Interpersonal alignment in infra-slow EEG rhythms and bodily signals anticipates mutual recognition

Nicolás Gravel · Nicolò Formento · Tom Froese

Abstract Across multiple timescales, neural rhythms play a crucial role in coordinating cognitive and physiological processes, with slower frequencies potentially relevant during social interaction. While electroencephalography (EEG) has been widely used to study such processes, examining these slower aspects during social interaction presents unique methodological challenges. Here we address this issue by investigating infra-slow EEG, respiratory, and electrodermal signals recorded simultaneously during a perceptual crossing experiment (PCE)—a recently established paradigm in social cognition and EEG hyperscanning. Through innovative spectral-characterization methods and a novel dyadic regression approach, we establish a methodological framework for examining infra-slow dynamics that coordinate brain and body during social interaction. Our analysis revealed that, when time-locked to task responses, the spectral power of infra-slow oscillations (ISOs) at 0.05 Hz and 0.1 Hz showed enhanced inter-participant similarity in dyads achieving mutual recognition relative to those that did not. Although not strictly simultaneous, this inter-personal alignment in the spectral power of ISOs was accompanied by concurrent dynamics both in respiratory pressure and electrodermal activity, suggesting that ISOs reflect the integration of autonomic, cognitive, and social processes, with their alignment facilitating shared understanding and joint action. Crucially, we find that task-responses in participants who successfully engaged in the PCE task were coupled to the phase of the 0.1 Hz rhythm. Additionally, we show that ISOs and aperiodic activity tracked behaviorally relevant transitions, notably prior to and during the perceptual crossing task. Taken together, our findings highlight an important role for ISOs in mediating the temporal dynamics of social cognition and show that inter-participant alignment in ISOs and physiological signals can serve as a proxy for the complex interplay between body physiology, cognition, and social behavior.

Keywords Infra-slow EEG · Haptic stimuli · Interpersonal coordination

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1 Introduction

Neural rhythms occur across multiple spatial and temporal scales, ranging from circuit-level field potentials to system-wide communication between brain and body [1]. Together, they form a complex set of processes that serve as an integrated basis for cognitive and physiological regulation [2]. Across social species, these processes are well-aligned with social interaction [3]. Notably, in humans, the fine-grained production of linguistic utterances is closely associated with delta, theta, and gamma EEG rhythms [4]. Semantic content, in contrast, is highly context-sensitive, with narrative integration shown to occur at time scales of 10 sec and more [5, 6]. For example, meta-state transi-

tions in the BOLD signal tend to exhibit a periodicity of around 10 *sec*, and align with salient narrative shifts [7]. This suggests a relationship between slow body-wide physiological dynamics [8, 9] and meaningful transitions in social context [10], which should be detectable by other means—including EEG [11].

Here we investigate this relationship within the framework of the perceptual crossing experiment [12, 13] (PCE), a recently established paradigm in social cognition and EEG hyperscanning [14]. This paradigm is designed to facilitate the systematic analysis of real-time social interaction by employing a minimalist approach: it uses binary haptic and auditory feedback to enable intuitive, circular-motion interactions between two users in a shared virtual environment, allowing them to sense virtual objects and each other's virtual representation through touch or sound. Within this computer-mediated interaction, participants report becoming aware of each other's presence, the onset of which they mark by providing a button press. This enables the assessment of meaningful contextual transitions, including at the protocol level (*rest, pause, task*) and task level (*before-after button press*), which should be detectable in terms of infra-slow EEG rhythms. However, although fast-paced neural rhythms typically recorded with EEG have been considered in studies of slower aspects of social interaction [15], the potential of infra-slow EEG rhythms for this purpose remains less explored and calls for methodological and theoretical advancements. To address this challenge, we hypothesized that neuronal and physiological activity at these slow timescales aligns between individuals engaged in a social recognition task, and that such alignment would be detectable in infra-slow EEG activity.

To test this hypothesis, we examined infra-slow EEG, respiratory and skin conductance signals concurrently during the PCE. First, based on previous evidence linking infra-slow oscillatory activity around 0.05 Hz and 0.1 Hz to visceral autonomic states [16, 17, 18], we asked whether spectral decomposition methods could be used to establish the spectral content of infra-slow EEG activity within the of 0.016–0.2 Hz range available in the PCE dataset. Due to the sparse nature of the data (number of data points and cycles), we applied this analysis to a subset of the PCE data, namely trials including transitions from rest to task (which included a brief *eyes-open* pause in between). Second, we asked whether a dyadic regression approach centered around task responses could be used to reveal inter-personal alignment in the instantaneous power and if these responses were coupled to the phase of these infra-slow oscillations (ISOs).

