calculated on the dyads for the epochs of the 3 conditions. This is the measures we employed for our simulation-based power analysis. Such coefficient can then be analysed generally with linear models (e.g., van Vugt et al., 2020). For example, we can compute the difference (i.e., t-test) between the CCor_{adj} for a sample of dyads by comparing the experimental condition and the alone condition, as well as comparing the experimental condition and the observation condition. We can then build empirical distributions that represent h_0 (i.e., broken synchrony or asynchrony) composed of t-values obtained by shuffling the data multiple times (e.g., 1000 times). These null distributions should be constructed using full permutation as suggested by Holroyd (2022). This means that, in addition to shuffling condition labels, individuals from different dyads are randomly paired. To account for signal auto-dependence in the null distribution, the shuffling should be performed over small segments. If the t-value exceeds the chosen significance threshold (e.g., .05), it strongly suggests that the synchrony observed during the experimental condition represents a meaningful divergence from the alignment seen during the alone and observation conditions. This provides evidence that such synchrony is not merely a result of neural entrainment or motor-induced dependency, or coincidental phase alignment.

The second statistical approach targets the possibility that two time series might be correlated at various time-lags, in agreement with the general definition of synchrony at the beginning of this work, potentially arising from a rotation relative to each other due to circular patterns—another form of synchronization that would go unnoticed with our first proposed approach (i.e., which is equivalent to suppress the dimension of time-lag in the cuboid in Figure 1). Generally, cross-correlation is applied to detect peaks in the cross-correlation function using peak detection algorithms. As reported in Fallah et al. (2024), a conventional Pearson's cross-correlation does not consider the circularity of the original phases. Therefore, a cross-circular-correlation (CCC) should also be employed. However, to the best of our knowledge, no specific work has been carried out on EEG phase data. Rybski et al. (2003) compute it by accumulating the phase and calculating the phase difference at a certain time lag k, plotting them into a certain number of bins (2π/bins). In the case of no synchronization such differences should be constant. Unfortunately, this method likely results in a biased estimation of synchrony in EEG data, as a consistent phase difference does not implicate the presence of a statistical dependence (Burgess, 2013).

The last proposed approach considers mutual information (MI), to test model-free independence of two variables. MI (equation 3 for a general formula) is a proxy of the entropy explained by the information of the other variable considered. In our case, the pairwise MI between $x = \phi(t)$ and $y = \varphi(t)$ will return a near-zero value when independency between the variables exists.

$$I\ (x, y) = \sum_{x,y} P_{xy}(x, y) \log_2 \frac{P_{xy}(x,y)}{P_x(x)P_y(y)} \qquad (3)$$

Information-based approaches have the advantage of not having assumptions on the distributions and the relationship between the variables under observation. They have been adapted for phase data (Burgess, 2013; Kraskov et al., 2004) and they possess high flexibility. For example, a time-lag can be added (Wilmer et al., 2012) to account for previous states of the phase time series x in predicting y (phase transfer entropy) to analyse the information flow between the two phase time series. Lastly, such approach might be useful if we observe significant inter-condition differences in arousal, quantifiable using cardiac, or electrodermal, or pupillometry-based measures (e.g., Bach et al., 2010; Pulopulos et al., 2021), which could point at attention-enhanced component. In that case, it could be useful to compute the conditional mutual information (CMI), that helps quantify the relationship between two variables while removing the effect of a third one, in a similar fashion to partial correlation, but with no linear constraints (Ince et al., 2017). This statistical approach can help ensure that the difference in neural alignment in the experimental condition is not attributable to physiological arousal or attentional levels, thereby adhering more closely to our definition of IBS.

2.6 Transparency and Openness

All code has been made publicly available on OSF.io and can be accessed at [https://osf.io/ecbfg/?view_only=7b3fe35155e9496ba56fc4ca326bd553].

