

1 **Dynamic and stationary brain connectivity during movie watching as revealed by functional MRI**

2 Xin Di ^{1*}, Zhiguo Zhang ^{2,3}, Ting Xu ⁴, Bharat B. Biswal ^{1*}

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4 1. Department of Biomedical Engineering, New Jersey Institute of Technology, Newark, NJ, 07102, USA

5 2. School of Biomedical Engineering, Health Science Center, Shenzhen University, Shenzhen, China

6 3. Guangdong Provincial Key Laboratory of Biomedical Measurements and Ultrasound Imaging,

7 Shenzhen, China

8 4. Center for the Developing Brain, Child Mind Institute, New York, NY 10022, USA

9

10 * Corresponding author:

11 Xin Di, Ph.D.

12 604 Fenster Hall, University Height

13 Newark, NJ, 07102, USA

14 xin.di@njit.edu

15

16 Bharat B. Biswal, Ph.D.

17 607 Fenster Hall, University Height

18 Newark, NJ, 07102, USA

19 bbiswal@yahoo.com

20

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23 **Running title:** Dynamic and stationary connectivity

24

25 **Abstract**

26 Spatially remote brain regions show synchronized activity as typically revealed by correlated functional
27 MRI (fMRI) signals. An emerging line of research has focused on the temporal fluctuations of
28 connectivity, however, its relationships with stationary connectivity have not been clearly illustrated. We
29 examined dynamic and stationary connectivity when the participants watched four different movie clips.
30 We calculated point-by-point multiplication between two regional time series to estimate the time-
31 resolved dynamic connectivity, and estimated the inter-individual consistency of the dynamic
32 connectivity time series. Widespread consistent dynamic connectivity was observed for each movie clip,
33 which also showed differences between the clips. For example, a cartoon movie clip, The Present,
34 showed more consistent of dynamic connectivity with the posterior cingulate cortex and supramarginal
35 gyrus, while a court drama clip, A Few Good Men, showed more consistent of dynamic connectivity with
36 the auditory cortex and temporoparietal junction, which might suggest the involvement of specific brain
37 processing for different movie contents. In contrast, the stationary connectivity as measured by the
38 correlations between regional time series was highly similar among the movie clips, and showed fewer
39 statistically significant differences. The patterns of consistent dynamic connectivity could be used to
40 classify different movie clips with higher accuracy than the stationary connectivity and regional activity.
41 These results support the functional significance of dynamic connectivity in reflecting functional brain
42 changes, which could provide more functionally related information than stationary connectivity.

43

44 **Keywords:** dynamic connectivity; movie connectome; movie watching; naturalistic stimuli; stationary
45 connectivity

46 **1. Introduction**

47 The human brain exhibits a highly synchronized structure of activity as revealed by functional MRI
48 (fMRI) in resting-state (Biswal et al., 1995, 2010), during task performance (Cole et al., 2014; Di et al.,
49 2020; Krienen et al., 2014), and during watching naturalistic stimuli such as movies (O'Connor et al.,
50 2017; Vanderwal et al., 2019). Functional connectivity, as measured by the correlations of observed
51 blood-oxygen-level-dependent signals (Biswal et al., 1995; Friston, 1994), have been widely used to
52 examine the organization of large-scale brain networks (Margulies et al., 2016; Salvador et al., 2005; Yeo
53 et al., 2011) and to parcellate small brain structures such as the thalamus and striatum (Di Martino et al.,
54 2008; Tian et al., 2020; Yuan et al., 2016). However, the spatial distribution of functional connectivity is
55 highly similar across different tasks and movie watching conditions (Cole et al., 2014; Di et al., 2020;
56 Krienen et al., 2014; Vanderwal et al., 2019). To localize functionally meaningful connections, it is
57 therefore critical to examine the time-varying fluctuations of connectivity (Allen et al., 2014; Di and
58 Biswal, 2020; Hutchison et al., 2013), as well as the changes of functional connectivity between different
59 task conditions (Di and Biswal, 2019; Fornito et al., 2012; Friston et al., 1997).

60 Time-varying dynamic connectivity is mostly studied in the resting state by using the sliding-
61 window approach (Allen et al., 2014; Hutchison et al., 2013; Lurie et al., 2020). It has been shown that
62 the variability of dynamic connectivity fluctuations is lower between regions from the same functional
63 networks and higher between regions from different networks (Fu et al., 2017), resulting in an overall
64 negative correlation with the stationary functional connectivity (Thompson and Fransson, 2015; Zhang et
65 al., 2018). However, because of the unconstrained nature of the resting-state, it is difficult to ensure that
66 the obtained dynamic connectivity estimates are functionally meaningful or simply resulting from noise
67 (Lindquist et al., 2014). Until recently, dynamic connectivity is also studied when the participants were
68 given complex stimuli, such as watching movie clips (Di and Biswal, 2020). The advantage of using a
69 movie stimulus is that the time course of dynamic connectivity can be compared across participants. If
70 there are high inter-individual similarity (Hasson et al., 2004; Nastase et al., 2019), then it may imply that

71 the observed dynamic connectivity is functionally meaningful and is relevant to the processing of the
72 video stimuli.

73 In our previous study, we have demonstrated the inter-individual consistency of dynamic
74 connectivity when different participants watched the same animated movie Partly Cloudy (Di and Biswal,
75 2020). By using a seed-based analysis, we identified highly consistent dynamic connectivity between the
76 supramarginal gyrus and posterior cingulate gyrus, two regions that are critical in the processes of
77 empathy and theory of mind (Richardson et al., 2018). Moreover, among a set of regions of interest, the
78 dynamic connectivity pattern was largely dissociated with the stationary functional connectivity that was
79 measured by the correlations of the time series from the entire run. For example, the stationary functional
80 connectivity between the supramarginal gyrus and posterior cingulate gyrus was close to zero, while the
81 windowed dynamic connectivity showed highly consistent fluctuations. To date, only handful of studies
82 have examined dynamic connectivity during movie watching (Cooper et al., 2021; Di and Biswal, 2020;
83 Freitas et al., 2020; Simony and Chang, 2020). It is still largely unknown how the spatial pattern is
84 modulated by different movie contents, and how dynamic connectivity is spatially distributed.

85 The central goal of this study is to compare dynamic connectivity and stationary connectivity in
86 the context of movie watching. In addition to the previously analyzed Partly Cloudy dataset (Richardson
87 et al., 2018), we also analyzed the Healthy Brain Network Serial Scanning Initiative (HBN-SSI) dataset
88 (O'Connor et al., 2017), where same participants watched three different movie clips. The video clips
89 were derived from different types of movies, ranging from a science fiction cartoon comedy, a science
90 fiction action film, to a court drama. It is reasonable to expect that different brain systems are involved in
91 the process of the different movie clips. However, Vanderwal and colleagues have examined the
92 stationary connectivity of the three movies, and showed very similar spatial patterns among them
93 (Vanderwal et al., 2019). We speculate that dynamic connectivity might be more sensitive to reflect the
94 changes in brain functions among the movie clips.

