

# 1 Spontaneous and deliberate modes of creativity: Multitask eigen- 2 connectivity analysis captures latent cognitive modes during creative 3 thinking

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## 11 Abstract

12 Despite substantial progress in the quest of demystifying the brain basis of creativity, several questions  
13 remain open. One such issue concerns the relationship between two latent cognitive modes during  
14 creative thinking, i.e., deliberate goal-directed cognition and spontaneous thought generation. Although  
15 an interplay between deliberate and spontaneous thinking is often indirectly implicated in the creativity  
16 literature (e.g., dual-process models), a bottom-up data-driven validation of the cognitive processes  
17 associated with creative thinking is still lacking. Here, we attempted to capture the latent modes of  
18 creative thinking by utilizing a data-driven approach on a novel continuous multitask paradigm (CMP)  
19 that widely sampled a hypothetical two-dimensional cognitive plane of deliberate and spontaneous  
20 thinking in a single fMRI session. The CMP consisted of eight task blocks ranging from undirected mind  
21 wandering to goal-directed working memory task, while also including two of the widely used creativity  
22 tasks, i.e., alternate uses task (AUT) and remote association task (RAT). Using data-driven eigen-  
23 connectivity (EC) analysis on the multitask whole-brain functional connectivity (FC) patterns, we  
24 embedded the multitask FCs into a low-dimensional latent space. The first two latent components, as  
25 revealed by the EC analysis, broadly mapped onto the two cognitive modes of deliberate and spontaneous  
26 thinking, respectively. Further, in this low-dimensional space, both creativity tasks were located in the  
27 upper right corner of high deliberate and spontaneous thinking (creative cognitive space).  
28 Neuroanatomically, the creative cognitive space was represented by not only increased intra-network  
29 connectivity within executive control and default mode networks, but also by a higher inter-network  
30 coupling between the two. Further, individual differences reflected in the low-dimensional connectivity  
31 embeddings were related to differences in deliberate and spontaneous thinking abilities. Altogether, using  
32 a continuous multitask paradigm and data-driven approach, we provide direct empirical evidence for the  
33 contribution of both deliberate and spontaneous modes of cognition during creative thinking.

34 **Keywords:** creativity; deliberate/spontaneous thinking; dual-process model; multitask fMRI; whole-brain  
35 functional connectivity; eigen-connectivity.

36

## 37 1. Introduction

38 It is commonly agreed that creativity refers to the ability to produce work that is both novel and  
39 appropriate (Sternberg and Lubart, 1999). As one of the most extraordinary capacities of the human brain,  
40 creativity drives the development of our society. From art and design to science and engineering, we often  
41 marvel at people's ingenuity. Given its central role, there has been an ever-growing interest in studying  
42 the neural basis of creative cognition. Although initial neuroimaging studies focused on revealing the  
43 contribution of individual brain regions to different aspects of creative thinking (Dietrich, 2004; Saggar et  
44 al., 2017, 2015), in recent years, this focus has shifted towards examining the interaction between  
45 multiple brain regions (as a network) during creative thinking (Beaty et al., 2019, 2017; Maillet et al.,  
46 2019; Saggar et al., 2019). However, data-driven evidence is still needed to confirm whether creative  
47 thinking depends on a single brain network or an interplay between multiple networks.

48 As a complex high-level cognitive phenomenon, creativity likely depends on a range of other lower- and  
49 higher-order processes, such as perception, working memory, semantic memory, and sustained attention  
50 (Dietrich, 2004; Lee and Theriault, 2013; Smeekens and Kane, 2016). Further, an interplay between two  
51 latent cognitive modes has been suspected during creative cognition, i.e., modes of spontaneous/implicit  
52 thinking and deliberate/explicit thinking. This interplay has been previously referred to as a dual-process  
53 model (Barr et al., 2015; Christoff et al., 2016; Dietrich, 2004; Finke, 1996; Sowden et al., 2015).  
54 Specifically, previous data suggest that while creative insights are often accompanied by defocused  
55 attention through spontaneous thinking (Baird et al., 2012; Eysenck, 1995; Gable et al., 2019; Zabelina et  
56 al., 2015), creativity can also stem from methodical problem solving via deliberate thinking (Benedek et  
57 al., 2014; Boden, 1998; Frith et al., 2019; Nusbaum and Silvia, 2011).

58 The interplay between deliberate and spontaneous thinking during creative cognition is hypothesized to  
59 correspond to two canonical brain networks: the executive control network (ECN) and the default mode  
60 network (DMN), respectively (Beaty et al., 2016, 2015; Ellamil et al., 2012). The ECN is typically  
61 elicited by tasks requiring externally driven attention, while the DMN is typically elicited by internally  
62 driven cognition. In the context of creativity, the ECN is thought to support goal-directed and strategic  
63 cognition required to guide and direct the creative thought process, inhibiting common ideas and  
64 strategically searching memory for task-relevant unique solutions (Beaty et al., 2016). The DMN, in  
65 contrast, is thought to support the spontaneous generation of candidate ideas from memory and  
66 imagination, consistent with its role in episodic/semantic memory retrieval and mental simulation  
67 (Buckner et al., 2008). The putative cognitive processes of ECN and DMN broadly map onto dual-process  
68 models of creativity that emphasize spontaneous thought and deliberate control (Beaty et al., 2015).

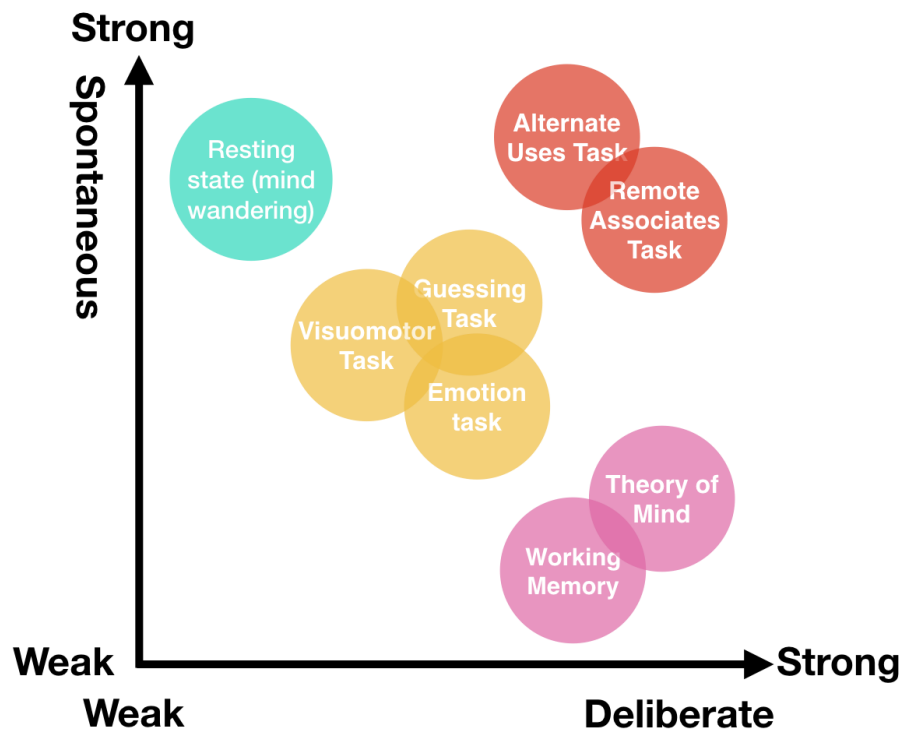
69 Together, these studies provide insights into the theoretical roles of DMN and ECN in spontaneous and  
70 deliberate cognition during creative performance. However, direct data-driven evidence for the  
71 involvement of these latent cognitive modes (i.e., deliberate/spontaneous thinking) remains elusive. That  
72 is, existing evidence does not unambiguously indicate that ECN and DMN support deliberate and  
73 spontaneous cognition during creative performance, while the cognitive roles of ECN and DMN have  
74 merely been speculated and inferred based on classic dual-process theories of creativity (e.g., Finke,  
75 1996).