3. Illustrative case of IBS within a nuclear family

In this section, we briefly outline an exemplary paradigm that employs our proposed methods to investigate IBS within nuclear families, specifically comprising three interacting individuals: a mother, a father, and their child. Previously, we posited that IBS could be studied in any interacting dyad or group engaged in a task that is replicable in both individual and group contexts, involving decision-making and shared intentionality. This is supported by, among others, the Relational Neuroscience and the multi-brain frameworks, as well as the Interactive Alignment theory (De Felice et al., 2024; Kingsbury & Hong, 2020; Pickering & Garrod, 2004). We argue that IBS research could also focus on populations with clear affiliative bonds, such as nuclear families. Previous evidence suggests the existence of synchrony in emotionally close relationships (Blasberg et al., 2023), and especially within family units, aligning with the biobehavioral synchrony model (Feldman, 2012). This model emphasizes the importance of synchrony across multiple levels during the formation of affiliative bonds in childhood and adolescence, particularly between family members and attachment partners. Regarding the experimental condition, we propose focusing on social cooperation, which currently presents the strongest evidence for the association between IBS and social behaviors, as demonstrated by meta-analysis findings (Czeszumski et al., 2022). While investigating synchrony through brain data is not a novel approach (Nguyen et al., 2021), our methods offer valuable contributions to enhancing the understanding of IBS, properly measured, and advancing applied research in family studies.

3.1 Research design for a triadic family study

Among the many cognitive tasks that could meet our requirements in Section 2.2, we chose tangrams. Tangram, an ancient game originating from China or Japan (Danesi, 2018), is a cognitive task that requires grasping basic geometrical rules and using visuospatial reasoning skills without linguistic representation interference. It is characterized by a trial-and-error strategy and creative thinking. Previous evidence shows that solving tangrams involves prefrontal cortex activity (Hu et al., 2019) and higher total hemoglobin concentration in the right hemisphere, with alterations during failed trials (Ayaz et al., 2012). Additionally, a positive correlation has been observed between behavioral performance in a tangram task and activation of the right angular gyrus (Hu et al., 2020). This task may be ideal for assessing both individual and cooperative performance. Tangram stimuli were previously used in Fishburn et al. (2018), where three participants solved the puzzles individually or in dyads while another participant observed, or watched a movie clip of hands solving the puzzles, with hemodynamic activation recorded via fNIRS. Also, Li et al. (2024) used it for measuring EEG IBS in mother-child dyads. Although their objectives are similar to ours, there are significant differences in the task or data analysis pipeline. According to our recommendations, a tangram-based paradigm to investigate IBS should include three conditions: alone, observation, and the experimental condition, which in this case will involve cooperation. Each block comprises multiple trials participants, under the different social conditions, attempt to solve a tangram puzzle using seven pieces (or tans, Figure 3a) to recreate a target shape (Figure 3b). Participants are instructed not to communicate with experimenters during the task. Each condition is expected to last several minutes, consistent with our Monte Carlo analysis where the unit of analysis, or epoch, is suggested to be approximately 70 seconds.

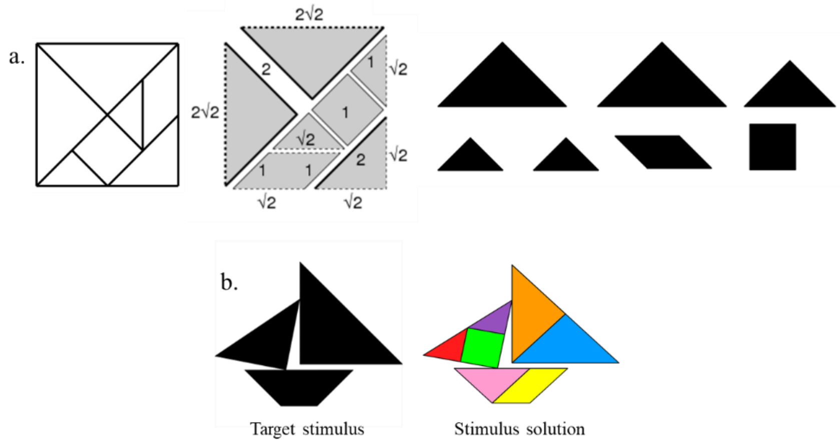

Figure 3. Details regarding the task. In a) the seven shapes to use to recreate the target stimulus. Their geometrical properties allow many combinations, more than 6000 tangrams are available. In b) an example of the target stimulus with its solution.

Adapted from the above, families consisting of a father, a mother, and their child represent a suitable population to investigate IBS. Families are invited into the experiment room, where, as explained in the Experimental Task section (2.2), participants are seated equidistantly from one another. The sets of EEG electrodes are positioned according to the standard 10-20 layout. After baseline recordings, the three counterbalanced conditions—alone, observation, and cooperation—are conducted.