95 Further, we systematically examine the relationships between dynamic and stationary
96 connectivity in terms of their spatial distributions and context modulations. The economic theory of brain

97 network organization has suggested that the maintenance of long-range between-system communications
98 is costly, and long-range and between-system connectivity may be more dynamic and depend on task
99 demands (Bullmore and Sporns, 2012). In line with this account, the dynamic connectivity between
100 different functional systems are more variable than within functional systems (Fu et al., 2017; Thompson
101 and Fransson, 2015), and task modulated connectivity are also likely to take place between regions from
102 different functional networks (Di and Biswal, 2019). Similarly, for the movie-watching data, we
103 speculate that dynamic connectivity might take place between regions from different functional modules.
104 In contrast, the stationary connectivity might tightly reflect the organizations of brain networks, i.e.,
105 higher stationary connectivity between regions from the same functional networks, and lower stationary
106 connectivity between regions from different networks. The dissociation might result in different spatial
107 patterns between the dynamic and stationary connectivity.

108

109 **2. Materials and Methods**

110 **2.1. fMRI dataset**

111 We analyzed two publicly available fMRI datasets when participants watched different movie clips, the
112 Partly Cloudy dataset (Richardson et al., 2018) and the HBN-SSI dataset (O'Connor et al., 2017). For the
113 Partly Cloudy dataset, we analyzed the adults' data where they watched the animated movie "Partly
114 Cloudy". And for the HBN-SSI dataset, we analyzed the data when the same participants watched three
115 different movie clips from different types of movies.

116 **2.1.1. Partly Cloudy dataset**

117 The Partly Cloudy data were obtained through openneuro (<https://openneuro.org/>; accession #:
118 ds000228). Consistent with our previous study, we only included the adult participants (n = 33) (Di and
119 Biswal, 2020). After dropping data due to large head motion (see below) and poor brain coverage, the
120 effective sample included 17 females and 12 males. The mean and standard deviation of age were 24.6
121 years and 5.3, respectively (age range: 18 to 39 years). The original study was approved by the

122 Committee on the Use of Humans as Experimental Subjects (COUHES) at the Massachusetts Institute of
123 Technology.

124 During the fMRI scan, the participants watched a 5.6-minute long silent version of Partly Cloudy
125 (Pixar, 2009). MRI images were acquired on a 3-Tesla Siemens Tim Trio scanner with the standard
126 Siemens 32-channel head coil. Blood-oxygen-level dependent (BOLD) sensitive fMRI images were
127 collected with a gradient-echo EPI sequence in 32 interleaved near-axial slices (EPI factor: 64; TR: 2 s,
128 TE: 30 ms, and flip angle: 90°). The participants were recruited for different studies with slightly
129 different voxel sizes and slice gaps. Three participants had 3.13 mm isotropic voxels with no gap, and 26
130 participants had 3.13 mm isotropic voxels with a 10% gap. All the functional images were resampled to 3
131 mm isotropic voxel size during preprocessing. 168 functional images were acquired, with four dummy
132 scans before the real scans to allow for steady-state magnetization. T1-weighted structural images were
133 collected in 176 interleaved sagittal slices with 1 mm isotropic voxels (GRAPPA parallel imaging,
134 acceleration factor of 3; FOV: 256 mm). More information can be found in Richardson et al. (2018).

135 **2.1.2. HBN-SSI dataset**

136 The HBN-SSI dataset was obtained through the project website
137 (http://fcon_1000.projects.nitrc.org/indi/hbn_ssi/). Thirteen participants were recruited in the study.
138 After removing data of four participants due to excessive head motion in any of the movie-watching
139 sessions, data from four females and five males were included in the current analysis. All the participants
140 are right-handed. The age range was from 23 to 37 years old ($Mean = 29.4$; $SD = 5.5$).

141 We selected the movie watching scans of three movie clips, Wall-E (Walt Disney Productions,
142 2008), The Matrix (Warner Bros., 1999), and A Few Good Men (Columbia Pictures, 1992), from the 12
143 repeated scanning sessions. Each movie clip was 10 minutes long and was watched by the same
144 participant four times in separate sessions. The order of the movie watching was counterbalanced across
145 sessions. The fMRI data were scanned using an EPI sequence with the following parameters, TR: 1,450
146 ms, TE: 40 ms, flip angle: 55°, and voxel size: 2.46 x 2.46 x 2.5 mm³ without any gap. Four hundred and
147 twenty images were scanned for each run. However, for one participant, there were only 410 images for

148 several sessions. We, therefore, used the first 410 images for the current analysis for all the subjects and
149 sessions.

150 Lastly, the MPRAGE image from the first sequential scanning session of each participant was
151 also used to assist preprocessing of the fMRI and DWI data. The scanning parameters include TR, 2,730
152 ms; TE 1.64 ms; flip angle, 7°; voxel size 1 x 1 x 1 mm³ with no gap. More information about the study
153 design and MRI acquisitions can be found in O'Connor et al., (2017).

154 **2.2. fMRI data preprocessing**

155 The fMRI data preprocessing was performed by using SPM12 (SPM, RRID: SCR_007037) under
156 MATLAB environment (<https://www.mathworks.com/>). The two datasets were preprocessed using very
157 similar pipelines. Specifically, the anatomical image of each participant was first segmented into gray
158 matter, white matter, cerebrospinal fluid, and other tissue types, and normalized into standard Montreal
159 Neurological Institute (MNI) space. The functional images of each session and subject were aligned to
160 the first image of their specific session and were coregistered to the skull stripped anatomical image of the
161 subject. The deformation field maps obtained from the segmentation step were used to normalize all the
162 functional images into MNI space. The fMRI images from the Partly Cloudy dataset were resampled to 3
163 x 3 x 3 mm³ voxel size; and the images from the HBN-SSI dataset were resampled to 2.5 x 2.5 x 2.5 mm³,
164 which were chosen according to their respective original voxel sizes. All the functional images were then
165 spatially smoothed using an 8 mm Gaussian Kernel. Lastly, we defined a generalized linear model
166 (GLM) for each session and subject by using 24 head motion variables (Friston et al., 1996) and a
167 constant term as regressors, with implicit high-pass filtering at 1/128 Hz. After model estimation, the
168 residual images were saved for further analysis.

169 We calculated framewise displacement for translation and rotation for each session and
170 participant (Di and Biswal, 2015). For the Partly dataset, we used strict criteria of maximum framewise
171 displacement of 1.5 mm or 1.5° to discard data with large head movements. Two participants' data were
172 discarded accordingly. For the HBN-SSI dataset, a participant's data were discarded if any of the sessions
173 exceeded the criteria. We adopted a slightly liberal criterion of maximum framewise displacement

174 greater than 2.5 mm or 2.5° or mean framewise displacement greater than 0.2 mm or 0.2°. Four
175 participants' data were removed accordingly.

