Social Cognitive and Affective Neuroscience, 2025, **20**(1), nsaf028
DOI: https://doi.org/10.1093/scan/nsaf028
Advance Access Publication Date: 14 March 2025
Original Research – Neuroscience

Is what I think what you think? Multilayer network-based inter-brain synchrony approach

Heegyu Kim[1], Sangyeon Kim[2], Sung Chan Jun[3], Chang S. Nam[4,5]

[1]School of Electrical Engineering and Computer Science, Gwangju Institute of Science and Technology (GIST), #505 Dasan Building, 123, Choemdangwagi-ro, Buk-gu, Gwangju 61005, South Korea
[2]Division of Artificial Intelligence Engineering, Sookmyung Women's University, #515 Suryeon Faculty Building, Cheongpa-ro 47-gil 100, Yongsan-gu, Seoul 04310, Republic of Korea
[3]School of Electrical Engineering and Computer Science and AI Graduate School, Gwangju Institute of Science and Technology (GIST), 505 Dasan Building, 123, Choemdangwagi-ro, Buk-gu, Gwangju 61005, South Korea
[4]Department of Industrial and Systems Engineering Northern Illinois University, 590 Garden Rd, DeKalb, IL 60115, USA
[5]Department of Industrial and Management Systems Engineering, Kyung Hee University, 1732 Deogyeong-daero, Giheung-gu, Yongin-si, Gyeonggi-do, South Korea
*Corresponding author. Department of Industrial and Systems Engineering, Northern Illinois University, 590 Garden Rd, DeKalb, IL 60115, USA.
E-mail: csnam@niu.edu

Abstract

Social interaction plays a crucial role in human societies, encompassing complex dynamics among individuals. To understand social interaction at the neural level, researchers have utilized hyperscanning in several social settings. These studies have mainly focused on inter-brain synchrony and the efficiency of paired functional brain networks, examining group interactions in dyads. However, this approach may not fully capture the complexity of multiple interactions, potentially leading to gaps in understanding inter-network differences. To overcome this limitation, the present study aims to bridge this gap by introducing methodological enhancements using the multilayer network approach, which is tailored to extract features from multiple networks. We applied this strategy to analyze the triad condition during social behavior processes to identify group interaction indices. Additionally, to validate our methodology, we compared the multilayer networks of triad conditions with group synchrony to paired conditions without group synchrony, focusing on statistical differences between alpha and beta waves. Correlation analysis between inter-brain and group networks revealed that this methodology accurately reflects the characteristics of actual behavioral synchrony. The findings of our study suggest that measures of paired brain synchrony and group interaction may exhibit distinct trends, offering valuable insights into interpreting group synchrony.

Keywords: Hyperscanning; Electroencephalogram (EEG); Brain network; Multilayer network

Introduction

Social interaction lies at the heart of human behavior, intricately embedded into daily life in the form of interpersonal synchrony (Babiloni et al. 2006). The relationship between interpersonal behavioral synchronization and its underlying mechanisms has garnered significant attention, leading researchers to explore the functional significance of inter-brain synchrony within interpersonal interactions (Sinha et al. 2016). To investigate the neural dynamics for social interaction, Electroencephalogram (EEG)-based hyperscanning technology has enabled the investigation of neural mechanisms during real-time social interactions through simultaneous neural activity recordings from multiple subjects (Czeszumski et al. 2020).

These hyperscanning studies have traditionally analyzed phase synchrony in social interactions. They utilize functional connectivity between inter-brain activities, employing metrics such as Coherence (Coh) (Bertollo et al. 2016, Balconi and Elide Vanutelli 2018, Coomans et al. 2021), Phase Locking Value (PLV) (Deng et al. 2022, Dumas et al. 2010, 2012:1, Gugnowska et al. 2022, Jahng et al. 2017, Perry et al. 2010, Yun et al. 2012), and Circular correlation coefficient(CCorr) (Goldstein et al. 2018, Pérez et al. 2019, Zhou et al. 2021, Key et al. 2022, Zivan et al. 2022). Such analyses compare neural signatures across brains to estimate the similarity in neural information processing across frequency and time-frequency domains. Another study investigated spatial information from connectivity to estimate the spatial strength of between-brain synchrony, utilizing measures like efficiency, divisibility, and modularity (De Vico et al. 2010, Sporns 2011, Stam 2014, Fornito and Bullmore 2015, Bassett and Sporns 2017, Avena-Koenigsberger et al. 2018, Lynn and Bassett 2019).

Despite these various attempts, existing hyperscanning studies have a methodological limitation in fully capturing social

Received: 16 June 2024; **Revised**: 30 January 2025; **Accepted**: 13 March 2025

dynamics beyond a pair of two subjects. Most hyperscanning studies with a group of over three people have merely measured pairs of brains several times. For example, researchers have investigated neural (synchronization) effects in various areas and frequency bands through inter-brain coupling for understanding social synchronization and coordination behaviors (U. Hakim et al. 2023). Specifically, this study employed graph theory measures to spatially interpret brain synchrony within anatomical and functional connectivity. The functional network suggested that the effectiveness of synchronization is affected by the functional flow of inter-cognition. This approach attempted to examine the strength of connections based on the properties of each inter-brain network that contributes to interpersonal synchronization. Some extensions of graph-theoretic metrics to networks are limited to multiplex networks when modeling complex multimodal systems in real-world scenarios, such as the dynamics of information spreading and the emergence of cooperative behavior (Battiston et al. 2014; Boccaletti et al. 2014). These studies emphasize the need for measures that apply to larger multiplexes due to the influence of mutual relationships. Moreover, Sänger et al. (2012) suggested that the brain network approach, which estimates information flows from neural oscillations, should utilize multiparticle network analysis. This more accurately captured synchronization patterns by dividing hyperbrain structures into intra-brain and inter-brain component matrices. However, while the focus on brain-to-brain synchrony between dyads was valuable, it did not fully capture the complexity of social dynamics often seen in larger groups. Wing et al. (2014) demonstrated differences in cooperation patterns between dyad conditions and quartet synchronization during musical tasks, highlighting the need for a suitable model to account for these variations. Real-world social interactions are seldom restricted to pairs of individuals and various characteristics such as group cohesion, leadership, and collective decision-making will require study in larger groups.

To address this limitation, the present study aims to dissect layered neural activities that manifest within groups, which is more than dyad, providing a novel perspective on how interconnected brain activities influence group behaviors and social interaction. Our study proposes an innovative approach using multilayer network methods that have been used to explain complex connections (Hammoud and Kramer 2020). The multilayer network, often referred to as a "network of networks," examines the connections between networks, such as those based on multimodal data or distinct factors (Krendl and Betzel 2022). While network theory has effectively illuminated the complex organization of the human brain, quantifying brain networks using this approach helps simplify their intricacy. This simplification allows for a better understanding and assessment of network properties. However, there are limitations in applying this theory, especially when examining group dynamics that involve more than just two individuals. In such cases, dual-brain approaches categorize these dynamics as separate networks (independent engagement), which restricts the ability to detect mutual information flow. Multilayer networks have helped to develop a robust mathematical framework to comprehend the intricate multiscale organization of complex systems. In particular, inter-layer analysis plays a crucial role in defining the physical significance of inter-layer connections, especially in studies related to brain structure. Traditional networks typically capture only a single mode of interaction between units (Vaiana and Feldt Muldoon 2020), which improves the modeling of the intricate dynamics of the brain through multilayer network approaches (De Domenico 2017).

For instance, Functional magnetic resonance imaging (fMRI) and magnetoencephalogram (MEG) have been utilized to compare the functional connections within the structural network of individual brains between patients and healthy individuals. In multilayer brain networks, the primary objective is to investigate specific activities from either different brain regions or the same region under different components, such as frequency decomposition or time-varying elements. Each segmentation defines layers to study these diverse aspects (Vaiana and Feldt Muldoon 2020). In this study, our objective is to explore the development of a multilayer network based on social interaction using EEG data, pushing past the boundaries of conventional individual brain networks. We aim to investigate whether employing a multilayer network that mirrors the social structure of functional brain networks can help simplify the intricate nature of long-term social interactions. This approach builds on the foundation of dyadic analysis, extending it to accommodate the complexity of group interactions. We treat brain networks as interconnected layers to capture group dynamics beyond pairwise interactions, as shown in Fig. 1.