In the alone condition, participants are isolated and perform their trials simultaneously, with communication of any type being impossible. Their aim is to recreate the target shape exactly using all provided pieces in the shortest time possible. This condition serves to control exogenous and task-specific factors such as visual processing, visuo-spatial reasoning, and motor activity that may influence neural entrainment. In the observation trials, the family members are together, observing a group of confederates solving tangram puzzles. The biological sex of the confederates may either match that of the child or alternate to maintain balance. This condition is designed to control for neural entrainment and attention-enhanced components (e.g., influence of physical co-presence). In the cooperation condition (or experimental condition), the family works together to recreate the target and selects one member to press the button upon completion. A small, fixed rotating platform is positioned on the round table to ensure all participants have an equal view of the puzzle when needed. The seven shapes are initially placed on the platform by a researcher and can be accessed by everyone. The three conditions are illustrated in Figure 4.

Regarding additional data to be collected, physiological arousal, attentional levels and measures of individuals' visuospatial abilities (Vandenberg & Kuse, 1978) and cognitive flexibility (Tucha et al., 2012) would be beneficial (Tucha et al., 2012), given their involvement in the solution of tangram puzzles. Finally, the cooperation condition is expected to elicit IBS, and based on the signal processing and statistical analyses outlined in Sections 2.4 and 2.5, we anticipate a difference in neural dependence when comparing it to the other conditions (alone, observation). If this difference cannot be attributed to physiological arousal or attentional levels, we have reason to believe that the observed neural dependence is not a result of confounders or mere co-occurrence, but is *likely* influenced by social (familial) cooperation.

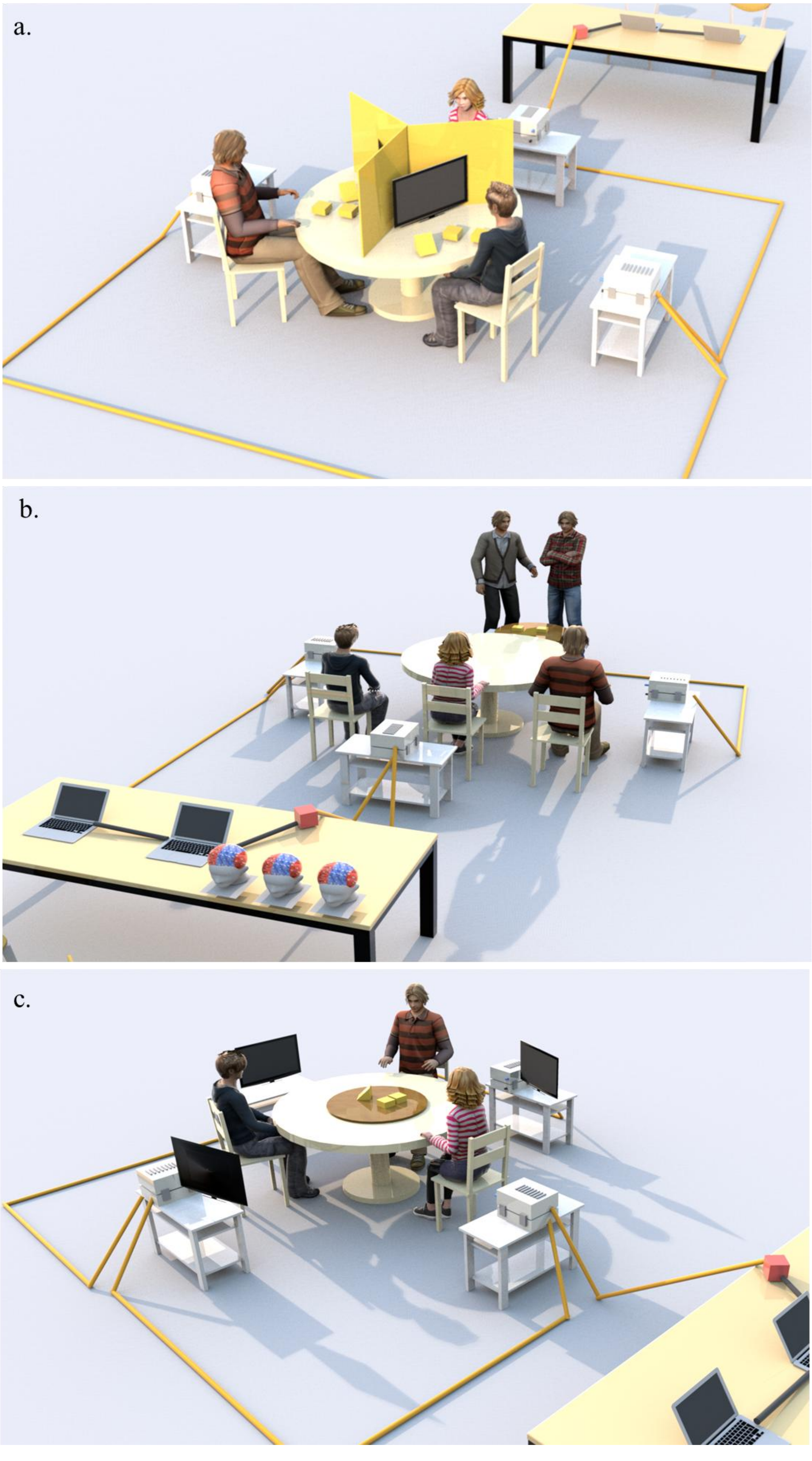
a.
b.
c.

