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Alpha and beta event-related synchronization as neural markers of self-other processing during sensorimotor coordination☆

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ABSTRACT

Interpersonal synchrony requires continuously balancing internally generated timing predictions with externally driven adjustments to a partner's behavior. Neural oscillations in alpha and beta bands have been implicated in prediction processes during joint action, yet their role in self–other integration remains unclear, particularly across varying levels of partner adaptivity. Here, we examined event-related desynchronization and synchronization (ERD/ERS) in the alpha (8–12 Hz) and beta (15–25 Hz) bands during a sensorimotor synchronization task. 47 participants performed a finger-tapping task with a virtual partner (VP) whose temporal adaptivity was manipulated (non-adaptive, moderately adaptive, and overly adaptive), whilst EEG activity was recorded. Behavioral results revealed that asynchrony decreased with increasing VP adaptivity. Neurally, we observed alpha and beta ERS instead of the typical ERD locked to the taps. For taps that came before tones (taps pre-tones), ERS was most pronounced over fronto-central areas, resembling auditory activity, and was highest when tapping with a non-adaptive VP. The spatial topography thus suggests that ERS reflects inhibition of sensory prediction of upcoming tones, and its modulation suggests that tone prediction is more inhibited when the VP is non-adaptive. For taps occurring after the tones (taps post-tones), ERS was observed over motor areas, with higher ERS when interacting with a more adaptive VP, suggesting enhanced inhibition of self-generated motor activity during interaction with an adaptive VP. Across conditions, higher ERS was associated with higher asynchrony. Together, these findings reveal that audio-motor neural components modulate self-other integration and give insight into how the adaptivity of the partner modulates action prediction and self-other balance.

1. Introduction

Human joint actions — such as playing music together, dancing, or synchronizing finger taps — require individuals to continuously coordinate their movements in time and space to achieve shared goals (Fairhurst et al., 2013; Konvalinka et al., 2010; Sebanz et al., 2006). This coordination does not arise from mere simultaneity, but from the ongoing alignment of self-generated actions with those of a partner, supported by internal predictive models and adaptive error correction (Harry et al., 2023; Keller et al., 2014; Steen et al., 2013). In rhythmic contexts, coordination quality depends on anticipating a partner's timing, correcting phase and period errors, and flexibly shifting between reliance on internal tempo representations and external sensory cues (Repp & Su, 2013). Computational and dynamical models formalize these processes as emerging from coupled oscillatory systems, in which within-person and between-person action–perception links determine whether dyads exhibit mutual adaptation, leader–follower dynamics, or self-focused (leading–leading) strategies (Heggli et al., 2019; Heggli et al., 2021). From a predictive-processing perspective, these dynamics rely on forward models that generate sensory predictions and update them based on prediction errors (Hadjiosif et al., 2020; Wolpert et al., 2001).

During interpersonal synchronization, prediction–adaptation loops operate bidirectionally: partners continuously generate expectations

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about each other's actions, monitor deviations, and engage in reciprocal error correction to restore coordination (Konvalinka et al., 2010; Müller et al., 2021). Behavioral studies of joint tapping have shown that stable synchrony emerges from continuous mutual correction rather than unidirectional control (Konvalinka et al., 2010), while hyperscanning evidence indicates that such reciprocal adaptation is supported by dynamically coupled neural activity across interacting brains (Müller et al., 2021). Dual electroencephalography (EEG) frequency-tagging studies further have demonstrated that neural tracking of self- versus other-generated movements flexibly shifts with leadership roles, and that maximal mutual adaptation is marked by inter-modulation responses reflecting self–other integration (e.g., Varlet et al., 2019). Together, these findings suggest that successful coordination depends not only on prediction accuracy, but on dynamically regulating the weighting of self-generated versus other-generated information. However, the neural mechanisms underlying the weighting of self and other during continuous interactions of sensorimotor coordination remain poorly understood.

In addition, only a limited body of research has examined how temporal errors modulate joint action dynamics, mainly focusing on self- and other-error monitoring (Loehr et al., 2013; Moreau, 2021). Evidence suggests that violations of interpersonal expectations are not merely disruptive but actively modulate coordination. For instance, Sacheli, Arcangeli, et al. (2021) have demonstrated task that a partner's error triggers an implicit corrective tendency in a musical turn-taking, even at the cost of individual efficiency, highlighting the role of sensorimotor signaling. Within the embodied cognition framework, observing others' actions activates corresponding sensorimotor representations (Blakemore & Frith, 2005; Grafton, 2009), enabling integration of self- and other-related action models. The Dyadic Motor Plan (DMP) account (Sacheli, Arcangeli, & Paulesu, 2018) proposes that during interactive tasks, individuals represent both their own and their partner's actions in terms of their joint contribution to a shared goal. When a partner's action deviates from this, adaptive responses are selected to restore alignment. Thus, mismatches between predicted and observed partner behavior are not simple prediction errors but signals that adjust the shared motor plan as a potential mechanism that preserves joint goals despite local deviations.

A central challenge in joint action is therefore maintaining a flexible balance between self and other. Over-reliance on internal models may produce rigid, self-oriented behavior, whereas excessive responsiveness to a partner may compromise autonomy and stability (Fairhurst et al., 2023; Mayo & Gordon, 2020). Optimal coordination instead emerges from a dynamic trade-off between interpersonal coupling and intrapersonal stability — echoing broader dynamical accounts in which strong coupling to others may coincide with reduced within-person coupling (Heggli et al., 2019; Konvalinka et al., 2026; Zimmermann et al., 2022) and self-regulation (Galbusera et al., 2019). In this view, self–other integration and segregation are not opposed but rather complementary processes that are flexibly regulated across time (Konvalinka et al., 2026). Neurocognitive accounts propose that this balance is implemented through oscillatory dynamics regulating integration and segregation within action–perception systems (Heggli et al., 2020).

Alpha oscillations have been implicated in functional gating and self–other distinction: suppression is associated with increased entrainment and integration, whereas enhancement reflects reduced reliance on external signals and stronger internal stabilization (Novembre et al., 2016). Beta oscillations, in turn, have been linked to maintenance of the current motor set — the so-called “status quo” signal (Engel & Fries, 2010; Kilavik et al., 2013). In joint tapping, beta power around ~20 Hz is jointly modulated by self- and other-generated movements, tracking reciprocal cycles of synchrony (Rosso et al., 2022), and enhanced beta modulation when adopting a first-person perspective on a partner suggests deeper incorporation of the other into one's own motor representation (Rosso et al., 2025). From a predictive-processing standpoint (Friston et al., 2015), event-related desynchronization (ERD) may index active model updating, whereas event-related synchronization (ERS), particularly post-movement beta rebound, may reflect inhibitory stabilization and resistance to updating. Reduced beta rebound predicts increased adaptation, whereas stronger rebound reflects maintenance of established timing (Torrecillos et al., 2015). Thus, alpha and beta ERD and ERS may provide temporally precise markers of shifts between flexible integration and stabilized segregation in self–-other coordination.

One way to experimentally explore this dynamic is by manipulating partner temporal adaptivity. Adaptive virtual partner (VP) paradigms parametrically vary error correction to bias leader–follower relations and perceived control (e.g., Fairhurst et al., 2014). In rhythmic sensorimotor coordination tasks, temporal adaptation refers to the degree to which one agent corrects their timing in response to asynchrony with a partner (Repp, 2005). Operationally, it reflects the proportion of phase error incorporated into the subsequent action (i.e., period or phase correction). High temporal adaptation implies strong reciprocal coupling and continuous error correction, whereas low adaptation implies rigid tempo maintenance and weak interpersonal coupling.