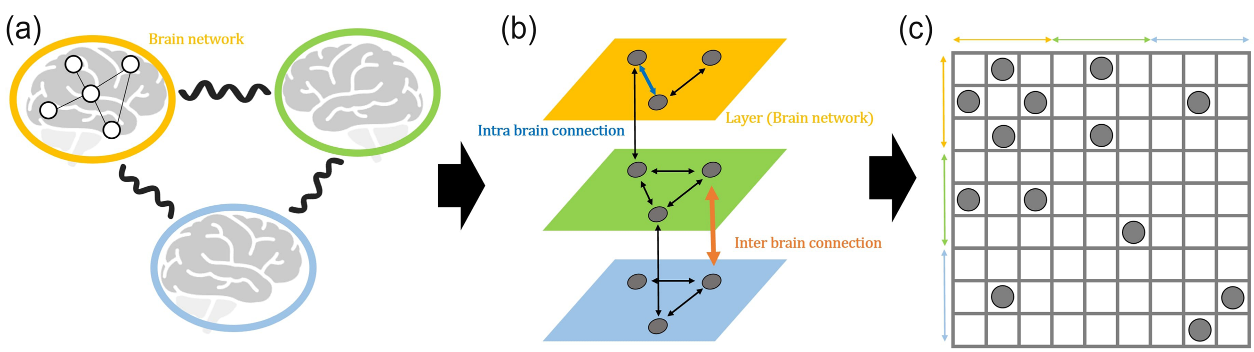

Figure 1. Overview of our proposed multilayer network approach. To construct the multilayer network, (a) each sub-network (layer) was assumed to be an individual brain network. (b) The inter-layer connections were assumed to be the inter-brain synchrony between two EEG channel locations; to reduce the influence of single-brain connections, the intra-brain connection was modeled as a bigraph (non-connected network). (c) A multilayer synchrony network was constructed for the triad, and network indices were used to quantify the connectivity. In this study, we construct a multilayer of three brain networks, with the intra-network designed as a zero network (bigraph) and depicted as a black box to focus solely on inter-synchrony factors.

This innovation allows us to explore how group contexts influence neural synchrony and social coordination. To validate our novel approach, we set two research questions:

> ***Research question 1 (RQ1)****: Can the multilayer network approach resolve the limitations of traditional hyperscanning studies that estimate group interactions based on paired neural synchrony, particularly with regard to issues that arise from behavioral differences between group and paired settings?*

Traditional analyses of paired synchrony may have yet to sufficiently capture the complexities of group behavior. Previous hyperscanning research estimated human social activities by constructing functional systems. The synchronization of information flow in brain activity is analyzed to estimate social cognition. This information flow is examined through functional connectivity to assess characteristics unique to interacting, and functional connectivity is used to construct brain networks to study the functional system (Bilek et al. 2015). Therefore, these studies explored the relationship between dynamic brain activities and synchronized tasks, influenced by social cognition, in enhancing functional brain organization among distinct regions of the functional anatomy. Thus, it indicates the relationship between neuronal coupling and interpretative action within the interconnectedness of cognitive processing brain regions. These studies typically regarded synchronization within and between brains as crucial elements of neuronal communication systems, primarily focusing on inter-brain synchronization and differences in activity patterns between brains (Jaegher De et al. 2010, Sänger et al. 2011, Keller et al. 2014). As a result, the analysis concentrated on inter-brain (paired brain) synchronization, even in group interaction studies. However, behavioral results from group environments showed differences between paired and small group settings (Lasito and Storch 2013, Dobao 2014), suggesting that the neural activities driving these behaviors exhibited similar variations. Therefore, reassessing how we measure and interpret neural synchrony in group settings may be necessary to better understand the underlying neural mechanisms of group dynamics. To address this, we will analyze paired (dyad) and group (triad) interactions as brain networks. Additionally, we will use the multilayer network approach to compare inter-layer relationships to interpret brain networks in group conditions.

> ***Research question 2 (RQ2)****: In a neural network based on brain synchrony, does a multilayer network characterized by group features reflect the characteristics of sub-network (layer) synchrony, thereby exhibiting differences between group and paired interactions?*

The neural networks of individuals within a group functioned as interconnected components of a broader group synchrony network, which supported social cohesion and collective behavior. We applied graph-theoretical approaches to interpret neural functional connections incorporating spatial information into brain network connectivity (Bullmore and Sporns 2009, De Vico et al. 2010, Sporns 2011, Stam 2014, Fornito and Bullmore 2015, Bassett and Sporns 2017, Avena-Koenigsberger et al. 2018, Lynn and Bassett 2019). These networks were used to analyze the characteristics of inter-brain connectivity, network structure, and functionality. If we estimate brain synchrony and structural characteristics from neural networks, we anticipate that the network's configuration could reveal structures conducive to group interactions. Therefore, employing a multilayer approach that has been used in biomedicine research to interpret complex biological networks, we aimed to analyze the influence between layers and extract features of group interaction from networks composed of interaction-reflecting sub-networks (layers). We also validated whether the proposed multilayer network reflects group interactions while retaining the characteristics of individual layers. Lastly, we verified our methodology by analyzing the correlation between individual layers and the multilayer network.

Materials and methods

Multilayer network approach in hyperscanning

Our study introduces a novel perspective in the realm of multilayer network approaches (Boccaletti et al. 2014), assuming each layer is a functional connectivity (synchrony) network in the individual brain. We represented each node as an EEG channel and each edge as a functional connectivity value, thereby forming each layer into an individual brain network. We also constructed a multilayer of three brain networks, with the intra-network designed as a zero network to focus solely on inter-synchrony factors, as shown in Fig. 1c. This configuration generates a group interaction network containing the inter-synchrony networks of three individuals. We utilize the multilayer network to extract graph-theoretical features, facilitating a comparison between networks of high and low synchrony among the three individuals' brains. By eliminating intra-network connections and focusing solely on inter-brain synchrony, we precisely isolated and measured the collective neural dynamics that underpin social coordination and group behavior. With these advantages, this multilayer approach can provide clearer insights into the neural basis of social interactions and enhance the reliability of detecting genuine synchronic relationships among group members.

Construction of multilayer network

A multilayer network with M layers can be defined as:

$$\mathrm{A}_{\mathrm{supra}} = \begin{bmatrix} A^1 & H^{1,2} & & H^{1,M} \\ H^{2,1} & A^2 & \cdots & H^{2,M} \\ \vdots & & \ddots & \vdots \\ H^{M,1} & H^{M,2} & \cdots & A^M \end{bmatrix}$$

where A^n is the intra-layer of n and $\mathrm{H}^{n,m}$ is the inter-layer from n to m. In this study, assume that $\mathrm{M}=3$, A is the zero-network with (channel × channel), and H is the inter-connectivity network with size (channel × channel). Thus, the multilayer network is constructed as a bigraph.

Network indices

Degree is defined as the number of links connected to this node (Newman and Girvan 2004). Using the supra-adjacency matrix, the total degree of node i, d_i, is defined as the sum of the weights of all edges ($e_{i,j}$) connected to that node both within the layer and across other layers, and that inter-layer degree ($\bar{d}$) of node i with all other $j=1, 2, \ldots$ nodes for each layer(l, m) is defined as:

$$\bar{d}_i^l = \sum_{l \neq m} \sum_{j}^{n} e_{i,j}^{l,m}$$

The degree, in weighted condition, represent scale of interactions in a weighted functional network usually focuses on reciprocal of close of local network organization (Sun and Bin 2018). The degree may be a sensitive measure of centrality in neurobiological networks with nonhomogeneous degree distributions (Newman and Girvan 2004).

Participation Coefficient (PC) is assumed to quantify the contribution of each node to each layer of the network (Guimera and Nunes Amaral 2005, Chen et al. 2019), so it represents the overall normalized strength of the network. PC is defined as multilayer degrees ($\bar{d}$), with size n node, from inter-layer,

$$P_{a_i^l} = n\frac{\overline{d_i^l}}{\bar{d}^l}$$

The participation coefficient measures the extent to which a node connects to sub-networks (layer) other than its own (Ruttorf et al. 2019). The participation coefficient measures how "well-distributed" the edges are in the brain network, indicating how efficient the functional (synchronized) processing systems are (Power et al. 2011).

Global Clustering Coefficient quantifies the degree to which the neighboring nodes in a network form a cluster (Watts and Strogatz 1998). The global clustering coefficient is the number of closed triplets (or triangles) over the total number of triplets (both open and closed) (Chen et al. 2019). Inter clustering coefficients are defined as the average of multilayer degrees ($\bar{d}$). Therefore, the intra-layer clustering coefficient computes the local clustering coefficient of each node within a layer without taking any of the other layers into account. The inter-layer clustering coefficient of a node is computed with respect to the average inter-layer edge strength.

$$\bar{C}_i^l = \frac{1}{\bar{d}_i^l\left(\bar{d}_i^l - 1\right)}\sum_{j,k}\bar{e}_{i,j}^l\bar{e}_{j,k}^l\bar{e}_{k,i}^l = \frac{1}{M-1}\sum_{m\neq l}e_{i,j}^{l,m}$$

The fraction of triangles around an individual node is known as the clustering coefficient and is equivalent to the fraction of the node's neighbors that are also neighbors of each other (Fagiolo 2007), such as detecting communities or clustering neural connections (Goldstein et al. 2018).

Characteristic Path Length (CPL) measures the minimum number of edges necessary to travel from one node to another in the network (Watts and Strogatz 1998). Its common measure is generally calculated using networks with matrix elements based on synchrony. CPL are defined as multilayer degrees ($\bar{d}$), with size n node, from inter-layer,

$$\mathrm{I_G} = \frac{1}{n(n-1)}\sum\overline{d_i^l}$$

The shortest path length between all pairs of nodes in the network is known as the characteristic path length of the network (Watts and Strogatz 1998) and is used as a measure of functional integration. High functional integration within a functional connectivity matrix suggests that the brain combines specialized and densely connected (segregated) areas through long-distance functional connections for more efficient information processing (Bertollo et al. 2016).