Figure 4. A 3-D rendering of the three pseudo-randomized conditions: alone (a), observation (b), and experimental/cooperation (c). The participants depicted are a mother, father and child. The brain activity of each participant is recorded with electroencephalography. One electroencephalogram (EEG) is behind each participant (not shown here) and is connected to the others through fibre-optic cables (i.e., the orange cable). We imagined a master device connected to two daisy-chained EEG that are connected to a trigger box (i.e., the red box) to a data acquisition computer and a task pc. In the *alone* condition (a), the individuals are isolated from each other and have a personal screen positioned on their table. In the *observation* condition (b), the family observes a separate social unit solving puzzles, composed of confederates. Lastly, in the *cooperation* condition, (c), the family collaborates to solve the Tangram puzzle, seated around a table with a rotating platform that holds the puzzle pieces. This is our experimental condition where we conjecture to observe inter-brain synchrony, IBS. Renderings were created using Sweet Home 3D (https://www.sweethome3d.com/).

3.2 Signal processing and statistical analysis for triadic purposes

In our example, the triad can be analysed at a bivariate level, comparing the dyads (mother-child, father-child, and mother-father), following the procedures outlined in Sections 2.4 and 2.5. It is important to note that the frequency boundaries considered should typically be lower in infants and children, who also tend to exhibit higher power in lower-frequency bands (Cellier et al., 2021). This comparison between the three experimental conditions using the $CCor_{adj}$ scores (i.e., $CCor_{adj\ xy}$, $CCor_{adj\ xz}$, $CCor_{adj\ yz}$) can help determine whether IBS is an electrophysiological phenomenon present in family social dynamics. We argue that this analysis can provide further information: as previously suggested (Hamilton, 2021), evidence of IBS at dyadic level, in a triadic context, strengthens the assertion that the observed phase alignment is not merely due to shared environmental stimulation.

Our paradigm also allows to focus strictly on triadic synchrony by adapting a recent method developed specifically for capturing synchronization among three time series (Wang et al., 2024). This measure, referred to as the adapted multiplied pairwise correlation (AMPC), is defined by the authors as in Equation (4).

$$AMPC = \tau \sqrt[3]{|r_{xy} r_{xz} r_{yz}|} \qquad \text{with } \tau = \begin{cases} 1\ for\ (r_{xy} > 0) \wedge (r_{xz} > 0) \wedge (r_{xz} > 0) \\ -1, otherwise \end{cases} \tag{4}$$

In Equation (3), the cubic root of the absolute product of the three Pearson's correlations (r_{xy}, r_{xz} r_{yz}) adjust by τ, where τ accounts for the sign of the triadic correlation. As showed by Wang et al. (2024), a key characteristic of AMPC is that under the null hypothesis, dyadic synchrony is still allowed, meaning that this method can effectively discard dyadic patterns from triadic, resulting in a near-zero magnitude for non-significant triadic synchrony. Since $CCor_{adj}$ (or CCor) ceases to be a circular metric, we can derive a version of AMPC that takes circular coefficients as input from Equation (2), leading to the formulation in Equation (5).

$$CAMPC = \tau \sqrt[3]{|CCor_{adj\ xy} CCor_{adj\ xz} CCor_{adj\ yz}|} \tag{5}$$

Once we have calculated the triadic coefficients, we can test the statistical differences between the experimental conditions, similarly to the previous dyadic procedure. As suggested by Wang et al. (2024), to build a null distribution that incorporates dyadic synchrony, but excludes triadic synchrony and accounts for auto-dependence to avoid inflated type 1-error, they recommended shuffling the time series not involved in the highest correlation in the data. This method ensures that dyadic synchrony is not incorporated into the null distribution. Furthermore, the shuffling should be performed on segments rather than individual time points to maintain the auto-dependence in the null distribution.