Therefore, in this context, partner adaptivity can directly modulate social predictability, which is the degree to which a partner's future timing can be inferred from their past behavior. For instance, a non-adaptive, jittered partner provides a more temporally stable but socially unresponsive structure: although the tapping sequence remains relatively stable, it does not incorporate feedback from the partner's behavior. In contrast, a moderately adaptive partner allows reciprocal correction, thereby increasing not only mutual adaptation but also predictability at the dyadic level. This is consistent with previous research showing that more predictable patterns of behavior can emerge when two partners mutually adapt to each other (Konvalinka et al., 2023). Over-adaptation, however, may introduce temporal instability by overcorrecting deviations and amplifying variability, thereby reducing higher-order predictability of the interaction (Heggli et al., 2021; Repp, 2005). In other words, a non-adaptive partner reduces mutual correction and may promote reliance on internal timing models, a moderately adaptive partner supports balanced mutual prediction and adaptation, while over-adaptivity may introduce some instability (Heggli et al., 2021; Repp, 2005). Recently, a finger tapping study showed that a moderate level of temporal adaptation from a VP yields the highest stability of synchrony (measured as standard deviation of asynchrony), while interacting with an overly adaptive partner leads to the highest variability in tapping behavior but at the same time lowest asynchrony (Gregorini et al., 2025).

Within this context, processes related to self–other integration and segregation are constantly involved, and their balance is further modulated by the temporal ordering of actions. Taps that precede the partner's response are supposed to rely predominantly on internally generated predictions, whereas taps that follow the partner's response can depend more strongly on external sensory evidence and online error correction (Harry et al., 2023; Steen et al., 2013). However, variations in the partner's adaptivity alter the relative weighting of internal predictions versus externally driven error-correction processes, thereby shaping self–other processes. Thus, oscillatory dynamics in the alpha and beta bands provide a mechanistic window into these processes. ERD reflects increased cortical excitability (or disinhibition) and updating, while ERS — particularly beta rebound — indexes inhibitory stabilization and maintenance of the current motor set (Engel & Fries, 2010; Pfurtscheller & Lopes da Silva, 1999). Taken together, this suggests that oscillatory desynchronization and synchronization detected at neural level may regulate the dynamic weighting of internal predictions and external signals, ultimately constraining or facilitating the emergence of stable interpersonal alignment.

1.1. The present study

Against this background, the present study aimed to investigate ERD

and ERS in the alpha- and beta-bands as potential markers of self-other balance, and to examine the role of VP modulation in temporal adaptivity during a finger-tapping task. Additionally, by separately analyzing taps that occurred before the tones (i.e., taps pre-tones) and taps occurring after the tones (i.e., taps post-tones), we explored the oscillatory signatures of predictive self-stabilization relative to those of reactive motor updating in the context of self–other processing.

Behaviorally, we hypothesized that reduced asynchrony would be associated with increased temporal adaptivity of the VP and that the SD of asynchrony would be reduced while the VP was moderately adaptive, in line with previous findings (Gregorini et al., 2025).

At the neural level, we hypothesized that oscillatory dynamics would reflect context-dependent shifts in self–other balance. More precisely, in line with previous findings (Peter et al., 2022; Pfurtscheller & Lopes da Silva, 1999), we hypothesized a movement-related decrease in power (ERD) in the alpha (8–12 Hz) and beta (15–25 Hz) bands over central regions during response preparation and execution, reflecting motor cortex engagement. This ERD was expected to be followed by a post-movement beta rebound (ERS), indexing the re-establishment of the sensorimotor set and internal model updating. Moreover, given that participants were required to process an auditory stimulus, we expected modulation of oscillatory activity over fronto-central regions as sites index of the functional coupling between auditory processing, motor planning, and sensorimotor integration, according to previous findings (Ross et al., 2022, 2016). Finally, since the task required synchronization to external auditory feedback, we further anticipated that oscillatory dynamics would not be restricted to primary motor regions but would extend to fronto-central networks involved in performance monitoring and auditory–motor coupling.

Drawing on this, variations in ERD and ERS magnitude were expected to reflect context-dependent adjustments in the balance between internally generated motor plans and externally driven sensory feedback. In relation to participants' behavioral dynamics (e.g., taps pre-tones and post-tones) and the level of adaptivity, ERD was expected to be higher and ERS lower when the temporal adaptivity increased. In this sense, we explored whether the ERD/ERS pattern would be different between the taps pre-tones and post-tones, as a function of VP adaptivity, with less adaptive VP shifting self-other processing more toward the self (segregation) while more adaptive VP– and presumably predictable – would shift the integration more toward the other (integration). Then, linking behavioral results with EEG activity, we expected that higher ERD and lower ERS would be associated with lower asynchrony, as a sign of greater engagement and involvement during the task.

2. Materials and methods

2.1. Participants

Forty-seven participants (M*age* = 24.3, SD*age* = 2.60; 55% females) were recruited at Technical University of Denmark (DTU) using flyers at campus sites and online advertisement boards. All participants reported basic English language skills, normal hearing, normal or corrected-to-normal vision, and no current use or history of psychotropic medication. Participants signed the informed consent before the experiment and received financial compensation for their participation. The study was conducted according to the Declaration of Helsinki and was approved by DTU Compute's Institutional Review Board (COMP-IRB-2022–10).

2.2. Procedure and stimuli

Participants were invited to perform a finger-tapping task in which they were asked to synchronize their taps with a VP, who adjusted the temporal adaptivity of their responses from non-adaptive to overly adaptive. During all the task the EEG activity was recorded. The finger-tapping task was programmed in MATLAB R2020b (Mathworks Inc., Natick, MA, USA) using the Psychtoolbox (version 3.0.17; (Brainard, 1997; Kleiner et al., 2007; Pelli, 1997)).

Before the task, participants were presented with a cover story, which led them to believe they were interacting with different real partners seated in separate rooms. Each trial began with 4 tones presented every 500 milliseconds (ms) while the word "HEAR" appeared on the screen, and participants were instructed to listen to the tones only and not tap. Then, when the word "TAP" appeared on the screen, participants were instructed to start tapping, pressing the spacebar on the keyboard, with the instruction to "keep the rhythm of the sound that you hear as best as you can". This is the algorithm we used to adjust the time intervals of the computer-based sound: $t_{tone(n+1)} = t_{tone(n)} + 500\ ms + (\alpha \times async_n)$ (similar to Fairhurst et al., 2013). Precisely, the duration of subsequent Inter-Onset Intervals (IOIs) between successive tones was defined by (1) the parameter α that is the degree of the error correction that was fixed within a trial by assuming one of three possible values as 0 (i.e., no phase correction, non-adaptive condition), 0.50 (i.e., moderate correction, moderately adaptive condition) and 1 (i.e., full correction, overly adaptive condition); and (2) by the asynchrony (async) that is the difference between the participant's previous tap and the tone (see Fig. 1 for more details). A random temporal jitter was added, sampled from a uniform distribution between ±20 ms to guarantee variability during the task. Compared to the non-adaptive conditions where the interaction was unidirectional (the sound was non responsive to the participants' taps), in the adaptive conditions (i.e., $\alpha > 0$), a negative asynchrony (i.e., the participant's tap preceded the tone) resulted in a shortening of the IOI for the next tone ($t_n + 1$) that, thus, occurred sooner as a function of the level of α. Conversely, if the participant's tap occurred after the tone, a positive asynchrony was registered, and the IOI for the next tone was delayed. This variation simulated a range of flexibility and cooperation, resulting in varying degrees of coupling among VP and the participant. The participants did not hear their own taps during all the experimental session. The task consisted of 90 trials divided into three randomized blocks, each corresponding to a different temporal adaptation condition, and a minimum of 18 taps was required to move to the next trial. Each trial lasted on average 13 s (*sec*). Audio from the computer was delivered via EEG-compatible earbuds (ER2C Tubal Insert Earphones, Etymotic Research Inc., USA) that provided high isolation from external noise (e.g., keyboard tapping). The participants were asked to sit still and avoid blinking and eye movements as

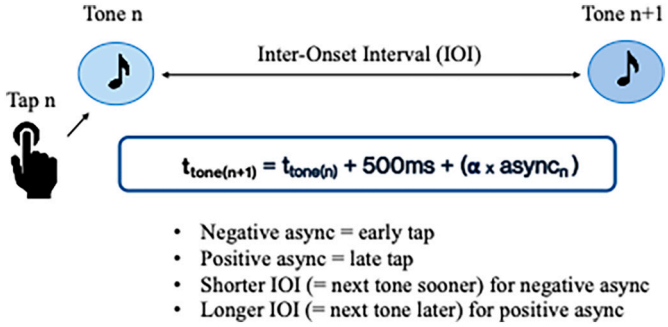


Fig. 1. Visualization of the coupling between the participants' taps and the tones of the virtual partner (VP). The timing of each subsequent tone was updated according to an adaptive algorithm where α determined the level of temporal adaptation (0 = non-adaptive, 0.50 = moderately adaptive, 1 = overly adaptive) and async refers to the difference between the participant's tap (Tap n) and the tone (Tone n). Negative asynchronies shortened the next Inter-Onset Interval (IOI), whereas positive asynchronies lengthened it. The IOI was defined as a function of the parameter α and the async thus the timing between the tones was updated in real time during the task. Namely, if the parameter α was equal to 0.50 and an asynchrony of −40 ms was registered (i.e., the tap of the participant preceded the tone by 40 ms), the subsequent IOI was shorter and set at 480 ms [500 + (0.5 × −40) = 480 ms].

much as possible throughout all experimental sessions.