Our first analysis revealed the state-dependent nature of ISOs, with the transition from dominant aperiodic $1/f$ distributed activity and 0.05 Hz ISO activity during rest, to the sudden flattening of $1/f$ activity before the task start (coincidental with a pause period in which the participants had to open their eyes to read instructions on a screen), and the subsequent appearance of 0.1 Hz ISO activity during the task. Interestingly, around task responses, both ISOs and physiological measurements (respiratory pressure and electrodermal activity) were significantly more aligned between participants who successfully engaged in the task than in those who performed poorly. Moreover, task responses in participants who successfully engaged in the perceptual crossing task were significantly coupled to the phase of the 0.1 Hz ISO, with button presses clustering towards the crest of the wave. Building on these findings, we propose that ISOs play an important role in mediating the temporal alignment between brain and bodily signals, thereby facilitating shared understanding and providing a temporal scaffold that coordinates faster neuronal and physiological dynamics across multiple timescales. Collectively, these results suggest that inter-participant alignment in ISOs serves as a reliable indicator of the emergent, complex interplay between physiology, cognition and social behavior.

2 Results

Our analyses concerned two questions: whether infra-slow EEG rhythms could effectively be shown in the data; and, if they would be able to track meaningful state-dependent, contextual and behavioral transitions. To address these questions, we first characterized the spectral content of the infra-slow EEG hyperscanning data. We then examined the temporal dynamics of two oscillatory peaks within this band, one at 0.05 Hz and another at 0.1 Hz, focusing on their relationship with task performance.

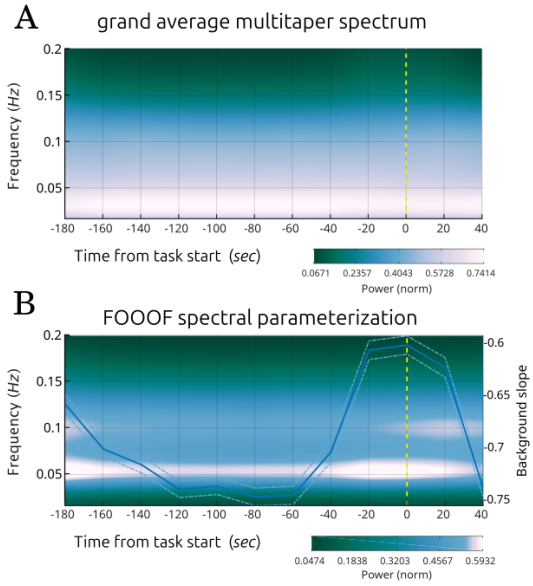

Fig. 1: Spectral content in the infra-slow EEG frequency band. (**A**) Multitaper power spectrum within the infra-slow EEG 0.016–0.2 Hz range. Colors indicate the magnitude of the spectral power (normalized across channels and trials). The grand average is dominated by $1/f$ distributed power, making oscillatory peaks hard to distinguish (note that, due to the limited temporal resolution of the spectral decomposition method, the last 20 *sec* of the 60 *sec* task are not resolved. See methods for details.). (**B**) Power spectral parameterization. Colors indicate the magnitude of the two Gaussian fit (R2 mean(standard deviation): 0.549(0.067)). The blue trace indicate the $1/f$ slope with magnitude in the right axis (R2 mean(standard deviation): 0.676(0.072). Dashed lines correspond to the 95 % confidence interval). The parameterized spectrum thus obtained revealed the temporal evolution of the different spectral components.

2.1 Infra-slow EEG components track contextual transitions at the protocol level

Figure 1A shows the spectral content of infra-slow EEG activity in the 0.016–0.2 Hz range. Here we emphasize the limitation inherent to Fourier based methods in capturing slowly evolving infra-slow activity. To further characterize infra-slow EEG dynamics (<0.2 Hz), we parameterized the PSD using a custom-implementation of the *fitting oscillations and one over f* (FOOOF) method [19]. In (**Fig 1B**) we show the results of this approach. The analysis revealed an increase of $1/f$ slope during resting state, followed by a decrease towards the pause period preceding the task, onset of which was variable across trials (see brown histogram in (**Fig S1B**) for details) and a subsequent decrease throughout the task. During the task, a distinct peak at $0.1Hz$ emerges, pointing to a mechanistic role in the social coordination task.

2.2 Inter-participant alignment in infra-slow EEG rhythms and bodily signals anticipates mutual recognition

We then went on to investigate the relationship of infra-slow EEG rhythms with task engagement, and asked whether this relationship was reflected in physiological responses (respiratory pressure (RP) and electrodermal activity (EDA)). To assess these questions, we examined the relationship of task performance with the amplitude and phase of the previous identified ISOs (**Fig 2A-B**). To achieve this, here we followed a *time-locked* approach (focusing on activity referenced to task responses) and used the linear regression slopes (β) to summarize the alignment of ISOs and physiological responses (**Fig 2C**) between participant pairs in the temporal vicinity of their respective button presses, which participants used to indicate the recognition of each other's presence in the virtual environment.

