

Research paper



Interpersonal synchronization in face-to-face vs. remote education: An EEG and ECG hyperscanning study

Michela Balconi^{a,b}, Katia Rovelli^{a,b}, Giulia Magni^{c,d,*}, Luana Amadini Genovese^{c,d},
Maurizio Mauri^e, Elena Sajno^{d,j}, Maria Sansoni^{c,d}, Stefano De Gaspari^{d,f}, Silvia Serino^g,
Daniele Di Lernia^{h,i}, Laura Angioletti^{a,b}, Allegrretta Roberta A.^{a,b}, Giuseppe Riva^{d,i}

^a International research center for Cognitive Applied Neuroscience (IrcCAN), Università Cattolica del Sacro Cuore, Milan, Italy

^b Research Unit in Affective and Social Neuroscience, Department of Psychology, Università Cattolica del Sacro Cuore, Milan, Italy

^c Department of Psychology, Catholic University of the Sacred Heart, Largo Gemelli, 1, Milan 20121, Italy

^d Humane Technology Lab, Catholic University of the Sacred Heart, Largo Gemelli, 1, Milan 20121, Italy

^e Research Center in Communication Psychology (PSICOM), Catholic University of Sacred Heart, Milan, Italy

^f Department of Computer Science, University of Pisa, Largo B. Pontecorvo, 3, Pisa 56127, Italy

^g Department of Psychology, University of Milano-Bicocca, Milan, Italy

^h Department of Theoretical and Applied Sciences, eCampus University, Novedrate, Italy

ⁱ Applied Technology for Neuro-Psychology Laboratory, IRCSS Istituto Auxologico Italiano, Via Magnasco 2, Milan 20149, Italy

^j Department of Computer Science, Università Degli Studi di Milano, 18, via Celoria, Milan, 20133, Italy

ARTICLE INFO

Keywords:

Education
Remote learning
Face-to-face learning
Interpersonal synchronization
Hyperscanning
Psychophysiology
Educational neuroscience

ABSTRACT

Background and aims: Interpersonal synchronization is a key component of effective teaching and learning, but little is known about how it differs between face-to-face and remote settings. This study investigates interpersonal synchronization in face-to-face (FTF) versus remote learning (RL) environments through electroencephalography (EEG) and electrocardiography (ECG) hyperscanning.

Methods: Eight groups of 3 students and 1 lecturer ($N = 32$) engaged in both conditions, consisting of a baseline, a 20-minute lecture, and a 20-minute interactive task. Neural synchronization was assessed using inter-individual Euclidean Distance (EuDist) across five EEG frequency bands (delta, theta, alpha, beta, gamma). Cardiac synchronization was assessed via intersubject correlation of heart rate (ISC—HR). Learning outcomes and perception were measured through a series of self-report measures and validated questionnaires.

Results: Results revealed a modest but significant effect of learning condition across all EEG bands, with significantly lower EuDist values in the FTF condition compared to RL, indicating higher inter-individual neural alignment when participants were physically co-present. Additionally, task-specific effects emerged in delta, theta, beta, and gamma bands, with interactive tasks generally associated with lower dissimilarity. Furthermore, ISC—HR was significantly higher in the FTF condition compared to the RL condition, while no significant task-specific differences emerged. Self-report measures further indicated higher perceived interpersonal closeness and lesson satisfaction in the FTF condition, while learning outcomes remained stable across modalities.

Conclusion: These findings demonstrate that physical co-presence enhances both cortical and autonomic synchronization during instruction, particularly under dialogic conditions, and underscore the role of embodied interaction in promoting shared cognitive and affective engagement in educational contexts.

1. Introduction

The educational landscape has faced a transformation led by the advent of technology-mediated learning, specifically in the context of remote learning [1]. This shift to online education was accelerated by

the COVID-19 pandemic, which has provoked significant interest in understanding the differences between traditional in-person education and distance learning modalities [2]. Consequently, research has shown an increased interest in investigating the implications of the latter on students' performance, interpersonal synchronization, and the overall

* Corresponding author.

E-mail address: giulia.magni@unicatt.it (G. Magni).

<https://doi.org/10.1016/j.tine.2026.100281>

Received 1 October 2025; Received in revised form 17 December 2025; Accepted 23 February 2026

Available online 24 February 2026

2211-9493/© 2026 The Authors. Published by Elsevier GmbH. This is an open access article under the CC BY license (<http://creativecommons.org/licenses/by/4.0/>).

educational experience. As educational institutions worldwide rapidly transitioned to online learning, the strengths and limitations of technology-mediated learning became more apparent [3,4]. While some studies emphasize the challenges associated with distance education, such as more anxiety and reduced motivation [5,6], others point to the opportunity for innovative teaching practices and improved accessibility [7–9]. In courses supported by adequate technological infrastructure, students appear to be positively impacted by the characteristics of flexibility and accessibility [10–12]. Nonetheless, challenges such as limited access to technology, health concerns related to extensive computer use, and reduced interpersonal interaction persist [13–16]. Despite these issues, distance learning facilitates access to education by removing traditional constraints related to time and place [17,18].

These developments prompt critical inquiries regarding the optimal implementation of e-learning and question its efficacy as a universally successful educational strategy [19]. Among the possibilities to reduce the gap between the two learning modalities, it is important to consider interpersonal synchronization, which is a critical aspect of the learning process and refers to the tendency of individuals to attune and align their physiological and behavioral states while interacting with each other [20]. According to predictive processing and interactive alignment models, synchrony emerges when individuals can continuously update their internal predictions based on temporally contingent cues from others [21,22]. Theory of collective mind further suggests that when information arrives synchronously to a group, individuals are more likely to represent their mental states as shared, which amplifies relational bonds and cooperative behavior [23]. In educational settings, co-experienced information in the classroom may support a unified collective mind among students and instructors, facilitating joint coordinated attention and shared representations. However, video-mediated communication is thought to weaken these contingency loops by degrading the fine-grained temporal and multimodal information essential for coordinating attention and shared experiences [24,25]. In the same direction, the disembodied disconnect hypothesis posits that digital platforms down-regulate “we-mode” processes (i.e., behavioral and physiological synchronization, shared attention, emotional attunement), which are considered foundational for interpersonal bonding and the development of collective identities. Taken together, these disruptions may have measurable consequences for learning, impacting social presence and immediacy as well as cognitive load [26,27].

Therefore, overall face-to-face (FTF) learning environments are thought to promote greater interpersonal synchronization due to the real-time interactions and enhanced social presence [28,29]. In contrast, online platforms allow students to reflect on their contributions before responding, which can foster more thoughtful and well-articulated interactions and, consequently, lead to an enhanced quality of discussions and deeper learning [30]. Additionally, the flexibility of remote learning (RL) can accommodate diverse communication styles, allowing students to engage in ways that feel most comfortable to them [31]. Ultimately, while some studies suggest that online learning can be as effective as traditional FTF learning [32], others highlight the importance of considering factors such as instructional strategies and learning environments [33,34].

While FTF settings provide richer social presence and more immediate, multimodal feedback, flexibility and accessibility offered by RL are a strong asset [35,36]. Existing research shows mixed outcomes for both modalities, suggesting that their effectiveness depends on a variety of factors such as instructional design, teacher behavior, and student engagement [37–39]. Understanding the underlying neurocognitive mechanisms becomes therefore crucial for explaining when and why such modalities can support learning more effectively.

From a neurocognitive perspective, the interactive dynamics between the educators and students remain an essential yet underexplored area of research. Early research has examined neurophysiological markers in learning settings [40,41], emphasizing that such interactions

are central for enhancing the learning process and engagement [42]. While traditional FTF communication naturally supports these dynamics through non-verbal cues (e.g., body movements and facial expressions), RL environments present significant obstacles. Importantly, in synchronous video-mediated environments, non-verbal information is substantially degraded, though not completely absent. Limited camera framing, reduced resolution, frame-rate variability, compression artifacts, and latency alter the richness and timing of facial expressions, gestures, and posture [43]. These qualitative degradations interfere with the natural temporal contingencies that sustain interpersonal synchrony during learning [44]. Consistent with this view, recent neuroimaging work comparing live “in-person” faces with visually matched “Zoom-like” faces has shown that social context matters, even when the visual features of the partner’s face are controlled [45]. Indeed, the overall findings suggest that FTF encounters uniquely engage neural mechanisms that support interpersonal synchrony and shared attention compared to video-mediated communication.

This disruption may impact learners’ cognitive engagement and weaken their emotional connection and sense of co-presence with the instructor and peers [46]. Consequently, video-mediated communication may require greater neural resources to integrate fragmented cues and maintain shared attention, thereby increasing cognitive load compared to face-to-face interaction [47].

According to the theory of collective mind, proposed by Shteynberg and colleagues [23], shared stimuli tend to foster a unified mental state in groups of individuals with convergent experiences. In FTF environments, this synchronous experience helps strengthen relational bonds and enhances cooperative behaviors, fostering and reinforcing interpersonal synchronization. In contrast, RL environments may lack the immediacy of real-time, co-experienced stimuli, resulting in less intense cognitive and emotional alignment between students and educators.

Despite a need for holistic approaches to study learning processes, multidisciplinary approaches that integrate educational psychology and pedagogy with evidence-based support from cognitive neuroscience remain rare [48,49]. Recent neuroscientific studies have explored asynchronous learning [50], lifestyle influences [51], and feedback dynamics for the education process [52]. In this context, hyperscanning (i.e., the simultaneous acquisition of neurophysiological data from two or more individuals engaged in a shared activity) has emerged as a highly informative methodological approach for investigating inter-individual coupling during social and cognitive interaction [53]. Among the diverse analytical approaches adopted within the hyperscanning framework, the computation of Euclidean Distances (EuDist) applied to normalized power spectral density (PSD) values constitutes a robust, non-directional metric of inter-individual neural dissimilarity. This index enables a fine-grained quantification of divergences in oscillatory cortical dynamics across distinct frequency bands, thereby providing insight into the degree of neural decoupling between interacting individuals [54–56].

Recent empirical evidence has underscored the frequency-specific sensitivity of EuDist metrics in capturing functionally distinct neurocognitive processes. Increased EuDist in the delta and theta bands has been linked to interpersonal divergence in processes related to attentional allocation, motivational salience, and the encoding of temporally extended information streams, dimensions critically involved in didactic and instructional settings [57,58]. Alpha-band activity, often interpreted as a marker of top-down inhibition and mental effort regulation, shows intersubjective desynchronization patterns that may reflect differential responsivity to task-relevant stimuli [59]. At higher frequencies, beta and gamma rhythms are associated with executive integration, semantic elaboration, and error-monitoring processes, which are typically mobilized during dialogic reasoning and collaborative problem-solving. Within this framework, the magnitude of EuDist across spectral topographies serves as a sensitive index of cognitive and attentional alignment – or misalignment – between individuals engaged in joint task execution, offering a window onto the dynamic interplay of

shared and divergent processing during educational interaction [60–62].

In addition to EEG, autonomic measurements such as heart rate variability (HRV) can indicate interpersonal physiological synchronization [63]. Prior studies have shown synchronized HRV in emotionally charged interactions [64], group performances [65,66], and in-person social interactions [67,68]. Fewer studies have applied this method to asynchronous contexts [69,70], although promising findings exist [71]. Within this framework, autonomic synchrony offers a complementary index to EEG-based metrics, reflecting the dynamic regulation of shared arousal states, affective alignment, and co-regulatory processes, critically involved in maintaining interactional stability and enhancing pedagogical experience over time.

Despite the methodological relevance of this multimodal framework, the use of hyperscanning-derived indices within educational research remains underexplored, not only concerning systematic comparisons between FTF and RL conditions, but also across distinct instructional formats. Existing studies have largely concentrated on dyadic exchanges or static paradigms, often neglecting how varying pedagogical structures, such as expository instruction (frontal lecture) versus collaborative problem-solving (group-based interactive task), modulate the dynamics of neurophysiological alignment [72,73]. Addressing this gap, the present study combines EEG-based EuDist metrics with ECG-derived intersubject correlation of heart rate (i.e. ISC—HR), offering a multi-level characterization of interpersonal synchronization across both passive and dialogic learning phases within ecologically grounded educational scenarios.