2.3. EEG recordings

EEG was recorded using the 64-channel Biosemi ActiveTwo EEG system (Amsterdam, The Netherlands) in a 10–20 configuration at a sampling rate of 2 kHz. Data were recorded in ActiView (v. 900). An EEG cap with 64 channels was positioned such that the Cz electrode was centered on the head at the midpoint between the nasion and inion, and the left and right ears. Conductive gel (Signal Gel Electrode Gel, Parker Laboratories, Farfield, NJ) was used to reduce the skin-electrode impedance, and the offset was kept below 20 mV. Four EOG electrodes were placed: two recorded the vertical electrooculogram, placed 1 cm above and 1 cm below the left eye, and two recorded the horizontal electrooculogram for the left and right eyes.

3. Data analyses

3.1. Behavioral analysis and association between behavior and EEG activity

The tapping performance was computed using the following behavioral measures: absolute asynchrony, signed synchrony, and the standard deviation (SD) of asynchrony (absolute values) (following the previous procedure; see Gregorini et al., 2025). The asynchrony in absolute values was calculated as the difference between the taps and the tones and served as an index of performance accuracy. Asynchrony indicates the magnitude of the delay looking at the earliness (negative asynchrony) or lateness (positive asynchrony) of the behavioral dynamics. Therefore, higher values indicate lower synchrony, while lower scores indicate higher synchrony. The stability was computed through the SD of the asynchrony, indicating how unstable the tap timing was around the pacing events: higher values indicate greater instability and variability in tapping. To assess the main effect of the conditions (the three levels of α) on the behavioral measures, we used generalized linear mixed models (GLMMs) for the absolute values and linear mixed models for the signed asynchrony. Thus, three different models were tested, with behavioral measures as dependent variables and conditions as fixed effects. Random effects were included in the models to account for the within-participant dependency of observations.

Regarding the neural activity, we analyzed the association between over pre-defined ROIs in alpha and beta bands and absolute asynchrony, since this measure is informative of the overall degree of synchrony during the task (Repp, 2005; Repp & Keller, 2008), as well as to extend previous findings (Gregorini et al., 2025).

Specifically, in line with our hypotheses, associations were tested only over the fronto-midline region (AFz, F1, Fz, F2, FC1, FCz, FC2) and the central left region (C5, C3, CP5, CP3). Thus, separate models for alpha and beta ERS in fronto-midline and central left regions (ROIs) were performed. For each band and ROI, we conducted one model (Model 1) to test the main effects of conditions and ERS on absolute asynchrony, and a second model (Model 2) to test the interaction conditions x ERS on absolute asynchrony. Effects were tested while accounting for the within-participant dependency of observations included as random effects. We used GLMMs with a Gamma distribution to test associations between behavior and neural activity, given that the data were not normally distributed (Bolker, 2015). Models were fitted using the package lme4 in R (R Development Core Team, 2022).

3.2. EEG preprocessing

Raw EEG data were high-pass filtered at 1 Hz and low-pass filtered at 40 Hz. Bad channels were manually removed based on visual inspection, and independent component analysis (FastICA method) (Hyvärinen, 1999) was used to detect components corresponding to eye movements, eye blinks, and muscle artefacts, with EOG electrodes included in this step. Then, bad channels were interpolated, and data were re-referenced to the common average. Epochs for each adaptivity condition were created around tap events using a window from −2.0 to 3.0 s. Then, a further division of epochs was made based on whether the tap occurred before or after the tone. To compute such epochs, for each tap event, we searched for the nearest tone event within an adaptive window (half the distance to the previous/next tap event, but never more than 1 s), and classification was performed such that event taps that preceded the nearest tone (negative asynchrony) were classified as taps pre-tones, while those that followed the tone (positive asynchrony) were classified as taps post-tones. Further analyses presented below were performed separately for taps preceding the tone and those following it. Epochs were then downsampled to 256 Hz, and bad epochs were automatically rejected.

3.3. ERD and ERS of alpha and beta bands

To specifically isolate the phase-locked component of oscillatory activity associated with movement execution, time–frequency decomposition was performed on the averaged ERP waveform. This approach allows estimation of evoked power, reflecting activity that is both time- and phase-locked to the tap, while minimizing the contribution of non-phase-locked (induced) oscillations (Cohen, 2014; Tallon-Baudry & Bertrand, 1999). Given that the task involved discrete, externally paced finger taps, focusing on the evoked component was particularly appropriate to capture event-specific motor-related synchronization. Time–frequency representations (TFRs) of the *evoked* EEG responses were computed by first averaging epochs within each condition and then applying Morlet wavelet convolution (1–30 Hz, 1 Hz steps; cycles: $3 + 0.125 \times$ frequency) to the resulting event-related potentials. To remove edge effects, the TFR was cropped from −1.8 to 2.8 s. Then, for each subject and condition, ERD and ERS in the alpha (8–12 Hz) and beta (15–25 Hz) bands were extracted by calculating the relative change (%) in power with respect to the average baseline, separately for each channel and time point. The baseline was established for each channel by taking the mean of the band-specific power across the entire time window from −1.8 to 2.8 s. ERD and ERS were extracted by calculating the proportional change from this baseline at each time point by subtracting the baseline power from the power at a given time point and dividing the result by the baseline power. Finally, the resulting ERD/ERS time series were cropped to a time window from −0.25 to 0.5 s.

3.4. Cluster permutation t-test

To assess condition differences in time-resolved ERD/S data (channels × time), we performed non-parametric, cluster-based permutation *t*-tests (Maris & Oostenveld, 2007). For each comparison, subject-level data from two conditions were stacked into arrays of shape (subjects × time × channels). Channel adjacency was defined based on sensor positions, while time adjacency was handled automatically. A cluster-forming threshold was set using a t-statistic at $\alpha = 0.01$, and spatio-temporal clusters were identified by randomly permuting condition labels across 10.000 iterations. Clusters with $p < 0.05$ (corrected) were considered significant. A global FDR correction was applied to account for the six different paired comparisons (non-adaptive vs. moderately adaptive, non-adaptive vs. overly adaptive, and moderately adaptive vs. overly adaptive for both types of taps). For each cluster with $p < 0.05$, we visualized the cluster's spatial topography, temporal profile, and condition-averaged waveforms.

4. Results

4.1. Behavioral results

As reported in Table 1, we obtained a significant main effect of conditions on all the behavioral measures. In line with our hypotheses

Table 1
Results of the models using behavioral measures as dependent variables and the conditions as the fixed effects.

	Absolute asynchrony		Signed asynchrony		SD asynchrony	
	β	*p*	β	*p*	β	*p*
Fixed effects						
Non-adaptive	−2.65	< 0.001	−0.06	< 0.001	−3.59	< 0.001
Moderately adaptive	−0.23	< 0.001	0.01	< 0.001	−0.11	< 0.001
Overly adaptive	−0.29	< 0.001	0.03	< 0.001	0.02	0.02

Note: β = Standardized Parameter Estimates.

we found that, at increasing VP adaptivity, both absolute (see Fig. 2A) and signed asynchrony (see Fig. 2B) decreased. For the SD of asynchrony (see Fig. 2C), a main effect of conditions was found, indicating that instability increased with non-adaptive or overly adaptive VP, whereas it decreased with moderately adaptive VP.

