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Investigating EEG Interbrain Synchrony: Methods to Gather Meaningful Evidence

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ABSTRACT

Synchrony has been proposed as a relevant phenomenon for investigating social neurophysiological and psychological processes, with interbrain 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 less robust empirical methods, might hinder progress in this field. To address this, we propose a definition of interbrain synchrony and link various theoretical contributions that might justify the existence of meaningful temporal alignment between different brain activities. Furthermore, we propose a set of methods aimed at minimizing bias in the collection of 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 the synchrony's confounding factors such as shared attention, cognitive, and motor dependencies, while also relying on simulation-based insight to refine the methodological specifics. We then propose multiple data analysis strategies, including circular statistics combined with permutation testing, the sliding technique for time-lagged dependencies, 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 interbrain synchrony is falsifiable. Whether this phenomenon is empirically supported or not, its investigation will contribute to advancing our understanding of the social brain.

1 | Introduction

1.1 | A Definition of Interbrain 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). The study of synchrony dates back to the physicist Christiaan Huygens, who is reported to be the first to observe and describe how pendulum clocks, interacting through a wooden support, could synchronize. Huygens' observation is explained by the reaction force of the support, which affects both pendulum clocks and drives them into synchronization (Wei et al. 2023). Various parameters (e.g., material stiffness, mass ratio, damping, eigen-frequency) influence this phenomenon, which has been investigated extensively since (Buescu et al. 2025; Peña Ramirez et al. 2016). Ubiquitous in

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nature, synchronous patterns have been researched across diverse fields (Hulthén et al. 2022; Provenzano and 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 behaviors of individual entities by themselves often do not fully represent the behavior of the overall system. The uniqueness of synchrony lies not in the mere cooccurrence of the components' behaviors but in the extent of their dynamic adjustments to each other.

We propose conceptualizing synchrony between two entities by considering three key dimensions: magnitude, time-lag, and the features under investigation. Accordingly, we can visualize it 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 analyzed 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.

In recent years, social interactions and various forms of synchrony have garnered major attention in neuropsychology and neuroscience (Uhlhaas and Singer 2006; Wheatley et al. 2024). Within interpersonal relationships, synchrony is believed to occur on a multimodal level during social interaction, encompassing both physiological (e.g., cardiac) and behavioral (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 results from decision-making processes involving mentalization and dynamic predictions (Kingsbury and 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 only partially 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 *interbrain 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 (2018), the current paper is structured as follows: first, we derive what appears to be the essential criteria for properly characterizing IBS, followed by our definition of the construct. Next, we outline a methodological proposition that aims at 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

