

**Representing creative thought: A representational similarity analysis of creative idea generation and evaluation**

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### Abstract

Dual process theories of creativity suggest that creative thought is supported by both a generation phase, where unconstrained ideas are generated and combined in novel ways, and an evaluation phase, where those ideas are filtered for usefulness in context. Neurocognitively, both the default mode network (DMN) and the executive control network (ECN) have been implicated in generation and evaluation, respectively. Importantly, generating and evaluating ideas implies that the same information, reflected in patterns of neural activity, must be present in both phases, suggesting that information should be ‘reinstated’ (i.e. multidimensional patterns must reappear) within and/or between network nodes. In the present study, we used representational similarity analysis (RSA) to investigate the extent to which nodes of the DMN and ECN reinstate information between a generation phase, in which participants generated novel or appropriate word associations to single nouns, and an evaluation phase, where we presented the associations back to participants to evaluate them. We showed strong evidence for reinstatement within the ECN dorsal lateral prefrontal cortex during the novel association task, and within the DMN medial prefrontal cortex during the appropriate association task. We additionally showed between network reinstatement between the ECN dorsal lateral prefrontal cortex and the DMN posterior parietal cortex during the novelty task. These results demonstrate the importance of both within- and between-informational reinstatement for generating and evaluating ideas, and implicate both the DMN and ECN in dual process models of creativity.

*Keywords: default mode network; executive control network; reinstatement; representational similarity analysis; creativity;*

### **1.1. Representing creative thought: A representational similarity analysis of creative idea generation and evaluation**

The human mind is a generative mind. While other species can categorize objects and use tools to achieve behavioural outcomes, humans have a remarkable ability to generate potentially infinite categories of varying abstractness and to use tools in potentially infinite ways to identify, characterize, and solve problems. Rather than being a psychological capacity that exists in only a few individuals, creative capacities are apparent in the behaviour of species in general and therefore reflect a basic feature of human cognition; thus, to understand how creativity works is to understand human cognition in the world (Barsalou and Prinz, 1997; Prinz and Barsalou, 2002). Creative thinking is often considered a two-stage process of idea generation (where candidate ideas are initially produced) and idea evaluation (where those candidates are scrutinized for their utility; Sowden et al., 2015). Prior studies have linked idea generation and idea evaluation to the brain's Default Mode Network (DMN) and Executive Control Network (ECN; Kleinmuntz et al., 2019), respectively, but the exact nature of this link remains unclear. In the present study, we use representational similarity analysis (RSA) to examine the extent to which neural patterns within DMN and ECN during idea generation are “reinstated” during idea evaluation, providing insight into how the brain represents and transforms information when thinking creatively.

### **1.2. Neurocognitive Models of Creativity and the Functions of the DMN and ECN**

Researchers have long recognized two phases that are crucial to creative output: generation and evaluation (Snowden et al., 2015 for an overview). It is thought that during the generation phase previously learned knowledge is activated and novel combinations of that knowledge are produced (Beaty et al., 2015; Benedek et al., 2014; Benedek et al., 2018; Ellamil

et al., 2012); during the evaluation phase, a subset of novel combinations are expressed usefully in context (Beaty et al., 2015; Ellamil et al., 2012; Mayseless et al., 2014). For instance, some models (Campbell, 1960) posit that generation is characterized by the activations of a wide collection of representations of the environment and possible manipulations of it, only some of which are retained when certain criteria are met. Such proposals have garnered support from a variety of sources (see Simonton, 1999; 2011). Relatedly, ‘simulation’ theories (those that adopt a predictive coding framework or more general embodied/grounded cognition frameworks, e.g., Dietrich & Haider, 2015; Prinz and Barsalou, 2002; Matheson & Kenett, 2020) suggest that creativity, at least in part, requires the activation of action possibilities and their intero- and extero-ceptive consequences before ultimately executing one of them (in terms of overt manipulation or linguistic output). All of these approaches are in line with major neuroscientific theories of brain function and organization that have been developed to address human categorization and conceptualization (e.g. Edelman, 1989; Parr, Pezzulo, & Friston, 2022). Importantly, common to all of these approaches is the idea that creativity is supported by the dynamics of these phases.

Neuroimaging research has investigated the neural correlates of idea generation and idea evaluation (e.g., Mayseless et al., 2014). Two functional brain networks (i.e., intrinsic connectivity networks)—the DMN and ECN—have been associated with creative tasks that emphasize generation vs. evaluation (Kleinmintz et al., 2019). One possibility is that the DMN may be important in the generation phase given its role in processes that entail activating knowledge from experience (i.e., past and future mental simulation; see Zabelina and Andrews-Hanna, 2016); conversely, the ECN may act as the filter during the evaluation phase, given its role in executive control tasks that require immediate action (Chrysikou et al., 2014; Miller &

Cohen, 2001; see Beaty et al., 2016 for details). This hypothesis reflects a prominent debate within the creativity literature about the relative importance of uncontrolled/associative processes vs. controlled/executive processes in creativity, with mixed evidence for the relative importance of both processes (see Barr, 2018; Beaty et al., 2014).

Under this view, if the DMN and ECN are engaged in dissociable functions, DMN and ECN activity should reflect the dynamics of creativity, specifically the iterative shifting of generation and evaluation phases (Beaty et al., 2015). Some research has explored this issue by directly manipulating the generation and evaluation of ideas. For instance, in a seminal fMRI investigation, Ellamil et al. (2012) had participants perform an iterative creativity task, shifting between periods of idea generation (sketching book cover illustrations) and idea evaluation (assessing their sketches). They showed that subregions of the ECN were more active during evaluation than generation phases while the DMN showed heightened activity in both phases (and the medial temporal lobe was particularly active in the generation phase). Similarly, Liu et al (2015) had participants generate and revise poems. During the generation of poems, a DMN hub (medial prefrontal cortex) showed increased activity, whereas an ECN hub (dorsolateral prefrontal cortex) showed decreased activity; conversely, during revision of poems, the ECN hub increased activity. Additionally, DMN and ECN show functional connectivity during divergent thinking (e.g., producing unusual uses for objects; Beaty et al. 2015) and the strength of DMN-ECN connectivity predicts person-level creativity (Beaty et al., 2018). Finally, recent results show that the ECN and DMN contribute uniquely to creative thinking, especially early in the process (Lloyd-Cox, Chen, & Beaty, 2022). Thus, consistent with general proposals about the role of the DMN and the ECN in creativity, these networks show evidence of dynamically interacting to support the generation and evaluation of ideas.

Importantly, DMN and ECN nodes are considered heteromodal association areas (i.e., neural ‘hubs’) that track associations and control information flow contained in the distributed cortical representations of sensorimotor and interoceptive experience (Bressler and Menon, 2010). Thus, in a very important sense, creativity stems from the activity of the same hierarchical neural systems that support the representation and use of knowledge in other cognitive domains (e.g., recognition and semantic memory; see Meyer and Damasio, 2009; Baraslou 1999; Lambon Ralph et al., 2017; Nastase and Haxby, 2017; Yee et al., 2014). From this perspective, DMN and ECN activation reflects the type of information they are involved in coordinating as neural hubs (see also Kenett et al., 2018), which will be determined by where they sit in distributed neural hierarchies (see especially Margulies et al., 2016).