4.2. Alpha and beta ERS for taps pre-tones

Regarding taps pre-tones, TFRs showed ERS locked to taps rather than ERD in both alpha and beta bands (see Fig. 3). Cluster-permutation *t*-tests revealed higher ERS in the alpha range (8–12 Hz) when comparing non-adaptive vs. moderately adaptive conditions ($p < 0.001$) in the frontal, central, and parieto-occipital regions in the time range from −0.07 to 0.21 s, as shown in Fig. 4 A (ERS time series) and C (ERS topography for the non-adaptive and moderately adaptive conditions, and the difference between them). This indicates a modulation of large-scale cortical inhibition mechanisms during motor execution and early post-movement processing. Moreover, when comparing non-adaptive to overly adaptive conditions, higher ERS was found ($p = 0.006$) in the time range from −0.08 to 0.09 s (Fig. 4 B) at fronto-central regions, resembling auditory activity (see Fig. S1 in the supplementary materials). This result may reflect increased sensorimotor monitoring and temporal updating demands under highly adaptive interpersonal coupling, in which the timing of subsequent tones is not corrected but fully adjusted to the participant's own tap. No differences were observed between the moderately and overly adaptive conditions.

Regarding beta activity (15–25 Hz), ERS was significantly higher in the non-adaptive condition compared to the moderately adaptive condition in the time range from −0.03 to 0.15 s ($p < 0.001$), as shown in Fig. 5 A (ERS time series) and B (ERS topography for the non-adaptive and moderately adaptive conditions, and the difference between them). Moreover, when comparing non-adaptive conditions with overly adaptive conditions in the time range from − 0.07 to 0.14 s, higher ERS was observed in the non-adaptive condition ($p < 0.001$) (see Fig. S2 in the supplementary materials). These indicate that stronger beta modulation may reflect increased inhibition under non-adaptive conditions, compared to more adaptive ones. There were no significant differences between the moderately and overly adaptive conditions in the beta band.

4.3. Alpha and beta ERS for taps post-tones

Regarding the taps post-tones, the results of the TFRs revealed ERS locked to taps rather than ERD in both alpha and beta bands (see Fig. 6). In the alpha band, a significant difference between non-adaptive and overly adaptive conditions ($p = 0.004$) emerged from 0.008 to 0.21 s in the central-left region, corresponding to motor-evoked activity contralateral to the moving hand as shown in Fig. 7 A (ERS time series) and B (ERS topography for the non-adaptive and overly adaptive conditions, and the difference between them). Increased alpha ERS in the overly adaptive condition may reflect greater involvement of sensorimotor control mechanisms required to continuously adjust tapping behavior in response to the dynamically changing temporal structure of the interaction. In particular, stronger coupling between action and external feedback in the overly adaptive condition may have increased the demands on movement monitoring and online motor updating. Additionally, significant differences emerged between moderately and overly adaptive conditions in the alpha band (see Fig. S3 in the supplementary materials). For beta activity, no significant differences were found.

4.4. Associations between absolute asynchrony and neural oscillations locked to the movement

To test the association between behavior and neural activity, we tested the main effect of conditions, ERS (over pre-defined ROIs and time-windows, and for alpha and beta bands), and conditions x ERS interaction on absolute asynchrony. For alpha ERS over fronto-midline regions, the model showed a significant main negative effect of conditions and a main positive effect of alpha ERS on absolute asynchrony, suggesting that, in this latter case, with increasing alpha ERS, absolute asynchrony increased. The effects are visualized in Fig. 8, which shows

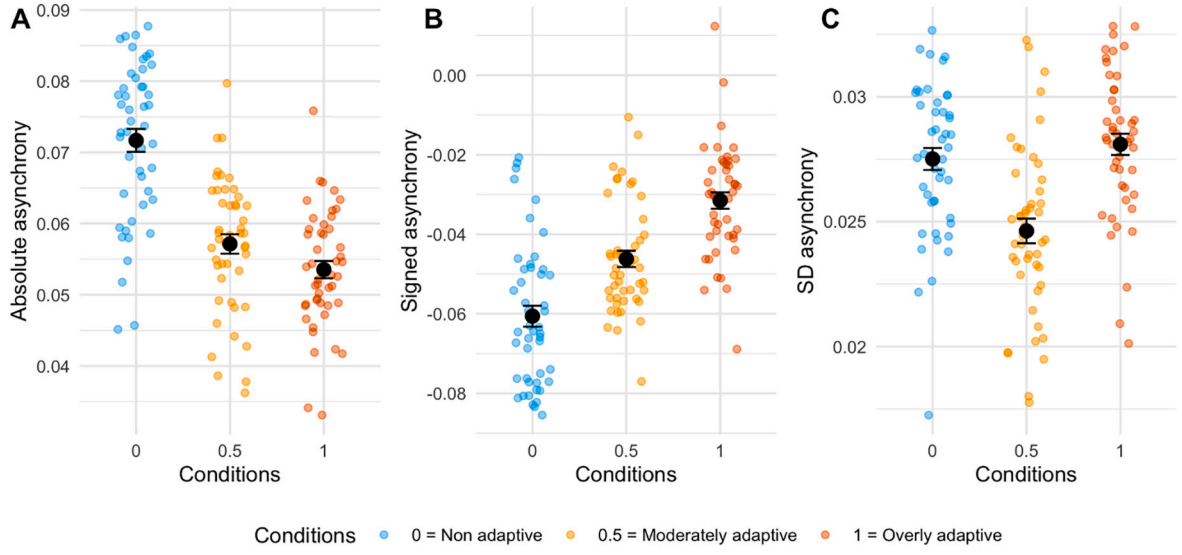


Fig. 2. Representation of the effect of the conditions on the behavioral measures: the Absolute asynchrony **(A)**, the Signed asynchrony **(B),** and the SD of asynchrony **(C)**.