4. Discussion

4.1 Novelty, performance standards, applicability

In this work, we outlined the principles for conducting research aimed to collect evidence in favour of differences in neural dependencies in interacting individuals using neuroimaging techniques.

Holryod (2022) identified three key challenges related to IBS: issues with definition, theory, and methodology. This article addresses the methodological concerns while also considering the first two. Initially, we sought to determine an abstract meaning of synchrony, focusing on its dimensions of magnitude, time-lag, and features investigated. Then, we reviewed the literature for a psychobiological rationale to support the hypothesis of IBS, first in a general social context and then specifically within the framework of cooperation and shared intentionality among family members. In this light, we offered theoretical plausibility in multiple ways. We aligned metatheory and theory with proper techniques for signal processing and statistical analysis. Our methods offer a strategy for investigating synchrony by performing multiple permutated comparisons between a condition where IBS should potentially be present and the related confounders. Lastly, our use case was the investigation of IBS using EEG data on nuclear families cooperating together.

At this stage, we believe this represents the best effort to achieve meaningful evidence for IBS using correlational techniques. We detailed the theory-informed steps, including task design, signal processing and various statistical analyses, and outlined the recommended precautions for collecting reliable evidence of IBS. These procedures, which are potentially applicable to any investigation of synchrony in tasks performed alone or with others, can be replicated and adapted according to the chosen sociopsychological construct, the target population, and the techniques employed.

4.2 Accuracy, robustness, and quantification of uncertainty

For accuracy, as discussed, we recommend employing the adjusted CCor and a permutation-based analysis for several reasons, including mitigating inflated results. Building a curve of probability under h_0 allows to control for spuriousness and uncontrolled factors. Moreover, theoretical distributions may not accurately represent the sample under investigation. When analysing EEG data with multiple comparisons, especially if not hypothesis-driven, classic correction methods should be avoided due to their potential drawbacks. Instead, conducting power analyses through simulations is highly advisable to establish a plausible effect of synchrony and determine the minimum sample size. Additionally, latency testing should be conducted to account for delays.

Hyperscanning research should embrace the principles of open science. Given the subjective nature of analytical choices and the potential for undisclosed details hindering replication, we advocate for researchers to include the following six pieces of information in their supplementary materials: 1) a formal definition of synchrony and its operationalization; 2) details of the experimental task; 3) description of the hardware set components; 4) methods used for online signal synchronization and verification; 5) complete details of the data analysis pipeline and its code (including specifics like simulation seeds or EEG references); and 6) the raw data itself. Additionally, we encourage pre-registration of study hypotheses and methods. Only through these practices can inter-brain synchrony be rigorously evaluated.

5. Conclusion

This work has several limitations. Although we can mitigate the influence of engagement using self-reports and physiological indicators, we cannot entirely eliminate the potential for our experimental conditions to inherently increase arousal, which could confound our findings with attention-enhanced dependencies. Nevertheless, we believe that our proposed approach represents the best effort for a neuroimaging study to investigate IBS without manipulating brain activity directly. Functionally, evidence for the existence of IBS does not demonstrate its clinical significance.

To run the simulations, we employed Fieldtrip Toolbox on MATLAB, many other toolboxes are available. It is worth mentioning that in our simulations other factors could be further considered: the lengths of the time windows created, the length of the data segments the coefficients are calculated on, introducing different coefficients or models for the estimation of IBS, considering different underlying structures of connectivity (e.g., multivariate autoregressive models). Although a single simulation has limited generalizability, approaches like the Monte Carlo method could guide the design of research studies. Simulations can provide much information within a stricter null hypothesis significance-testing environment. Lastly, the costs related to the apparatus we propose are extensive, in terms of trained personal, equipment, and expertise across fields ranging from psychology, electrophysiology and statistics.

Our work might be one piece supporting the empirical verification of IBS at a neuroimaging level. Yet, further contributions from mathematical-statistical modelling to biological theories of social interaction are needed. The latest advancements in non-invasive brain stimulation are encouraging and might help explain parts that have not yet fit into the picture. This could initiate a new and stimulating phase of research on social cognition; however, we should remember that extraordinary claims demand extraordinary evidence.

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