76 To tackle this issue, here, we adopted a data-driven approach to examine the interplay between  
77 spontaneous and deliberate thinking during creative cognition using functional magnetic resonance  
78 imaging (fMRI). Specifically, we developed a novel continuous multitask paradigm (CMP) - with seven  
79 cognitive task blocks and a resting-state block, in a single fMRI session. Using our CMP, we aimed at  
80 sampling a wide range of cognitive processes along a hypothetical two-dimensional plane of deliberate  
81 and spontaneous thinking. As shown in **Fig. 1**, we included two established creative tasks (i.e., alternate  
82 uses task (AUT) and remote associates task (RAT)), five other non-creative task blocks, and a resting-  
83 state block. Based on the theoretical framework by Christoff and colleagues (2016), we hypothesized that  
84 the two latent cognitive processes would be differentially recruited by these eight task blocks. For

85 example, tasks such as 2-back working memory that require higher cognitive load would occupy the  
86 lower right quadrant, i.e., relying heavily on deliberate thinking while inhibiting spontaneity. Similarly,  
87 rest or mind-wandering is likely to recruit spontaneous thinking with minimum deliberate control (top left  
88 quadrant). Other non-creative tasks, with a medium level of cognitive load, would reside in the cognitive  
89 space between resting-state and working memory. Critically, we hypothesized that creative cognition  
90 would require both deliberate and spontaneous thinking and hence occupy the top right quadrant.  
91 Leveraging information from a wider variety of cognitive tasks, we aimed to obtain a holistic overview of  
92 how creative cognition is related to other cognitive processes. Further, using our CMP we aimed at  
93 identifying the latent cognitive axes that may underlie creative cognition. Similar approaches have been  
94 recently used to assess the neural correlates of ongoing cognition (Gonzalez-Castillo et al., 2015; Krienen  
95 et al., 2014).

96 For a bottom-up data-driven validation of the latent cognitive modes across the eight task blocks, we  
97 performed the eigen-connectivity (EC) analysis on the task-related whole-brain functional connectivity  
98 (FC) patterns (Leonardi et al., 2013). The EC analysis can reveal the low-dimensional latent embeddings  
99 from the multitask FC patterns, i.e., the latent connectivity structures shared across tasks. We aimed to  
100 test our hypothetical cognitive space (shown in Fig. 1) by examining the low-dimensional embedding  
101 revealed by the EC analysis. Further, to estimate the utility of low-dimensional embeddings, we  
102 investigated the relationship between individual differences in the latent space embedding and  
103 corresponding behavior.

104



105

106 **Fig. 1.** Mapping multitask data to a hypothetical cognitive space with two putatively orthogonal dimensions of  
107 deliberate and spontaneous thinking. We hypothesize that tasks such as mind wandering would occupy the upper left  
108 quadrant as they are based on spontaneous processing with a minimum amount of deliberate control. In contrast,  
109 tasks with high cognitive load (2-back working memory or theory of mind task) would occupy the lower right  
110 quadrant as they are based highly on deliberate thinking. Other tasks like emotion classification, guessing, and  
111 visuomotor could be mapped in between deliberate and spontaneous thinking. Lastly, we hypothesized that if the

112 creativity tasks (alternate uses and remote association) require both deliberate and spontaneous thinking they should  
113 occupy the top right quadrant.

114

## 115 **2. Methods**

### 116 *2.1 Participants*

117 Thirty-two participants ( $30.4 \pm 5.4$  years, 13F, 4 left-handed) took part in our study. All participants  
118 reported no history of neurological disorder or psychotropic medication, with normal or corrected-to-  
119 normal vision. The study was approved by Stanford University's Institutional Review Board, and all  
120 participants gave written consent. Detailed demographic information can be found in Supplemental Table  
121 S1.

### 122 *2.2 Neuropsychological assessments*

123 A set of behavioral assessments were conducted outside the MR scanner to measure participants'  
124 creativity and executive function as proxies for spontaneous/deliberate thinking. Below, we briefly  
125 introduce these assessments.

#### 126 *2.2.1 Creativity*

127 The Torrance Test of Creative Thinking (TTCT-Figural; Torrance, 1972) is one of the most widely-  
128 accepted tests to measure divergent thinking ability in the visual form. This game-like test can engage  
129 participants' spontaneous creativity while being unbiased in terms of race, culture, socio-economic status,  
130 gender, and language (Kim, 2006). Participants were given 30 minutes to complete three activities in the  
131 TTCT-Figural assessment, i.e., picture construction, picture completion, and repeated figures of lines or  
132 circles. The TTCT-Figural assessments were scored by the Scholastics Testing Service, Inc  
133 (<http://ststesting.com>).

#### 134 *2.2.2 Executive function*

135 Participants' executive function was assessed using the Stroop Color-Word Interference Test (CWIT), a  
136 subtest of Delis–Kaplan Executive Function System (D-KEFS; Delis et al., 2001). CWIT consists of four  
137 parts: color naming, word reading, inhibition, and inhibition/switching.

### 138 *2.3 Imaging Data*

#### 139 *2.3.1 Imaging acquisition*

140 Participants were scanned using a GE 3T Discovery MR750 scanner with a 32-channel Nova Medical  
141 head-coil at the Stanford Center for Cognitive and Neurobiological Imaging. Functional scan parameters  
142 used are as follows: 1183 volumes, repetition time TR = 0.71 s, echo time TE = 30 ms; flip angle FA =  
143  $54^\circ$ , field of view FOV =  $220 \times 220 \times 144$  mm, isotropic voxel size = 2.4 mm, #slices = 60, multiband  
144 acceleration factor = 6. High-resolution T1-weighted structural images were also collected with FOV =  
145  $190 \times 256 \times 256$  mm, FA =  $12^\circ$ , TE = 2.54 ms, and isotropic voxel size = 0.9 mm.

#### 146 *2.3.2 Continuous multitask paradigm*

147 A novel continuous multitask paradigm (CMP) was conducted over two runs (duration for each run was  
148 ~14 min). The CMP included seven cognitive task blocks and a resting state block (Table 1). The  
149 cognitive tasks were chosen to sample along the two-dimensional hypothetical plane of deliberate and  
150 spontaneous thinking. Each task block lasted 90 s with a 12 s instruction between two task-blocks. A brief  
151 summary of the task blocks is provided in Table 1. The CMP was repeated in the second run in a  
152 randomized order with different sets of stimuli/questions. Participants were first familiarized with the  
153 rules of each task before entering the scanner. For the two creative tasks, alternative uses task (AUT) and  
154 remote associates task (RAT), we recorded participants' answers after the scan, consistent with previous  
155 studies (Beaty et al., 2019; Benedek et al., 2019).

156 **Table 1.** Task batteries included in the continuous multitask paradigm. ITI: inter-trial interval.

Name	Task description	#Trials/Duration	Reference
Alternative uses task (AUT)	Silently name uncommon uses of everyday objects (e.g. bricks) and press a button when you think of one.	3 trials; each trial lasted for 30 s	Mayseless et al. (2015)
Emotion task (Emotion)	Match one of two simultaneously presented emotionally-charged faces (angry or afraid) with an identical target face displayed below.	30 trials; each trial lasted 3 s	Hariri et al. (2002)
2-back working memory task (WM)	Match geometric shapes with the one presented two shapes before (5 shapes in total).	30 trials; each trial lasted 3 s	Gonzalez-Castillo et al. (2015)
Theory of mind task (ToM)	Read a story describing false beliefs and answer a yes/no question <sup>1</sup> .	5 trials; each trial lasted 18 s. Each trial consisted of 12 s for reading, 5 s for answering and 1 s ITI	Dodell-Feder et al. (2011)
Visuomotor task (VisMot)	Visually cued finger-tapping of a red target on a flashing checkboard.	3 trials; each trial lasted 30 s. Within each trial 18 s for stimuli and 12 s ITI	Drobyshevsky et al, (2006)
Guessing task (Guessing)	View a “?” and guess who “hides behind” the question mark (baby or adult). Receive monetary feedback indicating whether the answer is correct.	10 trials; each trial lasted 9 s. Within each trial, 3 s for guessing, 2 s for feedback and 4 s ITI	Delgado et al. (2000)
Remote Associates Task (RAT)	Produce a fourth related word based on the three cue words <sup>2</sup> .	9 trials; each trial lasted 10 s	Mednick (1962)
Mind wandering (MW)	Relax and fixate at the crosshair.	90 s duration	Raichle et al. (2001)

157

### 158 2.3.3 Preprocessing

159 We discarded the first 12 frames of functional data, after which we applied a standardized preprocessing  
 160 pipeline using fMRIPrep (v1.2.1, Esteban et al., 2019). The functional data underwent motion correction,  
 161 slice timing correction, susceptibility distortion correction, and were normalized to the Montreal  
 162 Neurological Institute (MNI152) template. Overall, we excluded 7 participants due to technical difficulty  
 163 (3), poor structural registration (1), excessive motion (1; mean framewise displacement > 0.2mm); and  
 164 participants’ dropping out or inability to scan (2). All later analysis included 25 participants.