Figure2 illustrates the results of this analysis. Here the relationship between infra-slow EEG rhythms (as reflected in the two ISOs) and physiological responses to task engagement was assessed by grouping the participants by task performance, defined as the successful or unsuccessful recognition of each other in the haptic virtual space (see *methods* for details on the perceptual crossing experiment). Task responses fell into three categories: joint success (JS), single success (SS), or wrong clicks (W), which we combined into two groups: one group consisted in pairs that successfully engaged in the perceptual crossing task, with both participants recognizing the other's presence (JS); and another group including pairs that failed to recognize the other's presence ($non-JS$). **Figure 2A** shows this relationship through the slope of the linear regression (β) between paired participants' spectral power in ISOs. The higher β in joint success (JS) pairs (dot-dashed lines) compared to unsuccessful ($non-JS$) pairs (dotted lines) indicate similar infra-slow neural dynamics during successful social interaction. This pattern

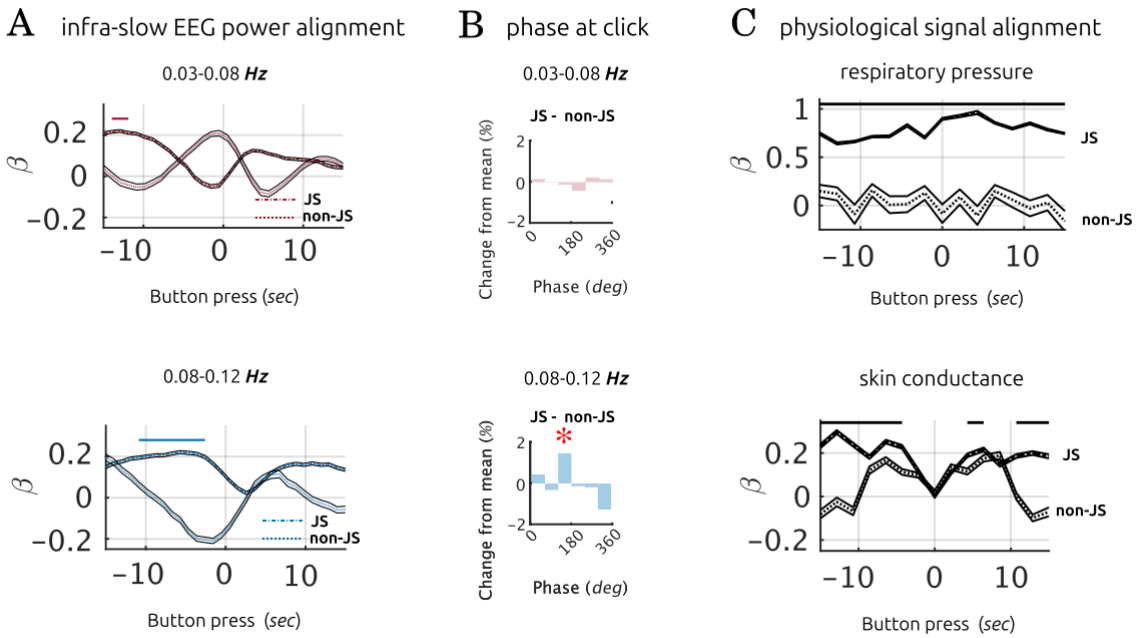

Fig. 2: Inter-participant alignment in task-locked ISO and physiological responses is increased during mutual recognition. (**A**) Inter-participant alignment in the spectral power of ISOs anticipates task success. Colored traces indicate the slope of the linear regression (β) for 1 *sec* epochs (with x–y as participant 1–2) respectively. Black traces indicate the 99 % confidence interval (obtained using 1000 bootstrap iterations with 80 % data resampling to compute the mean and the standard error of the mean). The horizontal colored lines on top of the panels indicate above chance levels for JS computed as the values above null. (**B**) Decisions that led to mutual recognition tended to occur past the crest of the 0.1 Hz ISO waves (between 120–180°). To test for phase preference we computed the differences in percentage change from the mean across channels between JS and $non-JS$ groups. The Rayleigh test for circular uniformity revealed a significant peak for phase preference past the crest of the wave (between 120–180°) for ISOs in the 0.1 Hz peak (Rayleigh test: $p = 0.00064873$, $z = 7.3397$, preferred phase marked by red asterisk) but not for those in the 0.05 Hz peak (Rayleigh test: $p = 0.055761$, $z = 2.8866$). (**C**) Inter-participant alignment in respiratory (RP) and electrodermal (EDA) around task response. Throughout the temporal window examined, the respiratory signals display stronger inter-participant coupling in JS (dot-dashed line) compared to $non-JS$ pairs (dotted line). Electrodermal activity, on the other hand, shows a decrease in alignment at the time of button click for both JS and $non-JS$ groups, suggesting that autonomic responses increase their variability as participants click the button, regardless on whether they mutually recognize each other's presence in the virtual environment.

was consistent for both the 0.05 Hz (red) and 0.1 Hz (blue) peaks. Shuffling button responses to scramble the alignment confirmed the statistical reliability of this finding, with alignment peaks significantly exceeding chance levels (black traces showing 99 %), demonstrating that this similarity in infra-slow neural dynamics was specifically tied to meaningful social interaction rather than coincidental signal fluctuations.