Datasets

We used the "Group Interaction datasets in the classroom" in our study (Dikker et al. 2017). Participants consisted of 12 healthy high school students (seven girls and five boys, aged 16–18 years). EEG was recorded simultaneously from 12 students and their teacher using wireless EMOTIV EPOC headsets (14 channels; sampling rate 128 Hz, band-pass filtering 0.5-35 Hz, notch filter; mastoid reference locations, Emotiv Systems Inc). 14 electrodes were used for study (AF3, AF4, F3, F4, F7, F8, FC5, FC6; T7, T8; O1, O2, P7, and P8). EEG was recorded for four distinct teaching styles (teaching leading, video, lecture, and discussion) for 2–5 min each for 11 days.

EEG preprocessing

The open data were band-pass filtered between 0.5 and 35 Hz using a device's built-in digital fifth-order Sinc filter. We applied Infomax Independent Component Analysis (ICA), which only select for components with a super-Gaussian activity distribution, and IC labels (Pion-Tonachini et al. 2019) to automatically remove artifacts such as eye blink and muscle components using a probability of 0.80. Finally, we segregated the EEG signal into the following four frequency bands: theta (4–8) Hz, alpha (8–13) Hz, low-beta (13–20) Hz, and high-beta (20–30) Hz using the fourth order Butterworth filter. The preprocessing analysis was performed using the EEGLAB toolbox (v.2022.0) (Delorme and Makeig 2004). Data from the students with the highest participation (1, 2, 3, 4, 5, 6, 8, 9, 10, and 12) were used from specific days in the video, lecture, and discussion conditions (2, 4, 6, 7, 8, 9).

Measurement of brain-to-brain synchrony

Coh, PLV, and CCorr values were calculated using functions of the HyPyP Python package (v.0.5.0b1) (Ayrolles et al. 2021). The values for each frequency band were calculated as an average of the values in the connectivity matrix corresponding to each electrode pair in the region and each frequency in the frequency band. The same analysis was done for both the pairs completing the task and the false pairs. False pairs were analyzed identically using data from the same task conducted in different sessions. The recorded multi-channel signals were divided into non-overlapped epochs of 5 s each from post-60 s for a single task. Upon 1000 replicated trials, all inter-connectivity values showed statistical significance (alpha < 0.05) through a cluster-based permutation test in a within pair permutation. This method introduces the idea that a single comparison has replaced multiple comparisons, so the multiple comparison problems no longer exists (Maris and Oostenveld 2007).

Coh is the traditional Fourier-based method of connectivity. The Welch estimate of coherence is:

$$\mathrm{Coh_{XY}}(\mathbf{x}) = \frac{|S_{XY}(x)|^2}{S_{XX}(x)S_{YY}(x)}$$

where $|S_{XY}|$ is the cross spectrum between the signals X and Y, and S_{XX} and S_{YY} are is the autospectrum of each signal X and Y. The calculation of coherence involves squaring the signal and a loss in polarity information (Guevara and Corsi-Cabrera 1996).

PLV is a measure of the consistency of the phase-difference but, as noted above, simply observing that there is a consistent phase relationship between two signals does not imply covariance or information exchange between them (Lachaux et al. 1999).

$$PLV_t = \frac{1}{N}\left|\sum^{\exp}(j\theta(t,n))\right|$$

Where θ (t, n) is the phase difference $(\phi_1(t,n) - \phi_2(t,n))$

CCorr is a direct parallel to the Pearson Product Moment Correlation Coefficient for circular data (Burgess 2013) and is given by:

$$\mathrm{CCorr} = \frac{\sum^{\sin}(\phi-\bar{\phi})\sin(\psi-\bar{\psi})}{\sqrt{\sum^{\sin^2}\phi-\bar{\phi}\sin^2\psi-\bar{\psi}}}$$

Where $\bar{\phi}$ and $\bar{\psi}$ are the mean directions for channels 1 and 2, respectively.

Table 1. The grand average of the functional connectivity value for each band ranges across channels and subjects for each class and the synchrony value (mean ± s.d.)

Task	Discussion			Lecture			Video		
Synchrony	Coh	PLV	Ccorr	Coh	PLV	Ccorr	Coh	PLV	Ccorr
θ (P)	0.19 ± 0.03	0.17 ± 0.02	0.11 ± 0.02	0.20 ± 0.03	0.18 ± 0.03	0.11 ± 0.02	0.20 ± 0.04	0.18 ± 0.04	0.11 ± 0.03
θ (N)	0.13 ± 0.10	0.12 ± 0.09	0.07 ± 0.06	0.13 ± 0.10	0.12 ± 0.09	0.07 ± 0.06	0.13 ± 0.10	0.11 ± 0.09	0.07 ± 0.06
α (P)	0.34 ± 0.04	0.31 ± 0.04	0.20 ± 0.04	0.34 ± 0.05	0.31 ± 0.05	0.20 ± 0.04	0.34 ± 0.06	0.32 ± 0.06	0.20 ± 0.06
α (N)	0.22 ± 0.17	0.20 ± 0.16	0.13 ± 0.10	0.22 ± 0.17	0.20 ± 0.15	0.13 ± 0.10	0.22 ± 0.17	0.21 ± 0.16	0.13 ± 0.11
l−β (P)	0.39 ± 0.04	0.27 ± 0.04	0.17 ± 0.03	0.39 ± 0.04	0.28 ± 0.04	0.18 ± 0.04	0.42 ± 0.12	0.28 ± 0.05	0.18 ± 0.05
l−β (N)	0.25 ± 0.19	0.18 ± 0.14	0.11 ± 0.09	0.26 ± 0.20	0.18 ± 0.14	0.11 ± 0.09	0.27 ± 0.22	0.18 ± 0.14	0.11 ± 0.09
h−β (P)	0.34 ± 0.03	0.30 ± 0.03	0.22 ± 0.03	0.35 ± 0.04	0.31 ± 0.04	0.23 ± 0.04	0.39 ± 0.15	0.34 ± 0.16	0.25 ± 0.13
h−β (N)	0.22 ± 0.17	0.20 ± 0.15	0.15 ± 0.11	0.23 ± 0.18	0.20 ± 0.16	0.15 ± 0.12	0.25 ± 0.22	0.22 ± 0.20	0.16 ± 0.16

In this table, P is Paired synchrony condition, and N is Non-synchrony condition..

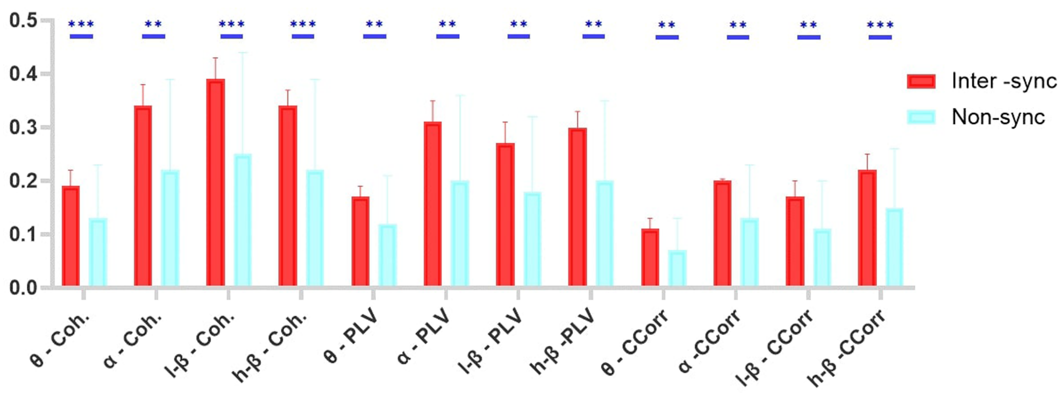

Figure 2. Comparing brain synchrony between inter synchrony and non-synchrony from pairwise comparison. Applying a t-test, the grand average of coherence-based synchrony, the grand average of PLV based synchrony, the grand average of CCorr based synchrony, and blue star indicated statistical significance (*p<0.05, **p<0.01, ***p<0.005)

Results

Brain synchrony

To verify the existence of brain synchrony between the EEG signals of each teaching style, we calculated the synchrony between EEG channels for each paired student. As the first result to present research question 1, we compared the two interaction conditions before constructing the multilayer network. This comparison was verified not to show synchrony in background brain waves but to demonstrate brain synchrony caused by actual social behavior and differences between all band waves and synchrony. Functional connectivity (Coh, PLV, CCorr, lags from 0 to +1) represented the performance of brain synchrony between EEG channels. Functional connectivity for paired synchrony was calculated based on actual interactions, but on nonsynchrony was calculated from data on the same tasks but on different days, excluding interaction, as shown in Table 1 and Fig. 2. All brain wave segments showed statistically significant differences in synchrony, indicating that the differences between sub-networks used in the multilayer approach were correctly structured.