Some authors have suggested that the DMN nodes sit at the very top of a sensorimotor-to-heteromodal gradient and integrate sensorimotor information in a way that abstracts across experience, making their information less relevant to the here and now. Because it abstracts across multiple modalities, the DMN tends to be involved in tasks that are more ‘internally’ directed like mind wandering; conversely, the nodes of ECN, which may sit at a slightly lower point in cortical hierarchies, integrate sensorimotor information (especially motor information and action plans) that is relevant for organizing behaviour in the here-and-now. Thus, the position of the ECN may account for its involvement in tasks that are more ‘externally’ directed (see Huntenburg, Bazin, & Margulies, 2018; Smallwood et al, 2021). Interestingly, person-level creativity (measured from divergent thinking performance) predicts how segregated the DMN is from sensorimotor cortex (the visual cortex specifically; see Huo, et al., 2022). Thus, because generating and evaluating ideas requires the activation of previous knowledge (sensorimotor information, past and possible future actions, and associated interoceptive experiences) and

predicting the consequences of the creative ideas (in terms of their short and long term sensorimotor and interoceptive effects in novel context of the here and now), we might expect both of these networks to be implicated in generating and evaluating ideas in complex ways.

Critically, the notion of *evaluating* creative ideas implies that previously *generated* cortical information must be active during its evaluation. This suggests that nodes within these networks must ‘reinstate’ information during creative tasks (see also Jung et al., 2013). Further, what information is reinstated should depend on the informational requirements of a task. For instance, generating a creative idea requires more novel information to be evaluated for the here and now, while generating a common idea requires information that has previously been learned, abstracted across experience. Which (if any) cortical nodes reinstate information remains unknown. The research to date on the involvement of the DMN and ECN in creativity has focused on the magnitude of their activity or the functional connectivity between them. While this approach usefully characterizes whether these networks are involved in creative thinking, it does not allow characterizing how these networks coordinate information during idea generation and evaluation. Investigating how these networks coordinate information during generation and evaluation will allow advancing and elaborating on neurocognitive models of creativity.

### **1.3. Representational Similarity Analysis and Informational Reinstatement**

To advance the study of idea generation and evaluation, techniques that directly characterize the information reflected in cortical activity are required. Representational similarity analysis (RSA) is an analytical technique that quantifies the relationships between patterns of brain activity to create abstract maps of the ‘representational geometry’ of cortical regions, i.e., the multivariate shape of neural activity patterns rather than their univariate signal strength (see Kreikenshort et al., 2008). One compelling application of RSA has been in the study of neural

reinstatement during memory encoding and retrieval, allowing for a direct test of whether the information activated during an encoding phase is active during the retrieval phase (see Danker & Anderson, 2010 for an extensive review of evidence).

For instance, Stawarczyk et al. (2020) had participants watch complex movies of an actor engaging in various actions. On a subsequent day, participants viewed the start of the movies and were then asked to describe the subsequent events of the movies in a retrieval phase. Using RSA, the researchers characterized the representational geometry of activity patterns within the medial temporal lobe and posterior medial regions of the DMN during the initial encoding phase and during the subsequent retrieval phase and then measured the strength of the similarity between them. With this approach, higher similarity between representational geometries indicates stronger reinstatement of the represented information. They showed that neural patterns were reinstated during the retrieval phase and that the strength of the reinstatement predicted performance (particularly reinstatement in the posterior midline regions associated with the DMN; see also Oedekoven et al., 2017; Staresina et al., 2012; Wing et al., 2015; Xiao et al., 2020). This application shows that RSA is a powerful technique for characterizing neural reinstatement.

#### **1.4. The Present Study**

RSA characterizes the representational geometry of cortical regions, providing insight into how information is represented in cortical activity. In the present study, we provide an extension of this approach to examine reinstatement during the generation and evaluation of ideas in the context of a creativity task. Specifically, we used RSA to investigate the informational reinstatement between and within nodes of the DMN and the ECN that occur during the generation and evaluation of ideas.

To study reinstatement during idea generation and evaluation, we used a simple word-association task in which participants were presented with a concrete noun (Prabhakaran et al., 2014). In the generation phase, they were asked to generate a single word association to the noun. In the evaluation phase, their associates were presented back to them, and they were asked to evaluate the novelty or appropriateness of their responses. On some trials, participants were instructed to generate an ‘appropriate’ association (e.g., if the cue was ‘belt’, ‘pants’ is an appropriate association); on other trials, participants were instructed to generate an ‘novel’ association (e.g., if the cue was ‘belt’, ‘stars’ would be a novel association). This approach allows us to assess reinstatement in a more creative context, which stresses novelty, and a less creative context, which stresses previously learned associations (Lloyd-Cox et al., 2022). Importantly, performance on this type of word association task has been shown to be predictive of person-level creativity (i.e., performance on other tasks of creative thinking as well as real-world creative achievement; Prabhakaran et al., 2014), supporting its validity and utility for investigating creativity more generally.

Information that is activated during generation should be reinstated during the evaluation phase between DMN and ECN hubs. Further, nodes within the DMN and ECN may reinstate information within themselves, pointing to their importance as coordinators of relevant information in a task-specific manner. Finally, we anticipate that the strength of reinstatement within particular hubs (or between hubs) predicts the quality of creative output (assessed computationally using distributional models of semantic distance; Beaty & Johnson, 2021). Overall, this study allows us to further characterize the role of these critical networks during idea generation and evaluation.

## **2.1. Methods**

## 2.2. Participants

A total of 35 young adults participated in the study. Participants received cash payment for their involvement. All participants were right-handed with normal or corrected-to-normal vision and reported no history of neurological disorder. One participant was excluded who failed to complete the task (24 females; mean age: 20; age range: 18-31). The study was approved by the Penn State Institutional Review Board. Informed consent was obtained prior to participation.

## 2.3. Word Association Task and Stimuli Selection

Participants completed a word association task in the scanner (see Procedure). They were presented with a series of 60 nouns during an idea generation phase (12 trials per run; 5 runs total). Stimuli were selected from a database of 1,716 nouns that appeared in several publicly available databases of psycholinguistic norms (Balota et al., 2007; Brysbaert et al., 2014; Cortese, 2004; Hoffman et al., 2013; Kuperman, 2012; Nelson et al., 2004; Schock et al., 2012; Warriner et al., 2013). This list was further reduced using the six following criteria: word frequency (below 400 occurrences per million), concreteness (below 4), imageability (below 5), valence (1.25 stds above and below the mean), semantic diversity (1.25 SD above and below the mean), and cue set size (QSS; 1.25 SD above and below the mean). This yielded a reduced list of 298 words, which was further reduced by manually removing all animate words (humans, animals, professions, body parts), resulting in 160 words. From these, we selected random lists of 30 words (1 list for the novel condition, 1 list for the appropriate condition), until there were no significant differences on any of the six word features (according to *t*-test analyses; see Table 1). The two lists, and their corresponding psycholinguistic features, are presented in the Appendix.