Beyond the alignment in the amplitude of ISOs, we investigated whether ISOs exhibited specific phase relationships to the performance in the task (**Fig 2B**). A Rayleigh test for circular uniformity on the difference between joint success (JS) and $non-JS$ responses (across participants, trials and channels revealed a distinct significant peak for phase preference towards the crest of the wave (between 120–180°) for ISOs in the 0.1 Hz (Rayleigh test: $p = 0.00064873$, $z = 7.3397$) but not for those in the 0.05 Hz peak (Rayleigh test: $p = 0.055761$, $z = 2.8866$). This frequency-specific phase preference suggests that the 0.1 Hz ISOs may create temporal windows that optimize social coordination, similar to how faster neural oscilla-

tions create optimal windows for perception and action [20]. We elaborate more on this point in the discussion section.

Finally, we examined the alignment of respiratory activity (RP) and electrodermal activity (EDA) (**Fig 2C**). Similarly as with ISOs, we computed the slope of the linear regression (β) between paired participants' physiological signals in the temporal vicinity of task responses. The results showed that respiratory signals were more aligned in JS. This alignment was particularly pronounced right after button click events, indicating that participants' breathing patterns became similar as they recognized each other and completed the task, even though this similarity did not occur simultaneously. Remarkably, EDA signals showed heightened alignment during successful interactions (JS), but decreased alignment during button presses for both JS and $non-JS$ groups, suggesting that autonomic responses become coordinated in anticipation, as well as after, participants responded, regardless of whether they mutually recognized each other's presence in the virtual environment.

Taken together, our findings demonstrate that not only is the alignment in the amplitude of infra-slow oscillations and specific phases at which task-related decisions occur, but also that this alignment extends to physiological processes. This biological meaningful integration of autonomic processes into a shared cognitive and physiological state may show up in participants that successfully recognized each other's presence (JS).

3 Discussion

Neuronal rhythms operate across multiple temporal scales, forming a complex basis for cognitive and physiological regulation. While fast oscillations have been extensively studied for their role in perception and attention, slower rhythms may provide a fundamental scaffold for integrating the brain's various network dynamics [21, 22] with allostatic bodily processes [9, 17] over the longer timescales necessary for social cognition [6]. Our findings align with this view, demonstrating that infra-slow EEG oscillations orchestrate neural dynamics during social interaction by temporally coupling brain and body activity—a prerequisite for successful joint action. In what follows we discuss the major findings of our study, their implications for understanding the role of infra-slow oscillations in social cognition, and the methodological considerations involved.

3.1 Methodological considerations

A major challenge in studying infra-slow brain oscillations lies in conventional EEG methodology. Standard recordings typically implement DC-rejection or high-pass filtering at the level of hardware, before digitization, often attenuating or eliminating signals below 0.2 Hz [23]. To overcome this limitation, we employed BrainAmp Standard (brainvision) DC-coupled amplifiers with ultra low cutoff (0.016 Hz). Importantly, we implemented two complementary preprocessing steps to detect lower frequencies.

To better interpret our findings, we complemented the spectral decomposition approach presented in (**Figure 1B**) with data-driven approach. (**Figure S1** reveals the spatio-temporal structure in infra-slow EEG activity using non-negative tensor factorization, a model free analysis that approximate parallel sources of variability as factors with weights in the spectral, temporal and spatial dimensions of the data. Although the ISO peaks did not match exactly the ones shown in (**Figure 1B**), the spectral aspects confirm the overall pattern, lending validity to our model based approach, while highlighting the scalp distribution contributing to the observed activity.

3.2 Possible roles for infra-slow rhythms during social coordination

Our protocol-level analysis revealed a striking sequence of transitions in ISOs that tracked meaningful changes in behavioral state, from rest to task. The sequential transition from a 0.05 Hz distributed ISO peaking at task onset to an increase in the preponderance of the 0.1 Hz ISO during task engagement, doubly corroborated in our protocol-level analyses (**Fig 2** and **Fig S1**), suggests that different infra-slow rhythms may reflect distinct functional states: preparation for social interaction and active engagement, respectively [24]. These findings could reflect a number of mechanisms, such as the combined effect of slow readiness potentials during task engagement [25, 20], of the accumulation perceptual evidence [26], and align with emerging evidence that infra-slow fluctuations correspond to different network configurations and cognitive states [22, 21, 27].

One remarkable finding that supports this view is that the $<0.05\ Hz$ component was more localized to the occipital and parietal regions (**Fig 2C**). As participants had their eyes open during this interim pause period, we speculate that this spatial pattern may reflect a role for this rhythm in the coordination of visual and motor processing streams at task onset, mirroring our previous findings on the temporal sequences of ISOs. In contrast, the $0.1\ Hz$ component was localized in frontal, temporal, and parietal areas, known to play a major role in the attentional control of visual processing [28]. Interestingly, given the haptic nature of the task, it is plausible that the interplay of these rhythms may reflect the recruitment of visual and motor areas during haptic exploration. A recent study using fMRI demonstrated a recruitment of foveal retinotopic cortex during haptic exploration of shapes and actions in the dark [29], which lends support to this idea. On the other hand, infra-slow EEG activity is known to be correlated with intrinsic fMRI activity [8, 30], lending extra support to a role of the $<0.05\ Hz$ in modulating visual and motor areas.