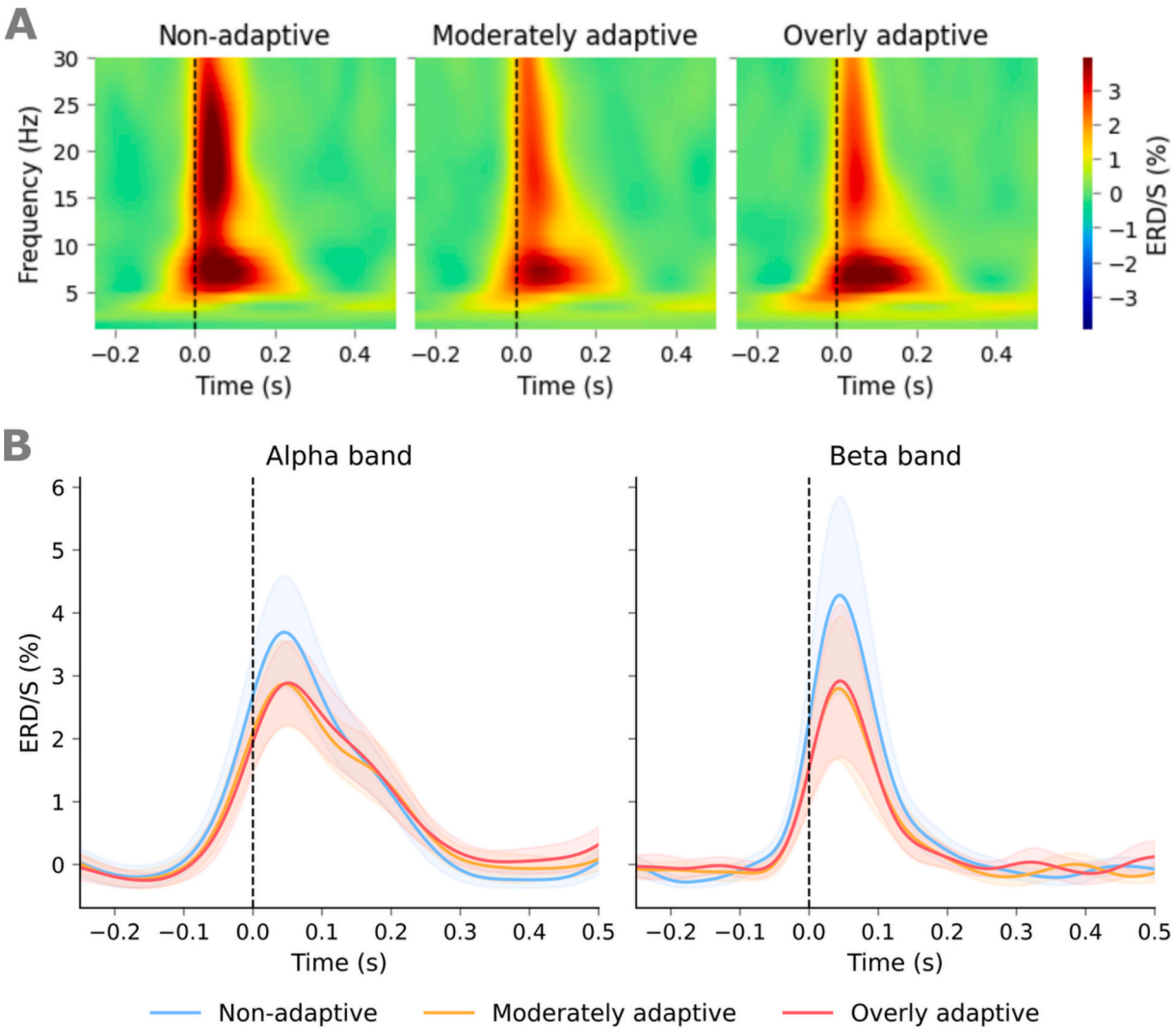


Fig. 3. **(A)** Evoked time-frequency representations during taps pre-tones for different adaptation levels in a central-left ROI (averaged over channels C3, C5, CP3, CP5) and respective **(B)** band-averaged ERD/ERS curves.

the effect of fronto-midline alpha ERS on absolute asynchrony across conditions. No significant interactions were observed. Results are reported in Table 2. In the central-left region, only the conditions reported a significant main negative effect on absolute asynchrony, whereas no significant main effect of alpha ERS neither the interactions emerged. Results are reported in Table S1 in the supplementary materials.

For beta ERS, we found only a main negative effect of conditions on absolute asynchrony over the fronto-midline and central-left regions but no significant main effect of beta ERS neither the interactions were observed. Results are reported in Tables S2 and S3 respectively (see the supplementary materials).

5. Discussion

In this study, we investigated the neural mechanisms underlying sensorimotor coordination and their modulation when interacting with a variable adaptive VP. First, as expected, we replicated previous findings revealing that higher partner adaptivity is associated with lower asynchrony, while the SD of asynchrony is lowest for the moderate level of partner adaptivity, suggesting that coordination stability is optimized under moderate reciprocal correction and "human-like" adaptivity (Fairhurst et al., 2013; Gregorini et al., 2025; Repp, 2005). Findings at the neural level unexpectedly revealed alpha and beta ERS, rather than the more commonly reported ERD, locked to the movement. Typically, alpha and beta ERD during movement followed by post-movement beta ERS has been interpreted as sensorimotor activation and subsequent return to an "idling" or inhibited state (Klimesch et al., 2007; Neuper et al., 2006; Peter et al., 2022). Studies have emphasized that both alpha and beta frequency reflect flexible top-down control, error evaluation, and maintenance of current sensorimotor or cognitive sets rather than simple motor engagement (Jahani et al., 2020; Mariman et al., 2023; Peter et al., 2022). Crucially, in the present task, alpha and beta ERS modulation were contingent on the movement, thus, consistent with recent findings (Sacheli et al., 2026), alpha synchronization may index a task-dependent state and an interaction-oriented processing mode that supports sustained monitoring of externally generated temporal information during continuous coordination.

Interestingly, different neural patterns emerged in relation to the behavioral dynamics of the participants – whether taps occurred pre or post-tones – which were modulated by the VP's temporal adaptivity during the interaction. Specifically, during taps pre-tones, neural differences between conditions showed fronto-central alpha and beta ERS time-locked to the tapping event, resembling auditory-evoked activity rather than purely motor-evoked activity. We speculate that this corresponds to temporal predictions of the upcoming auditory stimulus (i.e., the tone from the VP). When participants tended to anticipate the other, the higher ERS, and hence higher inhibition, likely reflects lowered sensory prediction of the upcoming tone. ERS was higher when the VP

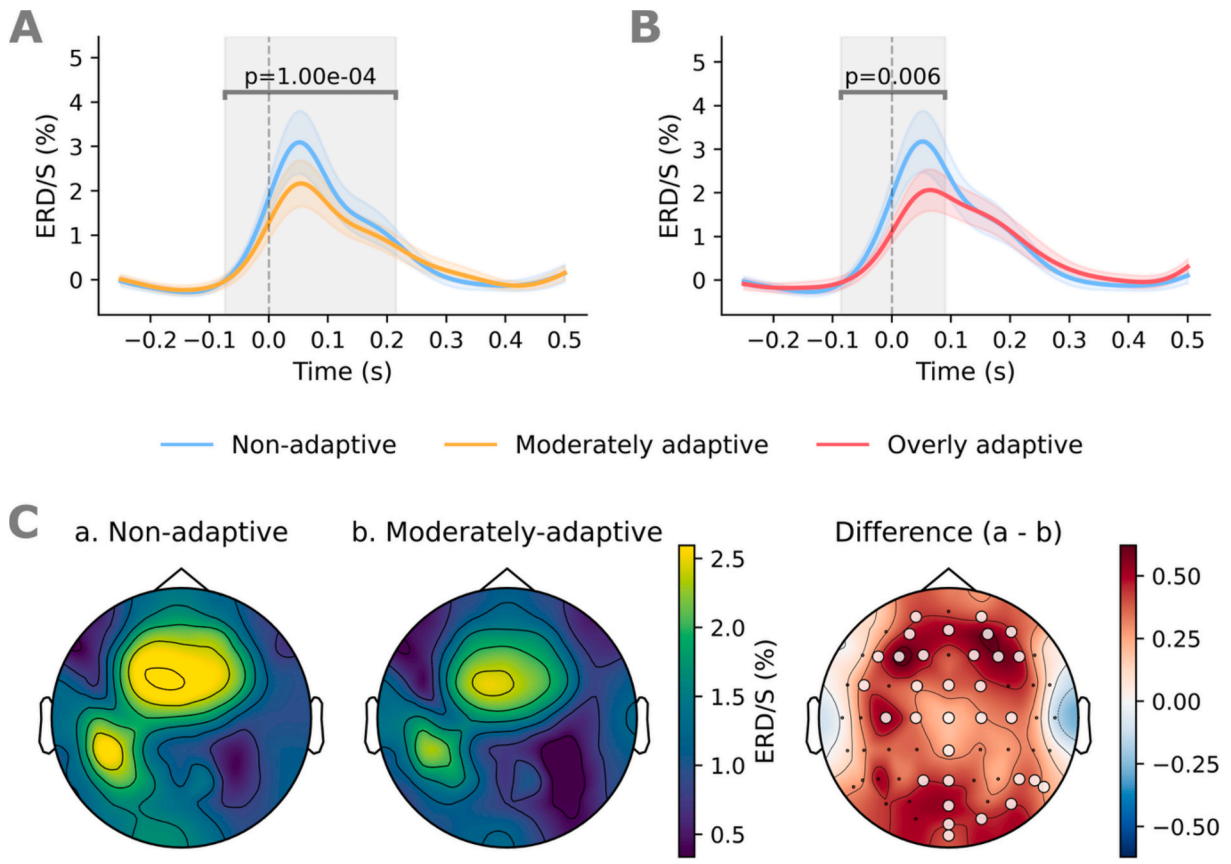


Fig. 4. Spatio-temporal cluster permutation test results in the alpha band, centered around taps pre-tones. **(A)** and **(C)** show one cluster where a significant difference was found between non-adaptive and moderately adaptive ERS in the time interval from −0.07 to 0.21 s. **(B)** Average ERD/ERS curves for a separate cluster corresponding to significant differences between non-adaptive and overly adaptive trials in the time interval from −0.08 to 0.09 s. The electrodes in the cluster are located in central and frontal regions (see Fig. S1 in the supplementary materials).

was non-adaptive and thus probably more difficult to predict, suggesting that participants may have disengaged more during interactions with a non-adaptive VP. Meanwhile, with an adaptive VP, lower ERS corresponds to less inhibition and, hence, potentially greater prediction of the other, compared to when the partner is non-adaptive. This aligns with the view that sensorimotor control relies on adaptive internal models to predict sensory outcomes and reduce prediction error, with the adaptivity of the VP shaping this process (Shadmehr et al., 2010; Wallach & Sawtell, 2023; Harry et al., 2023). In addition, this result is consistent with strengthened inhibitory gating and the maintenance of a robust internal model that shields predictive processes from unreliable external feedback (Jenson et al., 2014; Klimesch et al., 2007).