**Table 1**

*Psycholinguistic features of nouns used in the word association task*

|                           | Mean List1 | Mean List2 | Mean Difference | <i>t</i> | <i>p</i> | Cohens D |
|---------------------------|------------|------------|-----------------|----------|----------|----------|
| <b>Semantic Diversity</b> | 1.59       | 1.60       | .00             | -.08     | .937     | .02      |
| <b>Imageability</b>       | 6.35       | 6.28       | .07             | .80      | .426     | .21      |
| <b>Concreteness</b>       | 4.79       | 4.78       | .02             | .43      | .667     | .11      |
| <b>Frequency</b>          | 1666.57    | 1463.83    | 202.73          | .57      | .573     | .15      |
| <b>QSS</b>                | 14.60      | 14.87      | .27             | -.33     | .746     | .08      |
| <b>Valence</b>            | 5.75       | 5.69       | .06             | .35      | .724     | .09      |

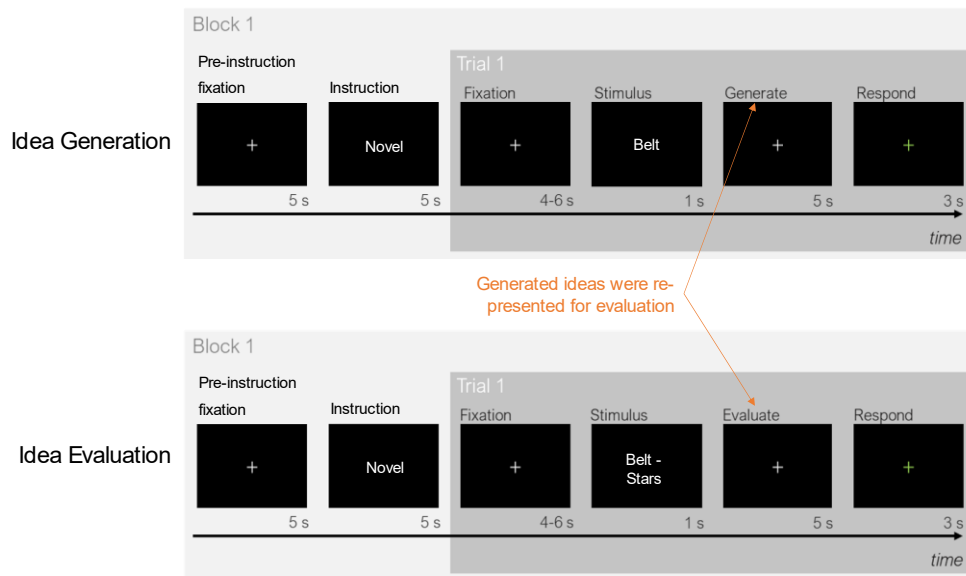
*Note.* QSS = cue set size.

## 2.4. Procedure

To study reinstatement during idea generation and evaluation, we used a simple single word-association task (see Figure 1).

Figure 1.

*Schematic of task and trial procedure.*



*Note.* In the Idea Generation phase, an instruction was given to participants to generate ‘appropriate’ or ‘novel’ associations. Participants were then shown a stimulus (noun) and generated associations to the nouns. The associations were verbalized and recorded by the experimenter who then created a new stimulus list combining the nouns and the participant’s responses. Immediately following this, in the Idea Evaluation phase, participants were cued to evaluate the ‘novelty’ or ‘appropriateness’ of their associations. On each trial, the participant’s response (and the associated noun) were re-presented back to them and participants evaluated the quality of the association on a 3 point scale.

In the *generation phase*, the participant was instructed to generate an ‘appropriate’ association (e.g., if the noun was ‘belt’, ‘pants’ is an appropriate association); on other trials, participants were instructed to generate a ‘novel’ association (e.g., if the noun was ‘belt’, ‘stars’ would be a novel association). Participants were asked to generate associations that were concrete nouns. The association instruction lasted 5s and appeared after a 5s pre-instruction fixation. Following a 4-6s jittered fixation cross presentation, a noun from the trial list appeared on the screen for 1s. Participants were then given 5s to generate an association, which was immediately followed by a 3s window to orally provide their response. If a participant could not think of an association, they were instructed to say “none.” All responses were recorded by a research assistant and inputted into a separate experiment script for the evaluation phase.

The *idea evaluation phase* occurred immediately after the generation phase (and a structural scan). Participants were asked to evaluate the novelty or appropriateness of their responses, based on the condition for each association (novel or appropriate). Similar to the generation phase, the association instruction lasted 5s and appeared after a 5s pre-instruction

fixation. Following a 4-6s jittered fixation cross presentation, participants viewed the noun paired with their response on the screen for 1s. To accomplish this, an experimenter listened to participants, who spoke their responses into a microphone; the experimenter entered responses into a pre-formatted text file, which was uploaded into the E-Prime script for evaluation; the structural scan was done in between generation and evaluation to allow the experimenter time to update the E-Prime files for evaluation. Participants were then given 5s to evaluate their association, which was immediately followed by a 3s window to orally provide their evaluation using a 3-point scale. The scale differed on whether the participant was instructed to evaluate appropriateness (1 = *not at all appropriate*; 2 = *somewhat appropriate*; and 3 = *very appropriate*) or novelty (1 = *not at all novel*; 2 = *somewhat novel*; 3 = *very novel*). Participants spoke their evaluations to equate the response modality across the two phases.

Participants completed six practice trials per phase (six for appropriateness, six for novelty). All trials were presented in white text on a black background via E-Prime 3 software on a PC laptop computer. Text and fixation crosses were presented in the center of the screen. Images were projected from the computer to a screen in clear view of participants lying supine in the MRI scanner and looking directly ahead at a mirror attached to the head coil. See Appendix A for exact instructions.

## 2.5. Semantic Distance

To assess the creative quality of word associations, we used the *SemDis* platform (Beaty and Johnson, 2021). *SemDis* is an open-access web application developed to automate scoring of verbal creativity ([semdis.wlu.psu.edu](http://semdis.wlu.psu.edu)). Semantic distance is increasingly used in creativity research to objectively quantify conceptual distance on verbal tasks (including word association tasks) by computing the inverse of the cosine similarity between word vectors in high-

dimensional semantic space (Hass, 2017a; 2017b; Kenett, 2019). Several studies have found that semantic distance values correlate strongly and positively with human judgements of novelty (Heinen & Johnson, 2018; Dumas & Dunbar, 2014) and creativity (Orwig et al., 2021; Beaty & Johnson, 2021), as well as established measures of creativity (e.g., creative achievement), supporting the construct validity of this approach (Beaty et al., 2021; Gray et al., 2019).

