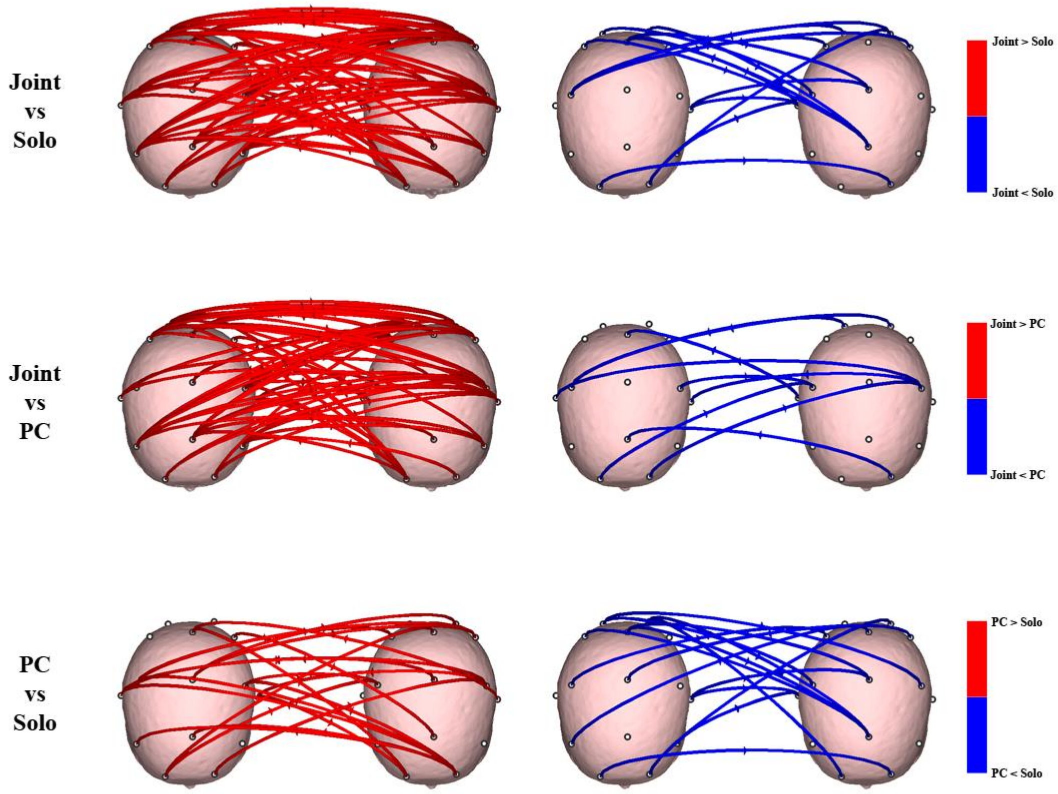

Fig.S1 - Statistical Inter-brain causality patterns in theta band. The networks were obtained by statistically comparing the three different levels of interaction: Joint vs Solo, Joint vs PC and PC vs Solo (paired t-test, p<0.05 FDR corrected). The heads are seen from above, the nose pointing to the lower part of the page. The arrows indicate the existence of a statistical causality between the activity recorded on the scalp of the two subjects (15 electrodes each).