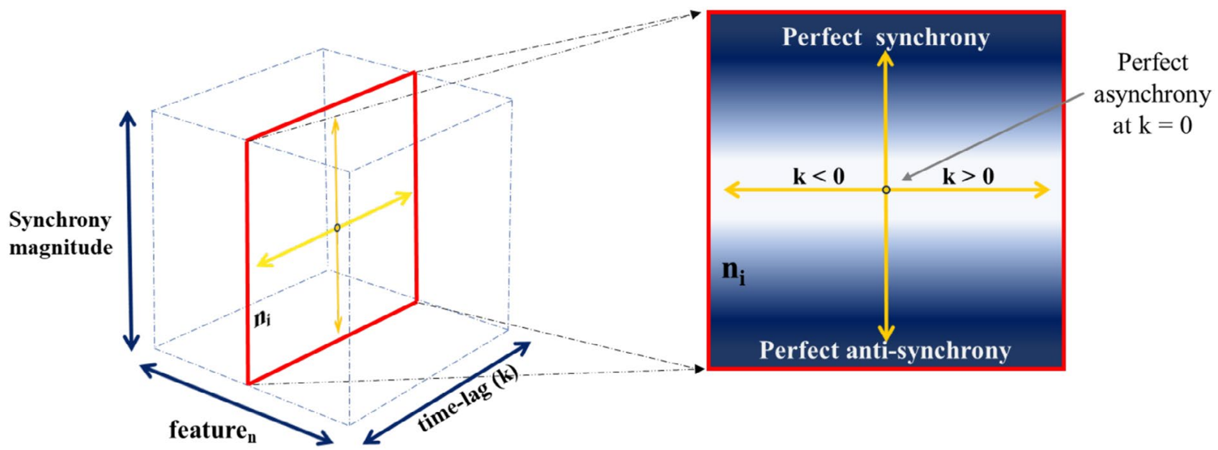

FIGURE 1 | A geometrical representation of synchrony considering three dimensions: Magnitude, time-lag (k), and the features (n) under investigation. Regarding magnitude, two entities (x, y) that are completely independent are in a state of perfect *asynchrony*. As the magnitude of synchrony increases, 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$_n$.

(i.e., triadic) family during cooperation. Finally, we discuss the necessary information we think researchers should share to enable replication and improve the comparability of IBS research. Further reflection is dedicated to robustness, accuracy, and quantification of uncertainty. Overall, this article aims to foster and contribute to a theoretical and methodological discussion previously initiated by other researchers (e.g., Burgess 2013; Holroyd 2022; Zimmermann et al. 2024) and potentially support future efforts in investigating synchrony between individuals.

When measuring IBS, a sine qua non condition is that the phenomenon cannot 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 important for accurately measuring 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 behavior 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 also be seen as part of this source of attention-enhanced dependence.

Beyond controlling for confounders, the following considerations may be worth exploring. 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 behavioral cues. Secondly, IBS, when measured with correlational techniques without experimental manipulation, seems to be 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 cooccurrence, randomness and spurious correlations should 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 nonlinear) intra-brain synchronizations that occur 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, we propose to define IBS, at a certain time lag and frequency, 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.

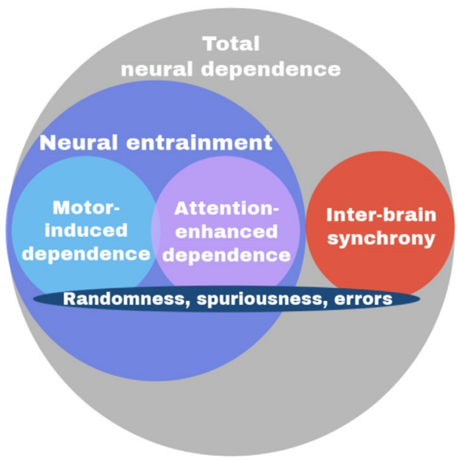

FIGURE 2 | An Euler diagram illustrating the concept of *interbrain synchrony* (IBS). IBS is conceptualized as the difference between the total neural dependence between signals of interacting individuals and that derived from confounders. Randomness, spuriousness and errors are factors that transversally impact all the components ranging from measurement to 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 and Gloor 2010), making it hazardous to equate 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 Interbrain Synchrony

Based on the introduced 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, coregulation, 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 coregulation between attachment partners. This synchrony would significantly impact 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 multibrain 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 behavior (Kingsbury and 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 and Garrod 2004), as cited in Schoot et al. (2016), builds on Friston and Frith's (2015) work. Schoot et al. (2016) argue that such interaction involves a nonstatic 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 outcomes during interactions with others, achieved through mutual prediction (de Bruin and 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 and 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 and Frith's theory (2015). This highlights two important considerations: first, it appears that 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 multibrain and Relational Neuroscience frameworks, with the Interactive Alignment Theory and the biobehavioral 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 efforts to develop methods for similar aims (Tamburro et al. 2024), we believe the issues highlighted above have yet to be fully considered in neuroimaging testing, which may contribute 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 behavioral team processes ($r = 0.45$, 95% CI [0.29–0.59], $n = 9$, $k = 24$, $p < 0.001$), 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, these results may be overestimated due to the absence of the considerations we propose. These include the lack of a clear definition and operationalization of IBS, insufficient controls for confounders, and statistical approaches that may not fully align with the nature of the data.