165 For the remaining 25 participants, we removed nuisance signal by regressing out the physiological noise  
 166 (white matter and CSF) and motion-related noise using the Volterra expansion of 6 motion parameters  
 167 and 2 physiological signals (Friston et al., 1996):  $[R \ R^2 \ R_{t-1} \ R_{t-1}^2]$ . Along with the nuisance signal  
 168 regression, detrending and temporal filtering between 0.008 and 0.18Hz were also simultaneously  
 169 performed using AFNI *3dTproject*. Despiking was performed using *3dDespike*, and spatial smoothing  
 170 was carried out using Gaussian kernel with FWHM = 6 mm. A parcellation with 375 regions of interest  
 171 (ROIs) were defined based on the parcellation previously used by Shine et al. (2019), which contains 333

<sup>1</sup> ToM example: Story: Laura didn't have time to braid her horse's mane before going to camp. While she was at camp, William brushed Laura's horse and braided the horse's mane for her. Yes/No question: Laura returns assuming that her horse's hair isn't braided.

<sup>2</sup> RAT example: Cue: dream – break – light. Answer: day.

172 cortical parcels from the Gordon atlas (Gordon et al., 2016), 14 subcortical regions from the Harvard–  
173 Oxford subcortical atlas (bilateral thalamus, caudate, putamen, ventral striatum, globus pallidus,  
174 amygdala, and hippocampus), and 28 cerebellar regions from the SUIT atlas (Diedrichsen et al., 2009) to  
175 ensure the whole-brain coverage. After dropping 12 ROIs with fewer than 10 voxels, the time series were  
176 extracted from the remaining 363 ROIs by first converting the residual signal to percentage signal change  
177 (i.e., voxel intensity was divided by the voxel mean) and then computing the average signal within each  
178 ROI. The two functional runs were concatenated, and time points with the framewise displacement  
179 greater than 0.5 mm were excluded from further analysis (time points discarded = 1.62%±2.32%).

#### 180 2.3.4 Estimating regularized functional connectivity (FC)

181 Sparse graphical models has been increasingly adopted by neuroimaging researchers in recent years  
182 (Allen et al., 2014; Rosa et al., 2015; Smith et al., 2011; Xie et al., 2019). Here, we employed graphical  
183 LASSO (Friedman et al., 2007) to estimate functional connectivity using the R package ‘glasso’. In short,  
184 graphical LASSO encourages a sparse solution of the task-specific precision matrix  $\theta$  (or inverse  
185 covariance matrix) by maximizing the following log-likelihood function  $L_1$

$$186 \quad L_1 = \log \det \theta - \text{tr}(s\theta) - \lambda \|\theta\|_1 \quad (1),$$

187 where  $\det$  denotes the matrix determinant;  $\text{tr}$  denotes the matrix trace;  $s$  represents the empirical  
188 covariance matrix;  $\lambda$  is a non-negative regularization parameter provided by users;  $\|\theta\|_1$  indicates the L1  
189 penalty on  $\theta$ .

190 A zero entry in the precision matrix reflects conditional independence between the signals of two brain  
191 regions, after regressing out all other ROI timeseries. A higher  $\lambda$  yields a sparser representation at the cost  
192 of goodness-of-fit. To achieve a good balance between the sparsity and goodness-of-fit, we tested a range  
193 of  $\lambda$  (0 - 0.2, step size = 0.02) and found an optimal  $\lambda$  (0.06 & 0.08) for each individual that maximizes  
194 the following log-likelihood  $L_2(\lambda)$

$$195 \quad L_2(\lambda) = \sum_{k=1}^K \log \det \theta_k - \text{tr}(s_0 \theta_k) \quad (2).$$

196 Here,  $s_0$  is the empirical covariance matrix estimated using all the time points, and  $K$  is the total number  
197 of tasks. This objective function was chosen given the expectation that task-specific FCs should be  
198 similar across multiple cognitive tasks for a given participant (Finn et al., 2015, also see Supplemental  
199 Fig. S1). Upon choosing the optimal regularization parameter, we estimated the regularized covariance  
200 matrix and subsequently converted it to regularized whole-brain FC, followed by Fisher-z transformation.

#### 201 2.3.5 Multitask eigen-connectivity analysis

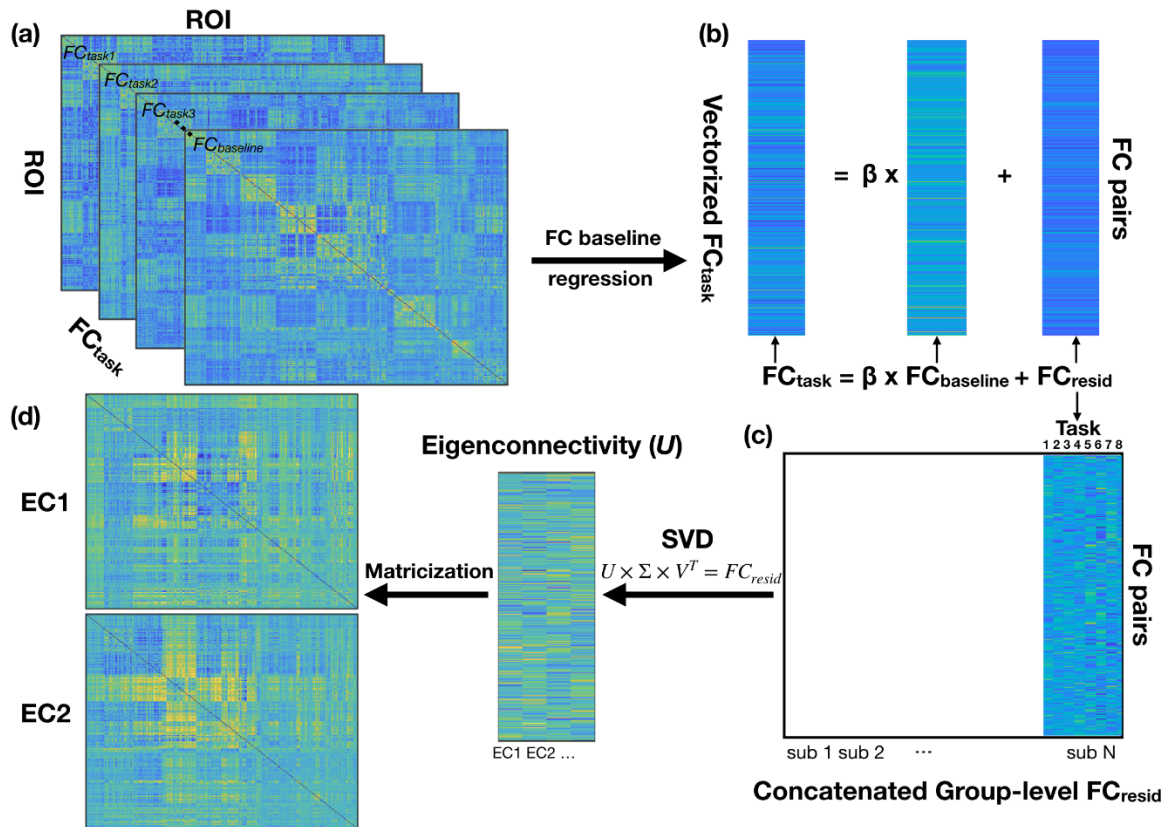
202 To delineate the latent cognitive processes sampled by the CMP, we extracted the latent FC structure  
203 from the multitask-FC using eigen-connectivity (EC) analysis developed by Leonardi et al. (2013). The  
204 EC analysis was originally developed to study time-varying FC dynamics during rest. Briefly, after  
205 computing task-specific FC matrices, we first vectorized the upper triangular FC matrices and regressed  
206 out the subject-specific baseline-FC to better reveal task-specific FC patterns (Xie et al., 2018a). Here,  
207 baseline-FC was characterized as the FC pattern estimated using time points from all eight task blocks for  
208 each participant. We then concatenated the residual FC vectors across participants and tasks, resulting in a  
209  $65,703 \times 200$  group-level residual FC matrix ( $FC_{resid}$ ) across 8 task blocks and 25 participants. Singular  
210 value decomposition (SVD) was applied on the group-level  $FC_{resid}$ .

$$211 \quad FC_{resid} = U\Sigma V^T \quad (3),$$

212 where  $U$  is a  $65,703 \times 200$  unitary matrix and the columns of  $U$  are orthonormal eigenvectors;  $V$  is a  $200$   
213  $\times 200$  unitary matrix;  $\Sigma$  is a  $200 \times 200$  diagonal matrix of singular values.