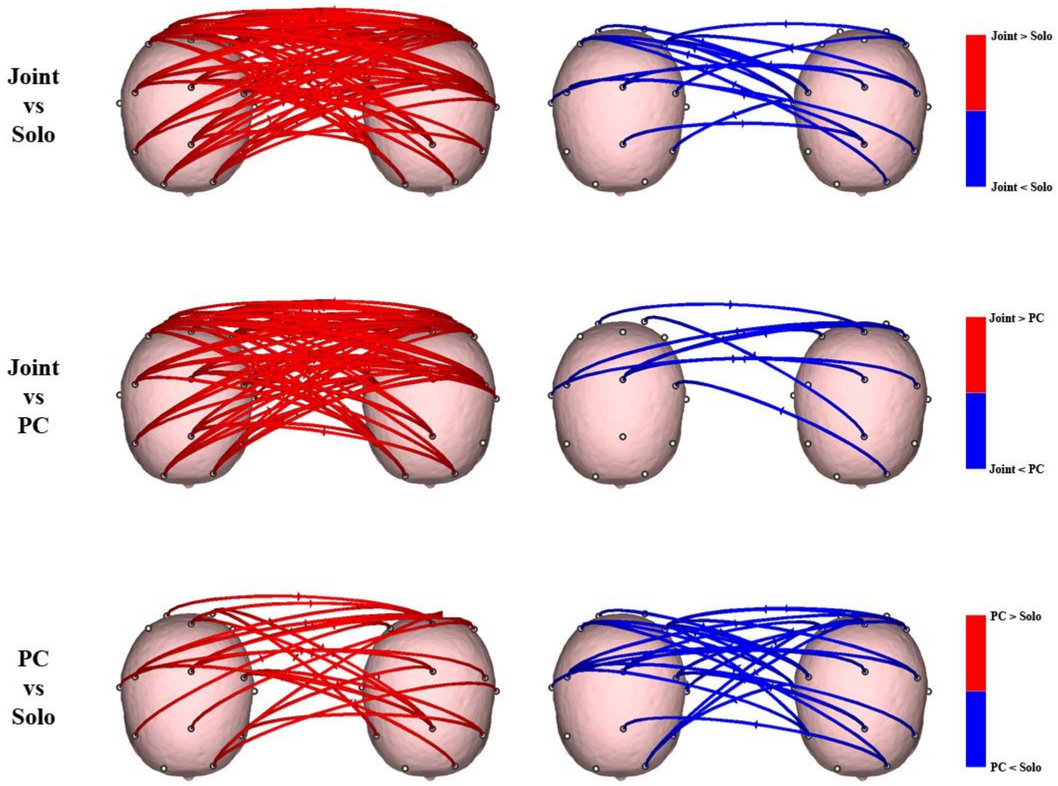

Fig.S2 - Statistical Inter-brain causality patterns in beta band. The networks were obtained by statistically comparing the three different levels of interaction: Joint vs Solo, Joint vs PC and PC vs Solo (paired t-test, p<0.05 FDR corrected). The heads are seen from above, the nose pointing to the lower part of the page. The arrows indicate the existence of a statistical causality between the activity recorded on the scalp of the two subjects (15 electrodes each).

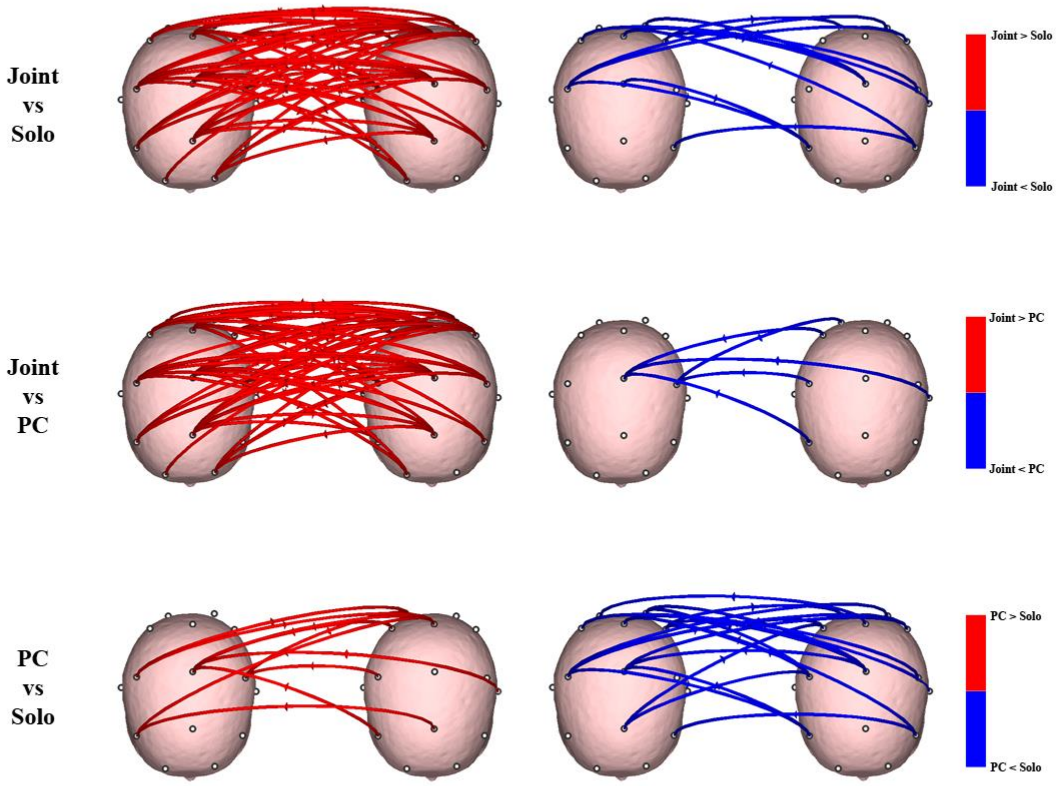

Fig.S3 - Statistical Inter-brain causality patterns in gamma band. The networks were obtained by statistically comparing the three different levels of interaction: Joint vs Solo, Joint vs PC and PC vs Solo (paired t-test, p<0.05 FDR corrected). The heads are seen from above, the nose pointing to the lower part of the page. The arrows indicate the existence of a statistical causality between the activity recorded on the scalp of the two subjects (15 electrodes each).