Only recently has the testing of the causal role of interbrain dynamics with noninvasive 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 inter-individual level remain poorly understood, with many temporal, spatial, and frequency 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 (20 Hz, 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, 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 ($r = -0.437$, $p = 0.048$) and tDCS group ($r = -476$, $p = 0.029$), 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 fully captures IBS as defined in our study, given its slow and variable nature of the underlying hemodynamic response function (Huppert et al. 2006).

Besides the promising reported studies in the literature, more evidence is still required (Carollo and Esposito 2024). A critical question remains: what are 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 and Davis 2023; Redcay and Schilbach 2019) and the ideas outlined previously, the aim of this methods paper is to describe analytically a methodological approach for gathering evidence for IBS using EEG data from individuals interacting together and to improve interbrain methodologies. If further confirmed, given the strong relationship between health and social interactions, the understanding of synchrony as a medium for interindividual 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 (Bizzego 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. 2024). 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 intragroup 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 ($d = 0.4$) in a dependent samples *t*-test, assuming standard error rates ($\alpha = 0.05$; $1-\beta = 0.9$) and that all assumptions are met, the required sample size is estimated to be $n = 55$. The biological sex of the participants could 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. Importantly, IBS estimates are sensitive to epoch length: shorter epochs tend to inflate synchrony values, with the frequency of interest moderating the decay coefficient of the epoch length–synchrony relationship (Zimmermann et al. 2024). As we show in the Figure S1, faster rhythms stabilize more quickly because they encompass a greater number of cycles. Researchers should therefore treat epoch length and frequency as critical parameters in their analysis, ensuring that estimates are sufficiently stabilized. Epochs shorter than 5–6 s seem to yield inflated results (Fraschini et al. 2016; Miljevic et al. 2022; Zimmermann et al. 2024, and Figures S2 and S3).

To move beyond heuristic approaches, researchers investigating interbrain dependence may begin by defining a model of connectivity that accurately represents IBS. They can then select appropriate models or statistical tests that align with their hypotheses, followed by the application 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 discuss in the Statistical section (2.5), validly detecting this relationship can be achieved using the adjusted circular correlation coefficient (Zimmermann et al. 2024), 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 23 h2). These simulations generated EEG time series data, with a specified connectivity structure. Although phase data are often modeled 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 and 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 ($\alpha = 0.01$; $1-\beta = 0.9$). We adhered to standard reporting practices for simulation studies (Siepe et al. 2023) and for functional connectivity simulations (Bastos and Schoffelen 2016). The code is available at https://osf.io/ecbfg/overview. 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. (2024). To maintain a simplified structure, we did not implement any delay matrix. This model (Figure 3a) 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 postlinear mixing to simulate white noise (0.5 standard deviation in the parameter "cfg.absnoise"). As explained