214 The column vectors of  $U$  were reshaped back into the matrix form ( $\#ROIs \times \#ROIs$ ). First few columns  
215 vectors of  $U$ , explaining large variance, can be used to define the low-dimensional connectivity-based  
216 embedding that is shared across all eight task blocks. The latent embeddings were referred to as EC  
217 patterns by Leonardi et al. (2013) when studying dynamic functional connectivity. The EC weights

218 correspond to the projections of these ECs, i.e., columns of  $V$  multiplied by the singular values of  $\Sigma$ .  
 219 Given our goal to anchor the cognitive processes into lower dimensions that can be visualized, we  
 220 focused on the first two ECs that explained the most variance in the group-level  $FC_{resid}$ , as well as the  
 221 corresponding weights, in order to match the latent cognitive processes of interest.



222  
 223 **Fig. 2.** A graphic summary of the EC analysis pipeline. (a) The eight task-specific FC ( $FC_{task}$ ) and a baseline-FC  
 224 ( $FC_{baseline}$ ) were computed and then vectorized for each participant. The baseline-FC was computed across the  
 225 entire scan time. (b) For each participant, the  $FC_{baseline}$  was regressed out from task-specific FCs using linear  
 226 regression. (c) Baseline-removed FC patterns ( $FC_{resid}$ ) were then concatenated across tasks and participants. (d)  
 227  $FC_{resid}$  were then submitted to singular value decomposition (SVD). The columns of orthonormal eigenvectors  $U$   
 228 (or equally principal components) were converted to matrix form, termed as eigen-connectivity (EC) patterns.

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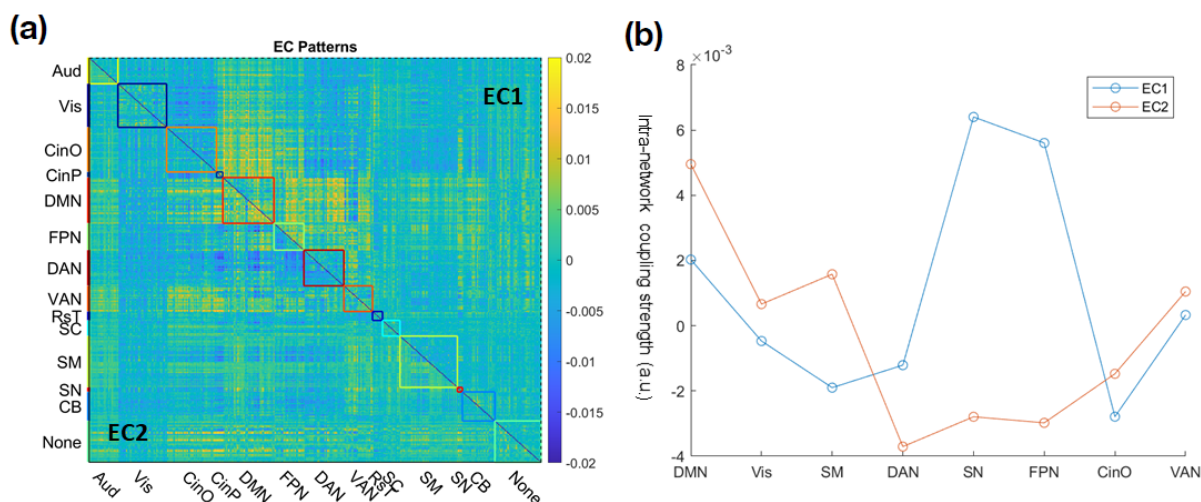
### 3. Results

232

#### 3.1 Characterizing the latent connectivity dimensions as revealed by EC analysis

233 We projected vectorized residual task-FCs to a low-dimensional space using the EC analysis. Here, we  
 234 focused on the first two dimensions/ECs in terms of the variance explained, in accordance with our  
 235 hypothesis. **Fig. 3a** shows EC patterns for the first two ECs. The strength of intra-network couplings for  
 236 the first two ECs are shown as line chart in **Fig. 3b**. Each EC pattern can be understood as a latent low-  
 237 dimensional embedding or spatial mode that captures shared variations across the multitask FCs. On the  
 238 network level, we observed that the EC1 (shown as upper triangle in **Fig. 3a**) was characterized by a  
 239 strong intra-network coupling of the ECN (i.e. fronto-parietal network (FPN)) and salience network (SN),  
 240 which were highest among all networks. On the contrary, the EC2 (shown as lower triangle in **Fig. 3a**)  
 241 was characterized by highest within network coupling strength of the DMN.

242 In sum, the latent space revealed by our multi-task EC analysis suggested two dominant latent  
243 dimensions: one dimension for deliberate thinking (characterized by high intra-ECN) and the other for  
244 spontaneous thinking (characterized by high intra- DMN).



245  
246 **Fig. 3.** (a) Visualization of the first two eigen-connectivity (EC) patterns with intra-network connectivity  
247 highlighted. EC1: the upper-triangle, EC2: lower-triangle. Aud: auditory; Vis: visual; CinO: cingulo-opercular;  
248 CinP: cingulo-parietal; DMN: default mode network; FPN: frontal-parietal network; DAN: dorsal attention network;  
249 VAN: ventral attention network; RsT: retrosplenial temporal; SM: sensorimotor; SN: salience network; SC:  
250 subcortical; CB: cerebellum; None: network not specified. (b) A line plot of the average intra-network coupling  
251 strength of major large-scale functional networks.

252

### 253 3.2 Embedding tasks into the latent cognitive space

254 To better examine the relationship between different cognitive tasks with respect to the revealed  
255 deliberate and spontaneous EC dimensions, we projected task-FCs through the first two ECs. Noticeably,  
256 and as hypothesized, the task-FCs projected into the low-dimensional plane were separable and highly  
257 resembled the hypothetical cognitive space (shown as an inset in **Fig. 4a**). Specifically, we observed that  
258 the task-FCs associated with two creative tasks (i.e., AUT and RAT) were projected together in the upper  
259 right quadrant. The mind wandering (MW) together with the visuomotor (VisMot) task were observed  
260 mostly in the upper left quadrant, as both required minimum deliberate control<sup>3</sup>. Working memory (WM)  
261 and theory of mind (ToM) tasks were also projected together to the lower right quadrant. These two tasks  
262 were arguably among the most cognitively demanding tasks while requiring very limited spontaneous  
263 thinking. Further, based on our hypothesis, grouping the tasks into four types: deliberate (WM and ToM),  
264 spontaneous (MW), moderate (Emotion, Guessing, and VisMot), and creative (AUT and RAT), revealed  
265 that the projection of creativity tasks on EC1 resembles deliberate processing and their projection on EC2  
266 resembles that of spontaneous processing (**Fig. 4b-c**). Altogether, providing data-driven evidence that  
267 creative cognition does require an interplay between both deliberate (EC1) and spontaneous thinking  
268 (EC2).

269 Additionally, we showed EC3 to EC10 and the low-dimensional projection using the first 3 ECs in the  
270 Supplemental Materials (**Fig. S2**). We also quantitatively evaluated the task separability of weights of all  
271 200 ECs using one-way ANOVA given the task labels. We found ECs beyond the first two can inform us