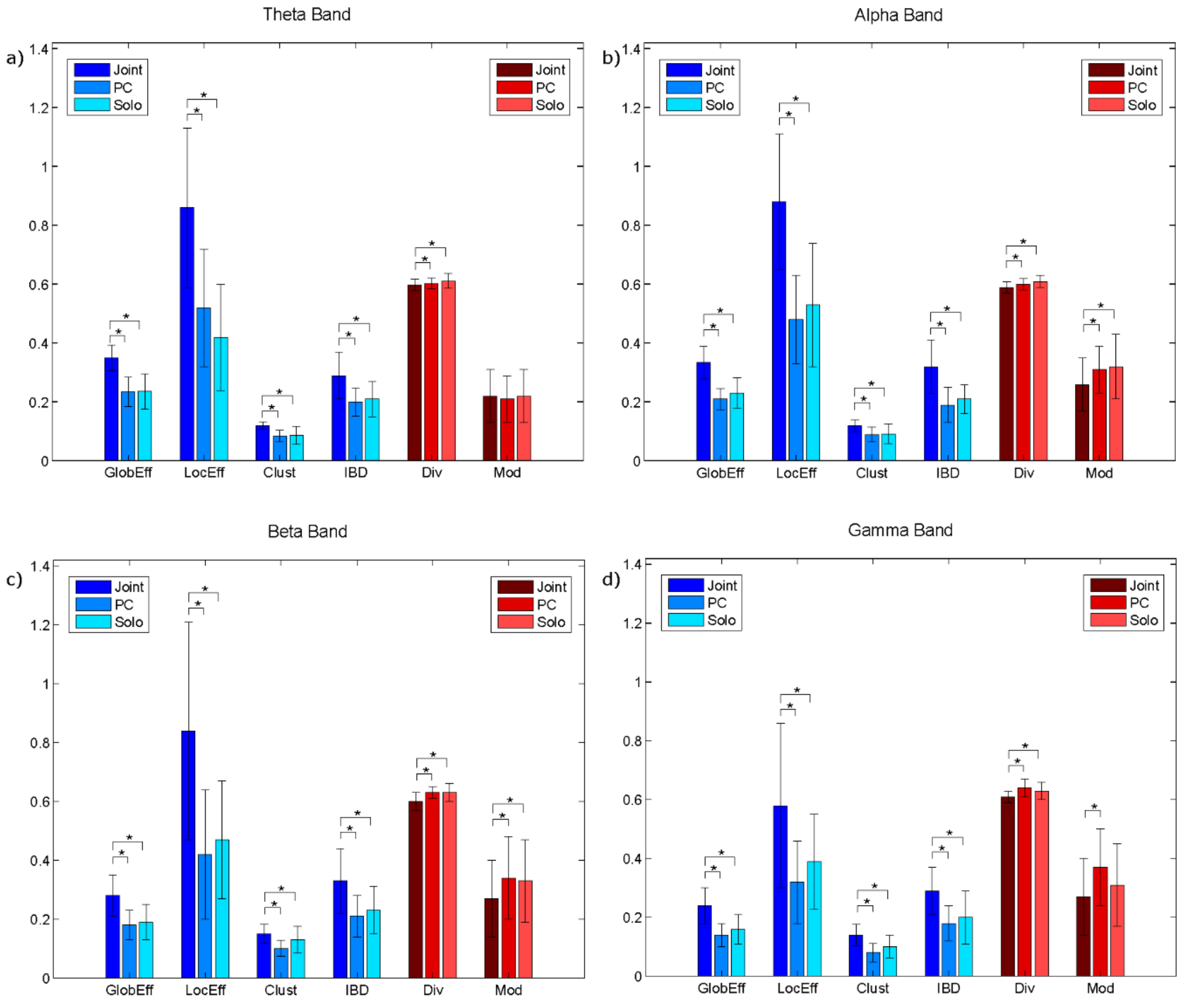

Fig. S4 - Results of the ANOVA performed on indices computed in the multiple-brain networks in theta (panel a), alpha (panel b), beta (panel c) and gamma (panel d) bands, considering as within factor the type of interaction (Joint, PC, Solo). Indices directly proportional to the network integration are reported in blue, while those inversely proportional are depicted in red. Corresponding F and p values are reported in Tab.1. Asterisks indicate statistically significant differences as returned by the Newman-Keuls post-hoc test. Note: GlobEff = Global Efficiency; LocEff= *Local Efficiency; Clust= Clustering; IBD= Inter-Brain Density; Div=Divisibility; Mod= Modularity.*