Specifically, we hypothesized that:

- FTF classes will induce higher inter-individual neural alignment, as indexed by lower EuDist values across EEG frequency bands, relative to the RL condition. This effect was expected to manifest particularly in the delta and theta bands, which are sensitive to attentional and motivational synchronization, as well as in the beta and gamma bands, which reflect higher-order integrative and executive processes. Moreover, task-related modulation was anticipated, with the interactive phase promoting enhanced synchrony compared to the lecture phase, due to its dialogic and co-regulated structure.
- FTF classes will promote stronger autonomic synchronization compared to the RL condition, measured by intersubject correlation indexes.

2. Methodology

2.1. Participants

A total of 25 unique participants took part in the study. Specifically, 24 students (13 female, $M_{\text{age}}=25.75$, $SD=3.08$) were divided into the eight groups, while the same lecturer (male, aged 46) conducted all sessions in order to account for variability in teaching style. The allocation to groups was randomized, in order to control previous acquaintances between participants, and all groups were maintained the same for both conditions. In order to control for familiarity with the group in the second session, the order of the conditions was counterbalanced (i.e., half of the groups started with the FTF condition, while the other half started with the RL condition).

Due to personal reasons, two students completed only one of the two conditions; however, they were included in the analyses within the available condition.

Sample size calculation was determined using G*Power software (v. 3.1.9.7) for a repeated-measures ANOVA model (baseline, lecture, interactive task). Based on previous observations, we assumed an alpha error probability of 0.05, power of 0.9, an effect size of 0.25, and an inter-measurement correlation of 0.65. The estimated minimum sample size calculated was equivalent to 26 participants. Inclusion criteria for study enrolment were: (a) being older than 18 years, (b) being proficient

in the language used for activities (i.e., Italian), (c) lacking prior acquaintance with the other participants (i.e., neither the teacher nor fellow students), (d) having joined classes (e.g., university, professional courses, etc.) within the past two-year period, (e) being right-handed, (f) having normal or corrected-to-normal hearing and visual abilities, (g) absence of medical history of burnout in the previous 6 months and (h) absence of medical or neurological, psychomotor and psychiatric conditions that could potentially interfere with EEG or ECG assessments (e.g., epilepsy, cardiac disorders) and with tasks.

The study received approval from the Ethics Committee of the Catholic University of the Sacred Heart, Milan, in May 2022 (approval code: 18/22 “*I meccanismi di sincronizzazione neurale interpersonale nella didattica in presenza e a distanza: uno studio EEG con tecnica hyperscanning*”).

2.2. Procedure and materials

The study employed a 3 (task: baseline, lecture, interactive task) x 2 (condition: FTF vs. RL) within-subjects design (Fig. 1).

2.2.1. Preliminary assessment

As stated in the previous section, all participants took part in both experimental conditions (i.e., RL and FTF) on two consecutive days, with the order of condition administration fully counterbalanced across the sample to control for potential sequence effects.

Each experimental session involved four participants (i.e. 3 students, 1 lecturer) and was conducted in a controlled laboratory setting.

Upon arrival, participants were individually welcomed and seated in a sound-attenuated room with stable lighting and temperature conditions. After being briefly introduced to the general aims of the study, they were informed of their rights as research participants, including the right to withdraw at any time without justifying, and were asked to sign the informed consent form.

Participants then completed a brief sociodemographic survey (age and gender), in order to collect data on general characteristics of the sample.

2.2.2. Experimental task

Following this pre-experimental phase, the research team fitted each participant with a 32-channel EEG cap, as well as ECG sensors for peripheral physiological monitoring. Signal quality was continuously monitored by a trained experimenter throughout the session.

The experimental session began with a 4-minute baseline recording (2 min eyes closed, 2 min eyes open). Participants then engaged in one of the two experimental conditions (RL or FTF). In the RL condition, students attended the lesson using iPads while seated in individual rooms. The visual field was constrained not to prevent mutual observation, as participants were already physically separated, but to eliminate extraneous visual stimuli (e.g., laboratory furniture, passing staff, equipment) and to standardize the visual experience across participants. This ensured that any differences in neural or physiological responses reflected the learning modality rather than environmental variability. The Skype interface was configured so that students could see only the lecturer’s video feed and the lecture slides. Students did not see each other, and the self-view window was disabled to minimise distraction and ensure uniformity across participants. In the FTF condition, the lecturer and the three students were seated at a standardized interpersonal distance of approximately 1.5 m, and this distance was kept identical across sessions and across all groups. Participants were arranged in a semicircle facing the lecturer to ensure equal visibility and comparable auditory access, while maintaining consistent social spacing across all groups.

The lesson structure was identical across conditions and consisted of two segments lasting 20 min each: (i) an instructional presentation by the lecturer (i.e. “lecture”), followed by (ii) a guided group discussion (i.e. “interactive task”). Although the educational content of the two sessions was not identical, both lessons focused on the same subject area to

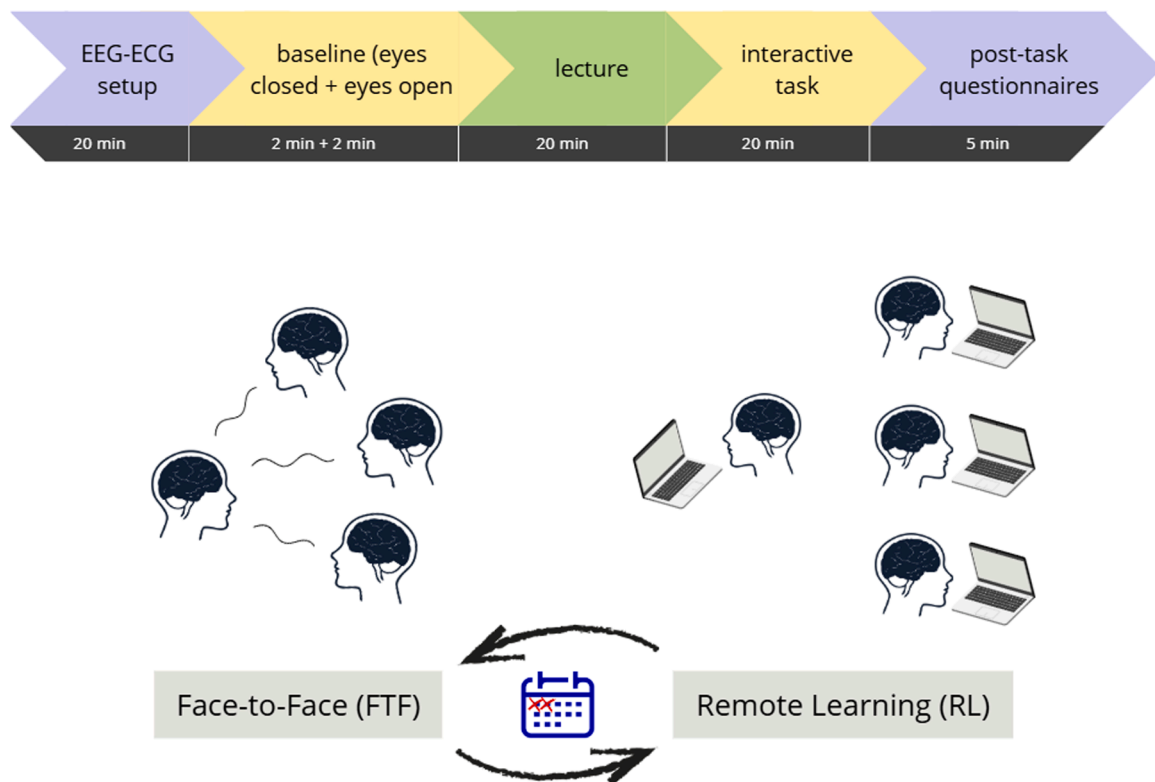


Fig. 1. Overview of experimental procedure and study design. Each session included a 20-minute EEG and ECG setup phase, followed by a 4-minute resting baseline (2 min eyes closed + 2 min eyes open), a 20-minute lecture, a 20-minute interactive task, and 5 min allocated for post-task questionnaires. The same protocol was carried out under two conditions: FTF, where all participants and the lecturer were present in the same physical space, and RL, where the session was conducted via Skype. Each participant completed both conditions across two consecutive days, in a counterbalanced order. EEG and ECG data were recorded throughout all experimental phases in both modalities.

ensure comparability. The instructor prepared two versions of the lesson that addressed the same topic and had similar complexity, length, and conceptual structure. This approach exposed participants to new, thematically equivalent content in both conditions, thus avoiding the effects of prior knowledge while maintaining ecological validity.

After each lesson, students participated in a problem-solving activity in which they collaboratively analyzed a short case study related to the lesson topic, discussing possible interpretations and solutions. This task was designed to stimulate joint reasoning, turn-taking, and dialogic exchange, using an identical structure and only differing in the mode of delivery (FTF vs RL). The total lesson duration was 40 min. For methodological and pedagogical reasons, the order of instructional segments remained fixed across sessions. Presenting the interactive task before the lecture would have created an asymmetrical cognitive structure because students would have been required to solve the task without first receiving the necessary content. Maintaining a lecture-first structure ensured ecological validity by reflecting the typical organization of university teaching.

2.2.3. Post-task evaluation

At the end of each session, the recording equipment (i.e., EEG and ECG) was removed, and participants completed a series of post-experiment measures. These included the Post-Experiment Satisfaction Questionnaire (PSQ), administered after each condition following the procedure outlined by Bevilacqua et al. [72], which comprised four Likert-scale items evaluating satisfaction, attention, and interest in the lesson.

Participants also completed the Inclusion of Other in Self (IOS) scale [74], which was administered to evaluate perceived closeness to the teacher after the experimental task, using a series of increasingly overlapping circle pairs from which participants selected the one that best

represented their sense of interpersonal closeness.

Finally, a Knowledge Evaluation Questionnaire (KEQ) was used to assess lesson-related learning outcomes through a content-specific checklist. This was composed of five questions concerning the topics covered in class, which required the participant to choose the correct answer out of four options. The questions were prepared by the teacher, in order to assure a coherence between what was explained and what was subsequently asked and then checked by the experimenters to assess the feasibility.

Each session concluded with a brief debriefing, during which the study's aims were further explained and any questions from the participants were addressed. Participants were then dismissed and provided with the research team's contact information for any subsequent inquiries.

2.3. EEG: Data acquisition and processing

EEG signals were continuously acquired throughout the baseline and task phases using a 28-channel direct current amplifier (SYNAMPS; Compumedics Neuroscan), operating in conjunction with the NEUROSCAN 4.2 acquisition suite. Electrode placement followed the international 10–20 system [75] with extensions based on the 10–10 system, comprising 27 active Ag/AgCl electrodes (Fp1, Fp2, F3, F4, F7, F8, Fz, FC1, FC2, FC5, FC6, FCz, C3, C4, Cz, CP1, CP2, CP5, CP6, T7, T8, P3, P4, P7, P8, Pz, O1, O2), with FCz used as reference. To monitor ocular artifacts, horizontal and vertical eye movements were recorded using two bipolar electrooculographic (EOG) channels positioned at the outer canthus and below the left eye. Electrode impedance was kept below 5 k Ω throughout the recording to ensure optimal signal quality. EEG data were sampled at 1000 Hz and filtered online with a 50 Hz notch filter to suppress line noise.

Baseline activity was recorded before the task in resting-state conditions (2 min eyes closed, 2 min eyes open). This single baseline recording, obtained at the beginning of each experimental session, was used to normalize the PSD values of both the lecture and the interactive task within that same session. Since participants completed the FTF and RL conditions on different days, baseline normalization was therefore performed separately for each condition and for each participant, and no pooled baseline across conditions was used. During each experimental condition (FTF and RL), EEG was continuously acquired across two distinct instructional phases: the lecture and the interactive task. For subsequent analyses, for each instructional phase (lecture, interactive task), a 3-minute segment of artefact-free EEG was extracted from a time window located near the central portion of the task, to ensure stable engagement while minimizing potential confounds related to task onset or fatigue. This approach ensured uniform data quality across participants.