A two-way analysis of variance (ANOVA) was implemented for the comparison of all continuous variables between groups. When indicated, a Bonferroni's correction was conducted for *post hoc* comparisons within and between groups (Pearson test, Bonferroni, Alpha < 0.05) using Matlab function (Matlab v.2020a). For each synchrony measurement, we compared the statistical differences between the interaction tasks and brain waves influencing synchrony. For Coh, the effect of the synchrony condition was F (1, 21) = 14.92, $P < .001$, and Bonferroni corrected, $P < .05$. For PLV, the effect was F (1, 26) = 13.74, $P < .001$, and Bonferroni corrected, $P < .05$. For CCorr, the effect was F (1, 23) = 14.88, $P < .001$, and Bonferroni corrected, $P < .05$.

Multilayer networks and network indices

This study aims to validate the comparison between a multilayer network reflecting group interaction and a multilayer network corresponding to pairwise analysis from previous research. The group factor estimated four network indices from a triad multilayer network in each condition. To reduce the quantitative differences in network indices based on network size and ensure a fair comparison, we added noninteracted brains to construct multilayer networks of equal size for comparison. The results of this study address Research Question 1, focusing on comparing group interaction characteristics derived from the multilayer network. To show that the multilayer network index confirms connections among triads, the study constructed multilayer networks from (i) the brains of three individuals sharing attention and (ii) the brains of two individuals sharing attention and one unrelated individual, showing how the two groups significantly differ. The grand average for the graph indices Global clustering coefficient (GCC) and CPL is shown in Fig. 3 and Table 2.

In a two-way ANOVA (Interaction task × frequency band) test with *post hoc* comparisons within and between groups (Bonferroni corrections, Alpha < 0.05), the effect of synchrony condition for GCC showed the following results: for the Coh. Network, (1.45, 31.25) = 49.25, $P < .001$; for the PLV. Network, F (3.35, 52.15) = 5.94, $P < .01$, and for the CCorr Network, F (2.35, 72.75) = 6.92, $P < .01$. For CPL, the results were: for the Coh. Network, F (2.42, 48.26) = 4.75, $P < .01$; for the PLV. Network, F (3.3, 61.82) = 2.95, $P < .05$; and for the

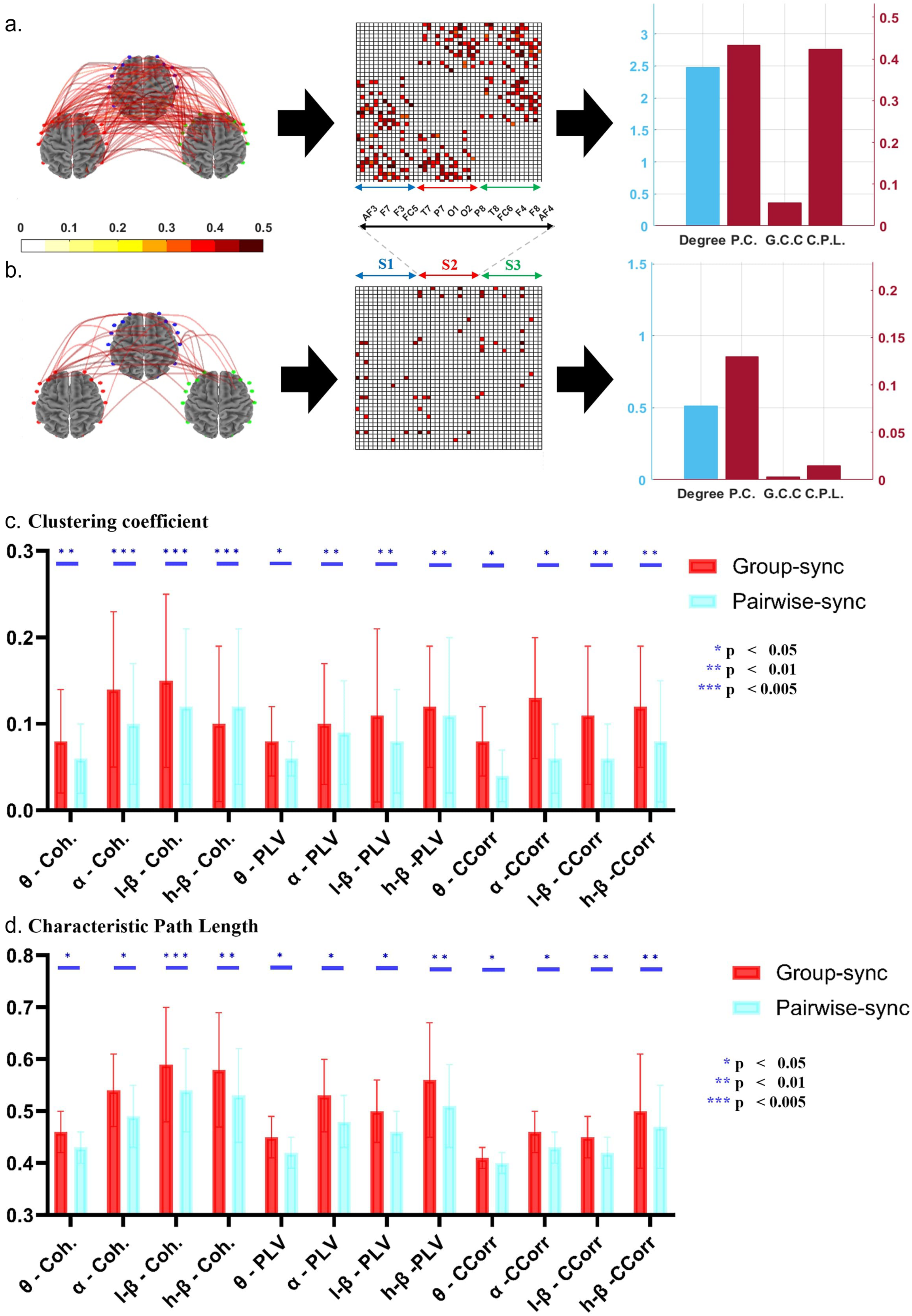

Figure 3. (a) and (b) demonstrate the process of building the multilayer network and computing network indices using brain synchrony data from subjects 1, 2, and 3. (a) displays the outcomes for the Group synchrony condition pertaining to the l-beta wave in the Coh, while (b) presents the pairwise condition pertaining to the theta wave in the Coh. Network (c) and (d) provide the average indices values of the multilayer network for GCC and CPL across all subjects. The blue star signifies statistical significance for the t-test (*p<0.05, **p<0.01, ***p<0.005).

Table 2. The grand average of the graph indices from the multilayer network for each band range across channels and subjects for each class and the synchrony value

Network index	Degree			Participation coefficient			GCC			CPL		
Synchrony	Coh	PLV	Ccorr	Coh	PLV	Ccorr	Coh	PLV	Ccorr	Coh	PLV	Ccorr
θ (G)	4.41 ± 1.88	4.00 ± 1.48	2.55 ± 1.07	0.24 ± 0.02	0.24 ± 0.02	0.25 ± 0.02	0.08 ± 0.06	0.08 ± 0.05	0.06 ± 0.04	0.46 ± 0.04	0.45 ± 0.04	0.41 ± 0.02
θ (P)	3.36 ± 1.44	3.02 ± 1.13	1.93 ± 0.83	0.20 ± 0.02	0.21 ± 0.02	0.21 ± 0.02	0.06 ± 0.04	0.06 ± 0.04	0.04 ± 0.03	0.43 ± 0.03	0.42 ± 0.03	0.40 ± 0.02
α (G)	7.75 ± 3.30	7.17 ± 2.65	4.57 ± 1.91	0.30 ± 0.03	0.31 ± 0.03	0.32 ± 0.03	0.13 ± 0.09	0.13 ± 0.08	0.09 ± 0.06	0.54 ± 0.07	0.53 ± 0.07	0.46 ± 0.04
α (P)	5.84 ± 2.49	5.39 ± 1.99	3.43 ± 1.46	0.26 ± 0.02	0.26 ± 0.02	0.27 ± 0.02	0.10 ± 0.07	0.09 ± 0.06	0.06 ± 0.04	0.49 ± 0.06	0.48 ± 0.05	0.43 ± 0.03
l–β (G)	10.13 ± 4.80	6.22 ± 2.31	3.99 ± 1.68	0.33 ± 0.03	0.34 ± 0.03	0.35 ± 0.03	0.17 ± 0.12	0.11 ± 0.07	0.08 ± 0.05	0.59 ± 0.11	0.50 ± 0.06	0.45 ± 0.04
l–β (P)	7.73 ± 3.79	4.71 ± 1.75	3.01 ± 1.30	0.28 ± 0.03	0.29 ± 0.03	0.30 ± 0.02	0.12 ± 0.09	0.08 ± 0.06	0.06 ± 0.04	0.54 ± 0.08	0.46 ± 0.04	0.42 ± 0.03
h–β (G)	9.59 ± 4.86	8.62 ± 2.60	6.22 ± 2.13	0.31 ± 0.03	0.31 ± 0.03	0.31 ± 0.03	0.15 ± 0.11	0.14 ± 0.10	0.10 ± 0.08	0.58 ± 0.11	0.56 ± 0.11	0.50 ± 0.11
h–β (P)	7.28 ± 3.91	6.59 ± 2.39	4.84 ± 2.18	0.26 ± 0.03	0.27 ± 0.03	0.26 ± 0.03	0.12 ± 0.09	0.11 ± 0.09	0.08 ± 0.07	0.53 ± 0.09	0.51 ± 0.08	0.47 ± 0.08

In this table, (G) is the Group interaction network condition, and (P) is Paired interaction network condition.