176 **2.3. Independent component analysis**

177 Because the main goal of the current study is to study connectivity across brain regions, we adopted
178 spatial independent component analysis (ICA) to define connectivity nodes. We extracted 20 and 80 ICs
179 to represent different spatial scales of brain networks. We first analyzed the local activity and
180 connectivity with 20-IC solutions to identify statistically significant local effects. We then calculated
181 connectivity using the 80-IC solutions to examine their spatial distributions. For spatial ICA, the number
182 of ICs that could be extracted depends on the number of time points for each participant/session.
183 Theoretically, $t - I$ components can be extracted where t represents the total number of time points. We
184 chose 80, which is roughly half of the time points for the Partly Cloudy dataset.

185 Group ICA of fMRI Toolbox v3.0b (Group ICA of fMRI Toolbox, RRID: SCR_001953) was
186 used for ICA (Calhoun et al., 2001). The ICA was performed for the Partly Cloudy and HBN-SSI
187 datasets separately. After extraction, we manually selected the ICs that were related to functional
188 networks and discarded the noise-like ICs. For the Partly Cloudy dataset, 16 and 65 ICs were considered
189 functionally meaningful ICs for the 20-IC and 80-IC solutions, respectively. And for the HBN-SSI
190 dataset, 16 and 54 ICs were kept. After ICA, the time series of each IC for each subject and session were
191 back reconstructed by using the group ICA algorithm. The time series were used for further activity and
192 connectivity analyses.

193 **2.4. Inter-individual consistency of regional activity**

194 For both regional activity and dynamic connectivity, we estimated the inter-individual consistency across
195 participants and sessions. Conventionally, the intersubject correlation was used to study the inter-
196 individual consistency (Chen et al., 2016; Hasson et al., 2004; Nastase et al., 2019). In our recent study,
197 we have shown that the principal component analysis (PCA) can be used to estimate the inter-individual
198 consistency, which is quantitatively similar to intersubject correlation (Di and Biswal, 2021). Specifically,
199 for a given region we have a t (# of time points) by n (# of participants) matrix X . X is a 168 x 29 matrix

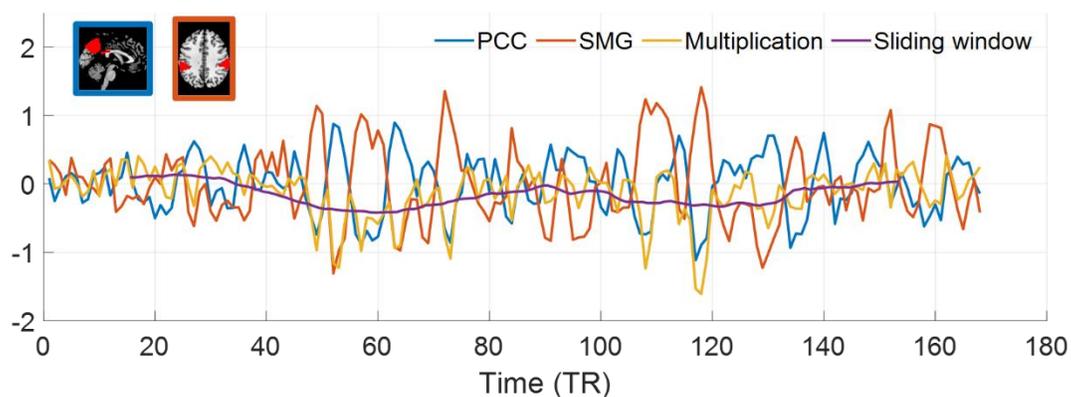
200 for the Partly Cloudy dataset and a 410 x 36 matrix ($36 = 9$ participants x 4 sessions) for each of the three
201 movie clips from the HBN-SSI dataset. We performed PCA on the matrix X and obtained the percent
202 variance explained by the first PC as a measure of intersubject consistency.

203 For the HBN-SSI dataset, there were four sessions for each participant and each movie. Ideally,
204 the multi-session and multi-participant design can be used to differentiate the consistent and idiosyncratic
205 responses. We have explored this issue and found that the within-participant consistency was mainly
206 driven by the overall across-participant consistency, but not participant-specific idiosyncratic responses
207 (see supplementary materials). Moreover, the idiosyncratic responses are not the focus of the current
208 study. Therefore, in the current analysis, we treated session and participant as separate data and
209 calculated inter-individual consistency across all the sessions and participants.

210 **2.5. Dynamic connectivity**

211 The sliding-window approach is the most commonly used method to estimate dynamic connectivity
212 (Allen et al., 2014; Di and Biswal, 2020; Fu et al., 2014). A recent development is to utilize point-by-
213 point multiplications of two time series to approximate their dynamic connectivity, a.k.a. edge-centric
214 time series (Faskowitz et al., 2020). The development comes from the intuition that the commonly used
215 measure of functional connectivity, i.e., Pearson's correlation coefficient, is the summation of the point-
216 by-point multiplications of two z transformed variables divided by the sample size minus 1. Therefore, if
217 we keep the original point-by-point multiplication time series, it can reflect estimates of dynamic
218 connectivity at every time point. In Figure 1, we show the averaged time series of two networks, i.e., the
219 posterior cingulate network and supramarginal network from the Partly Cloudy dataset. The averaged
220 sliding-window and point-by-point multiplication time series were also shown. Strong negative
221 multiplication values can be seen when the two original time series have strong anti-phase co-
222 fluctuations. Indeed, the peaks in the posterior cingulate network and supramarginal network represent
223 the theory-of-mind and pain empathy events, respectively, as indicated by the original paper (Richardson
224 et al., 2018). The point-by-point multiplication indicates strong negative connectivity during these
225 events. In contrast, the sliding window correlation can only reflect a smoothed trend of such interactions.