Offline preprocessing included bandpass filtering of continuous EEG signals between 0.01 and 50 Hz using a zero-phase IIR filter. Data were then segmented into consecutive 2-second epochs. Ocular and movement-related artefacts were manually identified and excluded through visual inspection by two independent researchers blinded to the experimental condition. Only artefact-free epochs were retained for further analysis. Across participants, the proportion of rejected epochs remained consistently low, with an average rejection rate below 2 % for

all conditions.

PSD was estimated via Fast Fourier Transform (FFT), applying a Hamming window to reduce spectral leakage, with a spectral resolution of 0.5 Hz. Absolute power values were extracted for standard frequency bands: delta (0.5–3.5 Hz), theta (4–7.5 Hz), alpha (8–12.5 Hz), beta (13–30 Hz), and gamma (30.5–50 Hz).

To assess inter-individual neural similarity within each group, EuDist were computed on normalized PSD values between all unique participant pairs (i.e., six combinations per group) for each frequency band, task phase (lecture, interactive task), and condition (FTF, RL). The normalized PSD values were computed for each channel and frequency band as:

$$\text{Normalized PSD} = \frac{\text{PSD}_{\text{task}} - \text{PSD}_{\text{baseline}}}{\text{PSD}_{\text{baseline}}}$$

For each dyad (i, j), EuDist D_{ij} was calculated across all selected channels $k = 1, \dots, N$ (where $N = 27$) and within each frequency band, as follows:

$$D_{ij} = \sqrt{\sum_{k=1}^N (\text{PSD}_{i,k} - \text{PSD}_{j,k})^2}$$

To derive participant-level indices, the five EuDist involving each participant (i.e., with the three other members of the group) were

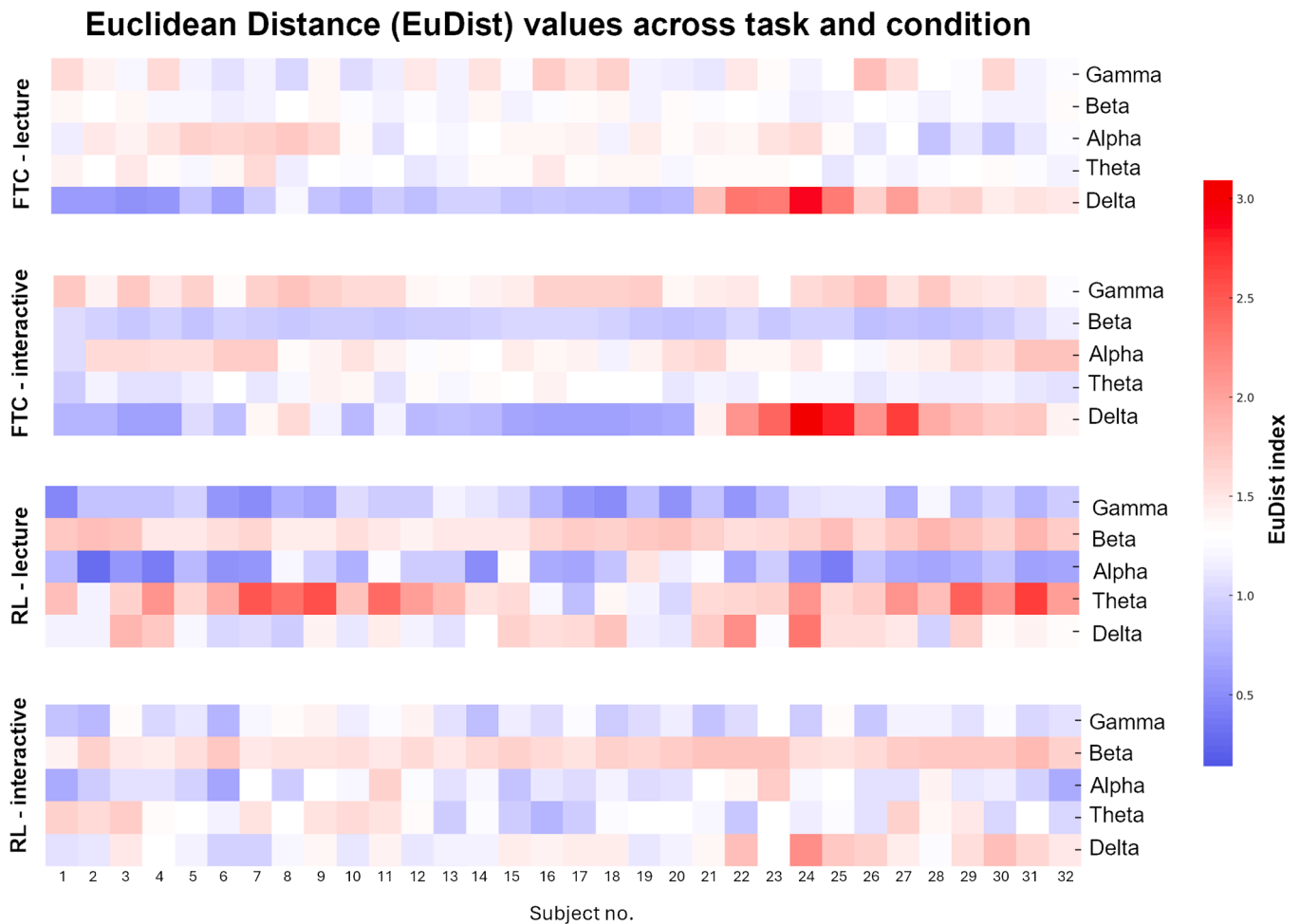


Fig. 2. Color-coded representation of the EuDist index for each participant, frequency band, task, and condition. Each column corresponds to an individual participant (subject ID 1–32), and each row represents the EuDist values for each experimental condition and task (FTF, lecture and interactive task; RL, lecture and interactive task). For each participant, the EuDist index represents the average Euclidean Distance between that participant and all the other members of the group (i.e., the three students and the lecturer) computed across all EEG channels within each frequency band. Colors reflect the magnitude of the EuDist, scaled across the full matrix and centered on the global mean: lower EuDist values are shown in blue, and higher values in red.

averaged, yielding a single dissimilarity score per participant, per condition, and per task phase (for each frequency band) (Fig. 2):

$$\bar{D}_i = \frac{1}{3} \sum_{j \neq i} D_{ij}$$

2.4. ECG: Data acquisition and processing

Cardiac activity was employed as an index of autonomic system activation, measured via ECG. The ECG signal was collected through BIOPAC Systems Inc (Goleta, CA, USA) for cardiac activity monitoring, examining heart rate frequency (HR), according to a 3-lead placement.

R studio (v. 4.4.0) was used to perform the analyses. Specifically, intersubject correlation of heart rate (ISC—HR) indexes, which are a measure of interpersonal synchronization, was computed for each experimental condition and task, in accordance with the procedure described in Pérez and colleagues [71]. Pre-processed IBI data were standardized in length by trimming them to the average length across participants to ensure alignment. Subsequently, linear interpolation was performed to estimate missing values within the time series by computing the average values, and remaining edge NAs were filled forward and backward to eliminate discontinuities. The interpolated IBI signals were then converted to HR, and each dataset was segmented into temporally consistent portions, calculated on the baseline length, in order to allow time-resolved ISC estimation. Within each segment, a correlation matrix was calculated and normalized using a Fisher-Z transformation, and individual ISC—HR scores were obtained by averaging the Z-values for each subject across all pairwise comparisons (Fig. 3). These values were then transformed using the inverse Fisher-Z formula to return ISC—HR scores on the original correlation scale. Finally, ISC—HR scores from the segments were averaged to obtain a single ISC—HR value per subject for each condition and task separately.

2.5. Statistical analyses

2.5.1. EEG EuDist analyses

For EEG EuDist statistical analysis, a set of five 2×2 repeated measures ANOVA (*Condition*, 2 levels: FTF vs. RL; *Task*, 2 levels: lecture, interactive task) as within-subject factor, was computed for each frequency band (delta, theta, alpha, beta and gamma band).

In cases where the assumption of sphericity was not met, the degrees of freedom were adjusted using the Greenhouse-Geisser correction to reduce the risk of Type I error. When statistically significant effects emerged, these were explored through pairwise post hoc comparisons corrected using the Bonferroni method. Effect sizes were quantified using partial eta squared (η^2_p) to estimate the proportion of variance attributable to each factor. The threshold for statistical significance was fixed at $\alpha = 0.05$.

Prior to conducting inferential analyses, the data underwent preliminary screening to assess univariate normality. Furthermore, a preliminary repeated-measures ANOVA was conducted to test whether dissimilarity scores differed between student-student and student-lecturer dyads across all five frequency bands. No significant effects emerged (all $p > .05$), indicating that neural dissimilarity was not modulated by dyadic role configuration. Accordingly, all pairwise combinations were considered equivalent and were retained in the final computation of inter-individual neural distance metrics

Skewness and kurtosis coefficients were inspected to ensure that values remained within the acceptable range for parametric testing (± 2.0). All analyses were carried out using *Jamovi* (version 2.6.22; The Jamovi Project, 2022).

2.5.2. Cardiac synchronization analyses

For ECG data, a 2×3 repeated-measures ANOVA (*Condition*, 2 levels: FTF vs. RL; *Task*, 3 levels: baseline, lecture, interactive task) was conducted on the ISC—HR indexes, with *Condition* and *Task* as within-

subjects factors. This approach was motivated by the within-subject experimental design, maintaining methodological consistency with the EEG analyses. Given that the primary aim of the study was to compare average synchronization patterns across instructional contexts rather than to model individual differences or hierarchical variance components, a repeated measures framework was deemed appropriate for the present data. Effect sizes are reported as partial eta squared (η^2_p) and interpreted according to Richardson's [76] criteria (small = 0.01, medium = 0.06, large = 0.14). The alpha level was set to 0.05 for all analyses. Prior to statistical analyses, outliers were identified and addressed separately within each condition and task according to the interquartile range method to preserve the integrity of within-cell variability. Outliers (1.04 % of the data) were therefore imputed using the mean of the corresponding condition \times task cell, in order to avoid distortion in the between-condition comparisons and case-wise elimination in the repeated measures ANOVA. Assumptions for the ANOVA method were met by looking at diagnostic plots and carrying out the Shapiro test for normality and the Levene's test for homogeneity of variance. Since the Levene's test was significant, Greenhouse-Geisser correction was used to account for violation of the homogeneity assumption. Regarding pre-processing of the data, recordings were aligned in time between subjects and then, the raw ECG signals were processed using Kubios HRV Scientific (v. 4.1.2.1) [77], a software tool for HR analyses. Within Kubios, R-peaks were first detected automatically using the built-in QRS detection algorithm. To ensure signal integrity, each ECG signal was then manually inspected and corrected. This step allowed for the identification and removal of artifacts or noise that were not adequately detected by the automatic algorithm. Manual adjustments focused on ensuring the precision of R-peak detection and preserving physiologically plausible IBI sequences.

2.5.3. Self-report and behavioral analyses

Self-report and behavioral data (i.e., IOS, PSQ, KEQ) were analyzed using paired-samples *t*-tests comparing FTF and RL conditions. This approach was selected to estimate mean within-subject differences and corresponding effect sizes, which were estimated using Cohen's *d*. Assumptions were evaluated through visual inspection of Q-Q plots and Shapiro-Wilk tests on difference scores. Given the focus on effect estimation and the robustness of paired *t*-tests to moderate departures from normality, parametric analyses were retained. All analyses were carried out using *Jamovi* (version 2.6.22; The Jamovi Project, 2022).

3. Results

3.1. EEG EuDist results

EEG EuDist results are reported below for each band (Fig. 4).