SINGLE - SUBJECT

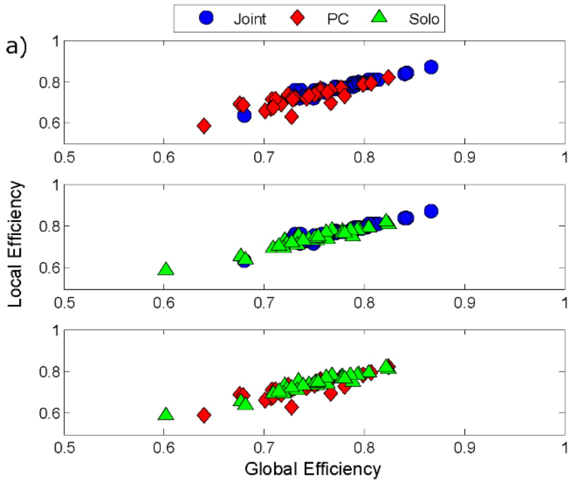

Fig. S5 - Scatterplots reporting the values of Global Efficiency (on x-axis) and Local Efficiency (on y-axis) computed on single-subject networks in Alpha band. The scatterplots report the three different modalities of social interaction (Joint: blue circles, PC: red diamonds, Solo: green triangles).

Graph Indices	***Formulation***	***Definition***
global efficiency (GlobEff)	$E_g = \frac{1}{N(N-1)} \sum_{i \neq j} \frac{1}{d_{ij}}$	Global efficiency is the average of the inverse of the geodesic length d_{ij} and represents the efficiency of the communication between all the *N* nodes in the network (Latora and Marchiori, 2001)
local efficiency (LocEff)	$E_l = \frac{1}{N} \sum_{i=1}^{N} E_g(G_i)$	Local efficiency is the average of the global efficiencies computed on each sub-graph G_i belonging to the network and represents the efficiency of the communication between all the nodes around the node *i* in the network (Latora and Marchiori, 2001)
clustering (clust)	$C = \frac{1}{n} \sum_{i \in N} \frac{t_i}{(k_i^{out} + k_i^{in})(k_i^{out} + k_i^{in} - 1) - 2\sum_{j \in N} g_{ij} g_{ji}}$	The clustering coefficient describes the intensity of interconnections between the neighbors of a node. It is defined as the fraction of triangles around a node or the fraction of node's neighbors that are neighbors of each other (Watts and Strogatz, 1998)
inter-brain density (IBD)	$IBD = \frac{2}{N^2} (\sum_{\substack{i \epsilon S_1 \\ j \epsilon S_2}} G_{ij} + \sum_{\substack{i \epsilon S_2 \\ j \epsilon S_1}} G_{ij})$	The inter-brain density (IBD) is the number of statistically significant inter-subject connectivity links for each condition normalized by the maximum number of possible inter-brain connections. It quantifies the number of significant links between the two brains' activities (Astolfi et al., 2014)
path length (PL)	$L = \frac{1}{n} \sum_{i \in N} L_i = \frac{1}{n} \sum_{i \in N} \frac{\sum_{j \in N, j \neq i} d_{ij}}{n-1}$	The characteristic path length is the average shortest path length in the network, where the shortest path length between two nodes is the minimum number of edges that must be traversed to get from one node to another. (Sporns et al., 2004)
degree (deg)	$deg_k = \sum_{\substack{i \epsilon N \\ i \neq k}} G_{ik} + \sum_{\substack{j \epsilon N \\ j \neq k}} G_{kj}$	The degree of a node consists of the number of links connected directly to it. In directed networks, the indegree is the number of inward links and the outdegree is the number of outward links. Connections weight is ignored in calculations (Sporns et al., 2004)
divisibility (div)	$D = \frac{W}{\sum w_{ij} [1 - \delta(C_i, C_j)] + k}$	Divisibility quantifies how well the general connectivity network including intra- and inter-brain subnetworks) can be divided into two sets of nodes, corresponding to the brains of the two subjects. (Newman, 2006)
modularity (mod)	$Q = \frac{1}{w} \sum_{ij} \left(w_{ij} - \frac{s_{j^{out}} s_{j^{in}}}{W} \right) \delta(C_i, C_j)$	Modularity measures the difference between the fraction of arcs connecting nodes belonging to the same community in the actual graph and its expected value in a random graph. Here, the two communities correspond to the two subjects' brains (Arenas et al., 2007)