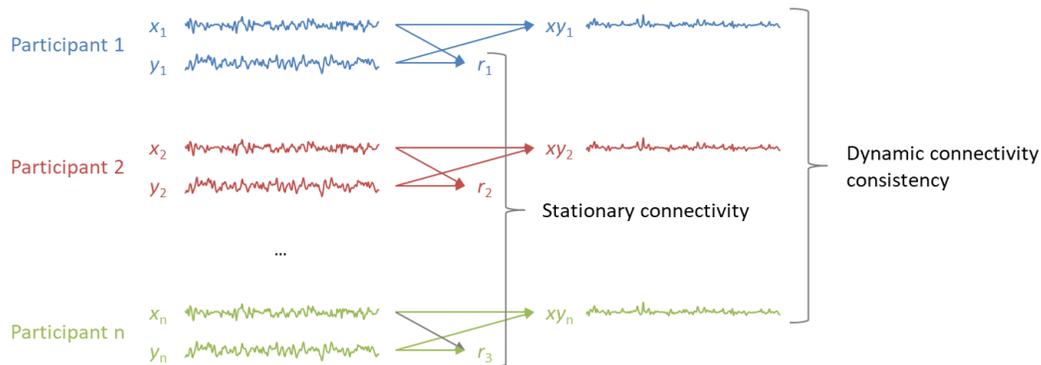
226 The point-by-point multiplication approach can avoid overly smoothing the time series data as done by
227 the sliding-window approach, therefore providing better interpretability of the results. On the other hand,
228 the multiplication term may be noisier and more prone to physiological noises and head motion artifacts.
229 But this may be less problematic for movie watching data, where we can estimate the consistent effects
230 cross individuals. We have performed statistical analyses on the Partly Cloudy dataset, and confirmed
231 that the point-by-point multiplication approach had better statistical sensitivity (see Supplementary
232 Materials). Therefore, we adopted the point-by-point multiplication approach to estimate dynamic
233 connectivity.



234
235 **Figure 1** Averaged time series of regional activity in the posterior cingulate (PCC) network and
236 supramarginal network (SMG), and their point-by-point multiplication and sliding-window dynamic
237 connectivity when watching an animated short movie Partly Cloudy. The two brain networks shown in
238 the inserted slices correspond to independent components #15 and # 6 in Figure 2, respectively.

239
240 We calculated the point-by-point multiplication between each pair of networks (ICs). The time
241 series from each network (IC) were first z transformed, and then point-by-point multiplied. PCA was
242 then performed on the multiplication time series across participants. To determine the statistical
243 significance of the variance explained by the first PC, we performed circular time-shift randomization to
244 determine the null distribution (Di and Biswal, 2021; Kauppi et al., 2010). The time series from the two
245 network ICs from all the participants were circular-shifted with random delays. Point-by-point

246 multiplications were then calculated for each participant, and PCA was performed. The randomization
247 was performed 10,000 times for each pair of networks from the 16 networks. The real values were
248 compared with the null distribution to perform statistical inferences. This resulted in a 16 x 16 matrix.
249 False discovery rate (FDR) correction was used to correct for multiple comparisons (120: 16 x 15 / 2).



250

251 **Figure 2** Illustration of the calculation of the consistency of dynamic connectivity and stationary
252 connectivity.

253

254 For the HBN-SSI dataset, we also compared the differences in variance explained by the first PC
255 among the three movies. For a pair of networks ICs, the multiplication between two IC time series were
256 first calculated, forming a 410 (time point) x 36 (participant/session) matrix for each movie. The matrices
257 from the three movie clips were concatenated to a 410 x 108 matrix, and permutation was performed
258 along the individual/session dimension to define three permuted matrices. The differences in variance
259 explained by the first PC between each movie clip and the other two clips were calculated and compared
260 with the permuted distributions of 10,000 times. FDR correction at $p < 0.05$ was used to correct
261 multiple comparisons of all three movie clips.

262 The randomization-based statistics were performed for all the analyses in the 20-IC solutions.
263 For the 80-IC solution, the goal of the analyses was not to identify specific statistically significant
264 connections. Rather, we examined the spatial distributions of the dynamic connectivity, and their
265 relations to stationary connectivity.

266 **2.6. Relations to stationary connectivity**

267 Next, we examined how the spatial distribution of consistent dynamic connectivity is associated with
268 stationary connectivity. Here we focused on a finer spatial scale of 80-IC solutions. To assess the
269 stationary connectivity, we calculated Fisher's z transformed Pearson's correlations across the included
270 networks (ICs). The matrices were averaged across individuals, and transformed back to r quantities.
271 First, we examined whether the dynamic and stationary connectivity has similar spatial distributions. For
272 both matrices, the upper triangular part was converted to vectors, which were in turn correlated with each
273 other between different movie clips. We adopted Spearman's correlation coefficients to avoid violations
274 of Gaussian distributions of the matrix data.

275 Next, we calculated connectivity gradients (Margulies et al., 2016; Vos de Wael et al., 2020)
276 based on the stationary connectivity patterns in the HBN-SSI dataset. By calculating gradients, the brain
277 networks (ICs) can be placed into a 2-D space based on their relative stationary connectivity strengths.
278 The 2-D gradients reflect large-scale brain organizations between unimodal networks and higher-order
279 transmodal areas (e.g. the default mode network) and between visual and sensorimotor regions (Margulies
280 et al., 2016). We can next display dynamic connectivity in the 2-D space to illustrate whether the
281 dynamic connectivity takes place between proximal or distal regions in the 2-D space. Specifically, we
282 first calculated the gradients for each movie clip based on the group stationary connectivity matrices
283 using the BrainSpace toolbox (Vos de Wael et al., 2020). The gradients were then aligned across the
284 movie clips with Procrustes alignment. The default diffusion-embedding and row-wise threshold (top
285 10% percentile) were used. After model fitting, the first two gradients were obtained. The network ICs
286 were mapped into the 2D gradient space. Lastly, the dynamic connectivity from the three movie clips
287 was plotted on the 2-D layout.

288 **2.7. Movie clips classification**

289 In addition to univariate analysis, we also explored whether the dynamic connectivity, stationary
290 connectivity, and regional activity can reliably reflect an individual's movie-watching condition (Finn et
291 al., 2015). The analysis was performed based on the 54 network ICs from the 80-IC solution. For each

292 participant of the HBN-SSI dataset, we calculated a connectivity or activity measure for each movie clip,
293 and also the corresponding connectivity or activity measure for the remaining 8 participants. We
294 compared three types of measures. First, we calculated the inter-individual consistency of point-by-point
295 multiplications. The individual's consistency was calculated across the four sessions of the same movie
296 clips. The consistency of the remaining participants was calculated across 32 participants/sessions. The
297 lower diagonal of the matrices was converted into a 1,431 ($54 \times 53 / 2$) by 1 vector to perform the
298 classification analysis. Second, we calculated mean stationary connectivity for the individual (averaged
299 across 4 sessions) and the remaining participants (averaged across 32 sessions). Third, we calculated the
300 inter-individual consistency of the regional activity. Similarly, individual measures were calculated
301 across the four sessions, and the remaining participants' measures were calculated for the 32
302 participants/sessions. Each measure was a 54 by 1 vector, which was used for the classification analysis.

303 We used a winner-take-all algorithm to perform the movie clip classifications. To classify the
304 individual measure's state (movie clips), the individual's measures were correlated with the remaining
305 participants' measures from the three movie clips. The movie clips with the highest correlation were used
306 as the predicted class. The classification was performed for each of the 9 participants and 3 movie clips,
307 from which we calculated confusion matrices among the three movie clips and the overall classification
308 accuracy of all the three movie clips. Because three movie clips were used for the classifications, the
309 chance level accuracy is 33.33%. To determine statistical significance, we adopted a permutation
310 procedure to randomly shuffle the predicted movie label 10,000 times.