Delta Band. The repeated-measures ANOVA revealed a significant main effect of *Condition* ($F(1, 31) = 33.55, p < .001, \eta^2_p = 0.520$), indicating higher EuDist values in the RL condition compared to the FTF condition. A significant main effect of *Task* also emerged ($F(1, 31) = 6.21, p = .018, \eta^2_p = 0.167$), with higher EuDist observed during the lecture phase relative to the interactive task. The *Condition* \times *Task* interaction was likewise significant ($F(1, 31) = 30.81, p < .001, \eta^2_p = 0.498$). Post hoc comparisons confirmed significantly higher EuDist in the RL condition compared to the FTF condition during both the lecture ($p < .001$) and the interactive task ($p < .001$). Furthermore, within the RL condition, EuDist was significantly higher during the lecture than during the interactive task ($p < .001$).

Theta Band. A significant main effect of *Condition* was found ($F(1, 31) = 270.7, p < .001, \eta^2_p = 0.897$), with higher EuDist in the RL condition. A main effect of *Task* was also found ($F(1, 31) = 130.1, p < .001, \eta^2_p = 0.808$), with higher EuDist in the lecture task. The *Condition* \times *Task* interaction was significant ($F(1, 31) = 34.9, p < .001, \eta^2_p = 0.530$). Post hoc comparisons showed higher EuDist values in the RL condition compared to the FTF condition for both the lecture ($p < .001$) and

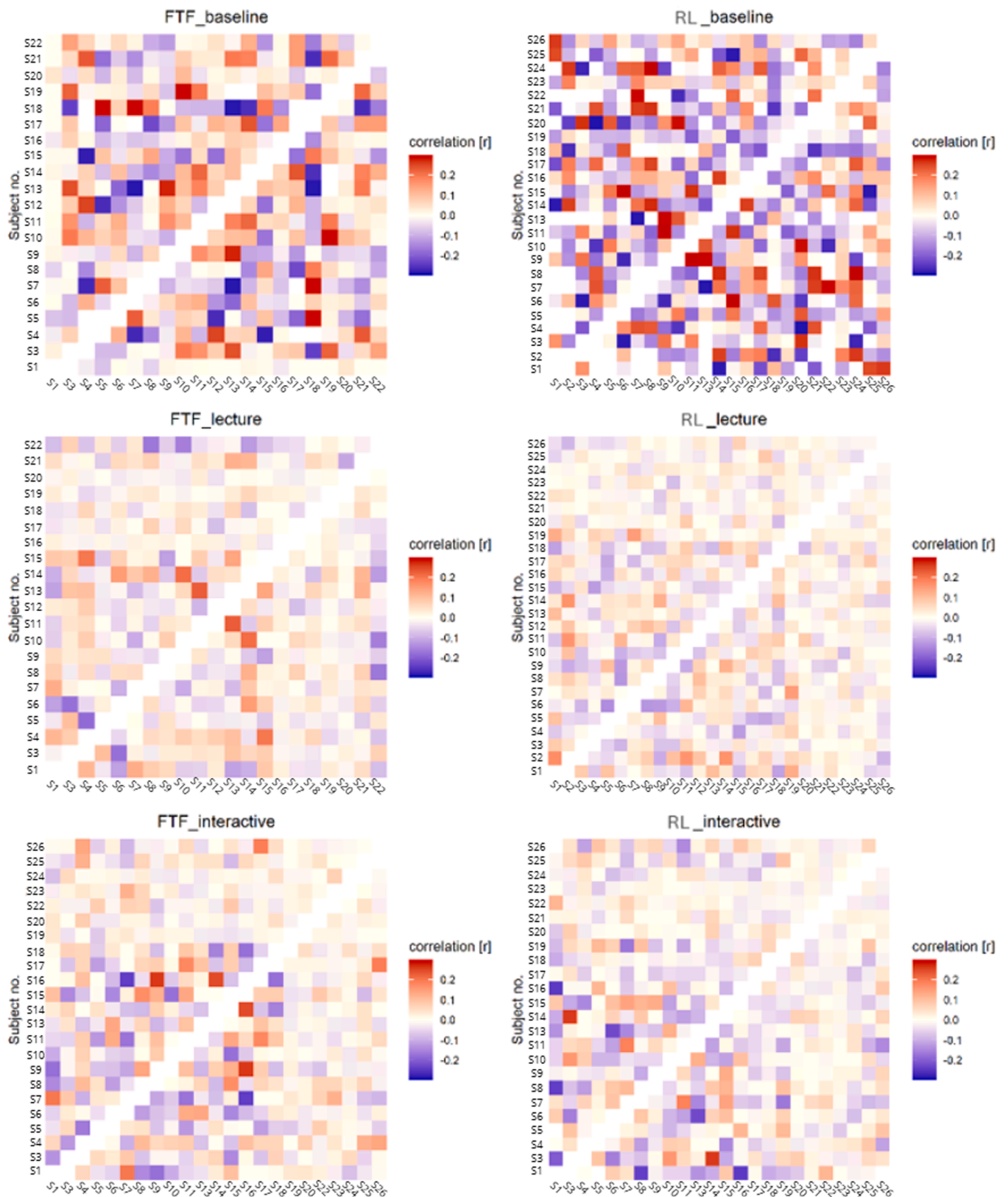


Fig. 3. Correlation matrices of ISC—HR, computed pairwise between all participant couples, shown separately for each task (baseline, lecture, interactive task) and learning condition (FTF, RL). Each cell represents the Pearson correlation coefficient (r) between ISC—HR time series for a given subject pair. Warmer colors (red) indicate higher positive synchrony, while cooler colors (blue) reflect anti-correlation or desynchronization.

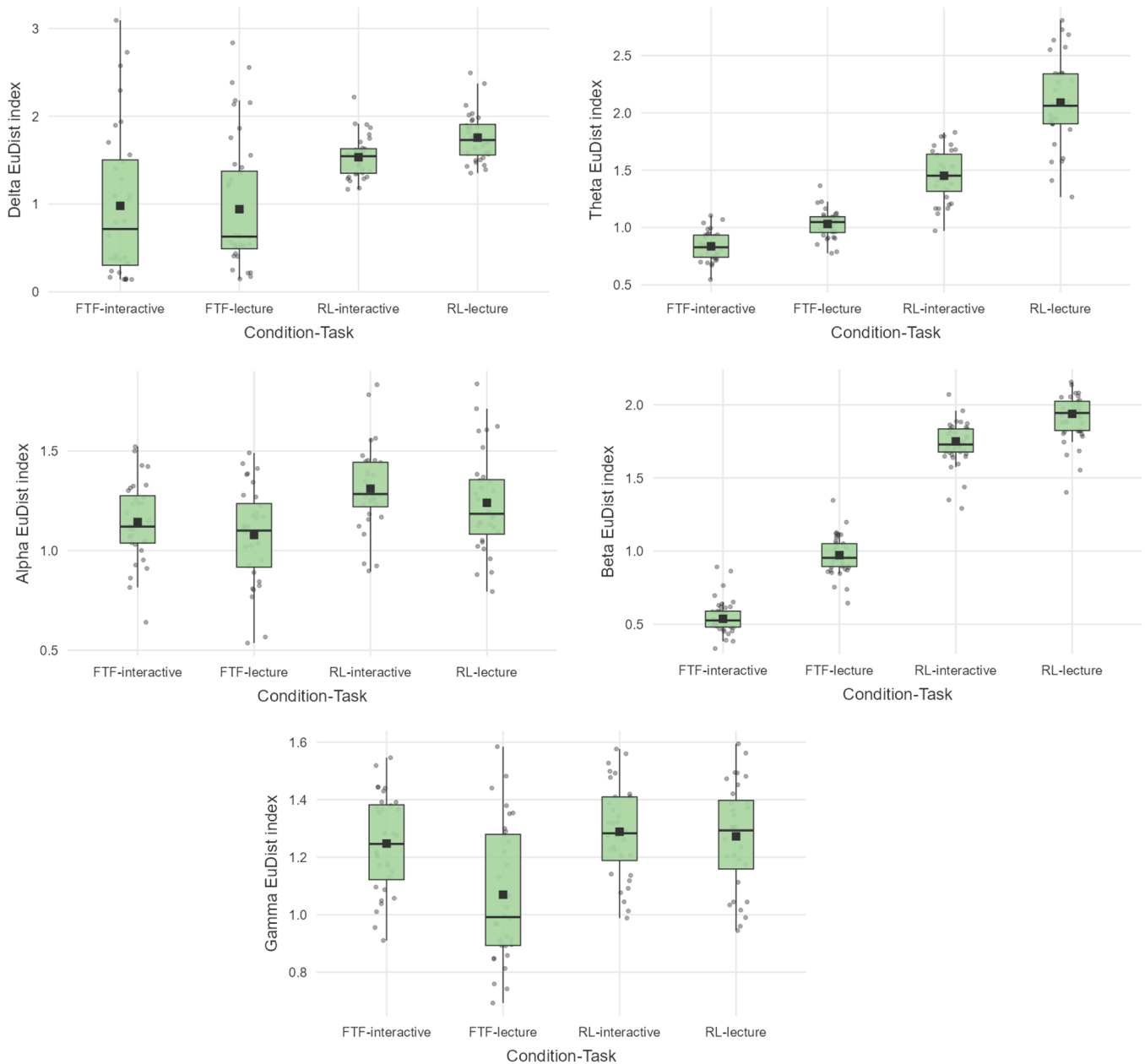


Fig. 4. Boxplots of EuDist index across frequency bands (Delta, Theta, Alpha, Beta, Gamma), as a function of Condition (FTF, RL) and Task (Lecture, Interactive task). Black squares indicate group means; dots represent individual data points.

interactive task ($p < .001$). Within the RL condition, EuDist was higher in the lecture task than in the interactive task ($p < .001$). Within the FTF condition, the lecture task was also associated with higher EuDist than the interactive task ($p < .001$).

Alpha Band. The analysis showed a significant main effect of *Condition* ($F(1, 31) = 12.07, p = .002, \eta^2_p = 0.280$), with higher EuDist in the RL condition compared to the FTF condition. No significant main effect of *Task* ($p = .087$) or *Condition* \times *Task* interaction ($p = .937$) was observed.

Beta Band. The ANOVA revealed a significant main effect of *Condition* ($F(1, 31) = 3043.9, p < .001, \eta^2_p = 0.990$), with higher EuDist in the RL condition. A significant main effect of *Task* was also observed ($F(1, 31) = 456.2, p < .001, \eta^2_p = 0.936$), with higher EuDist in the lecture task. The *Condition* \times *Task* interaction was significant ($F(1, 31) = 73.6, p < .001, \eta^2_p = 0.704$). Post hoc comparisons indicated higher EuDist values in the RL condition compared to the FTF condition, during both the lecture ($p < .001$) and interactive task ($p < .001$). Within each condition, the

lecture task was associated with higher EuDist than the interactive task ($p < .001$).

Gamma Band. A significant main effect of *Condition* was found ($F(1, 31) = 10.69, p = .003, \eta^2_p = 0.256$), with higher EuDist in the RL condition. The main effect of *Task* was also significant ($F(1, 31) = 8.09, p = .008, \eta^2_p = 0.207$), with higher EuDist in the interactive task. Finally, also the *Condition* \times *Task* interaction was significant ($F(1, 31) = 7.25, p = .011, \eta^2_p = 0.190$). Post hoc analyses showed higher EuDist values in the RL condition during both tasks compared to the lecture task in the FTF condition ($p = .006$ and $p = .002$, respectively). In the FTF condition, the interactive task was also associated with higher EuDist than the lecture task ($p = .006$).