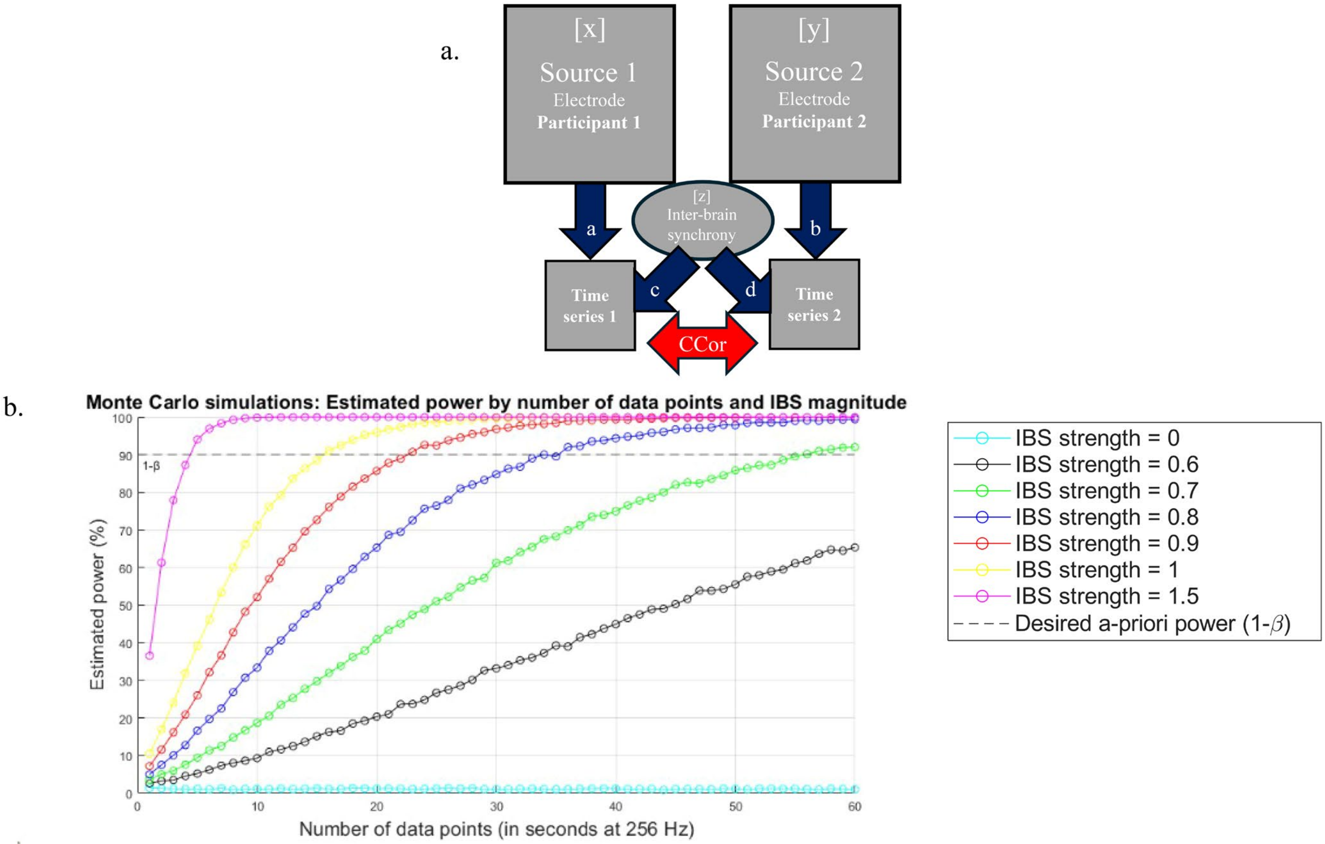

FIGURE 3 | (a) The model used for simulations in FieldTrip to conduct Monte Carlo simulations. The model generates two time series (time series 1 and time series 2, assumed to be from two participants, Participant 1 and Participant 2), from three unobserved components: Source 1 (x), source 2 (y), and 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 represent 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 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 $1-\beta = 0.9$ and $\alpha = 0.01$. The generated signal is filtered within the theta rhythm (4–8 Hz). 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). A more comprehensive simulation study that incorporates different rhythms, is provided in the Supporting Information.

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 to 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 s of artifact-free data at a sampling rate of 256 Hz (256 data points per epoch). Thus, we examined effective data ranges between 256 and 15,360 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 = 0.6; 0.7.; 0.8; 0.9; 1; 1.5) which can account for different effects. These coefficients represent scaling factors that define the strength of projection from the unobserved sources to the generated signals. The chosen range corresponds to effective clean recorded data, which is realistic in ecological terms, to which a total percentage of 20%, has to be added for data removal due to artifacts, noise, and other reasons (nonnecessarily overlapping between participants). The results, which we believe provide a robust estimate for adequately powered IBS detection, are presented in Figure 3b. According to the analysis, an optimal time window of analysis would be in the order of 55 s (+20%), assuming a modest IBS magnitude (with a parameter set at cfg.mix = 0.7). No missing values were observed. For each scenario and sample size, we computed the MCSE. Across all simulations, the highest observed MCSE was $MCSE_{max} = 0.005$.