311

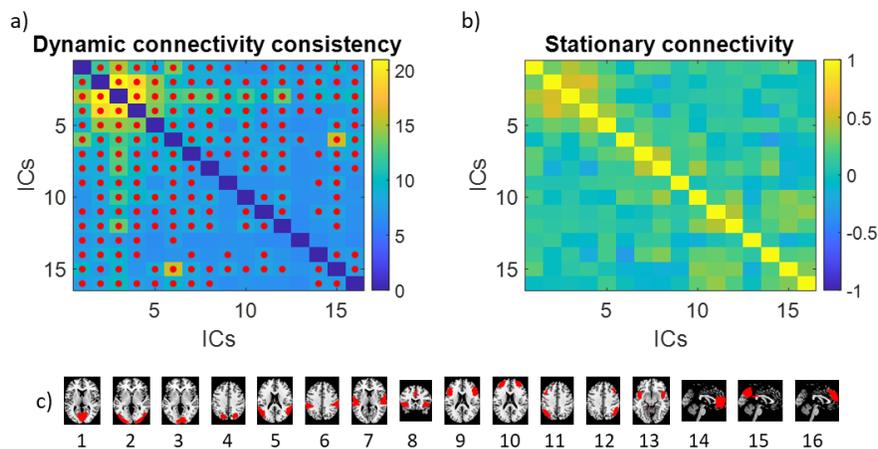
312

313 **3. Results**

314 **3.1. Dynamic and stationary connectivity in 20-IC solution**

315 We first examined the dynamic connectivity by calculating point-by-point multiplications between each
316 pair of 16 networks (IC) on the Partly Cloudy dataset (Figure 3a). We found widespread inter-individual
317 consistent effects at $p < 0.05$ of FDR correction. We also applied the sliding window approach, which

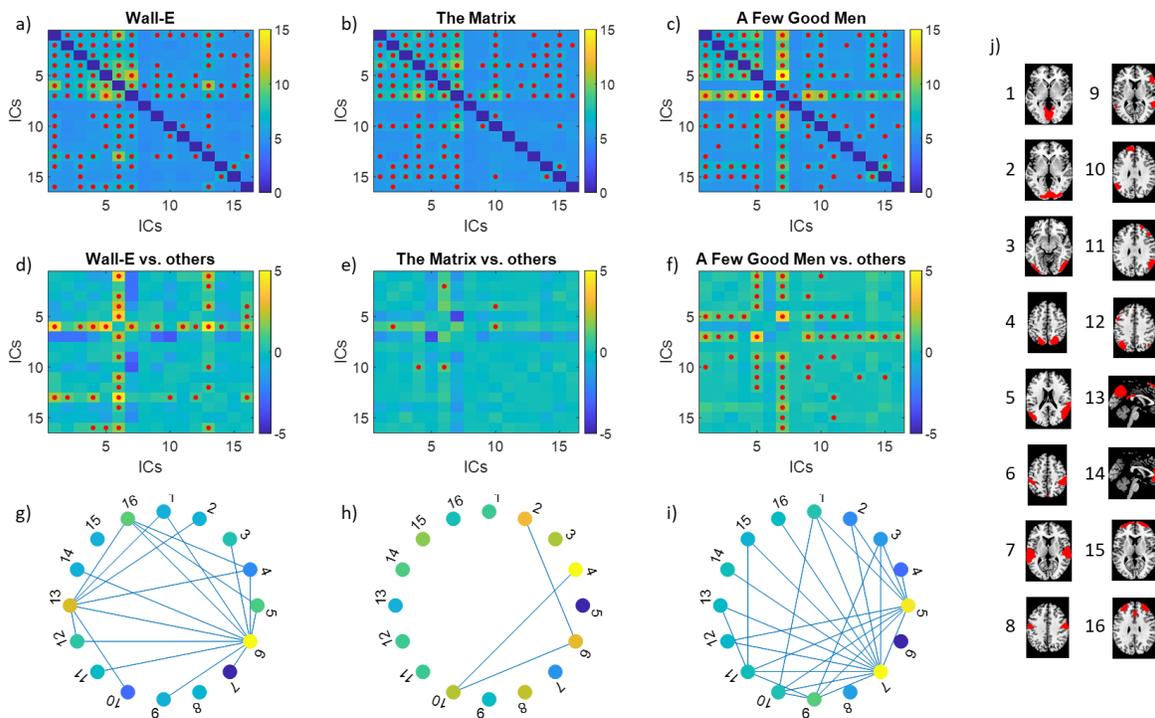
318 only yielded statistically significant effects on six pairs of networks (supplementary materials). This
319 suggests that the point-by-point multiplication approach has better sensitivity to detect dynamic
320 connectivity than the sliding-window approach. Although widespread, higher inter-individual
321 consistency was found mostly involving one network of the higher visual networks (IC# 2, 3, and 4 in
322 Figure 3c). And more interestingly, high inter-individual consistent dynamic connectivity was also found
323 between the supramarginal and default mode network (IC # 6 and 15), which was similar to our previous
324 analysis using a different analytic approach. In contrast, the stationary connectivity showed different
325 spatial patterns than the dynamic connectivity (Figure 3b). The networks with known functional
326 relations, e.g., all the visual related networks (IC # 1, 2, 3, and 4), had higher stationary connectivity,
327 which showed square-like structures along the diagonal.



328
329 **Figure 3** a) Inter-individual consistent point-by-point multiplications (dynamic connectivity) across the
330 16 networks (independent components, ICs) from the Partly Cloudy dataset. The colors in the matrix
331 represent the percent variance explained by the first principal component of the point-by-point
332 multiplication. The red dots indicate a false discovery rate (FDR) $p < 0.05$ using a circular time-shift
333 randomization procedure. b) Mean stationary connectivity across the 16 network ICs. The networks are
334 ordered roughly according to their functions. The locations of the networks are shown in c).

335

336 Figures 4a through 4c show the consistent point-by-point multiplications among the 16 networks
337 (ICs) for the three movie clips in the HBN-SSI dataset. Consistent with the Partly Cloudy dataset,
338 widespread consistent dynamic connectivity was observed. The networks that had more consistent
339 dynamic connectivity were higher visual networks and the auditory network (IC 7). We further directly
340 compared the consistency of dynamic connectivity among the three movies (Figure 4d through 4f).
341 Compared with the other two movie clips, the Wall-E clip showed more consistent dynamic connectivity
342 between the supramarginal network (IC 6) and many other networks, and between the posterior cingulate
343 network (IC 13) and visual related networks. Compared with the other movie clips, the clip of The
344 Matrix showed greater consistency between only three pairs of networks, among the posterior visual
345 cortex, posterior parietal network, supramarginal network, and a left frontoparietal network. And lastly,
346 compared with the other two movie clips, the A Few Good Men clip showed greater consistency in the
347 multiplication of the auditory cortex (IC 7) with other networks, and between the temporoparietal junction
348 network (IC 5) and other networks.