3.2. Cardiac synchronization results

The ANOVA revealed a significant main effect of *Condition* ($F(1, 31) = 6.84, p = 0.014$), indicating greater overall ISC–HR in the FTF

condition compared to the RL condition. The associated effect size was small ($\eta^2_p = 0.014$), indicating a modest magnitude of the condition effect. There was no significant main effect of *Task* ($F(1.31, 40.64) = 0.26, p = .678, \eta^2_p = 0.008$), suggesting that baseline, lecture, and interactive tasks did not differ significantly in overall ISC—HR (Fig. 5). Concerning the *Condition* \times *Task* interaction, no statistically significant result was found ($F(1.49, 46.32) = 2.19, p = .136, \eta^2_p = 0.066$), indicating that the effect of condition did not vary depending on the task.

3.3. Self-report and behavioral measures

The paired samples *t*-test revealed a significantly higher IOS score in the FTF condition compared to the RL condition ($t(23) = 5.09, p < .001$, Cohen's $d = 1.04$), indicating a stronger perceived interpersonal closeness with the lecturer during the FTF modality.

Concerning the PSQ, participants reported significantly higher overall lesson satisfaction in the FTF condition compared to the RL condition ($t(19) = 3.77, p = .001$, Cohen's $d = 0.84$). This result suggests greater subjective engagement and appreciation of the lesson when instruction occurred in physical co-presence.

Finally, no significant difference emerged between FTF and RL conditions in knowledge acquisition, as measured by the KEQ ($t(20) = 0.56, p = .584$, Cohen's $d = 0.12$). This suggests that, despite differences in interpersonal and affective dimensions, learning outcomes were comparable across instructional modalities.

4. Discussion

The present study aimed to investigate interpersonal synchronization in educational contexts by comparing neurophysiological alignment across FTF and RL modalities. Using EEG and ECG hyperscanning, the inter-individual similarity in cortical oscillatory activity (i.e. EuDist) and

autonomic synchrony (i.e. ISC—HR) was assessed during both passive (lecture) and active (interactive discussion) instructional phases. The findings reveal relevant differences between learning conditions.

Firstly, EEG analyses revealed a systematic modulation of inter-individual neural similarity as a function of learning condition across all examined frequency bands. EuDist values were consistently higher in the RL condition relative to FTF, indicating reduced inter-brain alignment in the absence of physical co-presence [78–80]. This effect was statistically robust across delta, theta, alpha, beta, and gamma bands, underscoring the widespread impact of embodied interaction on cortical convergence during group-based instructional settings.

Beyond this global effect, the interaction between Condition and Task revealed frequency-dependent differentiation. In the slower bands (delta and theta), both factors (i.e., Condition and Task) contributed independently and interactively to neural dissimilarity.

These bands are typically associated with attentional engagement, temporal integration, and encoding processes [78,81,82], and the observed pattern is consistent with the interpretation that physical co-location, combined with dialogic interaction, enhances alignment in these low-frequency rhythms.

EuDist values were highest during RL lectures, and consistently lower during interactive phases, especially in FTF settings. These findings point to the joint influence of spatial proximity and dialogic structure in stabilizing attentional and motivational synchrony.

In contrast, alpha-band results showed a different profile. While a significant main effect of Condition emerged (again with higher EuDist in RL) no effects of Task or Condition \times Task interaction were found. This may indicate that alpha-band similarity is modulated primarily by the spatial configuration of the learning environment, rather than by the phase of the instructional task. Given the established role of alpha oscillations in attentional gating and cortical inhibition [59,79], this pattern may reflect a general tonic modulation of attentional readiness,

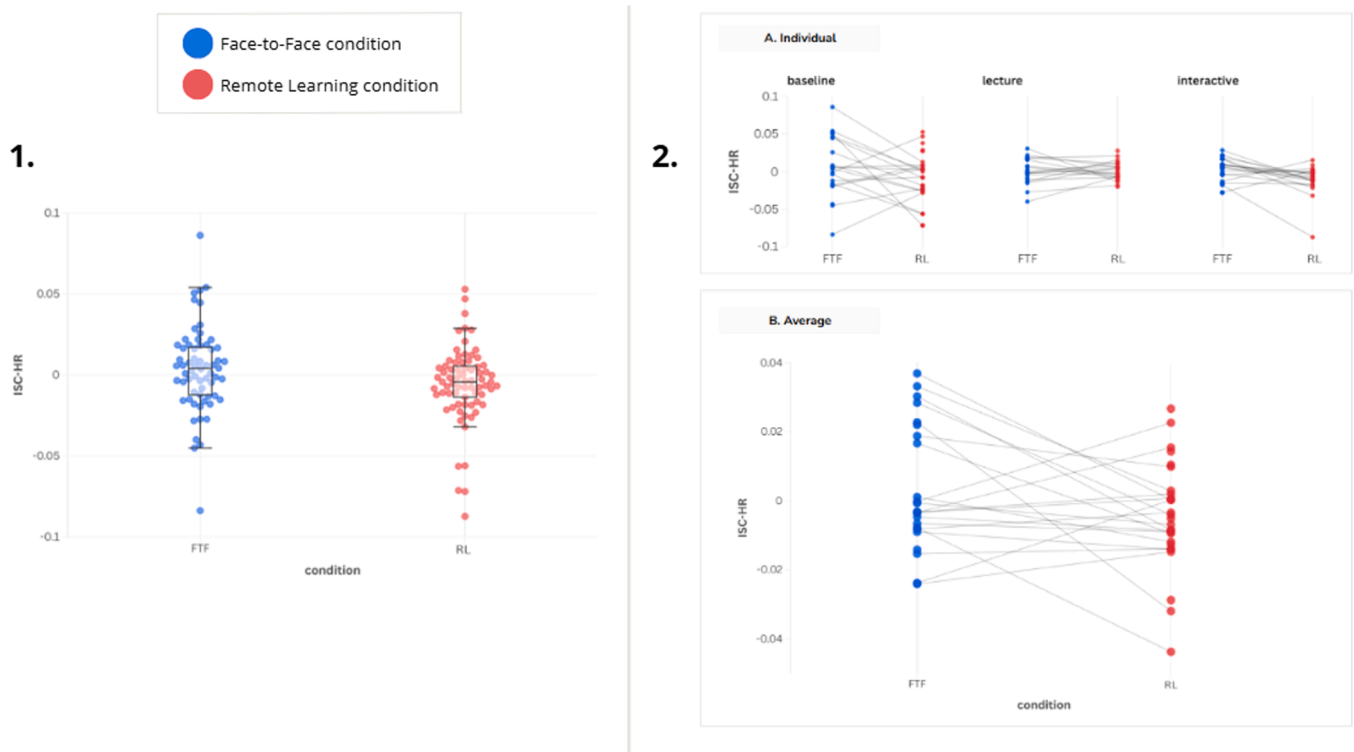


Fig. 5. Part 1: Distribution of ISC—HR values by learning condition (FTF in blue, RL in red) across all participants and tasks. The central line represents the median, the box indicates the interquartile range, and whiskers extend to $\pm 1.5 \times$ IQR. Part 2: (A) Within-subject ISC—HR comparisons between FTF and RL across tasks. Each subplot represents one experimental phase (baseline, lecture, interactive task). Dots represent ISC—HR values for individual participants in the FTF (blue) and RL (red) conditions. Lines connect repeated measures from the same individual, illustrating task-specific changes in intersubject synchrony. (B) Task-averaged ISC—HR by learning condition. Mean ISC—HR across all tasks for each participant is plotted by condition.

influenced by physical co-presence but not substantially altered by variations in cognitive engagement between passive and active learning phases.

In both the faster frequencies – beta and gamma – significant effects of Condition and Task, as well as Condition × Task interactions, were observed. In beta, higher EuDist was found in RL compared to FTF, and during lectures compared to interactive tasks. These effects were more pronounced in RL, suggesting that beta-band synchrony is highly sensitive to both spatial separation and reduced interpersonal exchange. The interactive task, particularly in FTF, was associated with lower beta EuDist, consistent with prior research suggesting an involvement of this frequency range in predictive coding, motor simulation, and syntactic integration during socially coordinated action [83–85].

Gamma-band activity, while similarly affected by Condition and Task, exhibited an inversion of the task pattern observed in lower bands. Here, EuDist was higher during the interactive task than the lecture, in both RL and FTF, with the highest dissimilarity observed in RL-interactive. This result is compatible with the view that, unlike lower frequencies, gamma oscillations may be more sensitive to the semantic variability and individualized elaboration typical of spontaneous interaction [85–88]. Notably, although the interactive phase increased gamma-band dissimilarity in both conditions, the effect was markedly less pronounced in FTF, suggesting that physical co-presence may partially mitigate variability even during open-ended exchanges.

Taken together, these findings delineate a layered structure of

interpersonal synchronization across the EEG spectrum. While the effect of spatial proximity (FTF vs. RL) is globally observed across all bands, the influence of task structure (lecture vs. interaction) is more selective, with interaction enhancing alignment in slower bands and inducing divergence in gamma activity. Alpha-band responses appear to reflect generalized condition effects, insensitive to task demands. Importantly, the presence of non-significant effects, such as the absence of task modulation in the alpha band and the lack of interaction in that range, provides further support for the functional specificity of each frequency domain. This pattern supports a model in which neural synchronization during collaborative learning is structured along two primary axes: one determined by the physical configuration of the learning context, and the other by the cognitive and interpersonal demands of the instructional phase. Importantly, these neurophysiological patterns converge with subjective reports of interpersonal closeness. Participants reported significantly higher IOS scores in the FTF condition, indicating a stronger perceived relational bond with the lecturer. This subjective dimension aligns with the reduced EuDist observed across frequency bands, supporting the interpretation of neural synchronization as a correlate of perceived interpersonal connectedness during learning. Fig. 6

Secondly, analysis of ISC—HR data revealed a statistically significant, though small, cardiac synchronization in the FTF condition compared to the RL condition. This supports our hypothesis that in-person interactions enhance autonomic alignment among participants.

