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Reliability of Information-based Integration of EEG and fMRI Data: A Simulation Study

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Aim

The majority of EEG-fMRI studies rely upon linear correlation of EEG and fMRI features within the framework of the **General Linear Model (GLM)**. An alternative is **Information Theory (IT)** (Ostwald et al,2011), which measures, through Information and Entropy, how our knowledge of one variable X improves our knowledge of another variable Y.

GLM: linear relationship

$$Y_i = \beta_0 + \beta_1 X_1 + \cdots + \beta_N X_N + \varepsilon_i$$

IT: higher order relationship

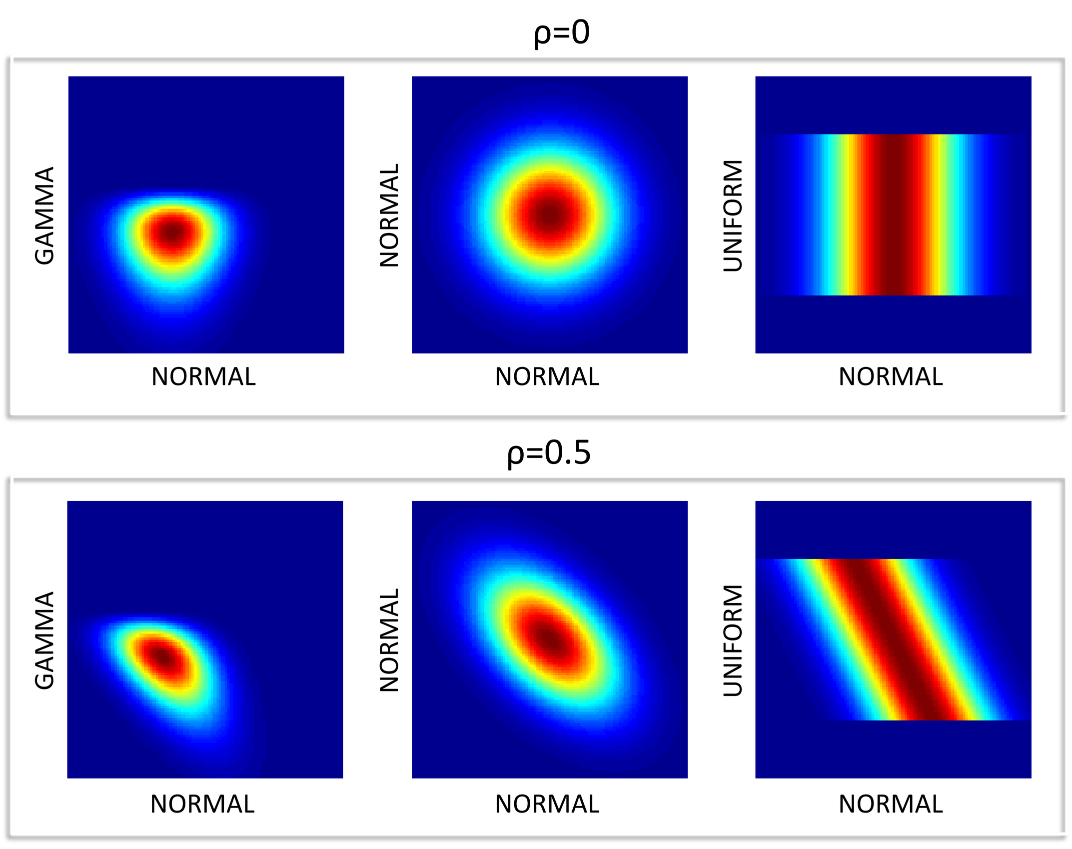
$$I(X;Y) = \sum_{x \in X} \sum_{y \in Y} p(x,y) \log \frac{p(x,y)}{p(x)p(y)}$$