CCorr Network, $F(3,52) = 3.14$, $P < .05$, and Bonferroni corrected, $p < .05$.

The robustness of our findings was further supported by the statistical significance observed in Fig. 3. Paired *t*-tests were conducted across four brain wave segments.

Relationship between multilayer network and sub-network

To observe the correlation between sub-networks and the multilayer graph indices related research question 2, we aimed to verify whether group synchrony is assumed by examining the correlation between the traditional pairwise interaction and the proposed group interaction indicator. We utilized Pearson correlation to compare linear relationships across each brain wave band between the group interaction factor and three synchrony values. This approach allowed us to estimate the influence of sub-networks. We verified the statistical significance using t-tests shown in Fig. 4 and Table 3.

Discussion

The present study proposed an EEG-based hyperscanning approach to investigate group synchrony using a network approach. Using an EEG dataset in a group condition, we implemented a multilayer network approach to construct brain networks reflecting group structures. We also created a nonsynchrony condition for comparison by generating conditions with synchrony differences. First, we identified differences in inter-brain networks using three types of functional synchrony connectivity across four brain waves and three tasks. Next, we constructed a multilayer network for the group of three individuals, utilizing network connection indices to identify statistical differences under group conditions. Finally, we confirmed that the connection features within the multilayer network reflect the synchrony characteristics from previous studies. Our two research questions are discussed further. This study uses a neuroscientific approach based on multilayer networks to interpret complex social interactions. It builds upon traditional hyperscanning studies, which typically analyze pairwise brain activity, by introducing a methodological advancement that allows for analyzing group conditions. Moreover, this research suggests expanding the multilayer network approach in neuroscience from individual-brain network analysis to inter-brain network analysis. Leveraging brain activity with high temporal resolution (EEG) presents a robust methodology for constructing brain networks and extracting significant network features in time-varying environments.

Measurement of group interaction factors using the multilayer network approach

Our first research question explored whether the multilayer network approach can overcome the limitations of traditional hyperscanning studies that rely on paired neural synchrony to estimate group interactions. To address this issue, we employed a multilayer network approach to create a group synchrony structure (network) and assessed the connectivity associated with group interactions using graph indices. These indices commonly measure overall connection patterns of cortical areas in brain activity during hyperscanning (Babiloni et al. 2006, Astolfi et al. 2007, 2010, De Vico et al. 2010, Léné et al. 2021, Deng et al. 2023, Maidhof et al. 2023), and this trend is also evident in the review of metrics of brain synchrony, highlighting consistent patterns across various studies (U Hakim et al. 2023).

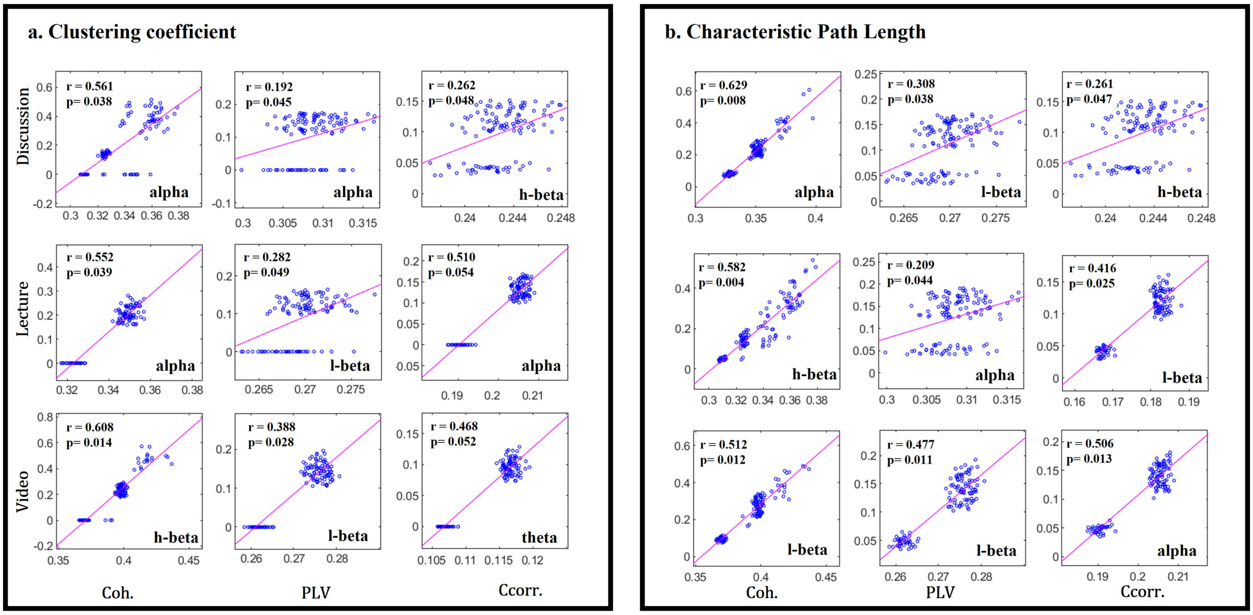

Figure 4. The graph shows the correlation between brain synchrony and various graph indices. It selectively highlights brain waves that exhibit either significant correlations or notably low p-values in the correlation graph.

In our research, we conducted a comparative analysis of three types of brain interactions across four band waves under inter-synchrony and nonsynchrony conditions. To ensure uniformity in the non-synchrony condition, we randomly selected pairs of subjects who performed the same task on different days (sessions) to match the size of the inter-synchrony condition. Our analysis revealed statistically significant differences in synchrony ($P < .01$) between the conditions, which informed the design of layers for the multilayer network. We constructed the multilayer network and examined whether the elements of the synchrony network for each layer exhibited differences between conditions with and without interaction. Our analysis of four network connection characteristics from the multilayer network demonstrated variations between group interaction and nongroup conditions in the alpha and beta bands. These findings confirmed that social interaction processing and synchronized behavior features are consistently represented in the group network. We speculated that the alpha band is linked to social information processing (Perry et al. 2010, Naeem et al. 2012, Algumaei et al. 2023, Tan et al. 2023). In contrast, the differences in both beta bands were likely due to attentive behavior during lecture leading, video watching, and synchronized tasks during discussions (Naeem et al. 2012, Konvalinka et al. 2014, Balconi et al. 2015, 2023, Novembre et al. 2017, Liu et al. 2024). The theta wave did not display significant differences, which we interpreted as being indicative of minimal adaptive behavior characteristics due to the uniform classroom setting.

The multilayer network graph index revealed significant network connectivity features in all brain waves except the theta wave, which is associated with adaptive behavior in human interaction (Billeke et al. 2014). Our study aimed to analyze the topological connections across layers within a multilayer network (Dittman et al. 2021). Within the multilayer network, the CPL measured the efficiency of information flow, while the GCC gauged the extent of group synchrony structure through triangle clustering across different layers. In the alpha band, a high CPL suggested that neural activity reflects social information processing in group behavior (Watts and Strogatz 1998, Wang et al. 2022). Similarly, a high GCC in the alpha band indicated the presence of social coordination structures as topological features. Furthermore, high CPL and GCC in beta waves suggested that concentrating behavior influenced the brain's ability to transfer information efficiently (Müller et al. 2018). Overall, the network metrics revealed topological properties can serve as spatial characteristics factors, highlighting the potential of using these factors to measure group synchrony in multilayer networks (Duan et al. 2015). These findings not only answer our initial research questions but also underscore the profound impact of the multilayer network approach. By demonstrating its superiority over traditional methods, we have opened new doors in the study of group interactions. Moreover, our research highlights the approach's unique ability to capture the intricate interplay of interactions within diverse group settings, further solidifying its potential in the field of cognitive neuroscience and networks.

The relationship between sub-networks (layers) and multilayer network

Regarding the second research question, our findings revealed that the degree index exhibited statistically significant positive correlations in the beta wave, indicating a link with neural organization stemming from attentive synchrony behavior. The GCC showed significant positive correlations across all three tasks in the coherence network, suggesting that the formation of triplet sets between layers influenced the neural communities in the triad. These findings suggest that higher levels of synchrony among connections within sub-networks are more likely to occur in adjacent layers. Additionally, they indicate that significant synchrony during interactions activates the same brain regions, facilitating information transfer between similar functional areas. These results imply that group characteristics are apparent in the activation of these regions.