At the task-level, we linked the results obtained from our data-driven spectral factor decomposition to task performance. To examine inter-participant alignment of brain rhythms, we analyzed the temporal relationship between infra-slow EEG oscillations in participant pairs. In this analysis we move forward from the spectral decomposition approach used previously and use absolute Hilbert envelopes as proxy for spectral power. When comparing spectral power in relationship to task responses (time-locked to button presses), our analysis revealed significantly stronger interpersonal alignment in spectral power for participants who successfully recognized each other compared to those who failed. This alignment was particularly evident in the interval surrounding mutual recognition events (5-10 sec before task responses). The alignment observed in the $0.05\ Hz$ and $0.1\ Hz$ bands was specifically associated with mutual recognition events and exceeded chance levels derived from jittered response onsets, which scrambles the behavioral aspect from the data without changing arbitrary signal properties. This alignment was mirrored by similar patterns in respiratory and electrodermal activity, suggesting enhanced coordination across multiple physiological systems during successful social interaction [31]. Previous research has demonstrated that coupling between infra-slow neural rhythms and autonomic processes occur at different time scales [32, 33, 34]. Illustrative of this, a recent study on joint co-fluctuations of global fMRI activity with physiological signals used cross-correlation to demonstrate two distinct temporal relationships: a negative-to-zero lag peak (-5 to 0 sec), suggesting physiological signals follow global fMRI fluctuations, and a positive lag peak (0–10 sec), indicating physiological signals may precede fMRI responses [18]. These bidirectional lags may likely point to the integration of top-down cortical modulation with bottom-up peripheral signaling, possibly reflecting system-wide autonomic regulation beyond local vascular effects. Our finding that $0.1\ Hz$ carried the strongest alignment with task responses, and that this alignment was coupled to the phase of the $0.05\ Hz$ ISOs, suggest that such an interplay may well play a role during interpersonal coordination, and that this interplay should be detectable in the EEG signal.

Furthermore, our complementary analysis of phase-task-response coupling revealed that successful mutual recognition events were preferentially clustered towards the crest (150–180 deg) of the $0.1\ Hz$ wave. This frequency-specific phase preference suggests that 10–sec cycle oscillations may reflect temporal windows that optimize social coordination, similar to how faster neural oscillations create optimal windows for perception and action [20]. Taken together, these findings lend further support to the notion that viscerosensory information modulate perception and cognition through temporal congruency [9], coloring them with value and motivational meaning. According to this view, individuals with greater interoceptive sensitivity may perform better and show enhanced recognition in memory and social tasks [35].

3.3 Broader implications for social cognition and embodied interaction

Our findings have broader implications for understanding the neural basis of social cognition and embodied interaction [36]. Traditional approaches have focused on fast oscillations and event-related potentials, but our results suggest that slower rhythms may as well play an important role in organizing social interactions over extended timescales. Although the precise contribution of visceral and physiological with perception and cognition still remains controversial, the alignment of infra-slow oscillations between individuals may represent previously overlooked mechanism

for establishing shared cognitive and physiological states necessary for successful inter-personal coordination [37, 38]. This perspective aligns with theories emphasizing the embodied and interactive nature of social cognition [12, 39], suggesting that the very slow dynamics of neural activity provide a temporal scaffold upon which more rapid cognitive processes unfold.

A recent study using EEG and magnetoencephalography (MEG) to study the dynamics of intentional behavior [40] have suggested that error detection arise from the interplay of two type of signals: a fast unconscious motor code, based on direct sensory and motor pathways, and a slower motor conscious intention that computes the required motor response given the stimulus and task instructions [41]. In accordance with this *dual-route* model of slow conscious versus fast nonconscious evidence accumulation, our finding that correct task responses were coupled to the phase of the 0.1 Hz extend the notion of this dual-route processing to the infra-slow timescale, suggesting a role for slower visceral nonconscious components in shaping intentional behavior. This role would be to provide a slower nonconscious physiological context for the interplay of slow-conscious and fast-nonconscious codes during the shaping of intentional and social behavior [40, 20].

Slow amplitude modulation of faster oscillations, which has been shown to be a mechanism for the integration of sensory information [20], could also help explain how infra-slow rhythms facilitate the temporal alignment necessary for successful joint action. However, further research is needed to elucidate the precise mechanisms underlying this relationship and how it may vary across different social contexts and modalities. As noted, the brain's amplitude modulation patterns crucial in shaping perception [42] and action may not be unique to the brain but extend to slower timescale that implicate the internal and external milieus in service of adaptive and efficient social behavior. Our findings support this view that infra-slow rhythms may serve role in social cognition, providing a temporal framework for coordinating complex interactions between individuals.

Future research should investigate whether these patterns generalize to other forms of social interaction and whether they can predict social outcomes in clinical populations with social impairments. Methodological advances enabling the simultaneous measurement of infra-slow brain activity and physiological processes across interacting individuals will be crucial for further understanding the multilevel coordination that characterizes successful social interaction. By elucidating the role of infra-slow EEG rhythms in social cognition, we may prompt new ways of looking into the neural mechanisms underlying shared understanding and joint coordination, with implications for both basic and clinical research in social neuroscience.