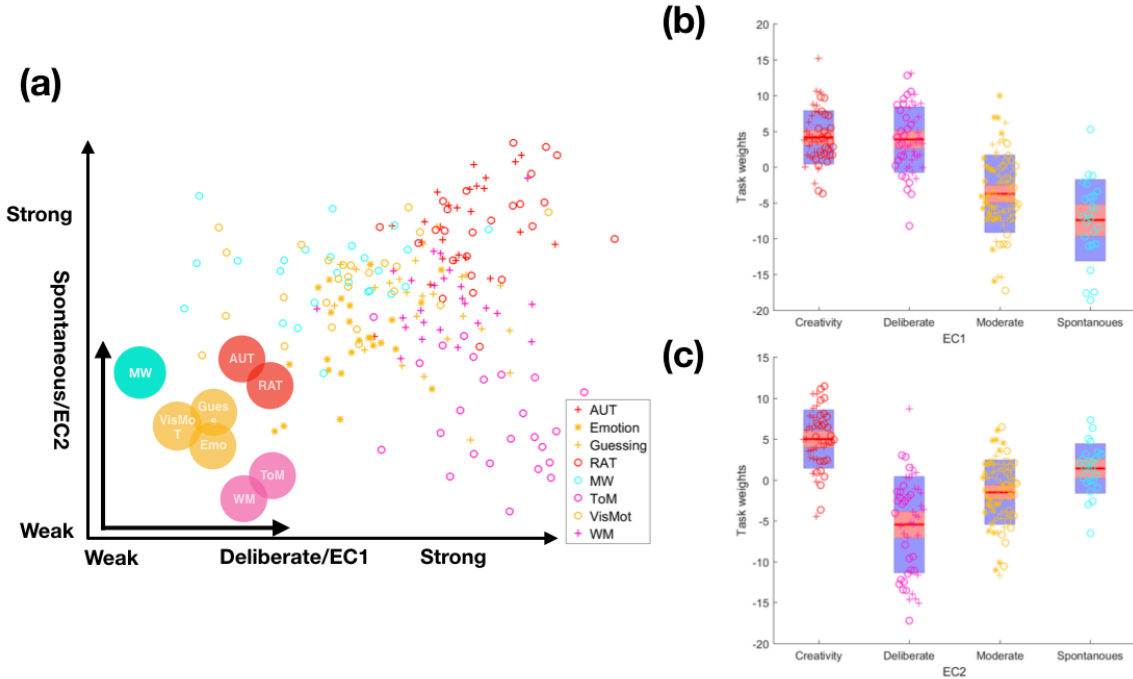
<sup>3</sup> It should be noted that participants spent 40% of the time during the visuomotor task on fixation in between trials, which could have explained VisMot-FCs being projected together with MW.



272 of underlying tasks, where EC weights from one task were significantly different from the rest (FDR-  
 273 corrected  $p < 0.05$ , **Fig. S3**).

274

275



276 **Fig. 4.** (a) Low-dimensional projection of task-FCs with the first two EC components, color-coded based on task  
 277 labels. Each symbol represents a projection of a task-FC, for a total of 200 symbols (25 per participant over 8 tasks).  
 278 Inset: the hypothetical cognitive space spanning across two putative cognitive axes, i.e., deliberate thinking (EC1)  
 279 and spontaneous thinking (EC2). (b-c) Graphical summary of low-dimensional projections along with the EC1 and  
 280 EC2, grouped based on the hypothesis. Creativity tasks: AUT and RAT; deliberate tasks: WM and ToM;  
 281 spontaneous task: MW; tasks requiring moderate level of spontaneous and deliberate thinking: Emotion, Guessing,  
 282 and VisMot.  
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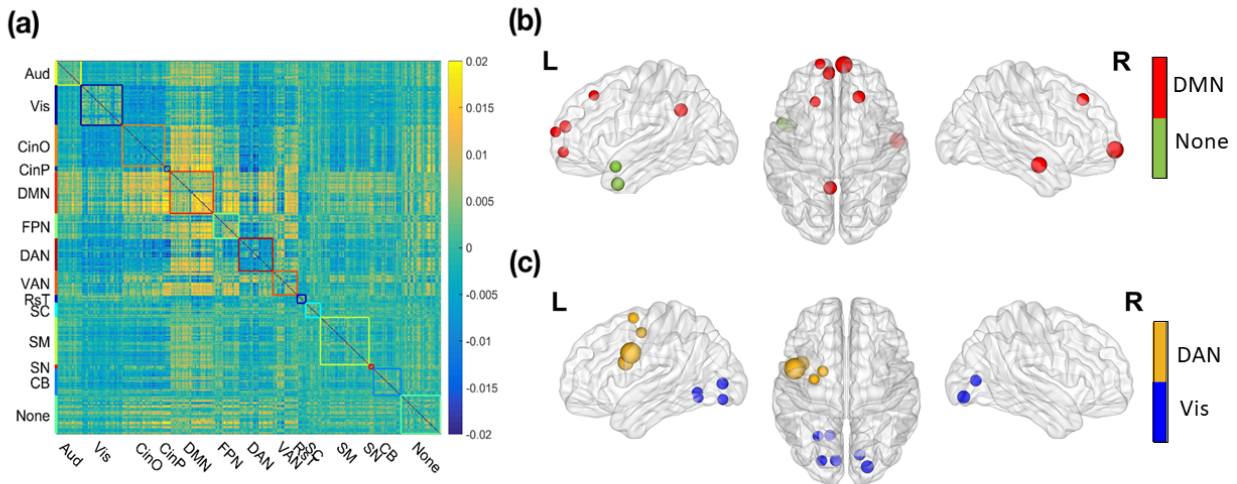
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### 285 3.3 Revealing the functional architecture of creative cognition

286 To further understand the functional architecture of the creative cognition space, we examined the  
 287 aggregated functional connectome across deliberate (EC1) and spontaneous (EC2) latent dimensions. We  
 288 hypothesized that given the observation that creative tasks were both embedded in the top right corner of  
 289 the EC latent space, suggesting an interplay between both deliberate (EC1) and spontaneous (EC2)  
 290 modes, a better understanding of the functional architecture of creative cognitive space can be acquired by  
 291 examining the aggregated connectivity pattern of EC1 and EC2. The aggregated pattern of EC1 and EC2,  
 292 through numerical addition, is shown in **Fig. 5a**. Besides the expected enhanced intra-network coupling  
 293 within default mode and fronto-parietal networks, we also observed high inter-network coupling between  
 294 default mode and fronto-parietal, cingulo-opercular, and cingulo-parietal networks.

295 In an attempt to understand the large-scale network architecture underlying the aggregated EC pattern, we  
 296 computed the node strength, and for visualization purposes, we showed the ten ROIs with the  
 297 highest/lowest node strength in **Fig. 5(b)&(c)**. In terms of hubs with the positive node strength (i.e.,  
 298 highly coupled regions), the majority was found in the brain regions that form the DMN as well as some  
 299 in the anterior temporal lobe. The ROI with the highest positive node strength was found to be the right

300 medial prefrontal cortex (mPFC, MNI coordinate: 4.8 65.1 -7.1) of the DMN. On the other hand, hubs  
301 with the largest negative node strength (i.e., regions decoupled from other regions) were found in the  
302 visual network and the DAN (left lateralized). The ROI with the highest negative node strength was found  
303 in the left inferior frontal gyrus (IFG, MNI coordinate: -45.2 2.7 32.4) within the DAN.



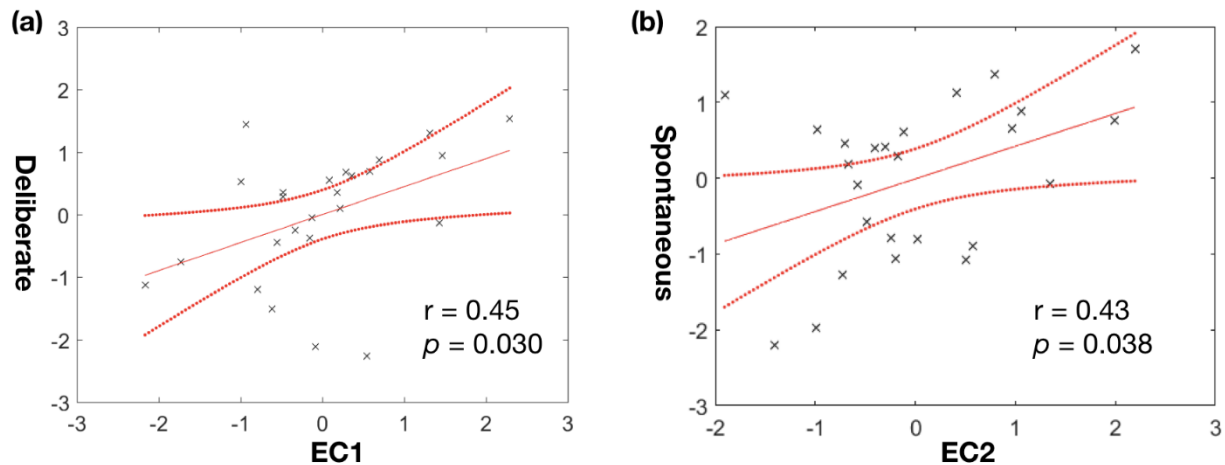
304  
305 **Fig. 5.** (a) The aggregated EC combining EC1 and EC2. (b) Ten ROIs with the most positive node strength. (c) Ten  
306 ROIs with the most negative node strength. The node size is proportional to the node strength, and the network label  
307 of each ROI is color-coded.