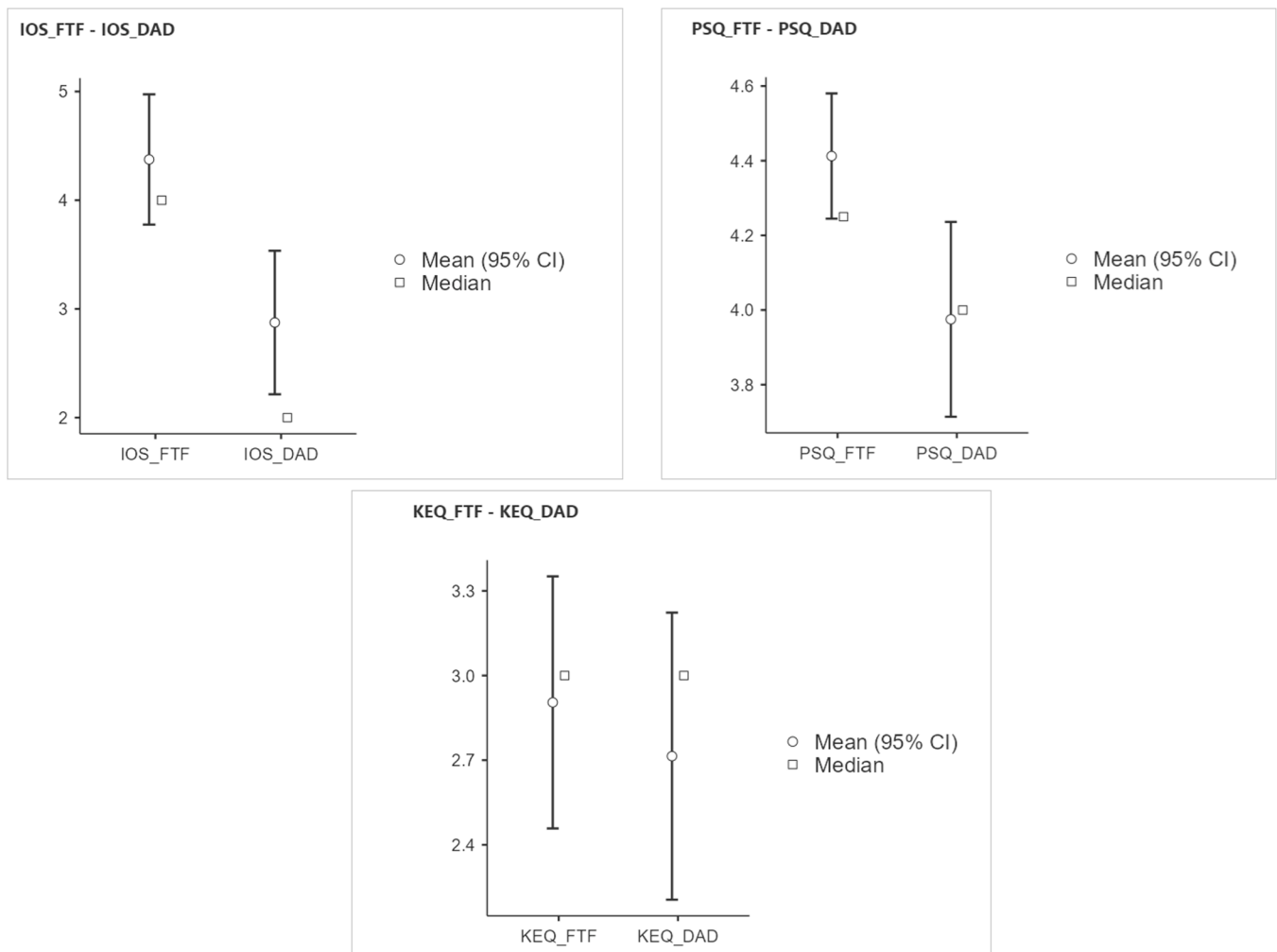


Fig. 6. Mean scores ($\pm 95\%$ confidence intervals) and medians for (a) Inclusion of Other in the Self (IOS), (b) lesson satisfaction (PSQ), and (c) knowledge evaluation (KEQ) in the face-to-face (FTF) and remote learning (RL) conditions. Paired-samples *t*-tests revealed significantly higher IOS and PSQ scores in the FTF condition, whereas no significant differences were observed for KEQ, indicating comparable learning outcomes across instructional modalities.

This finding is consistent with an increasing body of literature emphasizing that physical proximity and co-presence facilitate physiological synchronization, which may be interpreted as an indicator of shared engagement, joint emotional regulation, and effective social interaction [63,67,68]. While no significant differences were found between tasks (baseline, lecture, interaction) or Condition x Task interactions, the main effect of condition indicates that FTF environments naturally support autonomic synchronization regardless of the activity performed. This is consistent with prior findings showing that merely sharing the same physical space can induce physiological coupling among individuals [66,89]. The absence of task-specific effects may suggest that, within structured educational contexts, passive (lecture) and active (interaction) phases do not substantially affect cardiac synchrony, at least under the current experimental conditions. From a theoretical standpoint, higher ISC—HR in the FTF condition aligns with prior work suggesting that physical co-presence can facilitate autonomic co-variation during social interaction. In the present study, ISC—HR should therefore be interpreted as an index of shared physiological dynamics. Consistently, participants also reported greater overall lesson satisfaction in the FTF condition. Higher PSQ scores suggest enhanced affective engagement and perceived quality of the learning experience when instruction occurred in physical co-presence. Together with increased cardiac synchronization, these findings support the view that FTF environments facilitate shared emotional and motivational states, which may contribute to sustaining attention and interpersonal attunement throughout the instructional exchange. Additionally, recent evidence suggests that autonomic synchrony may also relate to socio-cognitive alignment in group settings [71,90]. On this basis, future research integrating validated behavioral, affective, and relational measures could help determine whether and how autonomic synchrony functions as a proxy for these dimensions in educational settings. Another important avenue for future research concerns the explicit examination of relationships between interpersonal synchrony and educational outcomes, such as learning performance and neurophysiological synchronization. The present study deliberately adopted a conservative analytic strategy focused on condition-level effects rather than correlational inference. This choice was motivated by several considerations, including sample size constraints for reliable correlation estimates, the group-level nature of EEG and ECG synchronization metrics, and the risk of overinterpretation in the absence of designs optimized for individual-level inference. Future studies could therefore employ larger samples and analytic frameworks explicitly aimed at linking synchrony measures with behavioral outcomes to clarify the functional significance of interpersonal alignment for learning.

Notably, despite marked differences in neural, autonomic, and subjective interpersonal measures, no significant differences emerged in objective learning outcomes, as indexed by the KEQ. This dissociation suggests that enhanced interpersonal synchronization primarily supports relational, experiential, and motivational aspects of learning rather than immediate factual acquisition. However, such pattern aligns with previous literature indicating comparable short-term learning performance across instructional modalities, despite divergent experiential quality. Additionally, the absence of a shared baseline assessment on the instructional content is a further limitation. Although lessons were designed to be equivalent in complexity and structure, the use of different contents precludes direct comparisons of absolute learning gains across conditions. Future studies could therefore explicitly incorporate baseline knowledge assessments or employ identical instructional material across sessions to further disentangle synchrony-related effects on learning efficiency from content-specific or familiarity-related influences.

5. Conclusion

To conclude, the present findings offer converging evidence that FTF instruction fosters higher interpersonal synchronization at both central

and autonomic levels. EEG analyses demonstrated significantly higher inter-individual neural similarity in FTF compared to RL, across all frequency bands examined. This effect was consistent yet spectrally differentiated: while slower rhythms (delta and theta) showed enhanced alignment, particularly during interactive tasks, higher-frequency components (beta and gamma) revealed sensitivity to both learning condition and instructional phase, with FTF-interactive phases yielding the higher convergence. Alpha-band synchrony appeared modulated only by condition, suggesting a tonic attentional effect of spatial proximity. Altogether, these results highlight the role of physical co-presence in supporting multi-frequency cortical alignment during learning, as captured by EuDist metrics.

Secondly, the insights from the cardiac synchronization dynamics revealing higher physiological coherence among participants in the FTF condition compared to the RL condition emphasize the need for intentional design strategies in remote education that enhance emotional resonance and interactivity in the absence of physical co-presence. Results from the present study highlight the importance of physical presence in promoting autonomic alignment and support the relevance of ISC—HR as an indicator of shared physiological dynamics during educational interaction.

Beyond neurophysiological indices, self-report measures further corroborated this pattern. FTF instruction was associated with higher perceived interpersonal closeness and greater lesson satisfaction, while learning outcomes remained comparable across modalities. Together, these findings indicate that physical co-presence primarily enhances the relational and affective dimensions of learning, without necessarily conferring an immediate advantage in knowledge acquisition.

When considered jointly, these neurophysiological and cognitive findings suggest that interpersonal synchronization in learning is not a unitary construct, but rather a multi-layered phenomenon involving distinct but interacting central and peripheral systems. EEG-based metrics reflect frequency-specific cognitive and attentional alignment, dynamically modulated by the instructional context, whereas ISC—HR captures broader patterns of emotional co-regulation and shared arousal. The convergence observed in FTF settings across both domains supports the hypothesis that physical co-presence enhances the temporal, semantic, and affective coupling required for collaborative learning. Conversely, the increased neural and physiological divergence observed in RL highlights the potential risks of disconnection in digitally mediated education, especially in the absence of embodied feedback and real-time reciprocity. These findings point to the value of integrated hyper-scanning approaches in evaluating educational synchrony and underline the need to design remote formats that preserve or simulate the inter-subjective affordances of in-person interaction.

However, some limitations must be considered. First of all, although the use of a single lecturer across all conditions ensured consistency, it may introduce individual effects that are not representative of the whole teaching population. Future studies should therefore aim to extend these findings using larger, more diverse cohorts. A further methodological limitation concerns the potential influence of interpersonal familiarity on synchronization. Indeed, although participants were assigned to groups to minimize prior acquaintance and reported no pre-existing relationships with each other or with the lecturer, familiarity naturally increased between the first and the second session. Since interpersonal familiarity is known to enhance interpersonal synchrony and co-regulatory dynamics (e.g., [91]), this sequential exposure may have contributed to increased alignment in whichever condition was completed second. Although the order of conditions was counter-balanced to mitigate this bias at the group level, it is nonetheless important to take into consideration this variability when interpreting the results. Additionally, the use of ISC—HR indexes for autonomic synchronization may offer limited granularity in distinguishing the cognitive and emotional contributions to engagement and synchrony. Future research should therefore focus on further investigating to what extent physiological synchronization indexes can foster emotional

connection and interactive engagement, promoting effective synchronization in remote learning environments.

Together, the findings from the present study highlight the need to rethink learning not solely as an individual cognitive outcome, but rather an embodied and relational process shaped by the dynamics of interpersonal alignment.

Ethical statement

The studies involving human participants were reviewed and approved by Department of Psychology, Catholic University of the Sacred Heart, Milan, Italy (approval code: 18/22 “I meccanismi di sincronizzazione neurale interpersonale nella didattica in presenza e a distanza: uno studio EEG con tecnica hyperscanning”). The participants provided their written informed consent to participate in this study.

Funding

The authors disclosed receipt of the following financial support for the research, authorship, and/or publication of this article: this work was supported by the funding D.3.2. 2024 “*Paradigmi culturali, innovazione e dinamiche cognitive-formative in società complesse e tecnologicamente avanzate*” – “*Cultural paradigms, innovation and cognitive-formative dynamics in complex and technologically advanced societies*”, Università Cattolica del Sacro Cuore, Milan, Italy. This work was also supported by the BRIC INAIL ID33/2022 project (CUP B83C2200795000) and by the D3.2 2024 UCSC Research Project “Extended Learning” (<https://www.extended-learning.com/>).

CRedit authorship contribution statement

Michela Balconi: Writing – review & editing, Validation, Supervision, Resources, Project administration, Methodology, Conceptualization. **Katia Rovelli:** Writing – review & editing, Writing – original draft, Visualization, Software, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Giulia Magni:** Writing – review & editing, Writing – original draft, Visualization, Software, Formal analysis, Data curation. **Luana Amadini Genovese:** Writing – review & editing, Writing – original draft, Investigation, Data curation. **Maurizio Mauri:** Writing – review & editing, Investigation. **Elena Sajno:** Writing – review & editing, Investigation, Data curation. **Maria Sansoni:** Writing – review & editing, Investigation, Data curation. **Stefano De Gaspari:** Writing – review & editing, Investigation, Data curation. **Silvia Serino:** Supervision, Methodology, Investigation, Conceptualization. **Daniele Di Lernia:** Supervision, Methodology, Investigation, Conceptualization. **Laura Angioletti:** Methodology, Data curation, Conceptualization. **Allegratta Roberta A. :** Methodology, Investigation, Conceptualization. **Giuseppe Riva:** Validation, Supervision, Resources, Project administration, Methodology, Conceptualization.

Declaration of competing interest

The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

References

- [1] C.N. Gunawardena, *Culture and Online Distance Learning. Handbook of Distance Education, 3rd Edition, Routledge, New York, NY, 2013, pp. 185–200.*
- [2] O.B. Adedoyin, E. Soykan, Covid-19 pandemic and online learning: the challenges and opportunities, *Interact. Learn. Environ.* 31 (2) (2023) 863–875, <https://doi.org/10.1080/10494820.2020.1813180>. Feb.
- [3] R.M.M. Codera, Relationship of teachers' essential task to the students' behavior and performance: a basis for an intervention plan, *IJRP* 104 (1) (2022), <https://doi.org/10.47119/IJRP1001041720223491>. Jun.