4 Methods

4.1 Experimental setup and data characteristics

We utilized an established paradigm known as the haptic perceptual crossing experiment (PCE) [12, 13], which enables systematic investigation of social interaction dynamics. In the PCE paradigm, participants attempt to recognize each other's presence in a minimalist virtual environment through haptic feedback, resulting in one of three possible outcomes: mutual recognition (joint success, JS), one-sided recognition (single success, SS), or no recognition (wrong click, W). Data were collected from 31 experimental sessions, each involving two participants completing eighteen 1-minute trials.

4.2 Data acquisition and preprocessing

Electroencephalography (EEG) data were acquired using a 64-channel actiCAP system with electrodes positioned according to the standard 10–20 international system. To ensure optimal signal quality, electrode impedance were maintained below 25–35 kΩ through a systematic preparation protocol. The acquisition was conducted using BrainVision Recorder software with a sampling frequency of 1000 Hz. To preserve infra-slow oscillations, we applied a hardware high-pass filter at 0.016-Hz without direct current rejection [24, 30], a critical consideration for capturing ISOs of interest (0.016–0.2 Hz). Additionally, during recording, a 60 Hz notch filter was applied to minimize line noise contamination. We also obtained respiratory pressure (RP) and electrodermal activity (EDA) data from the same participants. See [14] for detailed description of the preparation.

We then down-sampled the EEG data by a factor of 10 (from 1000 Hz to 10 Hz) and removed outlier data using spherical spline interpolation [43], with outliers defined as 10 consecutive

points (1 *sec*) exceeding 5 median absolute deviation above or below the median computed for a sliding window of 10 *sec*. To recover the spatial footprint of infra-slow EEG rhythms at the protocol level analysis, we spatially whitened the signals obtained in the previous step using generalized eigenvalue decomposition. We used the channel-level covariance data across its total length (rest, pause and task). This step scales the magnitude of the different sensor types relative to one another [44], effectively helping in the recovery of spatial patterns in noisy data with different magnitudes and artifacts across channels.

A total of 31 experiments were conducted, with each experiment involving two participants. Each participant completed 18 trials, resulting in a total of 558 trials across all experiments. However, only 206 trials contained EDA and RP data. After selecting trials with button presses within the +-15*sec* from edges range 196 trials were selected for the task-level analysis. For the protocol-level analysis, we selected 62 trials with a resting state period of at least 3 minutes, followed by a short interim period of 10 *sec* before task onset. This resulted in a total of 124 repetitions.

4.3 Spectral parameterization of infra-slow EEG activity

To track state-dependent transitions at the protocol level, we decomposed the preprocessed EEG data into its spectral components using the multitaper method [45, 46, 47]. This method provides optimal estimates of spectral concentration by applying multiple orthogonal tapers (Slepian functions) to the signal, reducing variance while maintaining good frequency resolution. First, for all eligible trials, the spectrum was computed across frequencies from 0.016 to 0.2 Hz in steps of $0.005Hz$ using 3 Slepian tapers. A sliding time window of 60 seconds was applied with frequency smoothing of ± 0.005 Hz with an overlap of 20 *sec*. To ensure that the resulting spectrograms were comparable across participants, we normalized the spectral power by dividing each trial's power by its temporal standard deviation. This normalization step allowed us to account for arbitrary differences across participants while preserving the relative dynamics of spectral power.

To separate oscillatory from $1/f$ activity we adapted the *fitting oscillations and one over f* (FOOOF) method [19]. FOOOF models the PSD as the sum of a broadband aperiodic component ($1/f$ background) and periodic oscillatory peaks, enabling quantitative comparison of spectral features across conditions. Whereas FOOOF relies on the Welch's spectral decomposition method, we chose a small number of Slepian (discrete prolate spheroidal sequences (DPSS)) tapers. This choice was motivated by the limited number of data points and cycles available in the infra-slow EEG range, where Welch's segmentation and averaging can produce unstable and biased estimates. Slepian tapers provide optimal spectral concentration and reduced leakage, yielding more reliable power estimates for ultra-low frequencies with sparse data. Given the small number of frequency bins and prior evidence for canonical infra-slow rhythms, we predefined the center frequencies of the Gaussian peaks in the FOOOF model at 0.05 Hz and 0.1 Hz. Only the Gaussian widths and amplitudes were allowed to vary, minimizing overfitting and ensuring biologically meaningful parameterization of oscillatory components. We modeled the $1/f$ slope in log-log space and subtracted it from the PSD at each time bin. The residual PSD was then modeled as the sum of two Gaussian peaks (centered at 0.05 Hz and 0.1 Hz). This procedure was performed separately for each channel and trial using 5-fold cross validation on permuted trials (testing prediction fits on 20% of leave out data after permuting 500 times). Mean and standard deviation across channels and folds was then reported.

4.4 Dyadic regression analysis

After establishing the temporal extent and magnitude of infra-slow oscillations (ISOs) in the previous step, we went on to quantifying the alignment in their spectral power between participants locked to task-responses (± 15 *sec* around button clicks). Informed by the first analysis, we applied a zero-phase Butterworth filter of order 4. We then computed the analytical signal by computing the analytical signal using Hilbert transform on the filtered signals. For each channel, the instantaneous phase and the absolute magnitude of the amplitude envelope thus obtained was used as a proxy for instantaneous power.