308

### 309 *3.4 Examining whether individual differences in embedding can predict behavior*

310 Individual differences were characterized in terms of EC-based latent-space embedding. We hypothesized  
311 that the observed individual differences in the latent-space embedding could be associated with individual  
312 differences in behavior. We limited this analysis to the two creativity tasks only. Specifically, the  
313 individual differences in the weights of deliberate dimension (EC1) could be related to deliberate thinking  
314 ability, while the variability in the weights of spontaneous dimension (EC2) could be related to  
315 spontaneous thinking ability. The behavioral correlates of deliberate and spontaneous thinking were  
316 computed as follows. We used the behavioral performance on the color-word interference task (CWIT) as  
317 a proxy of participants' deliberate thinking ability. To operationalize behavioral performance of  
318 spontaneous thinking, we regressed the CWIT score from the Torrance Test of Creative Thinking task  
319 score (TTCT-F). Hence, by removing the variance associated with deliberate thinking from the creativity  
320 score, we attempted to use the residuals as a proxy for spontaneous thinking.

321 After controlling for age, handedness, and gender, we found that the weights of EC1 during the AUT  
322 were significantly positively correlated with deliberate thinking score ( $r = 0.45, p = 0.030$ ), and EC2  
323 during the AUT was significantly positively correlated with spontaneous thinking score ( $r = 0.43, p =$   
324  $0.038$ ), as shown in Fig. 6. We did not observe any significant brain-behavior relationship using EC  
325 weights for the second creativity task (RAT).



326

327 **Fig. 6.** Brain-behavior relationship using EC weights during AUT. The EC weights and behavioral scores are z-  
328 scored. (a) The scatterplot of EC1 weights vs deliberate thinking score; (b) EC2 weights vs spontaneous thinking  
329 scores. Dotted lines represent 95% confidence intervals.

330

331

#### 332 4. Discussion

333 Human creativity is a vast construct, seemingly intractable to scientific inquiry, partially due to its  
334 multifaceted nature (Jung, 2013). It has been long suspected that creative cognition is supported by two  
335 latent cognitive modes (i.e., deliberate and spontaneous modes of thinking). However, the neural evidence  
336 for the contribution of spontaneous and deliberate cognition in creativity has been indirect and  
337 inconsistent (Mok, 2014). Here, to validate the involvement of these latent cognitive modes in creative  
338 thinking and to identify their neural substrates, we adopted a data-driven approach and sampled across a  
339 wide range of cognitive space using an 8-task continuous multitask paradigm (CMP). We hypothesized  
340 that by sampling a wider cognitive space we will better understand how creative cognition is related to  
341 other lower- and higher-order cognitive processes.

342 Since creative cognition does not seem to be confined to any localized brain region (Dietrich and Kanso,  
343 2010), we decided to focus on examining the large-scale network architecture using whole-brain  
344 functional connectivity (FC). We first computed the task-FCs and then extracted latent connectivity  
345 patterns across all tasks using eigen-connectivity (EC) analysis (Leonardi et al., 2013). The first two latent  
346 dimensions were observed to represent the deliberate and spontaneous modes of thinking, respectively.  
347 When the task-FCs were embedded into a 2-dimensional latent space of deliberate/spontaneous thinking,  
348 we observed creativity tasks to be embedded in the region with both strong deliberate and spontaneous  
349 thinking. The embeddings of other tasks also followed as expected. For example, the cognitively  
350 demanding tasks such as the theory of mind and n-back working memory appeared to tax deliberate  
351 thinking heavily yet requiring little spontaneous thinking. On the contrary, resting state (mind wandering)  
352 and visuo-motor task were embedded higher on the spontaneous mode of thinking. Further, the individual  
353 differences in EC weights were observed to be related to behavioral differences in the ability of deliberate  
354 and spontaneous cognition during a creative task. Altogether, our findings demonstrate the potential of  
355 using a data-driven approach to pool information across multiple cognitive processes in order to extract  
356 latent cognitive dimensions associated with creative cognition.

357 Early research on creative cognition focused on isolating specific brain regions associated with creative  
358 performance. Although domain-specific assessment of creative cognition proved somewhat successful in

359 teasing out regions specific to each domain, e.g., musical (Limb and Braun, 2008), verbal (Bechtereva et al., 2004), and figural (Ellamil et al., 2012; Saggar et al., 2017, 2015), the domain-generic assessment of  
360 creativity revealed a large variance in findings across studies (Boccia et al., 2015). Recently, researchers  
361 have shifted gear towards studying the whole-brain functional architecture related to creative cognition.  
362 These network-based studies have highlighted a putative role of the default mode network (DMN) and  
363 executive control network (ECN) during creative thinking (Beaty et al., 2015; Zhu et al., 2017). In  
364 general, while the DMN has been suggested to support spontaneous cognition, such as mind-wandering,  
365 introspection, autobiographical memory, and mentalization (Raichle, 2015), the ECN (operationalized as  
366 the frontal-parietal network (FPN)), is commonly considered as a key player in deliberate, goal-directed  
367 cognition. With regards to creative thinking, the current consensus is that an interplay between deliberate  
368 (ECN) and spontaneous thinking (DMN) is required for creative cognition. However, no data-driven  
369 validation exists regarding how this interplay facilitates creativity.  
370

371 To address this issue, here, we used a continuous multi-task fMRI paradigm consisted of a wide range of  
372 cognitive tasks including creativity, and explored the latent dimensions using eigen-connectivity analysis.  
373 Interestingly, the first two latent dimensions were mapped onto deliberate (FPN-dominated intra-network  
374 coupling) and spontaneous (DMN-dominated intra-network coupling) axes. We also examined the extent  
375 of inter-network coupling for each latent dimension. For the deliberate axis, i.e., EC1, we observed  
376 greater inter-network connectivity between DMN and task-positive networks (including FPN, dorsal  
377 attention network (DAN), and cingulo-opercular network (CinO)). Our observation coincided with an  
378 earlier finding of increased DMN connectivity with task-promoting regions across six tasks regardless of  
379 task-associated activation (Amanda Elton and Wei Gao, 2015). For the spontaneous axis, i.e., EC2, we  
380 observed reduced intra-network coupling of the FPN as well as stronger within-network connectivity in  
381 the DMN. The weakened within-FPN coupling might allow for flexible reconfiguration during  
382 spontaneous thinking, which has been shown to positively correlate with creativity across the visual and  
383 verbal domains (Zhu et al., 2017). Moreover, an overall decoupling was observed for DAN, possibly  
384 reflecting down-regulated top-down attention modulation (Zabelina and Andrews-Hanna, 2016). Lastly,  
385 as creativity required both cognitive modes (EC1 and EC2), we aggregated first two EC patterns and  
386 revealed strengthened within-network coupling in the DMN and FPN, as well as an overall increase in  
387 inter-network connectivity between the two. Overall, our findings extend network neuroscience research  
388 on creative cognition by identifying patterns of intra- and inter-network connectivity associated with  
389 latent cognitive modes during creative task performance.

390 To pinpoint the key regions in the aggregated EC pattern underlying creative cognition, we examined the  
391 regions with the highest absolute node strength. The regions with the highest positive functional coupling  
392 were found in the DMN, such as mPFC, angular gyrus (AG), and posterior cingulate cortex (PCC), as  
393 well as regions in the anterior temporal lobe. The involvement of DMN in creative cognition has been  
394 well-documented. For example, higher creativity has been associated with increased FC between the  
395 mPFC and the PCC (Takeuchi et al., 2012). A lesion study found that lesions in the mPFC were  
396 associated with impaired originality (Shamay-Tsoory et al., 2011). Moreover, using connectome-based  
397 predictive modeling (Rosenberg et al., 2015), a recent study found regions in the DMN were among the  
398 top contributors to the so-called “high-creative network”, i.e., the network where FC strength positively  
399 predicted creativity scores (Beaty et al., 2018). Moreover, the anterior temporal lobe (or temporal pole)  
400 has an important role in many cognitive processes, including creative cognition, theory of mind, emotion  
401 processing, and semantic processing (Wong and Gallate, 2012). In short, our findings suggested that  
402 whole-brain integration of regions in DMN plays a pivotal role in creative cognition.

