Group-level synchronization of BOLD activity has previously been used as a measure of the degree of similarity of perceptual and executive processing across a group of healthy participants (Hasson *et al*., 2004; Naci *et al*., 2015), and also patients with DOC (Naci *et al*., 2014). To measure inter-subject neural synchronization in EEG data acquired while participants listened to *“Taken”*, we ran a correlated components analysis. Originally developed by Dmochowski *et al*. (2012), rCA was designed to identify discrete patterns of electrode activity that are maximally correlated between subjects during naturalistic stimulation. These components serve a similar purpose to those extracted from fMRI data using group-level ICA, in that they reflect common neural activity across subjects and can be used to investigate group-synchronization over time. A more recent version of the rCA procedure, formulated by Ki *et al*. (2016), was used in this study.

rCA operates by relying on many of the same principles as PCA (or ICA), including many of the same assumptions. PCA is non-parametric multivariate dimensionality reduction technique used to extract meaningful information from large, complex data sets. Specifically, this analysis computes a new linear basis of orthogonal vectors which re-express the activity of a dynamic system in a way that captures the greatest amount of variance, while minimizing redundancy and noise (Shlens, 2009). For example, raw EEG data typically take the form of an *n* × *t* matrix where *n* is the number of electrode channels and *t* is time. This data matrix **X** is a measure of the temporal fluctuations of voltage at each electrode site relative to the reference. However, in this format, it is unclear which data best reflect the underlying neurophysiological processes of the brain. Indeed, gleaning substantive information from raw EEG data is difficult; the electrical signals recorded at the scalp are a mixture of neural activity and noise (e.g., cardiac artifacts, eye blinks, movement, and electrical contamination), significant covariation between electrodes adds redundancy to the data, and some electrode sites do not capture the dynamic activity of the brain as well as others. PCA provides a means to recover the meaningful dimensions of these data by computing a linear transformation of X to find orthogonal configurations of electrode activity that best explain the most variance. This is accomplished by computing an eigenvalue decomposition of the covariance of X. A standardized symmetric *n* × *n* covariance matrix CX = XX*T* is transformed by a mixing matrix W into a new subspace Y such that its covariance matrix CY =YY*T* is diagonal. The eigenvectors w*i* calculated for CX are the principal components of X, and the diagonal eigenvalues λ*i* of CY are the variances of X along W (Shlens, 2009). The principal components of X are ranked in descending order based on the amount of variance each can account for in the data. PCA computes *n* – 1 principal components which, in EEG, are represented as spatial weights of electrode voltages across the scalp and their corresponding time course.

rCA is computationally similar to PCA in that it computes an eigenvalue decomposition of covariance data, but where rCA differs is in the source of the covariance; rCA operates on the pooled within-subject cross covariance

R*w*= R*kk*,

and pooled between-subjects cross covariance

R*b* = R*kl*

where

R*kl* = (x*k* (*t*) - x̄*k*) (x*l*(*t*) - x̄*l*)T

calculates the cross-covariance between participant *k* and participant *l* across all electrodes x at time *t*. The eigenvectors w*i* of the cross-covariance matrix R*w*-1R*b*,with the largest eigenvalues λ*i*calculated as (R*w*-1R*b*)w*i* = λ*i*w*i* are the components that maximize Pearson’s correlation between subjects in the data. Like the component ranking of PCA based on explained variance, components found using rCA are ranked-ordered by the magnitude of their correlation. The time courses and accompanying spatial weights of these correlated components represent patterns of evoked neural activity which are maximally correlated across all participants while listening to the “*Taken*” clip (Ki *et al*., 2016). In the current study, pooled within and between-subjects covariances were computed separately for the intact and scrambled audio conditions. Only the top component extracted from each condition (i.e., the spatial weights and time course which maximized Pearson’s correlation in the group-aggregate data) was considered for further analysis here. Although components *i* = 2…*n* undoubtedly encompass various aspects of the experience of listening to “*Taken*”, the top component reflects some neural processes that are most common across subjects and provides an optimal starting point to evaluate the utility of ISC as a means of capturing executive processing of the narrative.

Inter-subject correlation**.** To assess the reliability of the correlated component at the single-subject level, time-resolved ISCs were computed by back projecting the component vectors w*i* into the original subject data to derive a component time course for each participant. We did for each audio condition. With this per-subject time course, a measure of ISC encompassing the entire duration of the clip was computed first to quantify the magnitude of the correlation between each individual participant and the group and establish a distribution of synchronization in healthy controls; this is similar to the ISC analysis computed by Naci *et al*., 2015. To generate the distribution of ISCs, Pearson’s correlations were calculated between all possible pairs of subjects using a sliding window technique. A sliding window of five-seconds with a three-second overlap was used to generate a correlation coefficient between pairs at two-second intervals over the course of the audio. This yielded 152 correlation coefficients for each of the 105 comparisons. The correlations computed for all subject pairs were then standardized using a Fisher’s Z transformation and averaged at each time point to produce a mean ISC time course for the intact and scrambled audio conditions.

Statistical analyses**.** Non-parametric permutation statistics were used to test the significance of the group-averaged component time course for each of the two audio conditions. Null distributions of correlation coefficients were created by iteratively phase-shifting the computed component time course for each participant and computing mean of the pairwise correlations with the rest of the group for each of the 152 time windows (Theiler, Eubank, Longtin, Galdrikian, & Farmer, 1992). We did this 1000 times to generate a null distribution of potential correlation values. The upper 5% of each null distribution was used as the significance threshold for each time point. Significance levels were adjusted for multiple comparisons using a false discovery rate (FDR) correction. The number of significant two-second time windows was then compared between the intact and scrambled conditions using a Chi-square test of proportion with an alpha level set to .05.