The extent of alignment for each participant pair was then quantified using the slope of linear regression between their respective spectral power time series, with higher slope values indicating stronger alignment (with a unity slope representing perfect alignment), zero slope indicating

no alignment, and negative slopes indicating anti-alignment. We conducted this analysis on 1 *sec* epochs. Confidence intervals (CIs) were computed using a bootstrapping approach, where we randomly selected 80 % of the epochs and computed the linear regression slope between paired participants' data. This procedure was repeated 1000 times to generate a null distribution of regression slopes for each task outcome. For this analysis, task outcomes were grouped into a joint success (JS) and non-joint success ($non - JS$) categories. Single success (SS) and wrong (W) responses were grouped into a single "$non - JS$" category as they both represent instances where mutual recognition was not achieved. The 99% percentile of this distribution was used as CIs. To further validate our results, we created a null distribution by randomly jittering the response onset times (100 iterations) and recalculating the regression slopes. This procedure preserved the temporal structure of the signals while disrupting their relationship to behavioral influences unfolding in the temporal vicinity of the button press. Values exceeding the 99 percentile of the null distribution were considered statistically significant alignment patterns that could not be attributed to random fluctuations in the data or general task structure. We also tested random fluctuations in the physiological data. For respiratory pressure (RP) and electrodermal activity (EDA), we followed a similar procedure to that for infra-slow EEG rhythms, but with longer epochs (2–*sec*), mean computed from 100 permutations of 50 % random splits, and 30 random shifts on button click onset.

Finally, to examine the phase relationship between task responses and the oscillatory phase of infra-slow EEG rhythms, we constructed phase histograms by binning the instantaneous phase between 0–360 ° using 12 evenly spaced bins. We counted the number of task responses within each bin and converted the counts into percentage signal change from the mean. Since many electrodes were grouped, the resulting distributions were peaking at small changes in the relative frequency, of the order of magnitude of 2–4 percent frequency change. The instantaneous phase was extracted using the Hilbert transform, as described previously. To assess the statistical significance of phase preferences, we applied a Rayleigh test for circular uniformity on the difference between joint success (JS) and $non - JS$ responses. This approach allowed us to specifically test whether successful mutual recognition events had a different phase distribution compared to other task responses.

Across experiments and participants, data from 196 trials were eligible for the task-level analysis. From this pool, 145 trials belonged to the joint success (JS) group, 18 to the single success (SS) group, and 33 to the wrong click (W) group. The $non - JS$ category, which included both SS and W responses, included 51 trials. The number of trials in each group was not balanced, as the task was designed to elicit more successful interactions than unsuccessful ones. This imbalance is a common feature of social interaction tasks, where successful interactions are often more frequent than failures. To assess this unbalance, we used a resampling approach with bootstrapped confidence intervals, as well as jittered button presses to create a null distribution of regression slopes. This approach allowed us to account for the unbalanced nature of the data while ensuring that the results reflected the natural variability in social interactions.

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Acknowledgments

We are grateful to the Okinawa Institute of Science and Technology Graduate University (OIST) for providing the facilities and support for this research. We would also like to thank Finda Dwi Putri and Chen Lam Loh for their role in EEG signal acquisition and preprocessing. We also thank the participants for their time and effort in this study.

Funding: N. G. and T. F. were funded by the JST Grant Number JPMJPF2205.

Author contributions: N. G. and T. F. analyzed the data and wrote the manuscript. N. F. wrote code for the preprocessing.

Competing interests: There are no competing interests to declare.

Data and materials availability: The data used in this study is available from OSF at `https://osf.io/84wbf/`. The code used to analyze the data is available upon request from the corresponding author and will be made publicly available from GitHub after publication.

5 Supplementary materials

The supplementary materials include the following items:

- **Figure S1**: Factorization of the infra-slow EEG power spectrograms revealed by meaningful transitions at the protocol level.
- **Detailed methods**: Complementary preprocessing steps for the isolation of infra-slow EEG oscillations (ISOs) at the protocol level.