403 As for the ROIs with the greatest decrease in the connectivity of the aggregated EC, the majority were  
404 found in the DAN and visual network. The decoupling of the visual network is consistent with past work  
405 linking deactivation of the visual cortex to the suppression of external stimuli during creative thinking  
406 (Benedek et al., 2016; Ritter et al., 2018). On the other hand, as it is well-known that DAN is responsible  
407 for external attention (Maillet et al., 2019), decoupling of DAN may also signal loosened top-down

408 attention to external stimuli, potentially allowing for allocating more cognitive resources toward an  
409 introspective stream of consciousness (Zabelina and Andrews-Hanna, 2016). Interestingly, we observed  
410 left-lateralized decoupling for the DAN. This left-over-right decoupling pattern in DAN mirrors lesion  
411 studies linking left hemisphere lesions to increases in creativity (Seeley et al., 2008; Shamay-Tsoory et  
412 al., 2011; c.f. Chen et al., 2019). It has been suggested that, under an inhibitory mechanism, the right  
413 hemisphere's predominance in creative cognition may be inhibited by the left hemisphere in typical  
414 people, while such inhibition is weakened after damages to the left hemisphere, thus boosting creativity  
415 (Huang et al., 2013). In our case, the decoupled left-lateralized DAN (especially L IFG and surrounding  
416 ROIs) could be linked to the release of inhibition of the left hemisphere in a similar fashion that facilitates  
417 creativity, although the lateralized involvement may depend on the creativity domain (Chen et al., 2019).  
418 Moreover, Lotze and colleagues (2014) also noted that a reduced left- and inter-hemispheric connectivity  
419 of language areas, namely the left posterior area BA44 (left IFG), may lead to a more spontaneous and  
420 less constraining cognition. This is consistent with our observation that the left IFG showed the greatest  
421 decoupling in the aggregated EC pattern. Taken together, down-regulation in regions responsible for top-  
422 down externally-directed attentional control in the left prefrontal cortex (e.g. left IFG) appears to be a key  
423 neural feature for both creative cognition and related spontaneous cognitive processes, such as mind  
424 wandering (Christoff et al., 2009; Julia W. Y. Kam et al., 2013).

425 To sum up, our work sheds new light on the complex interaction between DMN and FPN during creative  
426 cognition. Our data-driven approach suggests these typically opposing networks may indeed cooperate  
427 during creative cognition as revealed by our EC analysis. Furthermore, decoupling of key regions in DAN  
428 and visual networks may also correspond to the shielding of internally directed attention from the external  
429 environment during creative thinking (Maillet et al., 2019), further facilitating creative cognition.

#### 430 *Limitations and future directions*

431 There are some methodological limitations associated with our study. The first issue concerns the  
432 relatively small sample size ( $N = 25$ ), which limited our statistical power in the brain-behavior analysis.  
433 Future studies with more participants are needed to further validate our findings, as a recent study  
434 suggests that it may require a consortium-level sample size to obtain a reproducible brain-behavior  
435 relationship (Marek et al., 2020). Second, previous studies have shown the inter-subject differences in FC  
436 patterns are dominated by stable individual differences other than transient cognitive/task modulation  
437 (Finn et al., 2015; Gratton et al., 2018; Xie et al., 2018a). We circumvented this issue by removing  
438 individual baseline-FCs (i.e., FC fingerprints). However, this is a rather simplified means of removing  
439 individual differences by assuming a linear relationship between task-specific and subject-specific FC  
440 patterns. Moreover, EC analysis assumes linearity, therefore, it can only capture linear relations among  
441 connectivity pairs. Future studies can consider nonlinear decomposition methods such as general principal  
442 component analysis (Vidal et al., 2005) and geometry-aware principal component analysis (Harandi et al.,  
443 2018). These nonlinear methods could help us more efficiently explore the nonlinear relationships  
444 between task-FCs. Third, given our goal of anchoring latent deliberate and spontaneous thinking during  
445 creative cognition, we narrowed our focus to the first two EC components. Our choice was partially  
446 justified by linking EC weights with behavioral data (Fig. 6), and matching EC patterns with previous  
447 neuroimaging findings in creative research. However, there is no doubt that the EC patterns beyond the  
448 first two could be meaningful, as many higher-order ECs also explained significantly more variance than  
449 those from the surrogate data and provided some task separability (Supplemental Fig. S4). Indeed, some  
450 interesting work has been conducted using EC analysis on the multitask data from Human Connectome  
451 Project, which looked at higher-order EC components to better identify individuals and tasks (Abbas et  
452 al., 2020; Amico and Goñi, 2018). However, as is often the case with any latent factor analysis, increasing  
453 the number of latent components/factors comes at the cost of interpretability. We believe that for our  
454 specific question, limiting our focus to the first two ECs was a reasonable trade-off. Future work could  
455 also look at a different set of tasks with different latent cognitive dimensions. For example, using different  
456 forms of creativity (e.g. figural, verbal, and musical) or parametrically modulating the cognitive load (1,

457 2, 3-back WM), we can delineate the potential confounding factors (e.g., creativity domains and task  
458 difficulties). Lastly, the rich spatiotemporal dynamics of the brain remain untapped in this study. Future  
459 work can also investigate the time-varying FC during task performance (Gonzalez-Castillo and  
460 Bandettini, 2018; Vergara et al., 2019; Xie et al., 2018b) as well as instantaneous activation patterns using  
461 Topological Data Analysis (TDA; Geniesse et al., 2019; Saggar et al., 2018). Additionally, our analysis  
462 also assumed that the functional parcellation remained unchanged despite the changing cognitive  
463 demands, which is subject to future evaluation (Salehi et al., 2019).

#### 464 *Conclusion*

465 Creativity theories have long emphasized dual-process models of spontaneous and deliberate thought, but  
466 bottom-up data-driven evidence supporting these theories has been largely absent. Using a data-driven  
467 eigen-connectivity (EC) analysis with a continuous multitask paradigm (CMP), we extracted latent  
468 connectivity patterns shared across multitask FCs - corresponding to deliberate and spontaneous thinking  
469 - and we showed that creative cognition may require a balance of these two latent cognitive modes. The  
470 EC pattern underlying creative cognition revealed a complex interaction between the two canonical and  
471 typically opposite brain networks. We observed creative cognition requires stronger intra-network  
472 connectivity in the default mode network (DMN) and fronto-parietal network (FPN), as well as stronger  
473 inter-network coupling between the two. We also found higher decoupling in the left-lateralized dorsal  
474 attention network (DAN) and visual network, which may facilitate creative thinking by shielding the  
475 brain from the external stimuli. In sum, our work provided a bottom-up validation of the latent cognitive  
476 modes of creative cognition, offering novel neural evidence for the classic theory of creativity.

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481

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- 712

713 **Supplemental Materials**

714 Table S1. Demographic information.

<b>Variable</b>	<b>N = 32</b>
<b>Sex</b>	
Male	19
Female	13
<b>Age</b>	
Mean $\pm$ SD	30.37 $\pm$ 5.41
Range	19-43
<b>Handedness</b>	
Right	28
Left	4

715

716 Table S2. Psychometric test results. TTCT: Torrance Test of Creative Thinking; CWIT: Color-Word Interference  
717 Test.

<b>Domain</b>	<b>Psychometric Tests</b>	<b>Mean</b>	<b>Std</b>
Figural creativity average	TTCT	119.19	22.70
Executive function composite score	CWIT	115.13	14.90

718

719 Table S3. In-scanner behavioral performance.

<b>Task</b>	<b>Accuracy (mean <math>\pm</math> std)</b>
Theory of Mind	0.67 $\pm$ 0.18
Emotion	0.96 $\pm$ 0.05
VisuoMotor	0.98 $\pm$ 0.04
Working memory	0.93 $\pm$ 0.08