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 and Astolfi 2014) while avoiding excessive trial repetition, yet remaining sufficiently standardized to minimize inter- and intraindividual differences. It should also ensure sufficient statistical power to detect small but significant differences in dependencies. Moreover, given the speculated association between neural synchrony and social behaviors, we propose to consider tasks that involve performance that is (1) replicable alone and with others (i.e., with multiple participants), (2) incorporating social decision-making and shared intentionality, and (3) minimizing learning-related effects.

We illustrate these recommendations by providing an example of a possible task design that satisfies these requirements. Our proposition consists of considering the task chosen by the researcher to investigate IBS and exposing participants to 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-s range per condition). A baseline recording can be included prior to each block to calculate the signal-to-noise ratio (SNR, in dB) per condition, aiding in the assessment of estimation accuracy.

In the *alone* condition, each participant is 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 nonverbal 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 copresence).

In the *experimental condition*, the social behavior that the researcher hypothesizes to be associated with IBS is 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 behaviors 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 would 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 beneficial to our aim, 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 proposed 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 system and minimize disruption to ecological validity. We believe that 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, we can 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 proposed a design 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 our 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).

Posttrial perceived difficulty and anxiety, perceived levels of engagement, should be gathered using visual analog scales. The task trials can be video recorded, as utilizing videorecording and behavioral coding approaches could help quantify the social behaviors that contribute most to IBS and provide further insight into the relationship between IBS and behavior. 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, 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) could 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 a 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 (e.g., 0.5 Hz high-pass filter and 30 Hz low-pass filter), removing noisy channels, referencing, epoching/segmentation, rejecting epochs 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. Overall, we advise caution in these preprocessing steps to avoid feature distortions that might lead to type-1 errors (e.g., Kang et al. 2015; Thatcher et al. 2020).

The common frequencies of interest, delta (0.5–4 Hz), theta (4–8 Hz), alpha (8–12 Hz), 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 behavior (Holroyd 2022).

We propose to focus the analysis 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., $\varphi = 2\pi \times (t - t0)/T$) and is generally expressed as an angle in radians. Phase information is particularly well suited for the estimation of interbrain measures for several reasons (Burgess 2013; Holroyd 2022; Zimmermann et al. 2024). 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 artifacts (Mezeiová and 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 $\phi'(t)$ 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 and Jupp 2000). To analyze 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 and 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, CCorr 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 ($\text{CCorr}_{x,y} = 0$).

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

Moreover, it was argued by Zimmermann et al. (2024) that while phase information is theoretically independent of amplitude, in practice, estimated phases can be influenced by various factors (van Diepen and 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. 2024). This adjusted form is defined in Equation (2), where the numerator $(R_{x-y} - R_{x+y})$ corresponds to $R_{x\pm y} = \left| \sum_{t=1}^{n} e^{i(\phi(t) \pm \varphi(t))} \right|$ and m and j are the adjusted means.

$$\text{CCor}_{adj}\,(x, y) = \frac{\left(R_{x-y} - R_{x+y}\right)}{2\sqrt{\sum_{t=1}^{n} \sin^2(\phi(t) - m) \sum_{t=1}^{n} \sin^2(\varphi(t) - j)}} \tag{2}$$

In the Figure S2, we simulated EEG data, following the same approach used for the earlier power analysis, to assess the performance of the adjusted circular correlation coefficient (CCor_{adj}) in comparison with the phase-locking value (PLV) and spectral coherence (COH), the latter calculated using Welch's method.