Table 3. The grand average correlation value between group synchrony and graph indices and significant value and statistically significant correlation values ($P < .05$) are indicated in bold.

		Degree			Participation coefficient			Clustering coefficient			CPL		
		Coh	PLV	Ccorr	Coh	PLV	Ccorr	Coh	PLV	Ccorr	Coh	PLV	Ccorr
Discus-sion	θ	r = 0.252 P = .051	**r = 0.248 P = .021**	r = 0.179 P = .074	r = 0.032 P = .124	r = 0.080 P = .056	r = 0.063 P = .065	r = 0.279 P = .065	r = 0.257 P = .067	r = 0.146 P = .074	r = 0.304 P = .079	r = 0.256 P = .059	r = 0.222 P = .056
	α	r = 0.078 P = .090	**r = 0.192 P = .036**	**r = 0.235 P = .027**	r = 0.073 P = .071	r = 0.088 P = .075	r = 0.097 P = .050	**r = 0.561 P = .038**	**r = 0.192 P = .045**	**r = 0.160 P = .008**	**r = 0.629 P = .008**	r = 0.295 P = .083	**r = 0.129 P = .050**
	l–β	r = 0.021 P = .079	r = 0.052 P = .057	**r = 0.543 P = .030**	r = 0.092 P = .058	r = 0.011 P = .121	r = 0.007 P = .093	**r = 0.261 P = .014**	**r = 0.140 P = .007**	**r = 0.119 P = .027**	**r = 0.044 P = .036**	**r = 0.308 P = .038**	**r = 0.096 P = .034**
	h–β	**r = 0.527 P = .017**	**r = 0.235 P = .027**	**r = 0.167 P = .020**	r = 0.027 P = .070	r = 0.007 P = .093	r = 0.014 P = .131	**r = 0.119 P = .034**	r = 0.128 P = .054	**r = 0.262 P = .048**	**r = 0.023 P = .020**	r = 0.068 P = .055	**r = 0.261 P = .047**
Lecture	θ	**r = 0.462 P = .001**	r = 0.514 P = .092	**r = 0.529 P = .008**	r = 0.004 P = .083	r = 0.057 P = .083	r = 0.051 P = .084	**r = 0.574 P = .011**	r = 0.507 P = .094	r = 0.476 P = .052	**r = 0.506 P = .006**	r = 0.495 P = .094	r = 0.466 P = .053
	α	**r = 0.493 P = .032**	r = 0.480 P = .058	**r = 0.534 P = .034**	r = 0.011 P = .157	r = 0.032 P = .074	r = 0.036 P = .053	**r = 0.552 P = .039**	r = 0.479 P = .088	r = 0.510 P = .054	**r = 0.419 P = .029**	**r = 0.209 P = .044**	r = 0.546 P = .078
	l–	r = 0.651 P = .096	**r = 0.248 P = .043**	r = 0.472 P = .081	r = 0.027 P = .050	r = 0.038 P = .122	r = 0.083 P = .103	**r = 0.689 P = .049**	**r = 0.282 P = .049**	r = 0.554 **P** = .071	**r = 0.626 P = .017**	**r = 0.482 P = .025**	**r = 0.416 P = .025**
	h–β	**r = 0.615 P = .036**	r = 0.602 P = .097	**r = 0.643 P = .028**	r = 0.108 P = .086	r = 0.142 P = .084	r = 0.016 P = .097	**r = 0.629 P = .017**	**r = 0.630 P = .014**	r = 0.602 **P** = .086	**r = 0.582 P = .004**	**r = 0.632 P = .030**	**r = 0.622 P = .014**
Video	θ	r = 0.437 P = .053	r = 0.433, P = .085	r = 0.373 P = .100	r = 0.091 P = .108	r = 0.013 P = .072	r = 0.031 P = .055	**r = 0.456 P = .010**	r = 0.468 P = .086	r = 0.468 P = .052	**r = 0.512 P = .025**	**r = 0.489 P = .028**	**r = 0.523 P = .001**
	α	r = 0.268 P = 067	r = 0.380 P = .093	r = 0.413 P = .086	r = 0.041 P = .074	r = 0.161 P = .067	r = 0.031 P = .060	r = 0.421 P = .099	r = 0.388 P = .057	r = 0.442 P = .067	**r = 0.466 P = .026**	**r = 0.434 P = .043**	**r = 0.506 P = .013**
	l-β	**r = 0.192 P = .036**	**r = 0.484 P = .024**	r = 0.457 P = .072	r = 0.062 P = .093	r = 0.021 P = .128	r = 0.075 P = .059	**r = 0.535 P = .021**	**r = 0.388 P = .028**	r = 0.403 P = .055	**r = 0.512 P = .012**	**r = 0.477 P = .011**	r = 0.490 P = .093
	h–β	**r = 0.574 P = .003**	r = 0.732 P = .088	**r = 0.377 P = .027**	r = 0.079 P = .068	r = 0.043 **P** = .072	r = 0.022 **P** = .078	r = 0.608 P = .014	r = 0.481 **P** = .095	r = 0.516 **P** = .075	**r = 0.694 P = .039**	r = 0.698 P = .091	**r = 0.738 P = .035**

Nevertheless, there are instances where the GCC is zero, even in synchrony. This could be due to passive synchrony behavior during group interactions. When examining the groups with zero values, we found that this only occurred when subject 12 was included. We believe this was due to the subject's specific synchrony behavior not exhibiting the expected characteristics in the GCC. Similarly, the CPL yielded results consistent with the GCC, indicating that efficient information processing was observed within the group as synchrony increased. As the network approached a regular distribution (stable condition), it tended to exhibit higher CPL values, as Rossini et al. (2020) suggested. This indicates that EEG synchrony oscillation is consistently distributed within the group. It suggests that significant synchrony within sub-networks contributes to the multilayer network in a nonrandom way, emphasizing the role of brain areas in stable group interactions.

In contrast, the Participant coefficient (PC) index did not show significant correlations with the characteristics of the layers or candidate brain hubs using the established PC index measure (Guimera and Nunes Amaral 2005). In brain network research, the degree related to the distribution of synchronized nodes and PC has a weak relationship (Power et al. 2014, Tamburro et al. 2024). Thus, in a group network, the centrality of spatial locations has a low correlation with individual synchrony values. Furthermore, our correlation analysis for the four graph indices indicated that clustering groups were formed in situations with low synchrony values. Significant elements decreased in networks with lower synchrony values, impacting group connectivity. The study focused on group interactions in a classroom setting to identify group characteristics from multibrain networks. By comparing the connection indices of multilayer networks with synchrony, several researchers have highlighted notable features, comparing them with previous research. Previous work has emphasized the dynamics and influencing factors as individual team members rely on or interconnect with others (Mesmer-Magnus and DeChurch 2009). Team processes create contextual structures that influence subsequent team processes (Kozlowski and Bell 2003, Tan et al. 2023), and the dynamic information exchange process is significantly more complex in multiperson interactions than in two or three-person situations (Quaresima and Ferrari 2019). Studies have demonstrated significantly higher values in surrogate data and shared focus tasks in team synchrony and inter-brain network topological properties (Rossini et al. 2020). Our study on group synchrony and group brain network topological properties revealed similar trends.

Additionally, classroom studies have reported interaction patterns in group members who assist their partners or in cases where non-collaborative patterns intermittently arise among some members (Watanabe and Swain 2007). The phenomenon observed in our study, GCC logical interpretation index (GCC), may reflect similar occurrences. It may also be attributed to a lower motivation to maintain the structure of collective perception, cognitive structure, or knowledge organization within the group (Kozlowski and Ilgen 2006, Vidergor 2021). This suggests that specific group behavior dynamics can impact network connectivity.

Limitation & future works

Although our proposed approach was successful, there are some limitations in this study. This study used publicly available data to analyze students' group synchrony in the high school classroom setting. In this dataset, some students did not attend every classroom session, resulting in selective data analysis. Their selective approach could have introduced bias in the results. To overcome this issue, we segmented each session into 5-s intervals to capture multiple synchronized functional connectivities, aiming to preserve the trends that could be missed in underrepresented sessions.

The dataset we used in this study only included task-related recordings without any information on resting-state EEG data. Using distinct quasi-stable states like the resting state may help clarify dynamic differences when comparing neural activity associated with the social cognitive process. This created a limitation is only using nonsynchronous states from task-related data instead, as resting-state EEG is generally preferred for comparing brain conditions under uniform environments. The absence of resting-state EEG restricted the depth of our comparative analysis. To deal with these limitations, we plan to collect and create a fresh dataset on neural activity for future studies aimed at group interactions. Our multilayer approach focused solely on inter-layer connections, assuming each layer represented an individual's brain network. This approach differs from traditional methods, which often use intra- and inter-layer connections to explore network dynamics. However, constructing the network with only inter-layer connections has the potential to weaken the overall network connectivity. Moreover, calculating graph indices from nodes across layers may produce insights that differ from those obtained through conventional multilayer network analyses. For future studies, integrating intra- and inter-layer connections could provide a more comprehensive analysis and strengthen the network connectivity, potentially offering much deeper insights into the complex dynamics of group interactions.