Here, *SemDis* was used to compute the distance between each cue word (e.g., *belt*) and its associative response (e.g., *stars*). *SemDis* generated a composite score from the average scores calculated from five different semantic spaces, mitigating the effects of a single semantic model and text corpus (e.g., textbooks vs. movie subtitles; Beaty & Johnson, 2021; Kenett, 2019). Three of these spaces are built upon continuous bag of words (CBOW) prediction models (cbowukwacsubtitle, cbowsubtitle, and cbowBNCwikiukwac) and two are built upon count models (GloVe and TASA). The CBOW models use a neural network architecture (Mandera, Keuleers, & Brysbaert, 2017) that predicts a given word from surrounding context words within a given text corpus. In this instance, the three CBOW models used 1) a concatenation of the ukwac web crawling corpus (~ 2 billion words) and the English subtitle corpus (~ 385 million words; cbowukwacsubtitle); 2) only the English subtitle corpus (cbowsubtitle); 3) a concatenation of the British National Corpus (~ 2 billion words), ukwac corpus, and the 2009 Wikipedia dump (~ 800 million words; cbowBNCwikiukwac). The two count models, which count the co-occurrence of words within text corpora, include 1) the global vectors (GloVe; Pennington, Socher, & Manning, 2014) model, which is trained on ~ 6 billion tokens across a concatenation of the 2014 Wikipedia dump and the Gigaword corpus (news publications from 2009-2010); and 2) the Touchstone Applied Science Associates (TASA) model, which uses LSA to compute co-occurrences across a text corpus of documents, textbooks, and literary words.

## 2.6. fMRI Acquisition

Structural and functional images were acquired using a Siemens 3T scanner equipped with a 20-channel head coil. Structural images were acquired with a 2300 ms TR, 2.28 ms TE, 256 mm field of view (FOV), 192 axial slices, and 1 mm slice thickness. Echo-planar functional images were acquired using an interleaved acquisition, 2500 ms TR, 35 ms TE, 240 mm FOV, 90° flip angle, 42 axial slices with 3 mm slice thickness resulting in 3 mm isotropic voxels.

### fMRI preprocessing

Data preprocessing was conducted offline using the fMRIB software library version 6 (FSL; Jenkinson et al., 2012; <http://fsl.fmrib.ox.ac.uk/fsl/fslwiki>). First, for each participant, we used the Brain Extraction Tool (BET; Smith, 2002) to eliminate voxels of non-interest (e.g. the skull). Adequate brain extraction was confirmed visually for each subject. We performed motion correction with a linear registration using the MCFLIRT tool (Jenkinson et al., 2002). Data were not spatially smoothed. Additionally, the functional data were temporally filtered with a highpass filter (100 second cut-off).

## 2.7. Data analysis

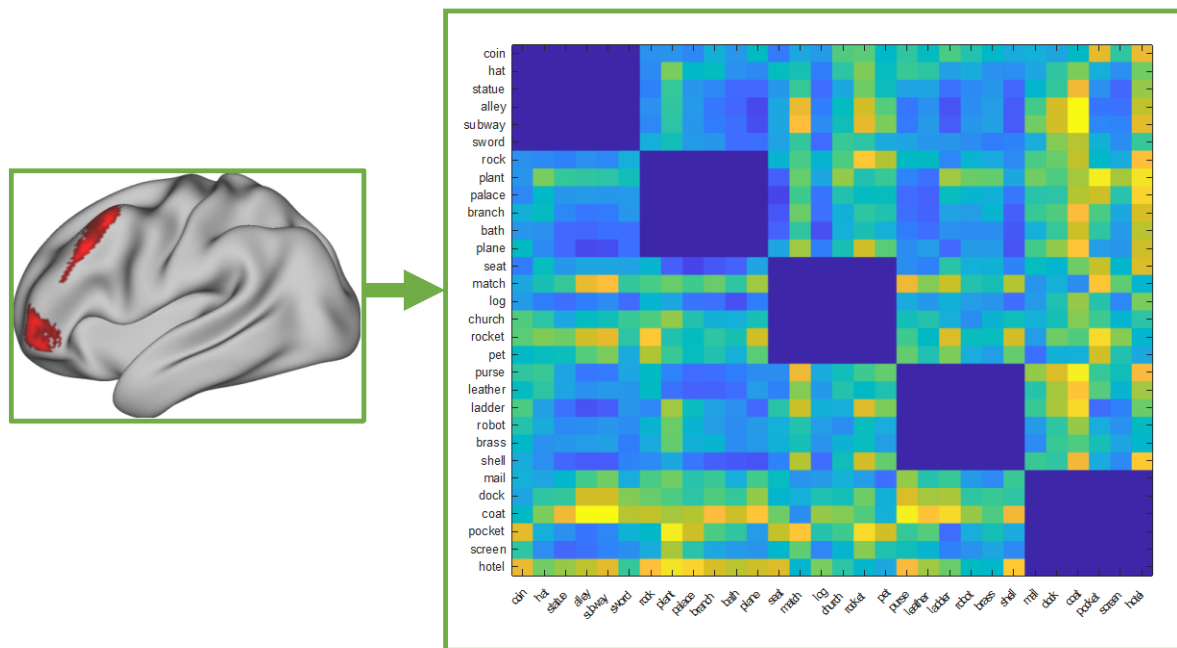
The fMRI Expert Analysis Tool (FEAT) was used to model BOLD responses in each run within each condition. For the first level analysis, each run was analyzed separately. Within each of the 5 runs in each condition, we created one predictor (i.e. explanatory variable (EV) for the generation/evaluation phase (i.e., the 5 second period after the word) within each condition (i.e., appropriate vs. novel). The fixation, stimulus, and response fixation periods were used as baseline, to account for incidental visual stimulation and vocal preparation. This resulted in one contrast of parameter estimate (COPE) for each generation/evaluation phase (for each voxel). These estimates were used as patterns for the RSA analysis. Images were registered in two steps.

First, functional images were registered using FLIRT (FMRIB's Linear Image Registration Tool; Jenkinson et al, 2001, 2002) by first aligning the functional data with the participant's high-resolution anatomical brain image. We then used a linear search with 12 degrees of freedom to align the participant's anatomical to the standard MNI-152 2mm atlas.

To conduct RSA, we used functions from the CoSMoMVPA toolbox (Oosterhof & Connolly, 2012) as it is implemented in MATLAB (Mathworks, Inc) and additional custom scripting. For each participant, we combined data from all runs to create four sets of brain patterns, corresponding to each of the four phases in our paradigm: generate-appropriate, generate-novel, evaluate-appropriate, and evaluate-novel. We then masked each of these data sets using large-scale network masks from the CONN toolbox (derived from independent components analysis of fMRI data from the Human Connectome Project,  $N = 497$ ; Little et al., 2018; Whitfield-Gabrieli & Nieto-Castanon, 2012), focusing on nodes within the DMN and the ECN. The DMN nodes included the left lateral parietal (ILP), right lateral parietal (rLP), medial prefrontal (MPFC), and the posterior cingulate cortices (PCC). The ECN nodes included the left lateral prefrontal (ILPFC), the right lateral prefrontal (rLPFC), the left posterior parietal (IPPC), and the right posterior parietal cortices (rPPC). Once masked, we then created neural dissimilarity matrices for individual participants within each condition  $\times$  ROI combination, where the patterns from one generate/evaluate period was correlated with patterns from every other generate/evaluate period (and  $1 - \text{correlation}$  was used for dissimilarity). An example of a dissimilarity matrix from one participant in one ROI and one condition is shown in Figure 2.

Figure 2.