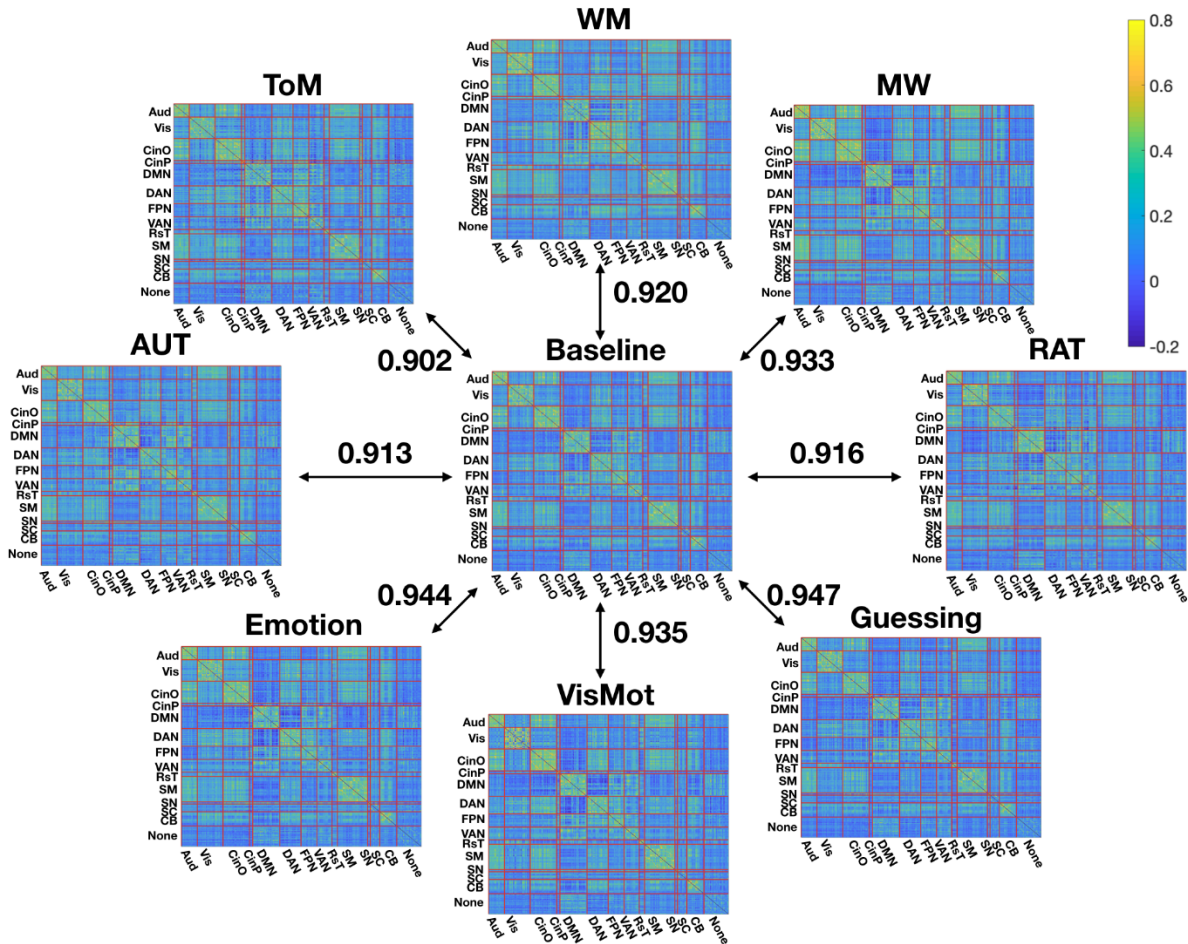
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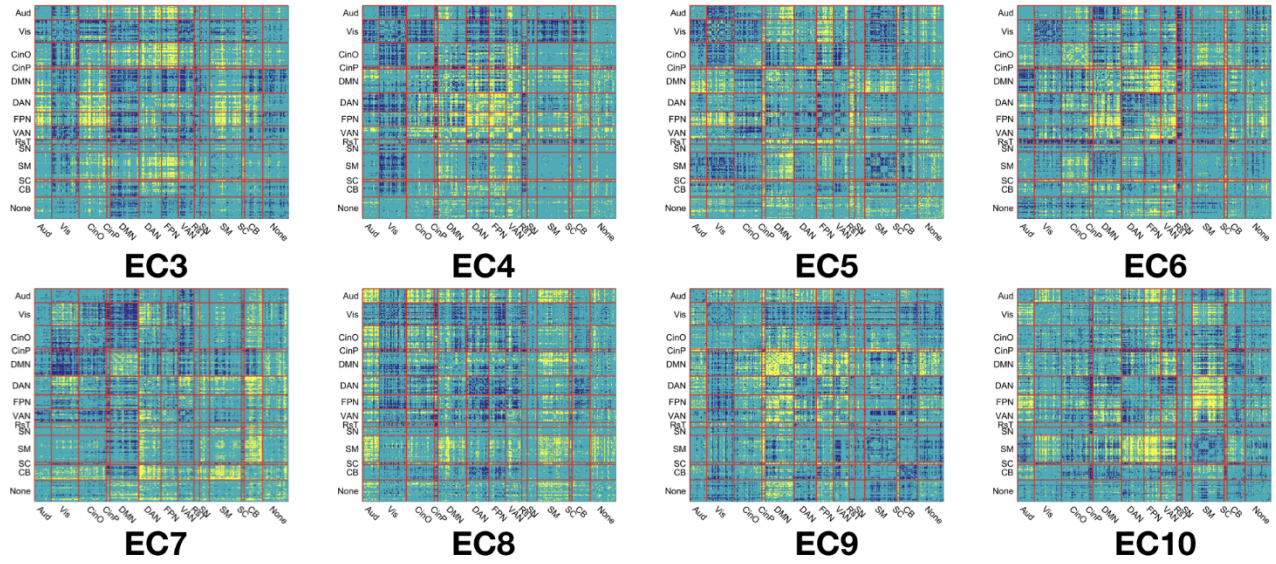
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726 Figure S1. The similarity between group-level task-FCs and baseline-FC was measured by Pearson  
 727 correlation. Task acronym: WM: working memory; ToM: theory of mind; AUT: alternative uses task;  
 728 Emotion: emotion task; VisMot: visuomotor task; RAT: remote associates task; MW: mind-wandering.  
 729 Network acronym: Aud: auditory; Vis: visual; CinO: cingulo-opercular; CinP: cingulo-parietal; DMN:  
 730 default mode network; DAN: dorsal attention network; FPN: frontal-parietal network; VAN: ventral  
 731 attention network; RsT: retrosplenial temporal; SM: sensorimotor; SN: salience network; SC: subcortical;  
 732 CB: cerebellum.  
 733

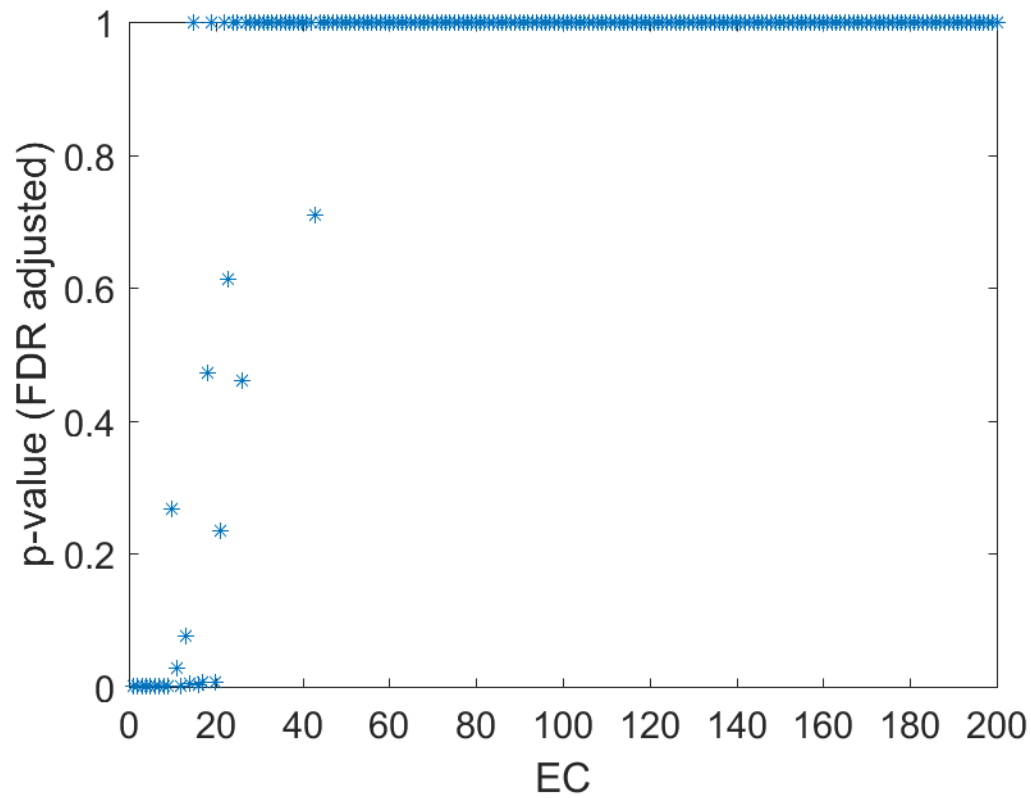


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736

737 Figure S2. Upper: Thresholded EC3-10 at 10% edge sparsity. Positive edges are shown in yellow and  
738 negative edges are shown in dark blue. Lower: Low-dimensional projection using the first three ECs.

739



740

741 Figure S3. Task separability of EC components. We performed a one-way ANOVA on each EC weight  
742 using task labels as grouping variables. Fifteen EC components had significantly different mean across  
743 tasks (FDR-corrected  $p < 0.05$ ), suggesting that EC components beyond the first two ECs contained  
744 cognitively relevant information.

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