Based on Equation (2), a set of CCor_{adj} scores is calculated on the dyads for the epochs of the three conditions. These are the measures we employed for our simulation-based power analysis. The resulting coefficients can then be analyzed using linear models (e.g., van Vugt et al. 2020), after applying a Fisher z-transformed, a variance-stabilizing procedure commonly used for correlational coefficients that also addresses the potential nonlinearity of bounded magnitudes (Silver and Dunlap 1987). 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., 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. If the t-value exceeds the chosen significance threshold (e.g., 0.05), 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 suppressing 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. 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). For this purpose, a cross-circular correlation (CCC) could be employed. Given k data points, the cross-correlation function can be defined using the CCor_{adj}, between the reference signal and the k-shifted version of the other signal, thereby unveiling lagged dependencies between phases. However, an analytical investigation of this approach, examining different delay matrices additional key parameters and its performance relative to other methods (i.e., time-frequency analysis) is still lacking.

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.

$$I\,(X, Y) = \sum_{x,y} P_{XY}(x, y) \log_2 \frac{P_{XY}(x, y)}{P_X(x) P_Y(y)} \tag{3}$$

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 analyze the information flow between the two phase time series. Lastly, such an approach might be useful if we observe significant intercondition differences in arousal, quantifiable using cardiac, electrodermal, or pupillometry-based measures (e.g., Bach et al. 2010; Pulopulos et al. 2021), which could point at an attention-enhanced component. In that case, it could be useful to compute the conditional mutual information (CMI), which 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/overview].

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 multibrain frameworks, as well as the Interactive Alignment theory (De Felice et al. 2024; Kingsbury and Hong 2020; Pickering and 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, 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 and the data analysis pipeline. According to our proposition, 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 consists of multiple trials in which participants, under the different social conditions, attempt to solve a tangram puzzle using seven pieces (or tans, Figure 4a) to recreate a target shape (Figure 4b). 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 s.

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 no communication of any type. 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, visuospatial 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 copresence). 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 5.

Regarding additional data to be collected, physiological arousal, attentional levels and measures of individuals' visuospatial abilities (Vandenberg and Kuse 1978) would be beneficial, 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 cooccurrence, but is *likely* influenced by social (familial) cooperation.

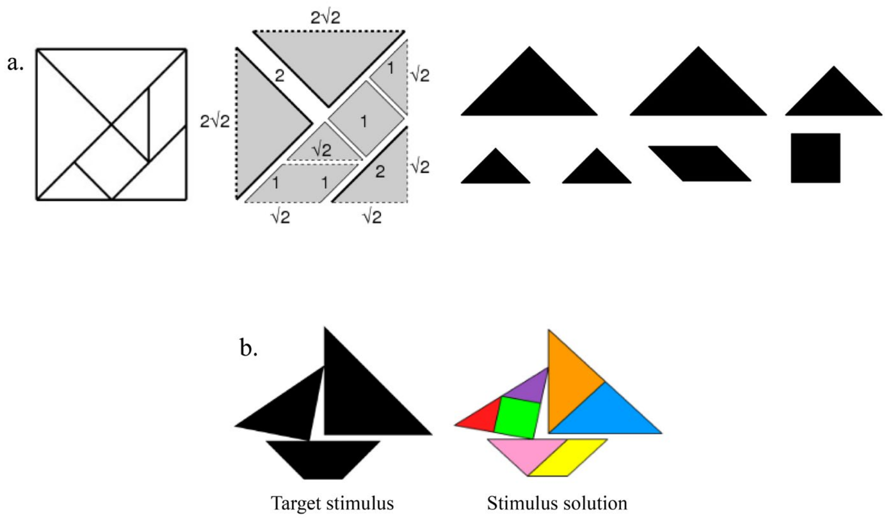

FIGURE 4 | Details regarding the task. In (a) the seven shapes to use to recreate the target stimulus. Their geometrical properties allow many combinations, more than 6000 tangrams are available. In (b) an example of the target stimulus with its solution.

3.2 | Signal Processing and Statistical Analysis for Triadic Purposes

In our example, the triad can be analyzed 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 $\mathrm{CCor}_{\mathrm{adj}}$ scores (i.e., $\mathrm{CCor}_{\mathrm{adj}\ xy}$, $\mathrm{CCor}_{\mathrm{adj}\ xz}$, $\mathrm{CCor}_{\mathrm{adj}\ yz}$) 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 the 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 us 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).