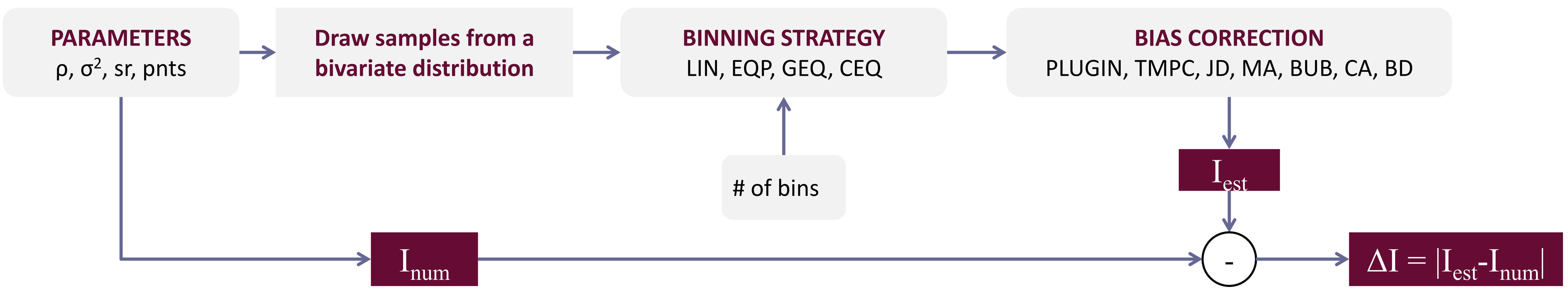
However, information-based measures should be bias-corrected since they require a large number of samples to obtain an unbiased estimate of the quantities of interest.

With simulations, we explored how the choice of parameters (number of samples/trials, the amount of correlation and binning strategy) interacts with different bias correction techniques to affect the accuracy of information estimates, for the distributions relevant to EEG and fMRI data.

Methods

We draw a sample of points (PNTS) from three bivariate distributions (Normal-Normal (NN); Normal-Uniform (NU) and Normal-Gamma (NG), which mimic the statistical properties of EEG-fMRI data) with sr as the ratio between the standard deviations of the two distributions, standard deviation σ_2 = sr·σ_1= sr·σ and correlation ρ. For each sample we calculated the information (I_{est}) using all possible combinations of 4 binning strategies (BS) and 7 bias correction techniques (BC). The estimated information was compared with its numerical counterpart (I_{num}).