Conclusion

This study introduces a multilayer network-based method to efficiently measure inter-brain synchrony emerging from group interactions. To validate this approach, we first established two main research questions and then conducted experiments with publicly available EEG data from group interaction scenarios to create a synchrony network for graph analysis. Specifically, the research questions were addressed to confirm the extraction of interaction factors from the group brain network using the multilayer approach. Our experimental results demonstrated the adaptability of our methodology to different element configurations, and its potential for scalability underscores the potential of a multilayer network approach to provide deeper insight into the spatial and dynamic aspects of group interaction in social neuroscience. The relationship between the multilayer network and its subnetworks was also thoroughly examined. The study employed the multilayer network approach to represent group characteristics in the network, which consists of multiple sub-networks (layers).

To ensure that the characteristics of sub-networks were consistently represented in the multilayer network, this study conducted a thorough analysis of the correlation between graph indices and synchrony. This analysis revealed a positive correlation for indices such as GCC and CPL, suggesting that focused behaviors significantly influenced the functional organization of information transfer. These findings suggest that the multi-brain network design effectively captures comprehensive information flow. Additionally, the study explored interaction characteristics in group scenarios featuring behavioral synchrony, thereby enhancing our understanding of group dynamics (Watanabe and Swain 2007, Lasito and Storch 2013). The correlation analysis revealed patterns consistent with prior research, emphasizing interaction opportunities typical of smaller group settings. These insights suggest that both paired-brain synchrony and group interactions reflect mutual information flow within group dynamics, offering a new perspective on interpreting group synchrony.

In conclusion, this study successfully presents a novel methodology for estimating group synchrony and constructing group brain networks using a multilayer network approach. It can show how the social network among participants can extend neural network to reveal communicative shared representations within a larger group. We believe this advanced approach would offer nuanced insights into complex social interactions within groups.

Conflict of interest: None declared.

Funding

This work was in part supported by the Ministry of Education of the Republic of Korea and the National Research Foundation of Korea (NRF-2023S1A5A2A01076552). This work was in part supported by the National Research Foundation of Korea grant funded by the Korea government (MSIT) (RS-2023-00210250). This work was in part supported by the National Research Foundation of Korea (No. RS-2024-00361688) This work was in part supported by Institute of Information & Communications Technology Planning & Evaluation (IITP) (No. 2019-0-01842).

Data availability

Not applicable

References

Algumaei M, Hettiarachchi IT, Farghaly M *et al*. The neuroscience of team dynamics: exploring neurophysiological measures for assessing team performance. *IEEE Access* 2023;**11**:129173–94.

Astolfi L, Cincotti F, Mattia D *et al*. Comparison of different cortical connectivity estimators for high-resolution EEG recordings. *Human Brain Mapp* 2007;**28**:143–57.

Astolfi L, Toppi J, De Vico Fallani F *et al*. Neuroelectrical hyperscanning measures simultaneous brain activity in humans. *Brain Topography* 2010;**23**:243–56.

Avena-Koenigsberger A, Misic B, Sporns O. Communication dynamics in complex brain networks. *Nat Rev Neurosci* 2018;**19**:17–33.

Ayrolles A, Brun F, Chen P *et al*. HyPyP: a hyperscanning Python pipeline for inter-brain connectivity analysis. *Soc Cognit Affective Neurosci* 2021;**16**:72–83.

Babiloni F, Cincotti F, Mattia D *et al*. Hypermethods for EEG hyperscanning. 3666–69 in *2006 International Conference of the IEEE Engineering in Medicine and Biology Society*. New York, NY: IEEE, 2006.

Balconi M, Angioletti L, Cassioli F. Hyperscanning EEG paradigm applied to remote vs. face-to-face learning in managerial contexts: which is better?. *Brain Sci* 2023;**13**:356..

Balconi M, Elide Vanutelli M. EEG hyperscanning and behavioral synchronization during a joint actions. *Neuropsychol Trends* 2018;**2018**:23–47.

Balconi M, Grippa E, Elide Vanutelli M. What Hemodynamic (fNIRS), Electrophysiological (EEG) and autonomic integrated measures can tell us about emotional processing. *Brain Cognit* 2015;**95**:67–76..

Bassett DS, Sporns O. Network neuroscience. *Nat Neurosci* 2017;**20**:353–64.

Battiston F, Nicosia V, Latora V. Structural measures for multiplex networks. *Phys. Rev. E* 2014;**89**.

Bertollo M, Tamburro G, Schinaia L *et al*. Hyperbrain features of team mental models within a juggling paradigm: a proof of concept. *PeerJ* 2016;**4**:e2457.

Bilek E, Ruf M, Schäfer A *et al*. Information flow between interacting human brains: identification, validation, and relationship to social expertise. *Proc Natl Acad Sci* 2015;**112**:5207–12.

Billeke P, Zamorano F, López T *et al*. Someone has to give in: theta oscillations correlate with adaptive behavior in social bargaining. *Soc Cognit Affective Neurosci* 2014;**9**:2041–48.

Boccaletti S, Bianconi G, Criado R *et al*. The structure and dynamics of multilayer networks. *Phys Rep* 2014;**544**:1–122.

Bullmore E, Sporns O. Complex brain networks: graph theoretical analysis of structural and functional systems. *Nat Rev Neurosci* 2009;**10**:186–98.

Burgess AP. On the interpretation of synchronization in EEG hyperscanning studies: a cautionary note. *Front Human Neurosci* 2013;**7**:881.

Chen Q, Beaty RE, Cui Z *et al*. Brain hemispheric involvement in visuospatial and verbal divergent thinking. *NeuroImage* 2019;**202**:116065.

Coomans E, Geraedts IK, Berend Deijen J *et al*. Intersubject EEG coherence in healthy dyads during individual and joint mindful breathing exercise: an EEG-based experimental hyperscanning study. *Adv Cognit Psychol* 2021;**17**:250–60.

Czeszumski A, Eustergerling S, Lang A *et al*. Hyperscanning: a valid method to study neural inter-brain underpinnings of social interaction. *Front Human Neurosci* 2020;**14**:39.

De Domenico M. Multilayer modeling and analysis of human brain networks. *Giga Science* 2017;**6**:gix004.

Delorme A, Makeig S. EEGLAB: an open source toolbox for analysis of single-trial EEG dynamics including independent component analysis. *J Neurosci Methods* 2004;**134**:9–21.

Deng X, Lin M, Zhang L *et al*. Relations between family cohesion and adolescent-parent's neural synchrony in response to emotional stimulations. *Behav Brain Funct* 2022;**18**:11.

Deng X, Yang M, Chen X *et al*. The role of mindfulness on theta inter-brain synchrony during cooperation feedback processing: an EEG-based hyperscanning study. *Int J Clin Health Psychol* 2023;**23**:100396.

De Vico F, Fabrizio VN, Sinatra R *et al*. Defecting or not defecting: how to 'read' human behavior during cooperative games by EEG measurements. *PLoS One* 2010;**5**:e14187.

Dikker S, Wan L, Davidesco I *et al*. Brain-to-brain synchrony tracks real-world dynamic group interactions in the classroom. *Curr Biol* 2017;**27**:1375–80.

Dittman Z, Munia TTK, and Aviyente S. Graph theoretic analysis of multilayer EEG connectivity networks. In *2021 43rd Annual International Conference of the IEEE Engineering in Medicine & Biology Society (EMBC)* Guadalajara, Mexico November 1-5, 2021. IEEE, 475–479, 2021.

Dobao AF. Attention to form in collaborative writing tasks: comparing pair and small group interaction. *Can Modern Language Rev* 2014;**70**:158–87.

Duan L, Dai R-N, Xiao X *et al*. Cluster Imaging of multi-brain networks (CIMBN): a general framework for hyperscanning and modeling a group of interacting brains. *Front Neurosci* 2015;**9**:267.

Dumas G, Nadel J, Soussignan R *et al*. Inter-brain synchronization during social interaction. *PLoS One* 2010;**5**:e12166.

Dumas TM, Ellis WE, Wolfe DA. Identity development as a buffer of adolescent risk behaviors in the context of peer group pressure and control. *J Adolescence* 2012;**35**:917–27.

Fagiolo G. Clustering in complex directed networks. *Phys Rev E* 2007;**76**:026107.

Fornito A, Bullmore ET. Connectomics: a new paradigm for understanding brain disease. *Eur Neuropsychopharmacol* 2015;**25**:733–48.

Goldstein P, Weissman-Fogel I, Dumas G *et al*.. Brain-to-brain coupling during handholding is associated with pain reduction. *Proc Natl Acad Sci* 2018;**115**:E2528–37.

Guevara MA, Corsi-Cabrera M. EEG coherence or EEG correlation?. *Int J Psychophysiol* 1996;**23**:145–53.

Gugnowska K, Novembre G, Kohler N *et al*. Endogenous sources of interbrain synchrony in duetting pianists. *Cereb Cortex* 2022;**32**:4110–27.