Representational geometry (i.e., dissimilarity matrix) of ILPFC node from one participant during the generate-novel condition



*Note.* The ILPFC node is shown on the left. Activity patterns within this node were recorded in response to each noun or noun-response pair in the experiment, in both the generate and evaluate phases. Shown on the right is an example dissimilarity matrix (of one participant) from the generate phase. Nouns (stimuli) from the novel condition are shown on the  $x$  and  $y$  axes, and each cell of the matrix codes the dissimilarity of patterns between the pairs of nouns (e.g. pattern dissimilarity of ‘rock’ compared to ‘coin’). The color scale represents the magnitude of the dissimilarity values ( $1 - \text{correlation}$ ) between patterns. Blue indicates higher similarity and yellow indicates higher dissimilarity. Thus, this matrix captures the ‘representational geometry’ of the ILPFC for this participant within this condition.

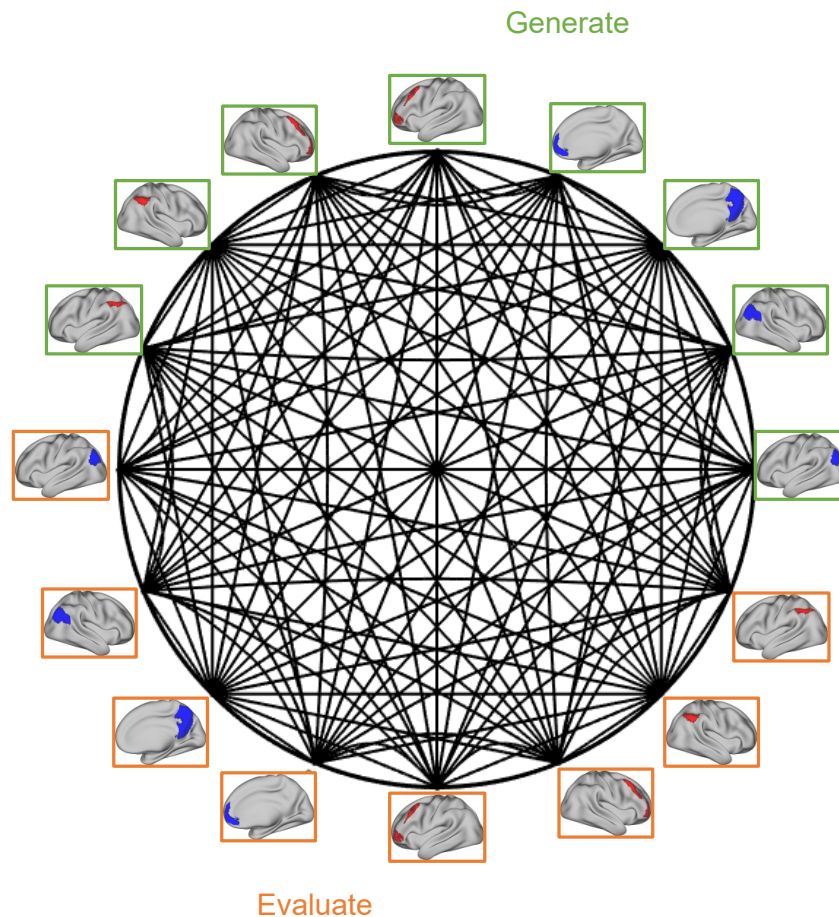
These neural dissimilarity matrices reflect the ‘representational geometry’ of each ROI during each condition. Note that neural patterns within runs are more strongly correlated than

neural patterns between runs due to uninteresting features of the scanning environment and that these correlations can artificially inflate reinstatement values when looking across tasks (Dimsdale-Zucker and Ranganath, 2018). Thus, to eliminate the effects of within-run correlations on our reinstatement estimates, we nullified every within-run correlation within each neural dissimilarity matrix (dark blue regions along the diagonal of Figure 2).

For every participant, we then performed pairwise correlations between the representational geometries (Figure 3), such that the 8 neural dissimilarity matrices in the generation phase and the 8 neural dissimilarity matrices in the evaluation phase were pairwise correlated, resulting in a  $16 \times 16$  correlation matrix for every participant. The off-diagonal correlations in this matrix reflect the extent to which the representational geometry of one condition/ROI is correlated with another (i.e., reinstatement). Higher correlations indicate higher second-order similarity in the representational geometries of the conditions/ROIs being compared. We would expect within-task reinstatement values to be high, as all nodes are engaged in the same task during each phase (i.e. generating or evaluating). Thus, these comparisons act as a type of statistical check on the validity of the RSA method we used here.

Figure 3.

*Schematic of the pairwise comparisons procedure used for RSA.*



*Note.* Representational geometry (i.e., dissimilarity matrix) of each node within the DMN (blue ROIs) and ECN (red ROIs) networks were pairwise correlated with every other node both within each phase and between phases (generation = green; evaluation = orange). Each black line is associated with one mean correlation value. Separate sets of pairwise comparisons were made within the novel and appropriate tasks.

To make inferences on the reinstatement (i.e., correlation between dissimilarity matrices) values, we performed Bayesian *t*-test analyses with default JSZ priors (Krekelberg, 2021), generating a Bayes Factor (BF) in favour of the hypothesis that the mean correlation across participants is different from 0 compared to the ‘null’ hypothesis that the mean is 0. The use of BFs has a number of advantages over traditional approaches (e.g. *t*-test). First, it obviates the need to make dichotomous decisions about *whether* an ROI shows reinstatement based on a *p*-value. Importantly, the BF reflects the magnitude of evidence and can be interpreted as how many more times favorable one hypothesis is over another (i.e., how much we should favour the belief that the mean correlation is different from 0). Thus, in our analysis, the magnitude of the BF reflects how strong our belief is that particular patterns of reinstatement occur. As a guideline, we interpret BFs of  $\sim 10$  to be strong evidence, and our confidence increases with increases in the size of the  $\text{BF} > 10$ ; thus, we emphasize those BFs approximately equal to or greater than 10 and for interest report any BF greater than 5 (Note, a BF of 3 is often observed when a traditional frequentist *t*-test is calculated on the same data and reveals a  $p < .05$ ; see Dienes, 2014 for discussion of interpretation of BFs). A second advantage of the use of BFs is that it helps us address concerns relating to the effects of multiple comparisons of long run probability estimates of *p*-values because we do not make inferences based on long term probabilities. Instead, the use of JSZ priors assumes rather strongly that there is little to no reinstatement (i.e., that the null hypothesis is likely) and therefore the BF tends to underestimate the confidence of the alternative hypothesis when available evidence is ambiguous, effectively punishing ambiguous data.

Finally, we analyzed whether person-level creativity (i.e., semantic distance) predicted the strength of neural reinstatement. To do so, we first calculated the mean SemDis score of each

item for every participant and used this as an index of person-level creativity. For every cell within our  $16 \times 16$  pairwise matrix, we correlated person-level creativity with the reinstatement score from that cell for that participant. Again, we calculated the BF for the correlation (assessing evidence in favor of a correlation greater than 1 vs. a correlation of 0) within each cell.