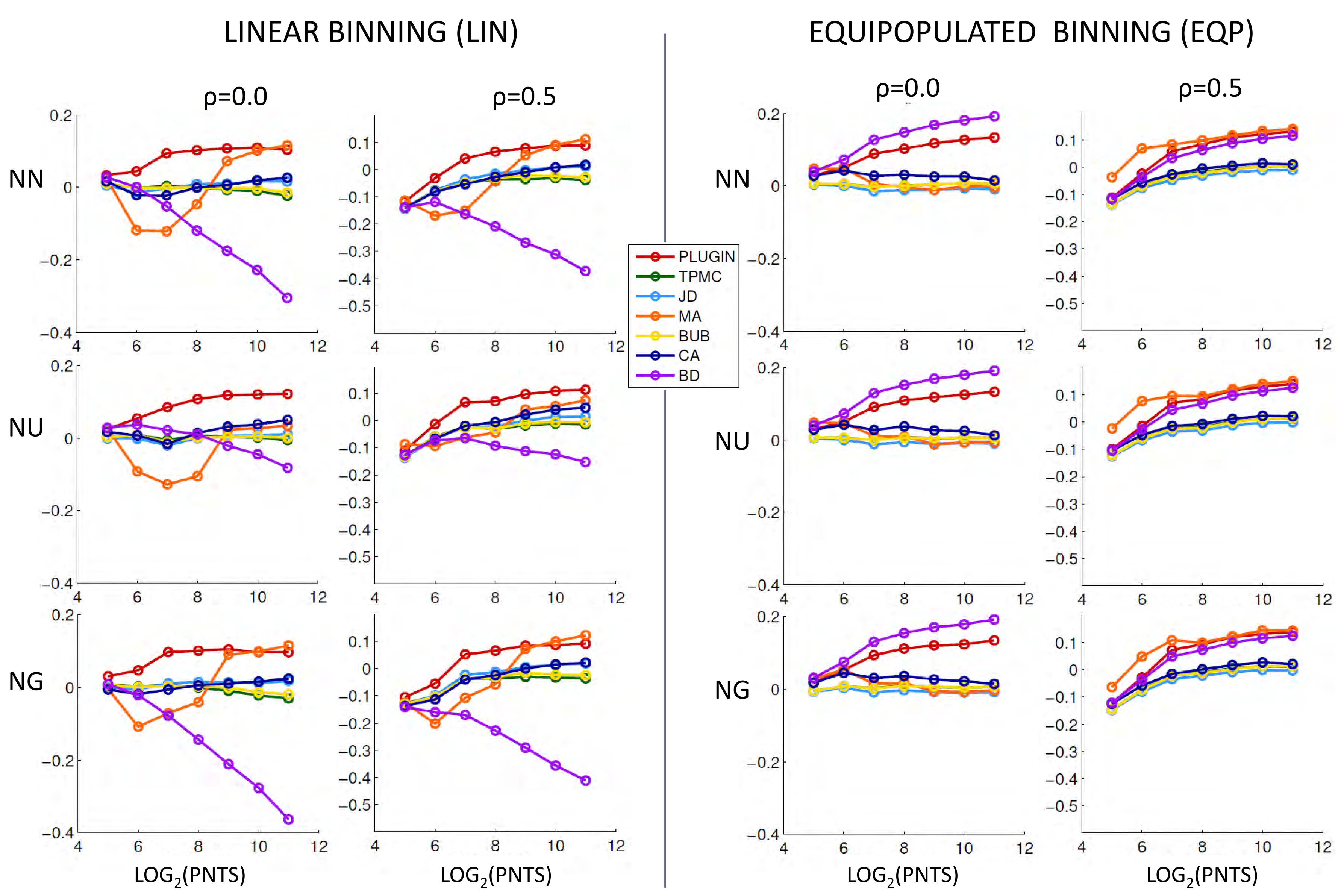


PARAMETERS	BINNING STRATEGY	BIAS CORRECTION (Statoolkit (Goldberg et al,2009))
ρ = [0.0, 0.3, 0.5, 0.7, 0.9]	• linearly spaced bins (LIN),	• Plugin estimate (PLUGIN)
σ² = [0.2, 0.4, 0.6, 0.8, 1]	• equipopulated bins (EQP)	• Asymptotically debiased (TMPC) (Treves et al,1995)
snr = [1 2 3 4]	• gaussian equispaced bins (GEQ)	• Jackknife debiased (JD) (Efron et al,1993)
pnts = [32, 64, 128, 256, 512, 1024, 2048]	• centered equispaced bins (CEQ)	• Debiased Ma bound (MA) (Ma,1981)
		• Best upper bound (BUB) (Paninski,2003)
		• Coverage-adjusted (CA) (Chao et al,2003)
		• Bayesian with a Dirichlet prior (BD) (Wolpert et al,1995)