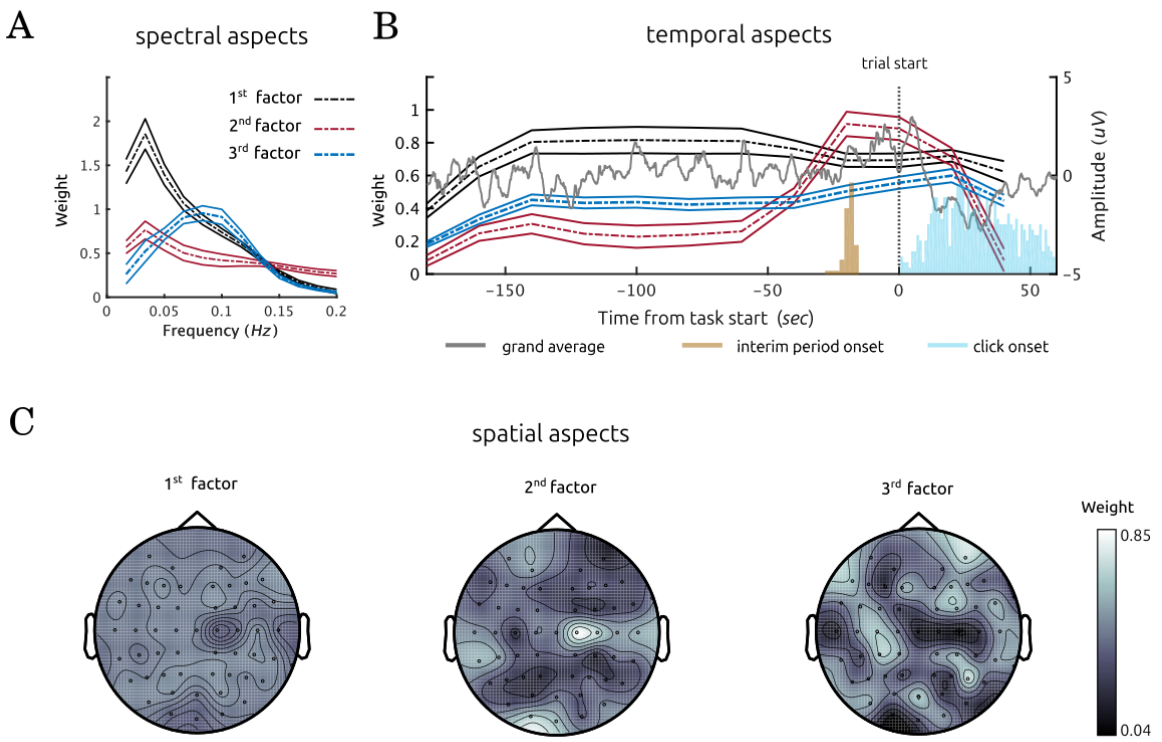

Fig. S1: Factorization of the infra-slow EEG power spectrograms revealed by meaningful transitions at the protocol level. (**A**) To reveal the footprint of ISOs in space and time, we used tensor factorization methods. This resulted in 3 factors with distinct weights for the frequency, temporal and spatial dimension of the tensor. For each dimension, weight magnitudes representing the relative contribution of each factor to the tensor, effectively summarizing the spectral power dynamics unfolding in space and time across the population. As such, the factors thus obtained represent meaningful spaces: $1/f$, the two oscillations identified previously (1), their temporal trajectory (**B**) and their location in the scalp (**C**). The brown and blue histograms are to mark the onset of the interim period and (**B**) the distribution of button presses during the task, respectively. The vertical dotted line indicates the start of the task.

To complement the analysis in **Figure 1**, which is model based in nature, we implemented a model free approach to disentangle the major sources of variability in the spectral content of the infra-slow EEG activity. For this we used non-negative tensor factorization, a data driven approach to help disentangling the data structure in a data driven way. This tensor was then factorized using canonical polyadic decomposition [48, 49]. This method decomposes the tensor into a sum of rank-one factors. Each factor is the outer product of vectors along different modes of the tensor, enabling the separation of frequency-specific patterns while accounting for their spatial footprint in the scalp (across channels). We implemented a nonlinear least squares algorithm with random factor priors to guide optimization toward an optimal solution [50] and ensure that all components are non-negative and interpretable. We repeated this procedure 10 times to account for random initialization effects, aligning equivalent factors based on their maximum correlation with the first estimation (taken as reference). The mean and standard error of the mean were then reported for the time-frequency factor. This approach allowed us to extract meaningful spectral components from the infra-slow EEG data while preserving their spectral, temporal and spatial structure.

In total, 124 trials were used, with trial-specific spectrograms normalized to 0–1 within experiment and participants. These normalized spectrograms were then averaged across all trials to obtain a mean representation of the spectral power dynamics over time. This resulting representation was then used to define non-the negative $[channel \times frequency \times time]$ tensor. We cross-validated the analysis using 5-folds cross-validation with 100 random initializations (testing prediction fits on 20% of leave out data). To assess the robustness of the tensor decomposition approach, we compared the tensor structure reconstructed using factors obtained from the training data to the empirical tensor derived from test data (the 20% validation fold). Although some studies have reported correlations between flattened versions of a tensor, we opted to preserve the spatiotemporal structure of the tensor. To achieve this, we projected the frequency dimension along the temporal dimension. This provided us with a tractable representation of the spectro-temporal structure across electrodes. We then compared this structure between the reconstructed tensor obtained using factors derived from training data to the empirical "test" tensor using Procrustes distance correlation, a method that allows comparing the two images by rotating and scaling a matrix. This analysis confirmed what Figure 1 already revealed, namely the presence of oscillatory dynamics together with changes in the 1/f distributed background activity. Interestingly, this analysis pointed to spatial aspects not readily available using parameterization. In future studies, this approach could be expanded to analyze spectral, temporal and spatial aspects on different tasks and clinical scenarios, such as the assessment of social skills in the neurodiverse population or during the recovery from mental uneasiness associated with psycho-social and neuropsychiatric disorders. We hope our approach helps in the assessment and treatment of inter-personal dynamics, where slow bodily determinants are clearly a key factor.