Conversely, when the participants tapped post-tones, resulting in positive asynchrony, such inhibition was observed over motor areas (contralateral to the moving hand) and was higher when the partner was more adaptive, but only in the alpha band. In this case, stronger inhibition in the alpha band can be interpreted as a strategic mechanism to hold back their own impulses and try to stay aligned with the other's behavior. Beta/alpha ERS and corticospinal inhibition are often linked to maintaining the current motor set, motor suppression, and preventing premature responses (Heinrichs-Graham et al., 2017; Hervault et al., 2021; Peter et al., 2022; Rhodes et al., 2024; Zhang et al., 2008; Zhang et al., 2024).

Given that taps pre-tones were associated with auditory-like neural responses, whereas the taps post-tones were associated with motor-like responses, we speculate that this reflects distinct neural mechanisms. For instance, neural activity corresponding to taps pre-tones indicates that participants make predictions of the upcoming auditory stimuli, and that these predictions are more inhibited when interacting with non-adaptive, and hence less predictable VP. Conversely, neural activity corresponding to taps post-tones indicates that participants are actively engaging motor-related areas, which are more inhibited when interacting with the VP when it is more adaptive – potentially reflecting higher self-inhibition. We speculate that this reflects a balance between self- and other-processing, with individuals focusing more on predicting the other and inhibiting the self when the other is responsive and also more predictable.

In addition, looking at the associations between asynchrony and ERS, we found that reduced alpha ERS over the fronto-midline regions, typically related to the processing of auditory sounds or social feedback, was associated with lower asynchrony regardless of the interactive conditions. This suggests that alpha ERS might be as a potential neural marker of temporal predictions of upcoming stimuli, which when disinhibited, facilitate better sensorimotor coordination.

Overall, these results highlight that the role of inhibition is also tuned by the partner's characteristics. Cardellicchio et al. (2020) and Dolfini et al. (2024) have revealed that slow corticospinal inhibition scales with partner predictability and supports online mutual co-adaptation (Cardellicchio et al., 2020; Dolfini et al., 2024). Combining this with our evidence, we could speculate that when a partner is reliable and adaptive, the system can form a strong predictive model of the partner's behavior and then upregulate inhibition to stabilize one's own motor output around those predictions, minimizing self-generated variability that in turn could disrupt synchrony (Cardellicchio et al., 2020; Dolfini et al., 2024; Sabu et al., 2020; Vescovo et al., 2024). This also fits with studies showing that, in joint action, dyadic motor plans and shared-goal representations shift control from self-driven execution toward prediction-based monitoring of the partner, with

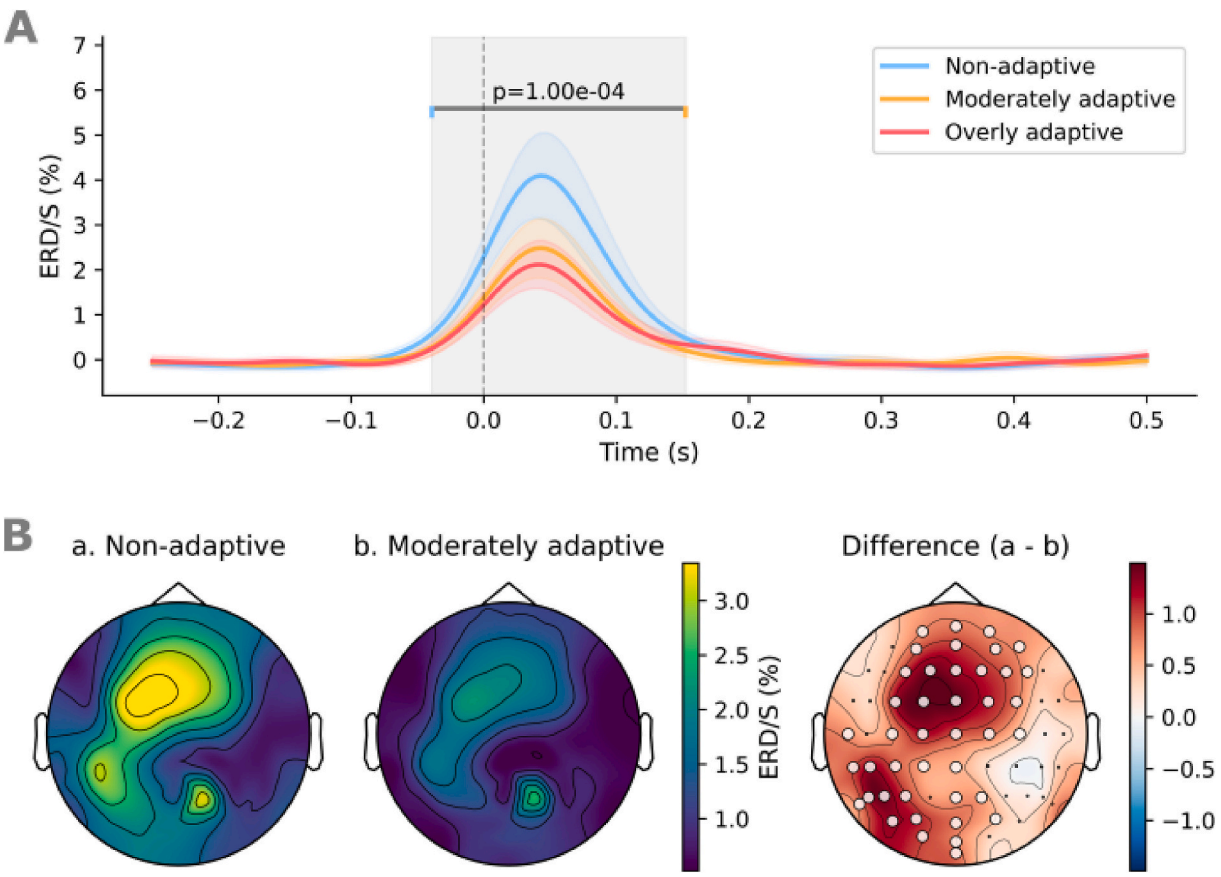


Fig. 5. Spatio-temporal cluster permutation test results in the beta band, centered around taps pre-tones, showing significant differences between non-adaptive and moderately adaptive conditions. **(A)** The cluster corresponds to the time segment from − 0.03 to 0.15 s.**(B)** Spatially, the cluster includes electrodes in the central-frontal and left central-parietal regions.

inhibitory mechanisms helping to suppress automatic imitation or self-initiated deviations that would break coordination (Sacheli et al., 2015; Sacheli, Tieri, et al., 2018; Rocca et al., 2023). Thus, lower inhibition of the other and higher inhibition of the self with an adaptive partner could be considered a hallmark of prediction-based processes, suggesting that the more predictable the other is, the more one's own impulses could be restrained to optimally track the other, while more resources are allocated to temporal prediction of the other.

Taken together, these results reveal that ERS, defined as an index of inhibition, might be modulated in relation to how the partner's action is processed and the characteristics of the other's action. Moreover, the inhibitory process appears to reflect a deeper mechanism related to self–other processing during shared interaction. The novelty of our findings lies in showing that the inhibitory process associated with action or movement and the prediction of social and sensory signals scales with the amount of reciprocal adaptation, which consequently modulates the amount of coordination achieved. By examining individual behavior in terms of anticipation (taps pre-tones) versus following (taps post-tones), we observed that anticipation processes exhibited greater auditory inhibition when interacting with a less adaptive VP. In contrast, when the taps followed the VP's response, greater motor inhibition was observed when the VP was more adaptive. Crucially, this pattern aligns with current accounts of self–other processing dynamics (Heggli et al., 2019; Liebermann-Jordanidis et al., 2021), coherently with higher self-other integration when interacting with adaptive partners, and more self-focus when interacting with non-adaptive, and hence unpredictable partners (Heggli et al., 2019). Prior studies have shown that accurate joint performance benefits from a dynamic trade-off between self–other integration and segregation, with alpha power indexing shifts along this continuum (Liebermann-Jordanidis et al., 2021; Novembre et al., 2016). Excessive reliance on internally generated predictions — reflected in heightened ERS — may stabilize one's own action plan at the expense of interpersonal attunement, echoing findings that enhanced alpha/beta power can mark self-other segregation and reduced entrainment when internal models dominate over external cues (Marques et al., 2022; Novembre et al., 2016). Thus, motor inhibition emerges as a key neurocognitive mechanism that constrains the construction of shared temporal alignment, complementing evidence that inter- and intra-brain beta dynamics pace both self-generated and partner-generated movements during synchronization (Rosso et al., 2022; Wikström et al., 2022). By integrating behavioral dynamics and neural oscillatory markers, the present study advances a mechanistic understanding of how the brain can cope with the tension between self-stability and interpersonal adaptivity during real-time interaction (De Vicariis et al., 2024; Mayo & Shamay-Tsoory, 2024; Pesquita et al., 2018; Sebanz & Knoblich, 2021; Heggli et al., 2019).