Results

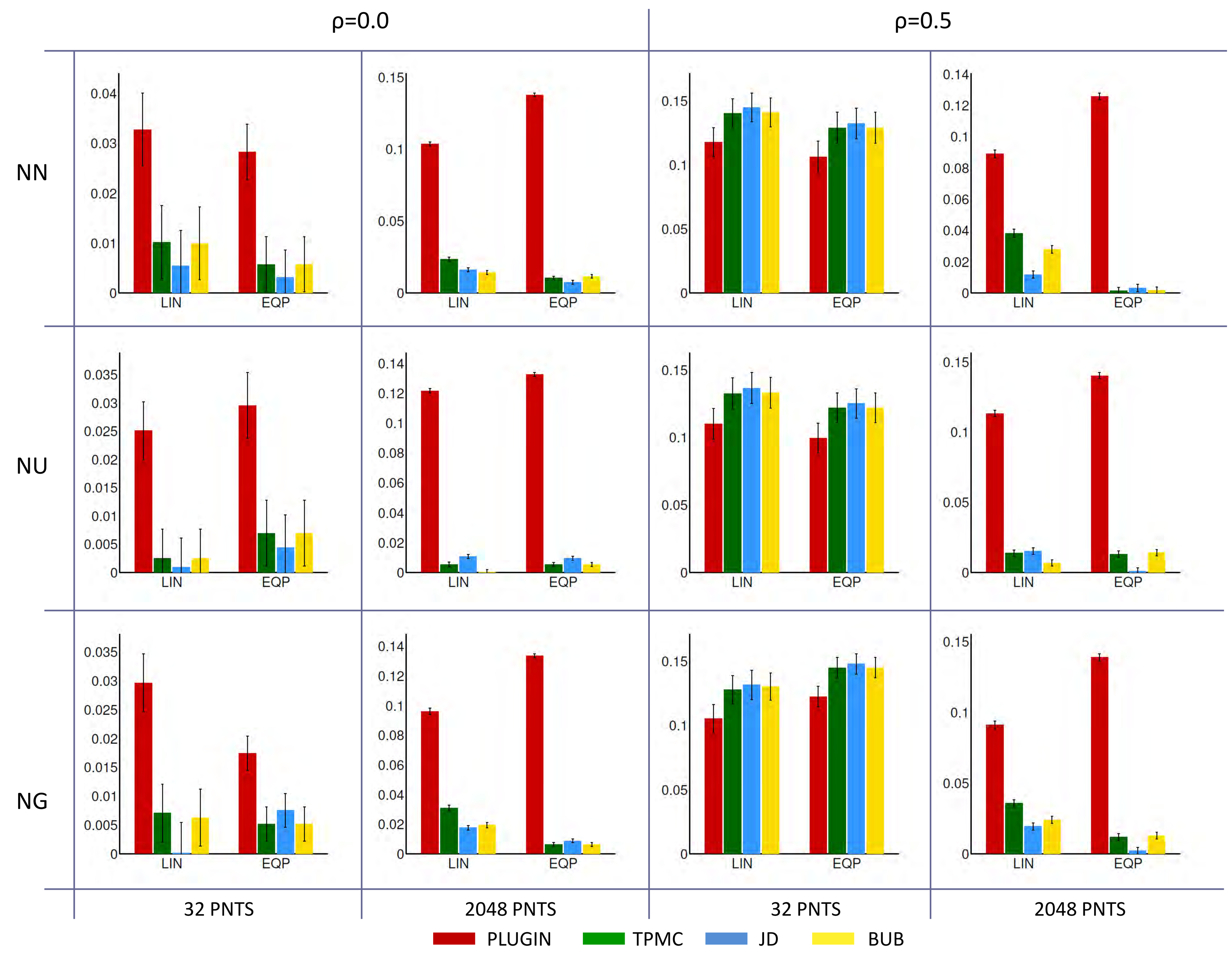
ΔI as a function of PNTS

Comparison of ΔI for NN, NU, and NG distributions, calculated for σ=1 and sr=1, in the uncorrelated and the highly correlated case for all the bias correction techniques considered.



ΔI across binning strategies

Comparison of ΔI for NN, NU, and NG distributions, calculated for σ=1 and sr=1, in the uncorrelated and the highly correlated case, for a subset of bias correction techniques.



We found that the particular combination of binning strategy and bias correction method affects the estimate of the information. We also found that TMPC, JD, and BUB give an estimate closer to the true value than other methods, regardless of the underlying distribution or the binning strategy. Increasing the correlation decreases the performance of the bias correction techniques, requiring a higher number of samples (or trials) to obtain an unbiased estimate.

Discussion

We found that the interaction between the binning strategy and the estimation method influences the accuracy of the estimate. We also found that the performance of a particular bias correction method is dependent on the underlying statistics (i.e, PNTS, ρ, distribution).

These effects are prominent in the low sampling regime and with underlying distributions relevant to EEG-fMRI experiments.

Further investigation using more realistic underlying models, which better represent electrophysiological and haemodynamic data, and additional correction for correlated signals (e.g. shuffling), is necessary to assess the reliability of information-based analysis of EEG-fMRI data.

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