- [4] A.N. Gossenheimer, T. Bem, M.L.F. Carneiro, M.S. De Castro, Impact of distance education on academic performance in a pharmaceutical care course, *PLoS One* 12 (4) (2017) e0175117, <https://doi.org/10.1371/journal.pone.0175117>. Apr.
- [5] L. Demetriou, L. Keramioti, D. Hadjicharalambous, Examining the Relationship between Distance Learning Processes and University Students Anxiety in Times of Covid19, *EJSSS* 6 (2) (2021), <https://doi.org/10.46827/ejss.v6i2.1012>. Feb.
- [6] K.-J. Kim, T.W. Frick, Changes in Student Motivation During Online Learning, *J. Educ. Comput. Res.* 44 (1) (2011) 1–23, <https://doi.org/10.2190/EC.44.1.a>. Jan.
- [7] J. Cavanaugh, S. Jacquemin, C. Junker, A look at student performance during the COVID-19 pandemic, *QAE* 31 (1) (2023) 33–43, <https://doi.org/10.1108/QAE-01-2022-0008>. Jan.
- [8] V. Gaidelys, R. Ciutienė, G. Cibulskas, An Assessment of the Impact of Distance Learning on Pupils' Performance, *Educ. Sci.* 13 (1) (2022) 3, <https://doi.org/10.3390/educsci13010003>. Dec.
- [9] H. Sokout, T. Usagawa, Improving Academic Performance Through Blended Learning: the Case of Afghan Higher Education, *Int. J. Emerg. Technol. Learn.* 16 (11) (2021) 104, <https://doi.org/10.3991/ijet.v16i11.20757>. Jun.
- [10] V. Ahmed, A. Opoku, Technology supported learning and pedagogy in times of crisis: the case of COVID-19 pandemic, *Educ. Inf. Technol.* 27 (1) (2022) 365–405, <https://doi.org/10.1007/s10639-021-10706-w>. Jan.
- [11] A. Anwar, H. Mansoor, D. Faisal, H.S. Khan, E-Learning amid the COVID-19 Lockdown: standpoint of Medical and Dental Undergraduates, *Pak. J. Med. Sci.* 37 (1) (2020), <https://doi.org/10.12669/pjms.37.1.3124>. Dec.
- [12] L. Puljak, et al., Attitudes and concerns of undergraduate university health sciences students in Croatia regarding complete switch to e-learning during COVID-19 pandemic: a survey, *BMC Med. Educ.* 20 (1) (2020) 416, <https://doi.org/10.1186/s12909-020-02343-7>. Dec.
- [13] N.K. Ibrahim, et al., Medical students' acceptance and perceptions of e-learning during the Covid-19 closure time in King Abdulaziz University, Jeddah, *J. Infect. Public Health* 14 (1) (2021) 17–23, <https://doi.org/10.1016/j.jiph.2020.11.007>. Jan.
- [14] P. Ndibalema, Constraints of transition to online distance learning in Higher Education Institutions during COVID-19 in developing countries: a systematic review, *E-Learn. Digit. Media* 19 (6) (2022) 595–618, <https://doi.org/10.1177/20427530221107510>. Nov.
- [15] M.N. Shagiakhmetova, E.V. Bystritskaya, S. Demir, R.A. Stepanov, E.E. Grishnova, N.I. Kryukova, Primary Teachers Difficulties Related to Compulsory Distance Education During COVID-19, *CONT ED TECHNOL.* 14 (2) (2022) ep357, <https://doi.org/10.30935/cedtech/11589>. Jan.
- [16] C.-Y. Yeh, C.-C. Tsai, Massive Distance Education: barriers and Challenges in Shifting to a Complete Online Learning Environment, *Front. Psychol.* 13 (2022) 928717, <https://doi.org/10.3389/fpsyg.2022.928717>. Jun.
- [17] M. Casarotti, L. Filliponi, L. Pieti, R. Sartori, Educational interaction in distance learning: analysis of one-way video and two-way audio system, *PsychNology J.* 1 (1) (2002) 28–38.
- [18] T. Tate, M. Warschauer, Equity in online learning, *Educ. Psychol.* 57 (3) (2022) 192–206, <https://doi.org/10.1080/00461520.2022.2062597>. Jul.
- [19] B. Gros, F.J. García-Peñalvo, Future Trends in the Design Strategies and Technological Affordances of E-learning, in: J.M. Spector, B.B. Lockee, M. D. Childress (Eds.), *Learning, Design, and Technology*, Springer International Publishing, Cham, 2023, pp. 345–367, https://doi.org/10.1007/978-3-319-17461-7_67.
- [20] L. Koban, A. Ramamoorthy, I. Konvalinka, Why do we fall into sync with others? Interpersonal synchronization and the brain's optimization principle, *Soc. Neurosci.* 14 (1) (2019) 1–9, <https://doi.org/10.1080/17470919.2017.1400463>. Jan.
- [21] G. Magni, L. Amadini Genovese, G. Riva, C. Repetto, Embodied metaphors and interpersonal synchrony in the digital age: the case of remote working, *Front. Psychol.* 16 (2025) 1648733, <https://doi.org/10.3389/fpsyg.2025.1648733>. Aug.
- [22] K. Friston, C. Frith, A Duet for one, *Conscious. Cogn.* 36 (2015) 390–405, <https://doi.org/10.1016/j.concog.2014.12.003>. Nov.
- [23] G. Shteynberg, et al., Theory of collective mind, *Trends Cogn. Sci. (Regul. Ed.)* 27 (11) (2023) 1019–1031, <https://doi.org/10.1016/j.tics.2023.06.009>. Nov.
- [24] J.N. Bailenson, Nonverbal overload: a theoretical argument for the causes of Zoom fatigue, *Technol. Mind Behav.* 2 (1) (2021), <https://doi.org/10.1037/tmb0000030>. Feb.
- [25] Y. Tian, S. Liu, J. Wang, A Corpus Study on the Difference of Turn-Taking in Online Audio, Online Video, and Face-to-Face Conversation, *Lang. Speech.* 67 (3) (2024) 593–616, <https://doi.org/10.1177/00238309231176768>. Sep.
- [26] A. Skulmowski, K.M. Xu, Understanding Cognitive Load in Digital and Online Learning: a New Perspective on Extraneous Cognitive Load, *Educ. Psychol. Rev.* 34 (1) (2022) 171–196, <https://doi.org/10.1007/s10648-021-09624-7>. Mar.
- [27] G. Riva, Invited article Neuroscience of distance learning: the impact of technology on neurobiological learning mechanisms, *Qwerty* 18 (2) (2023), <https://doi.org/10.30557/QW000073>. Dec.
- [28] C.J. Roseth, A.J. Saltarelli, C.R. Glass, Effects of face-to-face and computer-mediated constructive controversy on social interdependence, motivation, and achievement, *J. Educ. Psychol.* 103 (4) (2011) 804–820, <https://doi.org/10.1037/a0024213>. Nov.
- [29] A.J. Saltarelli, C.J. Roseth, Effects of synchronicity and belongingness on face-to-face and computer-mediated constructive controversy, *J. Educ. Psychol.* 106 (4) (2014) 946–960, <https://doi.org/10.1037/a0036898>. Nov.
- [30] R.G. Presley, D.M. Cumberland, K. Rose, A Comparison of Cognitive and Social Presence in Online Graduate Courses: asynchronous vs. Synchronous Modalities, *OLJ* 27 (2) (2023), <https://doi.org/10.24059/olj.v27i2.3046>. Jun.