Despite the novelty of these results, they should be interpreted in light of several limitations. First, the present study relied on a single-brain EEG approach, preventing direct examination of inter-brain dynamics during joint action. Future studies employing dual-EEG paradigms would allow investigation of cross-brain phase coupling, directionality of influence, and whether oscillatory inhibition at the individual level scales with dyadic neural entrainment. Second, although the analyses were specifically designed to minimize overlap between tap-related and auditory-evoked activity by locking the ERS analysis to the taps, which occurred at different times either before or after the tones, some residual contribution of auditory processing to the tap-locked signals cannot be entirely excluded, given that the sound produced by the keyboard upon tapping may not have been fully shielded by the earphones. Third, the interactive partner consisted of an

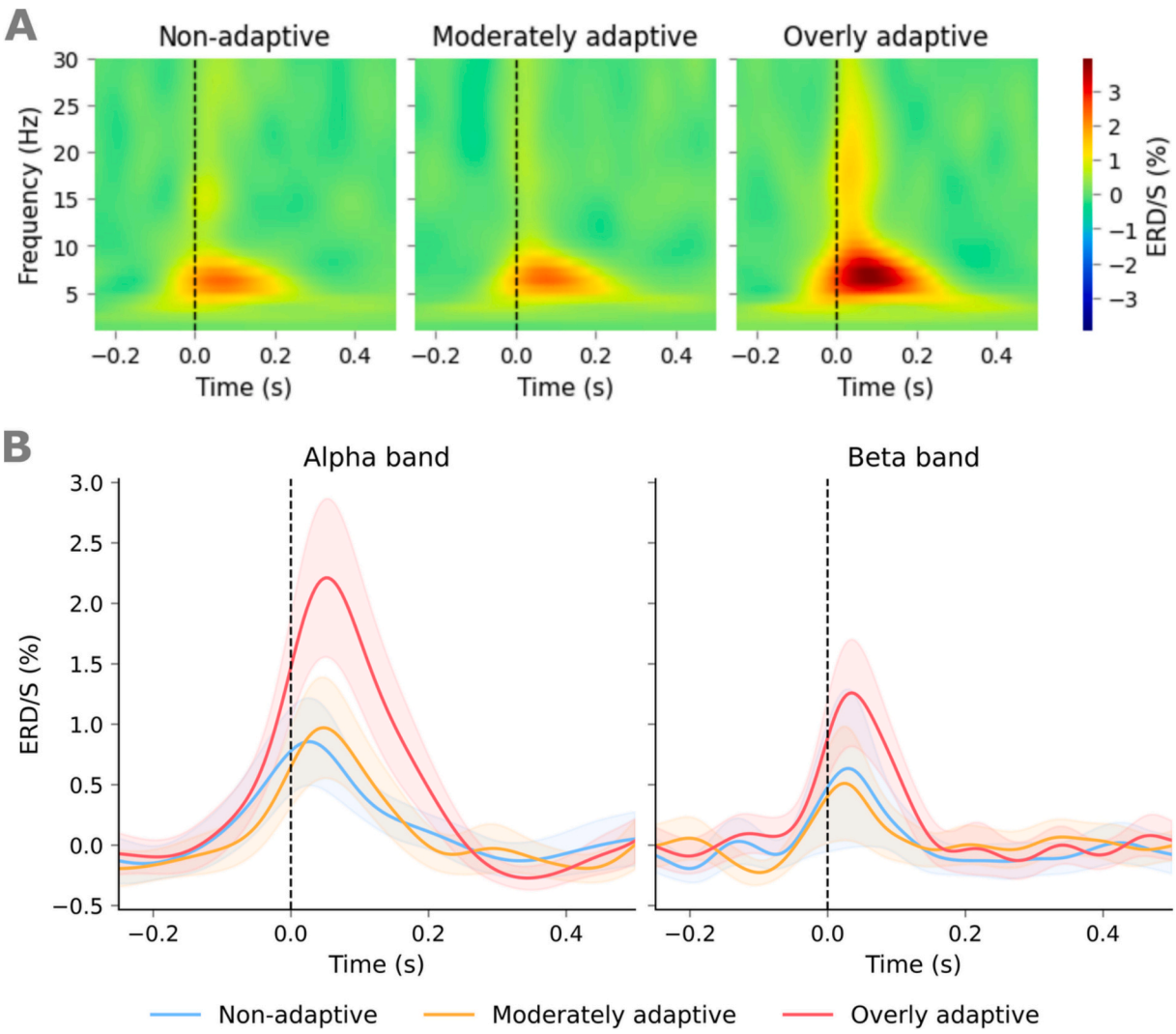


Fig. 6. **(A)** Evoked time-frequency representations during taps post-tones for different adaptation levels in a central-left ROI (averaged over channels C3, C5, CP3, CP5) and respective **(B)** band-averaged ERD/ERS curves.

artificial adaptive sound sequence rather than a human agent. While this manipulation ensured high experimental control over temporal adaptivity, it necessarily reduced the social and intentional dimensions of the interaction. Human–human coordination involves mentalizing processes, attribution of agency, and dynamic mutual prediction that may recruit additional neural systems beyond those engaged by algorithmic regularities. Moreover, we used the keyboard as a response device, so slight timing variability (~1–10 ms) should be taken into account. Finally, the present paradigm specifically isolates temporal aspects of interpersonal coordination within a sensorimotor synchronization framework. Although this approach enables precise investigation of interpersonal timing and adaptive error-correction mechanisms, it does not capture broader dimensions of joint action such as spatial coordination, complementary action planning, or fully shared task goals (Sebanz et al., 2006). Therefore, the present findings should be interpreted primarily in relation to temporal interpersonal coupling during sensorimotor coordination rather than complex social interaction more generally.

Future research is encouraged to test whether similar oscillatory signatures emerge when interacting with real human partners or humanoid agents capable of conveying communicative cues. Combining dual-EEG hyperscanning with manipulated partner predictability would clarify whether motor inhibition and predictive stabilization generalize to ecologically valid social contexts. More broadly, integrating these neural measures with computational modeling of mutual prediction could elucidate whether alpha–beta ERS reflects stabilization of internal models, regulation of self–other processing, or dynamic weighting of partner-related prediction errors. Such approaches would allow a more mechanistic understanding of how oscillatory inhibition contributes to the negotiation between self-stability and interpersonal adaptivity during real-time interaction.