Table S1 – Details about the graph indices used in the study

Graph Indices	Theta					Alpha					Beta					Gamma				
	F (2,62)	p	J vs S	J vs PC	PC vs S	F (2,62)	p	J vs S	J vs PC	PC vs S	F (2,62)	p	J vs S	J vs PC	PC vs S	F (2,62)	p	J vs S	J vs PC	PC vs S
GlobEff	11.48	0.00006	●	●		15.46	<0.00001	●	●		9.53	0.00025	●	●		7.41	0.0013	●	●	
LocEff	7.95	0.00084	●	●		7.92	0.00086	●	●		4.71	0.0125	●			3.75	0.029		●	
Clust	6.26	0.0033	●	●		4.18	0.019	●	●		1.63	0.204				9.31	0.0003		●	●
PL	0.17	0.84				1.27	0.29				1	0.372				0.46	0.634			

Tab. S2 - Results of the ANOVA executed considering the graph theory indices obtained for the single subject network as dependent variables and the type of interaction (Joint, PC, Solo) as within factor. The tests were computed separately for the four bands. For each ANOVA we reported the F-value, the corresponding significance level p and the results of Newman-Keuls post-hoc test (● p<0.05). Note: GlobEff = Global Efficiency; LocEff= *Local Efficiency; Clust= Clustering; PL= Path Lengh.*

		GlobEff			LocEff			Clust			PL		
		J vs PC	J vs S	PC vs S	J vs PC	J vs S	PC vs S	J vs PC	J vs S	PC vs S	J vs PC	J vs S	PC vs S
Theta	**GlobEff**				61	56	61	59	63	48	66	58	59
	LocEff							66	52	53	56	48	48
	Clust										59	44	45
	PL												
Alpha	**GlobEff**				56	58	48	58	56	55	58	59	55
	LocEff							58	58	52	55	42	56
	Clust										63	56	53
	PL												
Beta	**GlobEff**				**75**	61	59	66	58	58	59	59	50
	LocEff							50	55	50	56	63	45
	Clust										61	58	42
	PL												
Gamma	**GlobEff**				61	55	58	69	66	58	45	52	55
	LocEff							69	55	63	48	47	55
	Clust										53	55	61
	PL												

Tab. S3 – Classification accuracy achieved using graph indices derived from single-subject connectivity networks as features. A binary linear Fisher classifier was built for each pair of classes (Joint-PC, Joint-Solo, PC-Solo) and for each combination of graph indices (reported on x and y axis). Inter-Brain Density, Divisibility and Modularity between the two brains cannot be defined for single-subject networks and therefore they were not included in the analysis. The classification was repeated separately for the four frequency bands. Classification accuracies above 70% were highlighted in bold. Note: GlobEff = Global Efficiency; LocEff= Local Efficiency; Clust= Clustering; PL= Path Lengh.

Partial Directed Coherence and its multiple-subject extension

Partial directed coherence (PDC) (Baccalá and Sameshima, 2001) is a full multivariate spectral measure used to determine the directed influences between pairs of signals in a multivariate dataset, and demonstrated to be a frequency version of the concept of Granger causality (Granger, 1969).

Let *Y* be a set of time series:

$$Y = [y_1(t), y_2(t), \dots, y_N(t)] \quad (1)$$

where *t* refers to time and *N* is the number of signals considered.

Let us suppose that the following multivariate autoregressive (MVAR) process is an adequate description of the dataset *Y*:

$$\sum_{k=0}^{p} A(k)Y(t-k) = E(t) \text{ with } A(0) = I \quad (2)$$

where *Y(t)* is the data vector in time, $E(t) = [e_1(t),\dots,e_N(t)]^T$ is a vector of multivariate zero-mean uncorrelated white noise processes, *A(1),A(2),…,A(p)* are the *NxN* matrices of model coefficients, and *p* is the model order, usually chosen by means of the Akaike information criteria (AIC) for MVAR processes (Akaike, 1974).