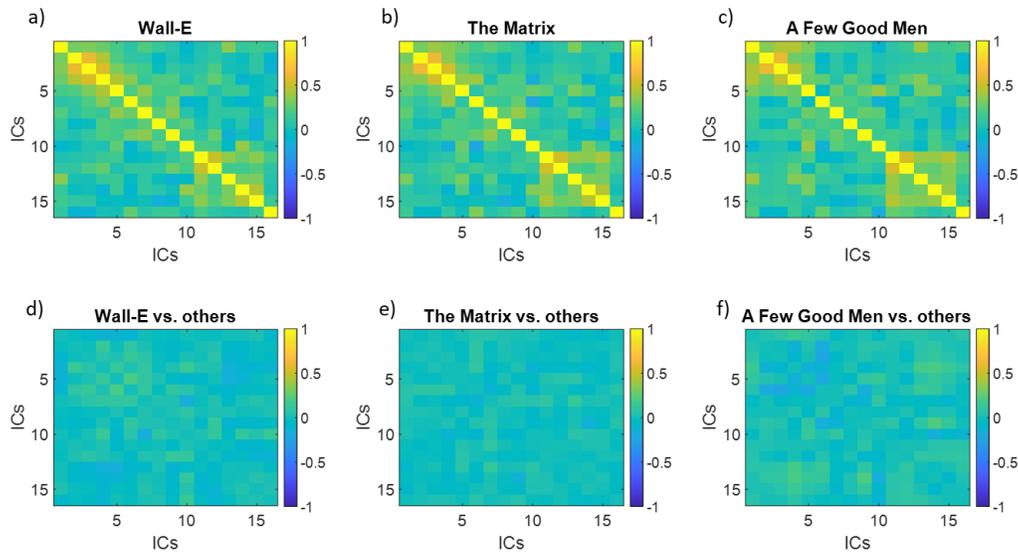


349

350 **Figure 4** a) through c), consistency of dynamic connectivity across 16 networks (independent
351 components, ICs) when watching the three movie clips in the Healthy Brain Network serial scanning
352 initiative dataset. The colors in the matrices represent the percent variance explained by the first principal
353 component of the point-by-point multiplication. d) through f), the differences in consistency of dynamic
354 connectivity between each movie clip and the other two clips. The red dots indicate statistical
355 significance at a false discovery rate $p < 0.05$ with permutation testing. The differences in consistency of
356 dynamic connectivity are also shown in graph representations in g) through i), where the node color
357 represents the consistency differences in regional activity. j) shows the representative maps for the 16
358 network ICs.

359
360 We also examined the relationships between regional activity consistency and dynamic
361 connectivity consistency. We first compared the variance explained by the first PC for regional activity
362 between the three movie clips (supplementary Figure S2). Four networks (ICs) showed higher
363 intersubject correlations in Wall-E compared with the other two movie clips, including the posterior
364 cingulate cortex, supramarginal gyrus, left fronto-parietal, and medial and lateral prefrontal networks.
365 Only one network covering the posterior parietal lobe showed higher intersubject synchronization in The
366 Matrix compared with the other two movie clips. Eight networks showed higher intersubject correlations
367 in A Few Good Men compared with the other movie clips, including the auditory cortex, medial visual,
368 temporo-parietal junction, and a few fronto-parietal networks. More interestingly, the regions with
369 greater consistency in regional activity in different movie clips seem to correspond well with the regions
370 with many consistent dynamic connectivities (Figure 4g through 4i).

371 We next examined the stationary connectivity among the 16 networks (ICs) (Figure 5). Not
372 surprisingly, the overall patterns in the three movies were very similar. When directly comparing the
373 differences among the three movies, no statistically significant differences were found even at the $p <$
374 0.05 threshold.



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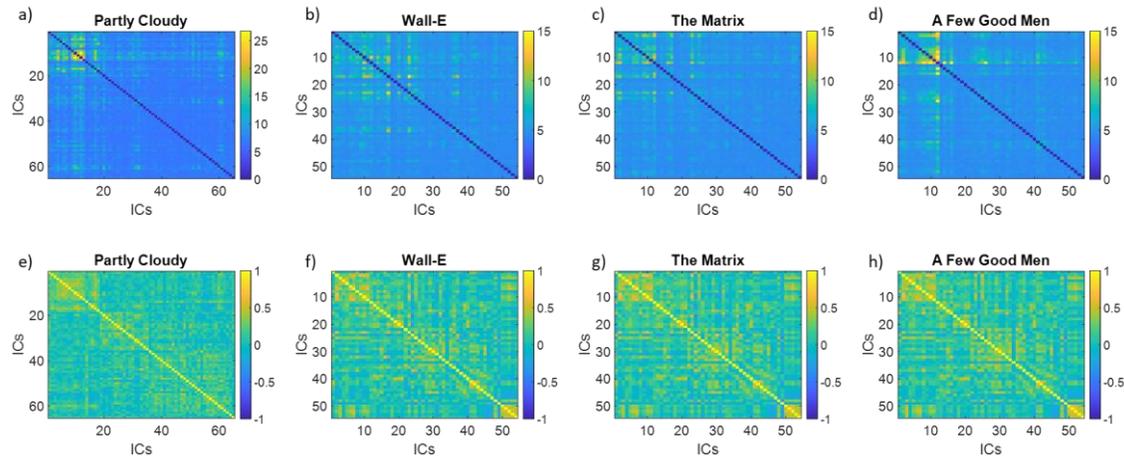
376 **Figure 5** Top row, stationary connectivity among 16 networks (independent components, ICs) when
377 watching the three movie clips from Healthy Brain Network Serial Scanning Initiative dataset. Bottom
378 row, differences in stationary connectivity between a movie clip and the other two clips. No statistically
379 significant difference was found even with an uncorrected threshold of $p < 0.05$.

380

381

382 3.2. Dynamic and stationary connectivity in 80-IC solution

383 We further studied the relations between dynamic and stationary connectivity in a larger spatial scale of
384 the 80-IC solution. Figure 6 shows the dynamic connectivity consistency and stationary connectivity
385 matrices for the four movie clips. The patterns are very similar to what with the 20-IC solution. That is,
386 the stationary connectivity matrices showed modular structures, and were very similar across different
387 movie clips. In contrast, the dynamic connectivity distributions were highly skewed, with greater
388 consistency between lower-level brain regions such as the visual and auditory cortex.