6. Conclusion

In conclusion, these findings can extend previous accounts of joint action by linking partner adaptivity, behavioral coordination, and neural oscillatory dynamics. Increasing adaptivity of the VP modulates asynchrony, with interactions with more adaptive partners leading to lower asynchrony, while moderate level adaptation of the partner leads to the most stable coordination patterns. Crucially, evoked alpha- and beta-band ERS over fronto-central and central sites indexed how the system resolved the trade-off between stabilizing internal timing models and flexibly incorporating social feedback. Increased fronto-midline ERS was associated with poorer synchrony, suggesting stronger inhibition of sensory predictions when interacting with non-adaptive, and unpredictable partners. At the same time, condition-specific ERS patterns in taps pre-tones versus taps post-tones indicate that the same oscillatory mechanism can support both the temporal prediction of the timing of

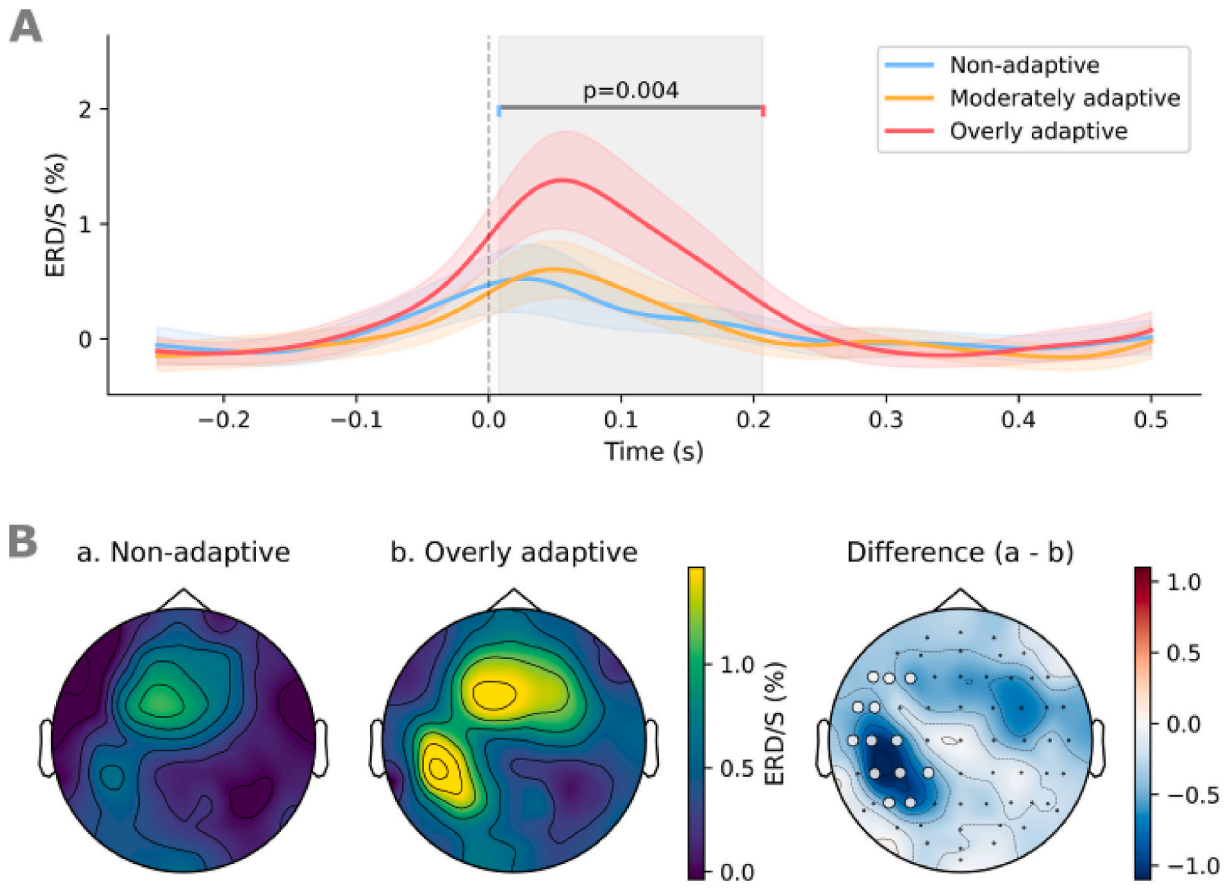


Fig. 7. Spatio-temporal cluster permutation test results in the alpha band, centered around taps post-tones. **(A)** The cluster captures significant differences between non-adaptive and overly adaptive conditions in the segment from 0.008 to 0.21 s. **(B)** The cluster includes electrodes in the central-leftarea.

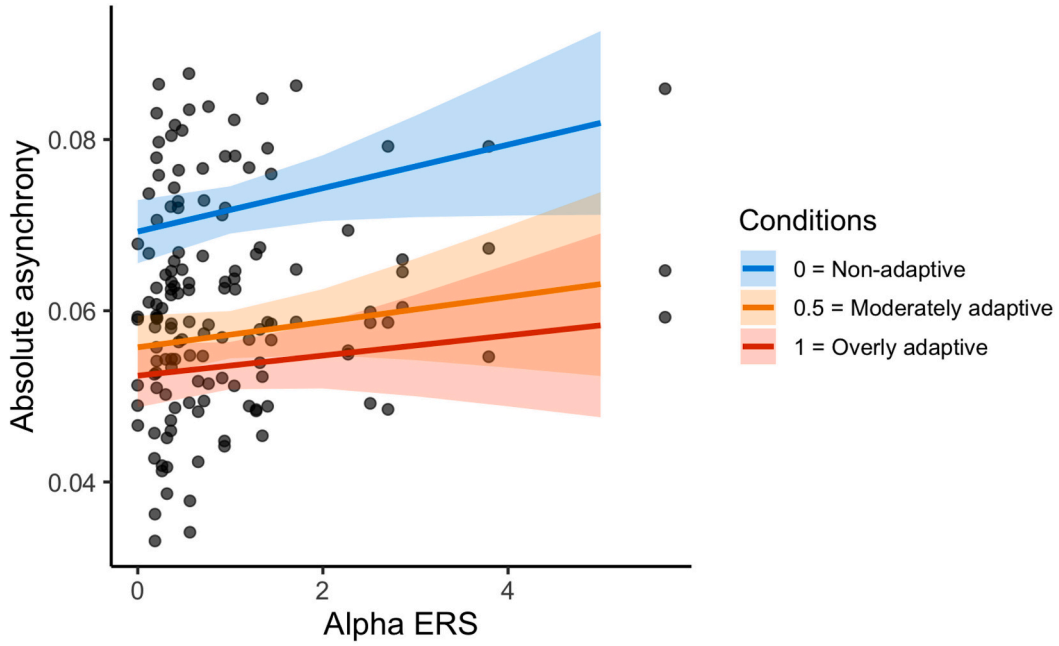


Fig. 8. Visualization of the main effect of alpha ERS on absolute asynchrony, shown separately for each of the conditions. There was no significant conditions x alpha ERS interaction. Shaded areas represent 95% confidence intervals for the mean point estimates.

Table 2
Results of GLMMs using absolute asynchrony as the dependent variable for Model 1: conditions and alpha ERS over the fronto-midline region as the fixed effects; Model 2: conditions, alpha ERS, and conditions x alpha ERS as fixed effects.

	Absolute asynchrony			
	Model 1		Model 2	
	β	*p*	β	*p*
Fixed Effects				
Non-adaptive	-2.69	< 0.001	−2.67	< 0.001
Moderately adaptive	−0.23	< 0.001	−0.26	<0.001
Overly adaptive	−0.29	<0.001	−0.33	<0.001
ERS	0.03	< 0.001	0.01	0.54
Moderately adaptive*ERS			0.02	0.44
Overly adaptive*ERS			0.02	0.34
LogLik.	509.3		510.1	
AIC	−1006.7		−1004.2	
Model comparison	$x^2 = 1.49$, $p = 0.47$			

Note: Model 1 = main effect of conditions and alpha ERS; Model 2 = Model 1 + interaction between condition and alpha ERS. β = Standardized parameter estimates.

social partners and the maintenance of one's own motor responses. Together, these results highlight alpha and beta oscillations as candidate mechanisms through which the brain dynamically respond to self- versus other-derived actions and predictions during joint action.

CRediT authorship contribution statement

Camilla Gregorini: Writing – review & editing, Writing – original draft, Software, Project administration, Formal analysis, Data curation, Conceptualization, Visualization. **Mario Medoni:** Visualization, Software, Formal analysis, Data curation. **Anna Zamm:** Writing – review & editing, Validation, Methodology. **Marco Petilli:** Writing – review & editing, Validation, Software. **Arianna Schiano Lomoriello:** Writing – review & editing, Supervision. **Ivana Konvalinka:** Writing – review & editing, Writing – original draft, Visualization, Validation, Supervision, Project administration, Methodology, Investigation, Funding acquisition, Formal analysis, Data curation.

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Declaration of competing interest

The authors declare no conflicts of interest.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.actpsy.2026.107679.

Data availability

Data will be made available on request.

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