- [31] J.E. Nieuwoudt, Investigating synchronous and asynchronous class attendance as predictors of academic success in online education, *AJET* (2020) 15–25, <https://doi.org/10.14742/ajet.5137>. Jan.
- [32] A.R. Hurlbut, Online vs. traditional learning in teacher education: a comparison of student progress, *Am. J. Distance Educ.* 32 (4) (2018) 248–266, <https://doi.org/10.1080/08923647.2018.1509265>. Oct.
- [33] Y. Chen, A.Y.C. Hou, L. Huang, Development of distance education in Chinese higher education in perspectives of accessibility, quality and equity under COVID-19, *AEDS* 11 (2) (2022) 356–365, <https://doi.org/10.1108/AEDS-05-2020-0118>. Mar.
- [34] T.C. Varkey, et al., Asynchronous learning: a general review of best practices for the 21st century, *JRIT* 16 (1) (2023) 4–16, <https://doi.org/10.1108/JRIT-06-2022-0036>. Mar.
- [35] R. Tulaskar, M. Turunen, What students want? Experiences, challenges, and engagement during Emergency Remote Learning amidst COVID-19 crisis, *Educ. Inf. Technol.* 27 (1) (2022) 551–587, <https://doi.org/10.1007/s10639-021-10747-1>. Jan.
- [36] R.-J. Wilcha, Effectiveness of Virtual Medical Teaching During the COVID-19 Crisis: systematic Review, *JMIR. Med. Educ.* 6 (2) (2020) e20963, <https://doi.org/10.2196/20963>. Nov.
- [37] A. Naciri, M. Radid, A. Kharbach, G. Chems, E-learning in health professions education during the COVID-19 pandemic: a systematic review, *J. Educ. Eval. Health Prof.* 18 (2021) 27, <https://doi.org/10.3352/jeehp.2021.18.27>. Oct.
- [38] A.M. Maatuk, E.K. Elberkawi, S. Aljawarneh, H. Rashaideh, H. Alharbi, The COVID-19 pandemic and E-learning: challenges and opportunities from the perspective of students and instructors, *J. Comput. High. Educ.* 34 (1) (2022) 21–38, <https://doi.org/10.1007/s12528-021-09274-2>. Apr.
- [39] Y. Salih, R.A. Ibrahim, Impact of Distance Learning on Mental Health During COVID-19: a Review, *IJEER* 1 (4) (2021) 76–79, <https://doi.org/10.46336/ijeer.v1i4.238>. Oct.
- [40] S. Scotti, M. Mauri, S. Cerutti, L. Mainardi, M. Villamira, Quantitative evaluation of distant student psychophysical responses during the e-learning processes, in: 2005 IEEE Engineering in Medicine and Biology 27th Annual Conference, 2005, pp. 1196–1199, <https://doi.org/10.1109/IEMBS.2005.1616638>. Shanghai, China: IEEE.
- [41] S. Scotti, et al., Automatic Quantitative Evaluation of Emotions in E-learning Applications, in: 2006 International Conference of the IEEE Engineering in Medicine and Biology Society, 2006, pp. 1359–1362, <https://doi.org/10.1109/IEMBS.2006.260601>. New York, NY: IEEE, Aug.
- [42] K. Watanabe, Teaching as a Dynamic Phenomenon with Interpersonal Interactions, *Mind Brain Educ.* 7 (2) (2013) 91–100, <https://doi.org/10.1111/mbe.12011>. Jun.
- [43] M.H. Nguyen, J. Gruber, W. Marler, A. Hunsaker, J. Fuchs, E. Hargittai, Staying connected while physically apart: digital communication when face-to-face interactions are limited, *New Media Soc.* 24 (9) (2022) 2046–2067, <https://doi.org/10.1177/1461444820985442>. Sep.
- [44] K. Schoenenberg, A. Raake, J. Koeppel, Why are you so slow? – Misattribution of transmission delay to attributes of the conversation partner at the far-end, *Int. J. Hum. Comput. Stud.* 72 (5) (2014) 477–487, <https://doi.org/10.1016/j.ijhcs.2014.02.004>. May.
- [45] N. Zhao, X. Zhang, J.A. Noah, M. Tiede, J. Hirsch, Separable processes for live “in-person” and live “zoom-like” faces, *Imaging Neurosci.* 1 (2023), https://doi.org/10.1162/imag_a_00027. Nov.
- [46] G. Cui, B. Locke, C. Meng, Building modern online social presence: a review of social presence theory and its instructional design implications for future trends, *Educ. Inf. Technol.* 18 (4) (2013) 661–685, <https://doi.org/10.1007/s10639-012-9192-1>. Dec.
- [47] R. Nadler, Understanding “Zoom fatigue”: theorizing spatial dynamics as third skins in computer-mediated communication, *Comput. Compos.* 58 (2020) 102613, <https://doi.org/10.1016/j.compcom.2020.102613>. Dec.
- [48] C. Halkiopoulos, E. Gkintoni, Leveraging AI in E-Learning: personalized Learning and Adaptive Assessment through Cognitive Neuropsychology—A Systematic Analysis, *Electron. (Basel)* 13 (18) (2024) 3762, <https://doi.org/10.3390/electronics13183762>. Sep.
- [49] M.S.C. Thomas, D. Ansari, V.C.P. Knowland, Annual Research Review: educational neuroscience: progress and prospects, *Child Psychol. Psychiatry* 60 (4) (2019) 477–492, <https://doi.org/10.1111/jcpp.12973>. Apr.
- [50] R. Kaplan-Rakowski, Addressing students’ emotional needs during the COVID-19 pandemic: a perspective on text versus video feedback in online environments, *Educ. Tech. Res. Dev.* 69 (1) (2021) 133–136, <https://doi.org/10.1007/s11423-020-09897-9>. Feb.
- [51] G.R. Tortella, A.B. Seabra, J. Padrão, R. Díaz-San Juan, Mindfulness and Other Simple Neuroscience-Based Proposals to Promote the Learning Performance and Mental Health of Students during the COVID-19 Pandemic, *Brain Sci.* 11 (5) (2021) 552, <https://doi.org/10.3390/brainsci11050552>. Apr.
- [52] M. Balconi, L. Angioletti, F. Cassioli, Electrophysiology and hyperscanning applied to e-learning for organizational training, *TLO* 30 (6) (2023) 857–876, <https://doi.org/10.1108/TLO-01-2023-0011>. Nov.
- [53] M. Balconi, G. Fronda, The Dialogue Between Two or More Brains: the “Hyperscanning” for Organization, *Front. Psychol.* 11 (2020) 598332, <https://doi.org/10.3389/fpsyg.2020.598332>. Oct.
- [54] L. Angioletti, K. Rovelli, C. Acconito, A. Daffinifmode\grave{a}else\grave{a}fi, M. Balconi, Electrophysiological Hyperscanning of Negotiation During Group-Oriented Decision-Making, *Appl. Sci.* 15 (11) (2025) 6073, <https://doi.org/10.3390/app15116073>. May.
- [55] U. Hakim, et al., Quantification of inter-brain coupling: a review of current methods used in haemodynamic and electrophysiological hyperscanning studies, *Neuroimage* 280 (2023) 120354, <https://doi.org/10.1016/j.neuroimage.2023.120354>. Oct.
- [56] X. Wang, R. Shi, X. Wu, J. Zhang, Decoding Human Interaction Type from Inter-brain Synchronization by Using EEG Brain Network, *IEEE J. Biomed. Health Inf.* (2023), <https://doi.org/10.1109/JBHI.2023.3329742>. PPNov.
- [57] J. Harper, S.M. Malone, W.G. Iacono, Theta- and delta-band EEG network dynamics during a novelty oddball task, *Psychophysiology* 54 (11) (2017) 1590–1605, <https://doi.org/10.1111/psyp.12906>. Nov.
- [58] G. Mai, W.S.-Y. Wang, Distinct roles of delta- and theta-band neural tracking for sharpening and predictive coding of multi-level speech features during spoken language processing, *Hum. Brain Mapp.* 44 (17) (2023) 6149–6172, <https://doi.org/10.1002/hbm.26503>. Dec.
- [59] W. Klimesch, Alpha-band oscillations, attention, and controlled access to stored information, *Trends Cogn. Sci. (Regul. Ed.)* 16 (12) (2012) 606–617, <https://doi.org/10.1016/j.tics.2012.10.007>. Dec.
- [60] A.K. Engel, P. Fries, Beta-band oscillations—mode—else—fignalling the status quo? *Curr. Opin. Neurobiol.* 20 (2) (2010) 156–165, <https://doi.org/10.1016/j.conb.2010.02.015>. Apr.
- [61] P. Fries, Rhythms for Cognition: communication through Coherence, *Neuron* 88 (1) (2015) 220–235, <https://doi.org/10.1016/j.neuron.2015.09.034>. Oct.
- [62] M.K. Rieder, B. Rahm, J.D. Williams, J. Kaiser, Human gamma-band activity and behavior, *Int. J. Psychophysiol.* 79 (1) (2011) 39–48, <https://doi.org/10.1016/j.ijpsycho.2010.08.010>. Jan.
- [63] R.V. Palumbo, et al., Interpersonal Autonomic Physiology: a Systematic Review of the Literature, *Pers. Soc. Psychol. Rev.* 21 (2) (2017) 99–141, <https://doi.org/10.1177/1088868316628405>. May.
- [64] R.W. Levenson, J.M. Gottman, Marital interaction: physiological linkage and affective exchange, *J. Pers. Soc. Psychol.* 45 (3) (1983) 587–597, <https://doi.org/10.1037/0022-3514.45.3.587>.
- [65] A. Hemakom, V. Goverdovsky, L. Aufegger, D.P. Mandic, Quantifying cooperation in choir singing: respiratory and cardiac synchronisation, in: 2016 IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP), 2016, pp. 719–723, <https://doi.org/10.1109/ICASSP.2016.7471769>. Shanghai: IEEE, Mar.
- [66] I. Konvalinka, et al., Synchronized arousal between performers and related spectators in a fire-walking ritual, *Proc. Natl. Acad. Sci. U.S.A.* 108 (2011) 8514–8519, <https://doi.org/10.1073/pnas.1016955108>. May.
- [67] M. Ardizzi, M. Calbi, S. Tavaglione, M.A. Umiltà, V. Gallesse, Audience spontaneous entrainment during the collective enjoyment of live performances: physiological and behavioral measurements, *Sci. Rep.* 10 (1) (2020) 3813, <https://doi.org/10.1038/s41598-020-60832-7>. Mar.
- [68] I. Gordon, et al., Physiological and Behavioral Synchrony Predict Group Cohesion and Performance, *Sci. Rep.* 10 (1) (2020) 8484, <https://doi.org/10.1038/s41598-020-65670-1>. May.
- [69] Y. Golland, K. Keissar, N. Levit-Binnun, Studying the dynamics of autonomic activity during emotional experience, *Psychophysiology* 51 (11) (2014) 1101–1111, <https://doi.org/10.1111/psyp.12261>. Nov.
- [70] B.K. Steiger, L.C. Kegel, E. Spirig, H. Jokeit, Dynamics and diversity of heart rate responses to a disaster motion picture, *Int. J. Psychophysiol.* 143 (2019) 64–79, <https://doi.org/10.1016/j.ijpsycho.2019.06.015>. Sep.
- [71] P. Pérez, et al., Conscious processing of narrative stimuli synchronizes heart rate between individuals, *Cell Rep.* 36 (11) (2021) 109692, <https://doi.org/10.1016/j.celrep.2021.109692>. Sep.
- [72] D. Bevilacqua, et al., Brain-to-Brain Synchrony and Learning Outcomes Vary by Student–Teacher Dynamics: evidence from a Real-world Classroom Electroencephalography Study, *J. Cogn. Neurosci.* 31 (3) (2019) 401–411, https://doi.org/10.1162/jocn_a_01274. Mar.
- [73] S.H.J. Tan, J.N. Wong, W.-P. Teo, Is neuroimaging ready for the classroom? A systematic review of hyperscanning studies in learning, *Neuroimage* 281 (2023) 120367, <https://doi.org/10.1016/j.neuroimage.2023.120367>. Nov.
- [74] A. Aron, E.N. Aron, D. Smollan, Inclusion of Other in the Self Scale and the structure of interpersonal closeness, *J. Pers. Soc. Psychol.* 63 (4) (1992) 596–612, <https://doi.org/10.1037/0022-3514.63.4.596>. Oct.
- [75] H.H. Jasper, *The Ten-Twenty Electrode System of the International Federation, Electroencephalogr. Clin. Neurophysiol.* 10 (1958) 371–375.
- [76] J.T.E. Richardson, Eta squared and partial eta squared as measures of effect size in educational research, *Educ. Res. Rev.* 6 (2) (2011) 135–147, <https://doi.org/10.1016/j.edurev.2010.12.001>. Jan.
- [77] M.P. Tarvainen, J.-P. Niskanen, J.A. Lipponen, P.O. Ranta-aho, P.A. Karjalainen, Kubios HRV – Heart rate variability analysis software, *Comput. Methods Programs Biomed.* 113 (1) (2014) 210–220, <https://doi.org/10.1016/j.cmpb.2013.07.024>. Jan.
- [78] G. Dumas, J. Nadel, R. Soussignan, J. Martinier, L. Garner, Inter-Brain Synchronization during Social Interaction, *PLoS One* 5 (8) (2010) e12166, <https://doi.org/10.1371/journal.pone.0012166>. Aug.
- [79] F. Babiloni, L. Astolfi, Social neuroscience and hyperscanning techniques: past, present and future, *Neurosci. Biobehav. Rev.* 44 (2014) 76–93, <https://doi.org/10.1016/j.neubiorev.2012.07.006>. Jul.
- [80] A. Czeszumski, et al., Hyperscanning: a Valid Method to Study Neural Inter-brain Underpinnings of Social Interaction, *Front. Hum. Neurosci.* 14 (2020) 39, <https://doi.org/10.3389/fnhum.2020.00039>. Feb.
- [81] M. Balconi, M.E. Vanutelli, Functional EEG connectivity during competition, *BMC Neurosci.* 19 (2018) 63, <https://doi.org/10.1186/s12868-018-0464-6>. Oct.
- [82] I. Konvalinka, M. Bauer, C. Stahlhut, L.K. Hansen, A. Roepstorff, C.D. Frith, Frontal alpha oscillations distinguish leaders from followers: multivariate decoding of

- mutually interacting brains, *Neuroimage* 94 (2014) 79–88, <https://doi.org/10.1016/j.neuroimage.2014.03.003>. Jul.
- [83] A.G. Lewis, J.-M. Schoffelen, H. Schriefers, M. Bastiaansen, A Predictive Coding Perspective on Beta Oscillations during Sentence-Level Language Comprehension, *Front. Hum. Neurosci.* 10 (2016) 175739, <https://doi.org/10.3389/fnhum.2016.00085>. Mar.
- [84] R. Hari, L. Henriksson, S. Malinen, L. Parkkonen, Centrality of social interaction in human brain function, *Neuron* 88 (1) (2015) 181–193, <https://doi.org/10.1016/j.neuron.2015.09.022>. Oct.
- [85] S. Dikker, et al., Brain-to-Brain Synchrony Tracks Real-World Dynamic Group Interactions in the Classroom, *Curr. Biol.* 27 (9) (2017) 1375–1380, <https://doi.org/10.1016/j.cub.2017.04.002>. May.
- [86] A.J. Shahin, T.W. Picton, L.M. Miller, Brain oscillations during semantic evaluation of speech, *Brain Cogn.* 70 (3) (2009) 259, <https://doi.org/10.1016/j.bandc.2009.02.008>. Mar.
- [87] C.G. Welle, D. Contreras, Sensory-driven and spontaneous gamma oscillations engage distinct cortical circuitry, *J. Neurophysiol.* 115 (4) (2016) 1821–1835, <https://doi.org/10.1152/jn.00137.2015>. Apr.
- [88] U. Hasson, A.A. Ghazanfar, B. Galantucci, S. Garrod, C. Keysers, Brain-to-brain coupling: a mechanism for creating and sharing a social world, *Trends Cogn. Sci. (Regul. Ed.)* 16 (2) (2012) 114–121, <https://doi.org/10.1016/j.tics.2011.12.007>. Feb.
- [89] V. Müller, U. Lindenberger, Cardiac and Respiratory Patterns Synchronize between Persons during Choir Singing, *PLoS One* 6 (9) (2011) e24893, <https://doi.org/10.1371/journal.pone.0024893>. Sep.
- [90] A. Tomashin, I. Gordon, S. Wallot, Interpersonal Physiological Synchrony Predicts Group Cohesion, *Front. Hum. Neurosci.* 16 (2022) 903407, <https://doi.org/10.3389/fnhum.2022.903407>. Jul.
- [91] E. Tsigeman, et al., Oxytocin dynamics in interpersonal sensorimotor synchrony: controlled experiments in humans, *Horm. Behav.* 175 (2025) 105817, <https://doi.org/10.1016/j.yhbeh.2025.105817>. Oct.