Guimera R, Nunes Amaral LA. Cartography of complex networks: modules and universal roles. *J Stat Mech Theor Exper* 2005;**2005**:P02001.

Hakim U, De Felice S, Pinti P *et al*. Quantification of inter-brain coupling: a review of current methods used in haemodynamic and electrophysiological hyperscanning studies. *NeuroImage* **280** 2023:120354.

Hammoud Z, Kramer F. Multilayer networks: aspects, implementations, and application in biomedicine. *Big Data Analyt* 2020;**5**:2.

Jaegher De H, Di Paolo E, Gallagher S. Can social interaction constitute social cognition?. *Trends Cognit Sci* 2010;**14**:441–47.

Jahng J, Kralik JD, Hwang D-U *et al*. Neural dynamics of two players when using nonverbal cues to gauge intentions to cooperate during the prisoner's dilemma game. *NeuroImage* 2017;**157**:263–74.

Keller MM, Chang M-L, Becker ES *et al*. Teachers' emotional experiences and exhaustion as predictors of emotional labor in the classroom: an experience sampling study. *Front Psychol* 2014;**5**:1442.

Key AP, Yan Y, Metelko M *et al*. Greater social competence is associated with higher interpersonal neural synchrony in adolescents with autism. *Front Human Neurosci* 2022;**15**:790085.

Konvalinka I, Bauer M, Stahlhut C *et al*. Frontal alpha oscillations distinguish leaders from followers: multivariate decoding of mutually interacting brains. *Neuroimage* 2014;**94**:79–88.

Kozlowski SWJ, Bell BS. Work groups and teams in organizations. *Handbook Psychol* 2003;**12**:333–75.

Kozlowski SWJ, Ilgen DR. Enhancing the effectiveness of work groups and teams. *Psychol Sci Public Interes* 2006;**7**:77–124.

Krendl AC, Betzel RF. Social cognitive network neuroscience. *Soc Cognit Affective Neurosci* 2022;**17**:510–29.

Lachaux J-P, Rodriguez E, Martinerie J *et al*. Measuring phase synchrony in brain signals. *Human Brain Mapp* 1999;**8**:194–208.

Lasito, Storch N. Comparing pair and small group interactions on oral tasks. *RELC J* 2013;**44**:361–75.

Léné P, Karran AJ, Labonté-Lemoyne E *et al*. Is there collaboration specific neurophysiological activation during collaborative task activity? An analysis of brain responses using electroencephalography and hyperscanning. *Brain Behav* 2021;**11**:e2270.

Liu Y, Zhang Y, Zhong Y *et al*. Favoritism or bias? Cooperation and competition under different intergroup relationships: evidence from EEG hyperscanning. *Cereb Cortex* 2024;**34**:bhae131.

Lynn CW, Bassett DS. The physics of brain network structure, function and control. *Nat Rev Phys* 2019;**1**:318–32.

Maidhof C, Müller V, Lartillot O *et al*. Intra- and inter-brain coupling and activity dynamics during improvisational music therapy with a person with dementia: an explorative EEG-hyperscanning single case study. *Front Psychol* 2023;**14**:1155732.

Maris E, Oostenveld R. Nonparametric statistical testing of EEG- and MEG-data. *J Neurosci Methods* 2007;**164**:177–90.

Mesmer-Magnus JR, DeChurch LA. Information sharing and team performance: a meta-analysis. *J Appl Psychol* 2009;**94**:535.

Müller V, Sänger J, Lindenberger U. Hyperbrain network properties of guitarists playing in quartet. *Ann NY Acad Sci* 2018;**1423**:198–210.

Naeem S, Duffy JE, Zavaleta E. The functions of biological diversity in an age of extinction. *Science* 2012;**336**:1401–06.

Newman MEJ, Girvan M. Finding and evaluating community structure in networks. *Phys Rev E* 2004;**69**:026113.

Novembre G, Knoblich G, Dunne L *et al*. Interpersonal synchrony enhanced through 20 Hz phase-coupled dual brain stimulation. *Soc Cognit Affective Neurosci* 2017;**12**:662–70.

Pérez A, Dumas G, Karadag M *et al*. Differential brain-to-brain entrainment while speaking and listening in native and foreign languages. *Cortex* 2019;**111**:303–15.

Perry A, Bentin S, Shalev I *et al*. Intranasal oxytocin modulates EEG Mu/alpha and beta rhythms during perception of biological motion. *Psychoneuroendocrinology* 2010;**35**:1446–53.

Pion-Tonachini L, Kreutz-Delgado K, Makeig S. ICLabel: an automated electroencephalographic independent component classifier, dataset, and website. *NeuroImage* 2019;**198**:181–97.

Power JD, Cohen AL, Nelson SM *et al*. Functional network organization of the human brain. *Neuron* 2011;**72**:665–78.

Power JD, Mitra A, Laumann TO *et al*. Methods to detect, characterize, and remove motion artifact in resting state fMRI. *Neuroimage* 2014;**84**:320–41.

Quaresima V, Ferrari M. Functional near-infrared spectroscopy (fNIRS) for assessing cerebral cortex function during human behavior in natural/social situations: a concise review. *Organizational Res Methods* 2019;**22**:46–68.

Rossini PM, Di Iorio R, Vecchio F *et al*. Early diagnosis of Alzheimer's disease: the role of biomarkers including advanced EEG signal analysis. Report from the IFCN-sponsored panel of experts. *Clin Neurophysiol* 2020;**131**:1287–310.

Ruttorf M, Kristensen S, Schad LR *et al*. Transcranial direct current stimulation alters functional network structure in humans: a graph theoretical analysis. *IEEE Trans Med Imaging* 2019;**38**:2829–37.

Sänger J, Lindenberger U, Müller V. Interactive brains, social minds. *Commun Integr Biol* 2011;**4**:655–63.

Sänger J, Müller V, Lindenberger U. Intra-and interbrain synchronization and network properties when playing guitar in duets. *Front Human Neurosci* 2012;**6**:312.

Sinha N, Maszczyk T, Wanxuan Z *et al*.. EEG hyperscanning study of inter-brain synchrony during cooperative and competitive interaction. 004813–18 in *2016 IEEE International Conference on Systems, Man, and Cybernetics (SMC)* Budapest, Hungary October 9-12 2016. IEEE, 2016.

Sporns O. The human connectome: a complex network. *Ann NY Acad Sci* 2011;**1224**:109–25.

Stam CJ. Modern network science of neurological disorders. *Nat Rev Neurosci* 2014;**15**:683–95.

Sun G, Bin S. A new opinion leaders detecting algorithm in multi-relationship online social networks. *Multimedia Tools Appl* 2018;**77**:4295–307.

Tamburro G, Bruña R, Fiedler P *et al*. An analytical approach for naturalistic cooperative and competitive EEG-hyperscanning data: a proof-of-concept study. *Sensors* 2024;**24**:2995.

Tan SHJ, Wong JN, Teo W-P. Is neuroimaging ready for the classroom? A systematic review of hyperscanning studies in learning. *NeuroImage* 2023;**281**:120367.

Vaiana M, Feldt Muldoon S. Multilayer brain networks. *J Nonlinear Sci* 2020;**30**:2147–69.

Vidergor HE. Effects of digital escape room on gameful experience, collaboration, and motivation of elementary school students. *Comput Educ* 2021;**166**:104156.

Wang X, Zhang Y, Yingyao H *et al*.. Dynamic inter-brain networks correspond with specific communication behaviors: using functional near-infrared spectroscopy hyperscanning during creative and non-creative communication. *Front Human Neurosci* **16**:2022:16.

Watanabe Y, Swain M. Effects of proficiency differences and patterns of pair interaction on second language learning: collaborative dialogue between adult ESL learners. *Language Teach Res* 2007;**11**:121–42.

Watts DJ, and Strogatz SH. Collective dynamics of 'small-world'networks. *Nature* 1998;**393**:440–442.

Wing AM, Endo S, Yates T *et al*. Perception of string quartet synchronization. *Front Psychol* 2014;**5**:103734.

Yun K, Honorio J, Chattopadhyay D *et al*. Two-person interaction detection using body-pose features and multiple instance learning. 28–35 in *2012 IEEE Computer Society Conference on Computer Vision and Pattern Recognition Workshops* Providence, Rhode Island, USA. 16–21 June 2012. IEEE, 2012.

Zhou X, Pan Y, Zhang R *et al*. Mortality threat mitigates interpersonal competition: an EEG-based hyperscanning study. *Soc Cognit Affective Neurosci* 2021;**16**:621–31.

Zivan M, Gashri C, Habuba N *et al*. Reduced mother-child brain-to-brain synchrony during joint storytelling interaction interrupted by a media usage. *Child Neuropsychol* 2022;**28**: 918–37.

Social Cognitive and Affective Neuroscience, 2025, 20(1), nsaf028, DOI: https://doi.org/10.1093/scan/nsaf028, Advance Access Publication Date: 14 March 2025, Original Research – Neuroscience

Received: 16 June 2024; **Revised**: 30 January 2025; **Accepted**: 13 March 2025