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

In Equation (3), the cubic root of the absolute product of the three Pearson's correlations (r_{xy}, r_{xz} r_{yz}) adjusts by τ, where τ accounts for the sign of the triadic correlation. As shown 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 nonsignificant triadic synchrony. Since $\mathrm{CCor}_{\mathrm{adj}}$ (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).

$$\mathrm{CAMPC}\,(x,y,z) = \tau\,\sqrt[3]{|\,\mathrm{CCor}_{adj\ xy}\mathrm{CCor}_{adj\ xz}\mathrm{CCor}_{adj\ yz}\,|} \tag{5}$$

Once the triadic coefficients have been calculated, statistical differences between experimental conditions can be tested, following an approach similar to, and adapted from, the previous dyadic procedure.

4 | Discussion

4.1 | Novelty, Performance Standards, Applicability

In this work, we proposed a set of methods and techniques, informed by the literature, aimed at exploring differences in neural dependencies among interacting individuals using neuroimaging techniques. Holroyd (2022) identified three key challenges related to IBS: ambiguity in its definition, as well as theoretical and methodological issues. This article attempted to address the methodological concerns while also considering the other two challenges. 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.

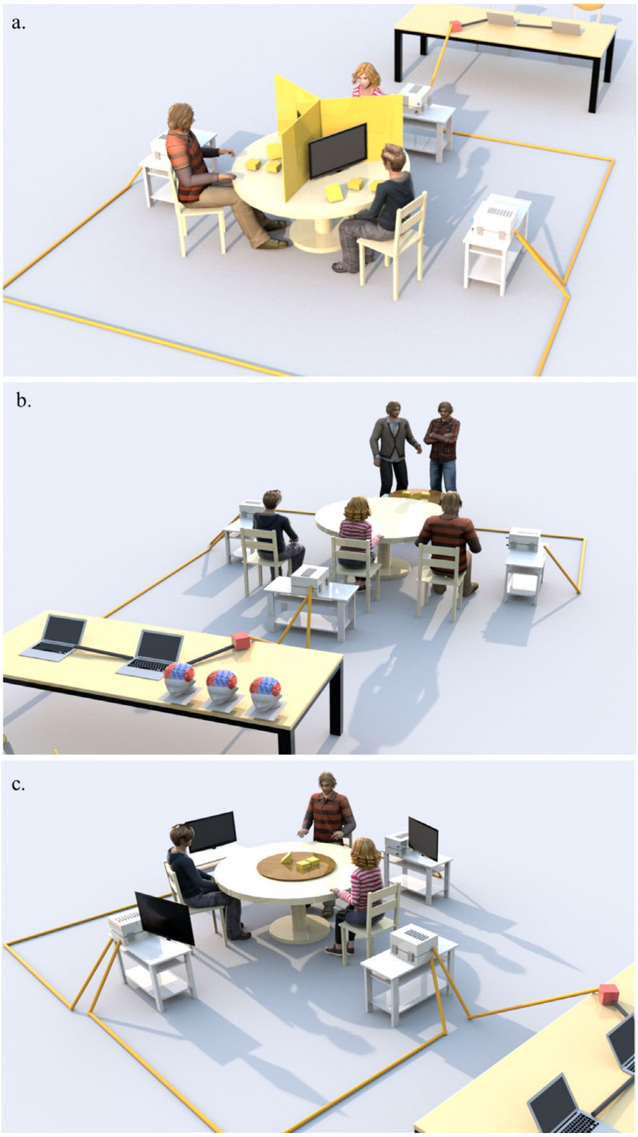

FIGURE 5 | A 3-D rendering of the three pseudo-randomized conditions: Alone (a), observation (b), and experimental/cooperation (c). The participants depicted are a mother, father and child. The brain activity of each participant is recorded with electroencephalography. One electroencephalogram (EEG) is behind each participant (the EEG caps are not shown in the figure) and is connected to the others through fiber-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 interbrain synchrony, IBS. Renderings were created using Sweet Home 3D (https://www.sweethome3d.com/).