### 3.1. Results

Our main interest was the reinstatement of neural patterns between the generation phase evaluation phase both within and between the DMN and ECN networks. That is, we were interested in whether the dissimilarity matrix of each node (independent variable) predicted the dissimilarity matrices in other nodes or within or between phases (dependent variable), *on average*. To assess this, dissimilarity matrices were correlated with each other in a pairwise manner, resulting in  $r$  values for each participant  $\times$  node  $\times$  condition. The average  $r$  value for each comparison was tested against 0 using a one-sample  $t$ -test. For each pairwise comparison, we interpret evidence of a correlation as an index of reinstatement. For simplicity, we adopt the convention of describing these correlations between dissimilarity matrices as *instances of reinstatement*. Thus, one node may reinstate information with another node, either within or between phases, or it can reinstate information within itself between phases.

We found several patterns of reinstatement. In the novel association task, the dissimilarity matrices of ECN left lateral prefrontal cortex during generation predicted (i.e.  $> 0$  correlations) dissimilarity matrices of three other nodes during evaluation (BFs  $> 10$ ). First, the ECN left lateral prefrontal cortex showed reinstatement within itself during evaluation,  $r = .06$ ,  $\text{BF}_{10} = 17.8$ . Second, it showed reinstatement within the ECN right lateral prefrontal cortex during

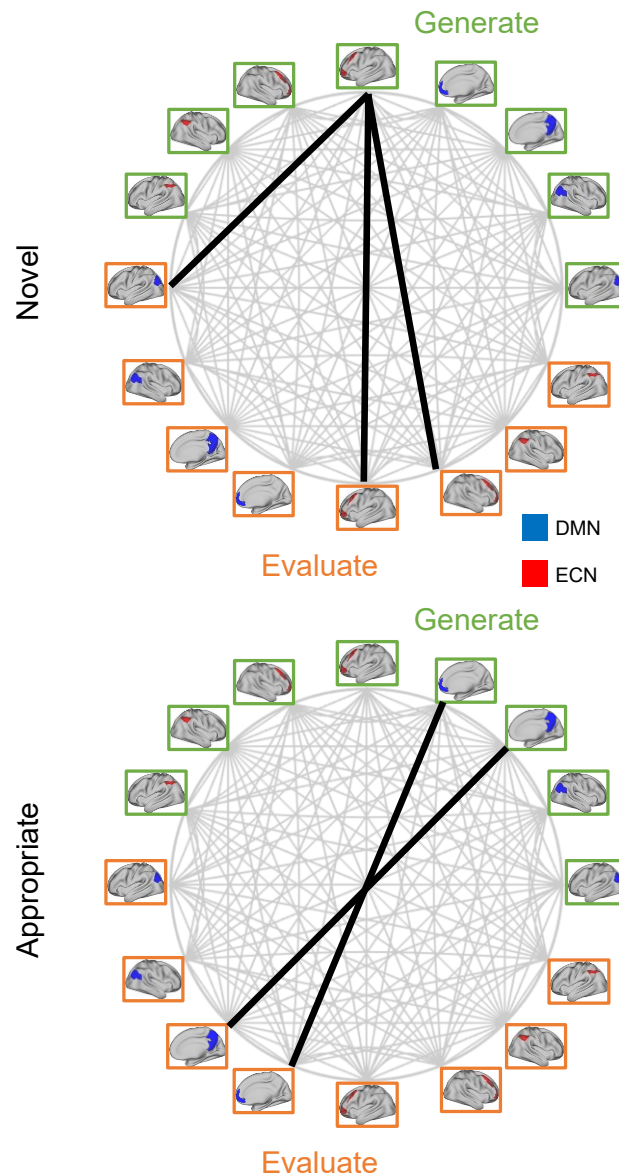
evaluation,  $r = .08$ ,  $BF_{10} = 131.0$ . Third, it showed reinstatement within the DMN left lateral parietal node during evaluation,  $r = .07$ ,  $BF_{10} = 17.3$ .

In the appropriate association task, two nodes showed reinstatement with themselves between generation and evaluation. First, the medial prefrontal cortex of the DMN during generation showed strong reinstatement with itself during evaluation,  $r = .08$ ,  $BF_{10} = 52.1$ . Second, the posterior cingulate cortex also showed reinstatement within itself,  $r = .04$ ,  $BF_{10} = 33.0$ .

Overall, we found strong evidence for within-ECN (specifically, the dorsal lateral prefrontal cortex) reinstatement during the generation and evaluation of novel associations, and within-DMN (specifically, the medial prefrontal cortex) reinstatement during the generation and evaluation of appropriate associations. Additionally, in the novel association task, we found both between- and within- network reinstatement. Specifically, we found between-network reinstatement involving the ECN lateral prefrontal cortex and the DMN left lateral parietal cortex between the two phases (see Figure 4).

Figure 4.

*Schematic representation of pairwise comparisons that show the reinstatement of representational geometries in the novel (top) and appropriate (bottom) conditions.*



*Note.* Schematic of the main results. Representational geometry (i.e., dissimilarity matrix) of each node within the DMN (blue ROIs) and ECN (red ROIs) networks were pairwise correlated with every other node both within each phase and between phases (generation = green; evaluation = orange). Separate sets of pairwise comparisons were made within

the novel and appropriate tasks. Each comparison is reflected by a line connecting one node to another. Bold lines indicate strong evidence for an average correlation between dissimilarity matrices (i.e. instance of reinstatement) with a  $BF_{10} > 10$ .

There were several cases of moderate evidence ( $BF > 5$  and  $< 10$ ) of reinstatement between networks and phases. Within the novel association task, the ECN left lateral prefrontal cortex during generation showed evidence of reinstatement within the DMN medial prefrontal cortex during evaluation,  $r = .07$ ,  $BF_{10} = 5.2$ . The ECN right lateral prefrontal cortex showed reinstatement with itself across phases,  $r = .05$ ,  $BF_{10} = 6.0$ . Finally, the DMN medial prefrontal cortex during generation showed reinstatement within itself during evaluation,  $r = .07$ ,  $BF_{10} = 9.4$ .

In the appropriate association task, the DMN right lateral parietal cortex during generation was reinstated in the ECN right lateral prefrontal cortex during evaluation,  $r = .04$ ,  $BF_{10} = 7.3$ . Further, the ECN left lateral prefrontal cortex during generation was reinstated within the ECN right lateral prefrontal cortex during evaluation,  $r = .05$ ,  $BF_{10} = 5.1$ .

In all other cases we found no evidence or only weak evidence ( $BF \sim = < 5$ ) of reinstatement across generation and evaluation. Importantly, as anticipated, the within-task correlations between nodes (i.e., during the generation task and during the evaluation task) were high with extremely strong evidence in favor of representational stability within tasks,  $r = .2 - .61$ ,  $BF_{10} > 1000$ . For full pairwise comparison results, see Tables 1 and 2.

Finally, contrary to our predictions, we found no evidence that person-level creativity (i.e., mean semantic distance of associations) predicted reinstatement values (i.e. none showed  $BFs > 5$ ).