Equation 2 can be transformed to the frequency domain as follows:

$$A(f)Y(f) = E(f) \quad (3)$$

where A(f) represents the frequency transform of the vector of parameters $A_{ij}(k)$ along the p lags considered according to the model order selected:

$$A_{ij}(f) = \delta_{ij} - \sum_{k=1}^{p} A_{ij}(k)e^{-sqrt(-1)2\pi fk} \quad (4)$$

where sqrt (-1) indicates the imaginary unit and $\delta_{ij} = 1$ whenever $i = j$ and $\delta_{ij} = 0$ otherwise.

$A(f)$ appears in the definition of PDC directed from signal *j* to signal *i* as follows:

$$\pi_{ij}(f) = \frac{\left|A_{ij}(f)\right|^2}{\sum_{m=1}^{N}\left|A_{mj}(f)\right|^2} \quad (5)$$

Squared versions of PDC in its different normalizations are usually adopted, due to higher stability and accuracy (Astolfi et al., 2006; Plomp et al., 2014). We adopted the formulation reported in (5).

The extension of PDC to the multi-subject case is performed by constructing an adaptive MVAR model including the data of the two subjects as a unique dataset. To account for individual differences, we normalized the data by computing the z-score of the EEG traces Y of each subject and then juxtaposed them for each dyad, obtaining a dataset of dimension $2N$, where the first *N* signals belong to the subject A and the second *N* signals belong to the subject B.

We therefore obtained a new dataset Y_{dyad} as follows:

$$Y = [y_1^A(t), y_2^A(t), \dots, y_N^A(t), y_1^B(t), y_2^B(t), \dots, y_N^B(t)\ ] \tag{6}$$

where the generic signal $y_i^j(t)$ represents the EEG sample recorded from channel i of subject j with $i = 1, \dots N$ and $j = A, B$.

The resulting multiple-subject MVAR model has the following structure:

$$A(f) = \begin{bmatrix} A_A(f) & A_{AB}(f) \\ A_{BA}(f) & A_B(f) \end{bmatrix} \tag{7}$$

where the matrices $A_A(f)$ and $A_B(f)$ describe the spectral transform of the intra-brain AR parameters for subject A or subject B, respectively. The matrices $A_{AB}(f)$ and $A_{BA}(f)$ express the spectral transform of the inter-brain AR parameters directed from subject B to subject A and vice versa.

Using MVAR coefficients in (7) to compute (5) we obtain the extension of PDC to the multi-subject case:

$$\pi(f) = \begin{bmatrix} \pi_A(f) & \pi_{AB}(f) \\ \pi_{BA}(f) & \pi_B(f) \end{bmatrix} \tag{8}$$

where the matrices $\pi_A(f)$ and $\pi_B(f)$ express the intra-brain connectivity for subjects A and B respectively, and the matrices $\pi_{AB}(f)$ and $\pi_{BA}(f)$ express the inter-brain causality directed from subject B to subject A and from subject A to subject B, respectively (see Fig.2).
For further details, see (Babiloni and Astolfi, 2014).

Effect size in statistical tests

In Table S4, we report the effect sizes associated to the repeated measures ANOVAs performed on graph indices. The table lists the values of partial eta squared parameter associated to each of the ANOVAs described in Tab.2. It is worth of note that all the ANOVAs' significant results (with the only exception of Local Efficiency in theta band for the AGENCY factor) were associated to a high effect size, categorized according to the criteria suggested by Cohen in 1992 (partial eta squared > 0.1379) (Cohen, 1973,1988, Richardson, 2011).

	GlobEff	***LocEff***	***Clust***	***PL***	***IBD***	***Div***	***Mod***	***Deg***
theta	**0.63**	**0.46**	**0.35**	0.09	**0.55**	**0.19**	**0.01**	**0.55**
alpha	**0.67**	**0.43**	**0.30**	0.02	**0.62**	**0.21**	**0.18**	**0.60**
beta	**0.48**	**0.36**	**0.40**	0.04	**0.59**	**0.34**	**0.25**	**0.59**
gamma	**0.53**	**0.29**	**0.52**	**0.32**	**0.61**	**0.36**	**0.33**	**0.63**

Table S4. Effect size for the ANOVAs. Partial eta squared for each of the ANOVAs reported in Tab.1. In bold, the values > 0.1379 (high effect size). Note: GlobEff = Global Efficiency; LocEff= Local Efficiency; Clust= Clustering; PL= Path Lengh; IBD= Inter-Brain Density; Div=Divisibility; Mod= Modularity; Deg= Degree.

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