At this stage, we believe our proposal represents a valid methodology for researchers interested in investigating synchronizing brains 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 can be replicated and adapted according to the chosen sociopsychological construct, the target population, and the techniques employed. At the same time, our approach is not a one-size-fits-all solution; IBS designs should be guided by research questions while balancing exploratory and hypothesis-driven inquiry.

4.2 | Accuracy, Robustness, and Quantification of Uncertainty

For accuracy, as discussed, we recommend employing the adjusted CCor or MI, along with a permutation-based analysis for several reasons, including mitigating inflated results. Our proposed pipeline may not be exhaustive, since synchrony is not necessarily confined to phase information. Nonetheless, we recommend that researchers investigating other signal features provide sufficient justification for their chosen IBS estimation method, supported by an evaluation of its performance relative to a baseline model of connectivity and alternative approaches. Building a curve of probability under h_0 allows us to control for spuriousness and uncontrolled factors. Moreover, theoretical distributions may not accurately represent the sample under investigation. When analyzing 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, conducting a latency test could help account for delays. Also, to assess the risk of biased IBS estimation, a baseline recording prior to each task block can help compare SNRs. An assessment of power within conditions could be useful as low SNR appears to be associated with the underestimation of IBS (Zimmermann et al. 2024).

Hyperscanning research could benefit from incorporating open science principles. Given the subjective nature of analytical choices and the possibility that undisclosed details may affect replication, we encourage researchers to consider including the following six pieces of information: (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 delay testing; (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 preregistration of study hypotheses and methods.

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. In addition, our design relies on a subtraction method that rests on specific assumptions and reflects a trade-off between ecological validity and experimental control. Choosing an unguided task preserves the authenticity of natural social interaction, albeit at the cost of added variability. Nevertheless, we believe that our proposed approach offers a practical way for a neuroimaging study to investigate IBS without considering brain stimulation. Importantly, evidence of IBS does not automatically imply either clinical relevance or functional significance.

Crucially, IBS, as a construct or mechanism, particularly as defined in this paper, does not equate to hyperscanning, which refers to the technique of simultaneously acquiring data from more than one individual. Similarly, phenomena that might be regarded here as "confounders," such as neural entrainment, motor coordination, and joint attention, constitute valuable and independent lines of research.

To run the simulations, we employed Fieldtrip Toolbox on MATLAB; many other toolboxes are available. Future studies could expand this framework by testing additional factors, such as varying window lengths, alternative connectivity models (e.g., multivariate autoregressive), or different synchrony coefficients. 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.

Further considerations regarding the expression of synchrony, not addressed here, include mechanisms involving intra-brain connectivity and more complex interactions in the time–frequency domain, such as cross-frequency coupling, in which the amplitude of higher frequencies is coupled with the phase of lower frequencies. Although the current literature has not yet established clear patterns, these mechanisms may represent important avenues for future investigation. Future research should also explore IBS dynamics in relation to shared knowledge accumulation, relational closeness, and individual differences in personality. Lastly, the costs related to the apparatus we propose are extensive, in terms of trained personnel, 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 modeling to biological theories of social interaction are needed. The latest advancements in noninvasive 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.

Author Contributions

Federico Cassioli: conceptualization, methodology, software, data curation, investigation, validation, formal analysis, visualization, project administration, writing – original draft, writing – review and editing, resources. **Nellia Bellaert:** conceptualization, formal analysis, methodology, software, visualization, writing – review and editing. **Matias M. Pulopulos:** 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.

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Conflicts of Interest

The authors declare no conflicts of interest.

Data Availability Statement

The data that support the findings of this study are openly available in osf at https://osf.io/ecbfg/overview.

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Supporting Information

Additional supporting information can be found online in the Supporting Information section. **Data S1:** psyp70199-sup-0001-FiguresS1-S3.docx.