Table 1. Pairwise correlation matrix from the novel association task.

|          |     | Generate |         |         |         |         |         |         |      | Evaluate |         |         |         |         |         |         |      |
|----------|-----|----------|---------|---------|---------|---------|---------|---------|------|----------|---------|---------|---------|---------|---------|---------|------|
|          |     | DMN      |         |         |         | ECN     |         |         |      | DMN      |         |         |         | ECN     |         |         |      |
| Generate |     | ILP      | rLP     | MPFC    | PCC     | ILPFC   | rLPFC   | IPPC    | rPPC | ILP      | rLP     | MPFC    | PCC     | ILPFC   | rLPFC   | IPPC    | rPPC |
| Generate | DMN | ILP      | 1.00    |         |         |         |         |         |      | ILP      | 1.00    |         |         |         |         |         |      |
|          |     | rLP      | 0.50*** | 1.00    |         |         |         |         |      | rLP      | 0.21*** | 0.22*** |         |         |         |         |      |
|          |     | MPFC     | 0.21*** | 0.22*** | 1.00    |         |         |         |      | MPFC     | 0.55*** | 0.50*** | 0.20*** |         |         |         |      |
|          |     | PCC      | 0.55*** | 0.50*** | 0.20*** | 1.00    |         |         |      | PCC      | 0.27*** | 0.22*** | 0.47*** | 0.28*** |         |         |      |
|          |     | ILPFC    | 0.27*** | 0.22*** | 0.47*** | 0.28*** | 1.00    |         |      | ILPFC    | 0.23*** | 0.25*** | 0.53*** | 0.29*** | 0.64*** |         |      |
|          |     | rLPFC    | 0.23*** | 0.25*** | 0.53*** | 0.29*** | 0.64*** | 1.00    |      | rLPFC    | 0.50*** | 0.39*** | 0.26*** | 0.49*** | 0.36*** | 0.32*** |      |
| Evaluate | DMN | IPPC     | 0.50*** | 0.39*** | 0.26*** | 0.49*** | 0.36*** | 0.32*** | 1.00 | IPPC     | 0.34*** | 0.60*** | 0.25*** | 0.47*** | 0.26*** | 0.50*** |      |
|          |     | rPPC     | 0.34*** | 0.60*** | 0.25*** | 0.47*** | 0.26*** | 0.50*** | 1.00 | rPPC     | 0.03    | 0.02    | 0.04    | 0.02    | 0.07**  | 0.04    | 0.02 |
|          | ECN | ILP      | 0.03    | 0.02    | 0.04    | 0.02    | 0.07**  | 0.04    | 0.02 | ILP      | 0.03    | 0.02    | 0.04    | 0.01    | 0.04    | 0.02    | 0.02 |
|          |     | rLP      | 0.03    | 0.02    | 0.04    | 0.01    | 0.07*   | 0.05    | 0.04 | rLP      | 0.00    | -0.01   | 0.07*   | 0.03    | 0.05    | 0.02    | 0.03 |
|          |     | MPFC     | 0.00    | -0.01   | 0.04    | 0.03    | 0.05    | 0.02    | 0.03 | MPFC     | 0.02    | -0.02   | 0.04    | 0.00    | 0.06**  | 0.05    | 0.02 |
|          |     | PCC      | 0.02    | -0.01   | 0.04    | 0.00    | 0.06**  | 0.05    | 0.02 | PCC      | 0.02    | -0.02   | 0.05    | 0.02    | 0.08**  | 0.05*   | 0.04 |
| Evaluate | ECN | ILPFC    | 0.02    | -0.01   | 0.04    | 0.00    | 0.06**  | 0.05    | 0.02 | ILPFC    | 0.02    | -0.02   | 0.05    | 0.02    | 0.08**  | 0.05*   | 0.04 |
|          |     | rLPFC    | 0.02    | -0.01   | 0.04    | 0.00    | 0.06**  | 0.05    | 0.02 | rLPFC    | 0.01    | -0.01   | 0.04    | 0.02    | 0.04    | 0.01    | 0.03 |
|          |     | IPPC     | 0.01    | -0.01   | 0.04    | 0.02    | 0.04    | 0.01    | 0.03 | IPPC     | 0.01    | -0.01   | 0.04    | 0.02    | 0.04    | 0.01    | 0.03 |
|          |     | rPPC     | 0.01    | -0.01   | 0.03    | 0.01    | 0.02    | 0.00    | 0.01 | rPPC     | 0.01    | -0.01   | 0.03    | 0.01    | 0.02    | 0.00    | 0.01 |

\*\*\*  $BF_{10} > 1000$ ; \*\*  $BF_{10} > 10$ ; \* $BF_{10} \sim 5$ ; all other vales  $BF_{10} < 5$

Table 2. Pairwise correlation matrix from the appropriate association task.

|          |     | Generate |         |         |         |         |         |         |         | Evaluate |         |         |         |         |         |         |         |
|----------|-----|----------|---------|---------|---------|---------|---------|---------|---------|----------|---------|---------|---------|---------|---------|---------|---------|
|          |     | DMN      |         |         |         | ECN     |         |         |         | DMN      |         |         |         | ECN     |         |         |         |
| Generate |     | ILP      | rLP     | MPFC    | PCC     | ILPFC   | rLPFC   | IPPC    | rPPC    | ILP      | rLP     | MPFC    | PCC     | ILPFC   | rLPFC   | IPPC    | rPPC    |
| Generate | DMN | ILP      | 1.00    |         |         |         |         |         |         | ILP      | 1.00    |         |         |         |         |         |         |
|          |     | rLP      | 0.52*** | 1.00    |         |         |         |         |         | rLP      | 0.22*** | 0.23*** |         |         |         |         |         |
|          |     | MPFC     | 0.22*** | 0.23*** | 1.00    |         |         |         |         | MPFC     | 0.55*** | 0.53*** | 0.22*** |         |         |         |         |
|          |     | PCC      | 0.55*** | 0.53*** | 0.22*** | 1.00    |         |         |         | PCC      | 0.29*** | 0.21*** | 0.43*** | 0.29*** |         |         |         |
|          |     | ILPFC    | 0.29*** | 0.21*** | 0.43*** | 0.29*** | 1.00    |         |         | ILPFC    | 0.26*** | 0.26*** | 0.51*** | 0.33*** | 0.60*** |         |         |
|          |     | rLPFC    | 0.26*** | 0.26*** | 0.51*** | 0.33*** | 0.60*** | 1.00    |         | rLPFC    | 0.54*** | 0.42*** | 0.23*** | 0.54*** | 0.40*** | 0.33*** |         |
| Evaluate | DMN | IPPC     | 0.54*** | 0.42*** | 0.23*** | 0.54*** | 0.40*** | 0.33*** | 1.00    | IPPC     | 0.39*** | 0.60*** | 0.21*** | 0.53*** | 0.25*** | 0.37*** | 0.50*** |
|          |     | rPPC     | 0.39*** | 0.60*** | 0.21*** | 0.53*** | 0.25*** | 0.37*** | 0.50*** | rPPC     | 0.01    | 0.03    | 0.04    | 0.02    | 0.03    | 0.01    | 0.02    |
|          | ECN | ILP      | 0.01    | 0.03    | 0.04    | 0.00    | 0.02    | 0.02    | 0.01    | ILP      | 0.01    | 0.02    | 0.04    | 0.01    | 0.02    | 0.01    | 0.02    |
|          |     | rLP      | 0.01    | 0.02    | 0.04    | 0.00    | 0.02    | 0.02    | 0.01    | rLP      | 0.03    | 0.02    | 0.08**  | 0.02    | 0.04    | 0.03    | 0.02    |
|          |     | MPFC     | 0.03    | 0.02    | 0.08**  | 0.02    | 0.04    | 0.03    | 0.02    | MPFC     | 0.03    | 0.03    | 0.03    | 0.03    | 0.04    | 0.02    | 0.03    |
|          |     | PCC      | 0.03    | 0.03    | 0.02    | 0.04**  | 0.03    | 0.01    | 0.02    | PCC      | 0.03    | 0.03    | 0.03    | 0.03    | 0.04    | 0.02    | 0.03    |
| Evaluate | ECN | ILPFC    | 0.03    | 0.03    | 0.03    | 0.03    | 0.04    | 0.02    | 0.03    | ILPFC    | 0.03    | 0.03    | 0.03    | 0.03    | 0.04    | 0.02    | 0.03    |
|          |     | rLPFC    | 0.03    | 0.04*   | 0.04    | 0.03    | 0.05*   | 0.02    | 0.03    | rLPFC    | 0.03    | 0.04*   | 0.04    | 0.03    | 0.05*   | 0.02    | 0.03    |
|          |     | IPPC     | 0.02    | 0.03    | 0.04    | 0.04    | 0.04    | 0.03    | 0.02    | IPPC     | 0.02    | 0.03    | 0.04    | 0.04    | 0.04    | 0.03    | 0.02    |
|          |     | rPPC     | 0.01    | 0.02    | 0.02    | 0.02    | 0.02    | 0.01    | 0.02    | rPPC     | 0.01    | 0.02    | 0.02    | 0.02    | 0.02    | 0.01    | 0.02    |