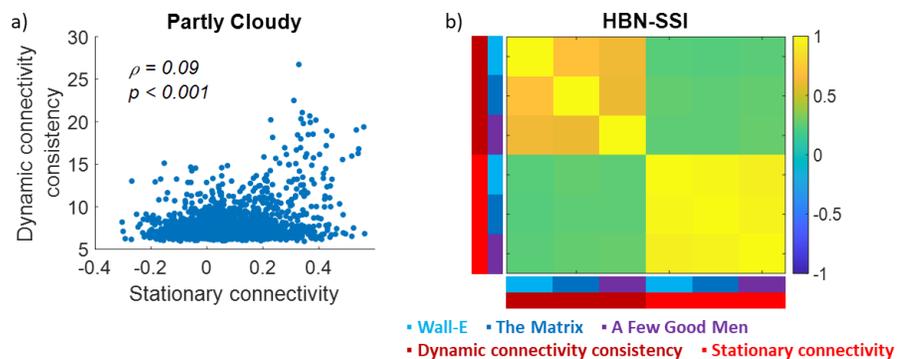


389

390 **Figure 6** Dynamic connectivity consistency (top row) and mean stationary connectivity (bottom row) for
 391 the four movie clips using the 80-independent-component solutions. Please note that the number of
 392 included independent components (ICs) are different between the Partly Cloudy dataset and the other
 393 three movie clips.

394

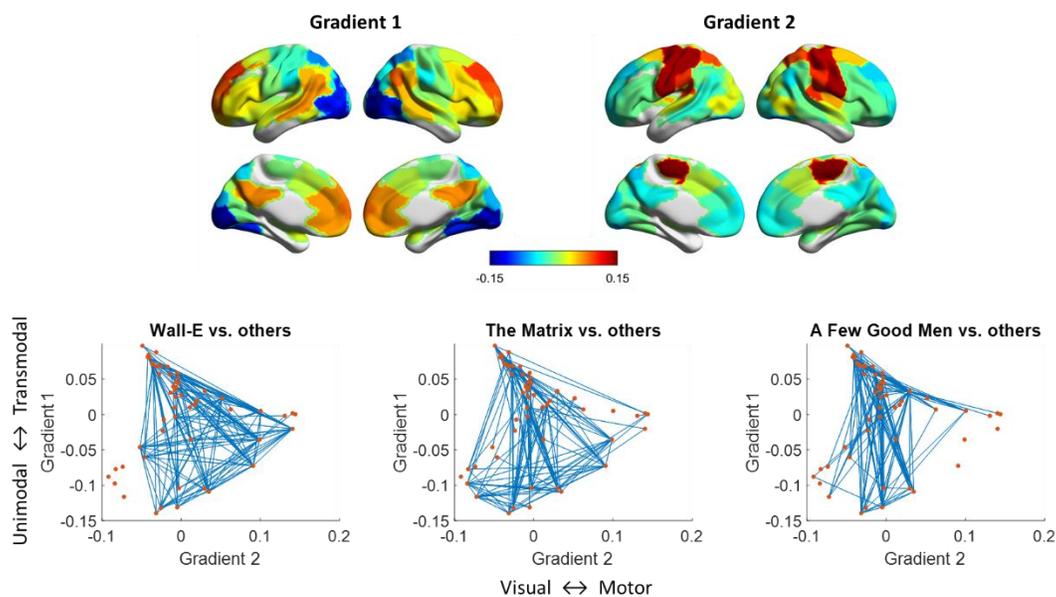
395 We next directly examine the correlations among the matrices. For the Partly Cloudy data, the
 396 correlation between stationary and dynamic connectivity consistency was only 0.09 (Figure 7a), although
 397 it was statistically significant due to the large number of IC pairs. The relations have been confirmed by
 398 the NBH-SSI dataset (Figure 7b). The stationary connectivity of the three movie clips had almost perfect
 399 correlations. On the other hand, the dynamic connectivity of the three movies had moderate correlations.
 400 There were very small correlations between the dynamic and stationary connectivity matrices.



401

402 **Figure 7** Correlations between stationary and dynamic connectivity for the Partly Cloudy dataset (a) and
403 Healthy Brain Network Serial Scanning Initiative (HBN-SSI) dataset (b). The connectivity matrices were
404 calculated based on 80-independent-component solutions. Spearman's rank correlation (ρ) was used.
405

406 In order to show the spatial distributions of dynamic connectivity in the context of global
407 stationary connectivity, we calculated connectivity gradients based on the stationary connectivity of the
408 three movie clips in the HBN-SSI dataset (Top row in Figure 8). The first and second gradients
409 represented unimodal to transmodal gradient and visual to motor gradient, respectively. Next, we plotted
410 the top 10% of dynamic connectivity in each movie clip compared with the other two movie clips
411 (Bottom row in Figure 8). It can be seen that the consistent dynamic connectivity for the three movies
412 usually took place between networks from far connectivity space, connecting visual, sensorimotor, and
413 higher-order association systems. There are also notable differences among the three movie clips. For
414 example, for the movie clips A Few Good Men, the consistent dynamic connectivity connected the
415 higher-order associate areas to visual and sensorimotor regions, separately. But direct connections
416 between visual and sensorimotor regions were rare.



417

418 **Figure 8** Top row, gradient maps of stationary connectivity in the Healthy Brain Network Serial Scanning
419 Initiative dataset. Bottom row, top 10% consistent dynamic connectivity in each movie clip compared
420 with the other two clips mapped to the connectivity gradient space.

421

422 **3.4. Movie clips classification**

423 Last we asked whether the dynamic or stationary connectivity pattern can enable individual-level
424 prediction of the different movie clips. For each participant from the HBN-SSI dataset, we classified one
425 of the three movie clips based on different measures. Overall, the consistency of dynamic connectivity
426 achieved the highest prediction accuracy (*Accuracy* = 92.6%), followed by the stationary connectivity
427 (*Accuracy* = 85.2%) and the consistency of regional activity (*Accuracy* = 74.1%). Compared with
428 chance level accuracy of 33.33%, all classification accuracies were statistically significant ($p < 0.001$)
429 based on permutation tests. The clip-to-clip classification results for the different features are shown in
430 Supplementary Table S1.

431

432 **4. Discussion**

433 In the current analysis, we have shown widespread dynamic connectivity that is consistent across
434 individuals when the participants watched the same movie clips. Different movie clips showed different
435 patterns of dynamic connectivity, suggesting that the moment-to-moment interactions between brain
436 regions may support the processing of context-specific information. For example, the two cartoon movie
437 clips showed similarly consistent dynamic connectivity between the posterior cingulate network and
438 supramarginal network. The action movie clip, *The Matrix*, showed more consistent dynamic
439 connectivity in networks related to attention. And the drama movie, *A Few Good Men*, showed more
440 consistent dynamic connectivity involving networks related to language processing, including bilateral
441 fronto-parietal networks and prefrontal cortex. In contrast, stationary connectivity showed very similar
442 spatial patterns in different movie clips, with few statistical differences. The dynamic connectivity

443 connected brain regions that are farther in the connectivity gradient space, and can better classify different
444 movie clips than the stationary connectivity and regional activity.

445 We first empirically compared the statistical results of inter-individual correlations of dynamic
446 connectivity measured by sliding window and point-by-point multiplication. Not surprisingly, the
447 multiplication approach showed higher statistical sensitivity than the sliding window approach, as
448 indicated by a much larger number of significant effects. It is not surprising because the point-by-point
449 multiplication has kept the information of every time point, while the sliding-window approach can be
450 seen as smoothed time series that could potentially filter out real signals. More specifically, the point-by-
451 point multiplication approach detected consistent interactions between almost every pair of network ICs.
452 This is in line with previous studies of regional activity, which also showed statistically significant effects
453 in almost all cortical regions (Chen et al., 2016; Di and Biswal, 2020). In contrast, the sliding window
454 approach can only detect a small number of the dynamic connectivity among higher visual networks, and
455 between supramarginal gyrus and posterior cingulate networks. This is probably because there is slow
456 time-varying dynamic connectivity between these regions (e.g., Figure 1), which can be detected by the
457 sliding window approach. This is in line with studies showing that higher-order brain regions process
458 longer time scale information (Baldassano et al., 2017). The results confirm the limitation of the sliding
459 window approach in studying dynamic connectivity.

460 Consistent dynamic connectivity is ubiquitous, but different movies clips were associated with
461 different patterns of dynamic connectivity. The movie clips from Wall-E showed a similar dynamic
462 connectivity pattern as another animated movie Partly Cloudy. Specifically, consistent dynamic
463 connectivity was mainly observed in connectivity with two networks, the supramarginal and posterior
464 cingulate networks. These regions involve higher-order social processes such as empathy and theory of
465 mind (Richardson et al., 2018; Schurz et al., 2021). This makes sense because understanding the cartoon
466 movies requires understanding the social interactions and intentions of the virtual characters. In contrast,
467 the court drama clip, A Few Good Men, showed higher dynamic connectivity consistency that involved
468 the auditory and temporoparietal junction networks. Because the court drama includes numerous

469 conversations, it is not surprising that the auditory cortex dynamically interacts with other cortical areas to
470 pass auditory information to those areas. The temporoparietal junction is thought to be responsible for
471 attributing other's mental states (Koster-Hale and Saxe, 2013; Wang et al., 2021), which may also be a
472 key component in understanding the conversations in the movie clip. Of course, these brain areas also
473 involve in many other higher-order brain functions, the correlational nature of the analysis doesn't allow a
474 specific function to the observed dynamic connectivity patterns (Poldrack, 2006).

475 In contrast to the dynamic connectivity, no differences were identified in stationary connectivity
476 among the three movie clips. In a larger spatial scale of 54/80 ICs, we further showed that the spatial
477 distribution of stationary connectivity was highly correlated among the three movie clips, which is
478 consistent in a previous study (Vanderwal et al., 2019). The largely similar patterns of connectivity
479 during watching different movies are also in line with the observations in conventional task fMRI. When
480 regressing out task activations (Cole et al., 2014; Di and Biswal, 2019) or using continuous task design
481 (Krienen et al., 2014), the stationary connectivity or task-independent connectivity showed largely similar
482 spatial patterns with each other and with what in resting-state. Similarly, the absolute correlation patterns
483 of trial-by-trial variability of the stop and go conditions in a stop signal task also showed similar patterns
484 with each other and with a separate resting-state run (Di et al., 2020). Taken together, all the results
485 convergently suggest that there is an overall connectivity pattern that may be related to the baseline brain
486 function, but may also be related to the underlying physiology (Chen et al., 2020) or anatomical network
487 structures (Laumann and Snyder, 2021). The lack of specificity of this global connectivity pattern makes
488 it less desirable as a measure of brain connectivity in specific cognitive and mental conditions. It should
489 be noted that when using multivariate classification analysis, the spatial patterns of stationary connectivity
490 can still be used to identify different movie clips, but with less accuracy than the dynamic connectivity
491 patterns. The high classification accuracy of the dynamic connectivity suggested that dynamic
492 connectivity could potentially be useful in predictive-based analysis to reflect individual differences (Finn
493 et al., 2015).

494 The spatial distributions of dynamic connectivity and stationary connectivity are largely
495 dissociated. On one hand, the dynamic connectivity could take place between regions within the same
496 functional systems, e.g., the visual system. This is less apparent when using the sliding-window
497 approach, probably due to that the sliding-window approach can only capture slow fluctuations of
498 dynamic connectivity. The point-by-point approach could capture the fast dynamics of the interactions.
499 It is reasonable that the lower-level sensory regions showed consistent interactions, but this may be
500 overlooked by using the conventional sliding window approach. On the other hand, the current results
501 also showed that dynamic connectivity could also take place between different functional systems, e.g.,
502 between visual areas and the default mode network. This is in line with the economic account of brain
503 network organizations, which suggests that transient communication between remote brain regions could
504 enable efficient information transmissions. When overlaying the dynamic connectivity on the
505 connectivity gradients space, it demonstrated more clearly that the dynamic connectivity took place
506 between higher association areas, such as the default mode network, and lower-level sensory or motor
507 regions.

508 One limitation of the current study is the sample size. The HBN serial scanning dataset has a
509 relatively small sample size ($n = 9$). However, each participant watched three different types of movie
510 clips and repeated four sessions, which enable us to directly compare connectivity among these diverse
511 movie types and ensure the robustness of the results within an individual. Although promising, a larger
512 sample size with an examination of behavioral scores is needed for future brain-behavioral association
513 studies (Finn and Bandettini, 2021), where researchers can directly examine the differences in behavioral
514 correlates between dynamic connectivity and stationary connectivity (Eichenbaum et al., 2021).

515 Secondly, the current analysis only focused on the spatial distributions of dynamic connectivity. Given
516 the ubiquitous dynamic connectivity identified in the current analysis, future studies could also examine
517 the time courses of the point-by-point multiplications, which could paint a more complete picture of the
518 dynamic connectivity.

519

520 **5. Conclusion**

521 By analyzing the inter-individual consistency of point-by-point multiplications between brain regions, we
522 were able to identify functionally meaningful dynamic connectivity during movie watching. We found
523 that compared with the stationary connectivity, the dynamic connectivity can be more sensitive to detect
524 functional changes due to different movie contexts. The spatial distributions of dynamic connectivity and
525 stationary connectivity were largely dissociated, with dynamic connectivity more reflect long-range
526 communications. Overall, dynamic connectivity may provide more functionally related information than
527 stationary connectivity.

528

529

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533

534 **Conflict of interest**

535 The authors declare that there is no conflict of interest.

536

537

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