\*\*\*  $BF_{10} > 1000$ ; \*\*  $BF_{10} > 10$ ; \* $BF_{10} \sim 5$ ; all other vales  $BF_{10} < 5$

## 4.1. Discussion

Current approaches to studying creative thought suggest two critical processes supporting creativity: idea generation and idea evaluation. Idea generation entails activating knowledge and combining it in novel ways while idea evaluation is thought to involve selecting novel combinations for their usefulness in a given context. Previous research has implicated the DMN and ECN in these processes (Kleinmuntz et al., 2019). Here, reasoning that evaluating ideas requires reactivation of the same information that has been previously generated, we investigated the reinstatement of activity patterns within and between nodes of the DMN and ECN during idea generation and evaluation. Participants generated novel or appropriate noun-noun associations in a generation phase and then evaluated their own associations in an evaluation phase. Using RSA, we reveal the patterns of neural informational reinstatement within and

between DMN and ECN that support these cognitive processes. We focus our discussion on cases of *strong* evidence for reinstatement as determined by BFs.

First, in the novel association task, the left lateral prefrontal cortex showed reinstatement within itself of both hemispheres across the two phases. In general, the prefrontal cortex is implicated in a wide variety of creativity tasks (see Gonen-Yaacovi et al., 2013 for a meta analysis; Zhang et al., 2020) and the specific regions we investigated here (more rostral and dorsal regions) are thought to reflect some of the highest regions in the cortical hierarchies that integrate information from lower-order regions in the service of organizing goal-directed behaviour (Badre and D'Esposito, 2009; Badre and Nee, 2018). The dorsal lateral prefrontal cortex in particular has been implicated in activating/inhibiting task relevant information shaped by goals of the task (see Chrysikou, 2019; Weinberger et al., 2017); further, this region has been directly implicated in verbal tasks, like ours, that require overcoming or emphasizing prepotent associations between words (e.g., Kenett et al., 2021; Zmigrod, Colzato, & Hommel, 2015). Given this, we can speculate about the role of the lateral prefrontal cortex in the current study. In our novel association task, participants had to generate and evaluate the novelty of their noun associates, perhaps requiring the selective activation/inhibition of common associates during generation and evaluation. Thus, our results suggest that the neural patterns necessary for coordinating the active/inhibited information during generating and evaluating creative ideas is reinstated within this node throughout both phases of the creative process, a finding consistent with its role in producing task-relevant behaviour in other domains. Note, because this node sits atop of an action planning hierarchy and may contribute relatively abstract action plans to the organization of behaviour, we can further speculate that this process is especially important when generating novel ideas (but less so for appropriate ones). This is consistent with the idea that

these nodes of the ECN are particularly important for managing ongoing task demands based on available stimuli (rather than on learned associations; see Smallwood et al., 2021). While previous research has implicated the ECN in evaluation in particular, we can speculate that reinstating abstract action information for use in the here-and-now is a critical component of generating *and* evaluating creative ideas.

The lateral prefrontal cortex also showed between network reinstatement within the DMN lateral parietal cortex across generation and evaluation. This finding is important for two reasons. First, it demonstrates that generation and evaluation is supported by nodes within both the DMN and ECN and, second, it demonstrates that different nodes of the ECN and DMN need to reinstate similar informational content to support creative thought. We speculate that the reinstatement of ECN information within the DMN may reflect the need to ‘check’ information relevant to the novel context (i.e. here and now) that is under control of the lateral prefrontal cortex against previously learned associations and the semantic content of the lateral parietal cortex. This finding is consistent with results showing the importance of posterior cortical regions in the generation of creative ideas, which requires the activation of relevant perceptual/semantic content (Chrysikou and Thompson-Schill, 2013; see Matheson et al., 2017 for parietal involvement specifically). This informational reinstatement between nodes also gives support to the core ideas of dual process models of creativity (Ward, Smith, and Finke, 1995), and suggests that generating and evaluating creative thought requires informational sharing between these networks.

During the appropriate association task, the DMN medial prefrontal cortex showed reinstatement within itself between generation and evaluation, thus implicating MPFC in the coordination of common associations. In general, the medial prefrontal cortex is known for its

involvement in ‘self referential’ (Gusnard et al., 2001), or perhaps more generally ‘self relevant’ (Abraham, 2013) tasks. We can speculate that information characteristic of periods of episodic simulation, supported by the diffuse activation of a wide variety of sensorimotor and interoceptive experience, is useful in accessing and assessing known associations that stem from experience. The medial prefrontal hub is also widely implicated in predicting the value or outcome of learned behaviors is based on long term knowledge (Euston, Gruber, and McNaughton, 2012), which likely accounts for its role in reinstating information when generating and evaluating previously learned associations between nouns; that is, finding appropriate associations requires finding associations that have been previously valued and rewarded (e.g. belts go with pants). Further, if nodes of the DMN sit at the very top of distributed neural hierarchies and integrate information from all sensorimotor regions, they are best suited to coordinate information related to self and previous experience. Thus, when the task emphasizes responses that rely on previously learned information, the DMN medial prefrontal cortex appears to reinstate critical information for generating and evaluating ideas.

Additionally, within the appropriate task, the DMN posterior cingulate cortex<sup>1</sup> showed reinstatement within itself across generation and evaluation, in another instance of within network reinstatement. As a part of the DMN, the PCC has also been implicated in ‘self referential’ processes associated with mind wandering and the valuation of outcomes. Similarly to our speculation above, one intriguing possibility is that the reinstatement of information related to previously learned knowledge is ‘checked’ against likely value in the PCC. One final consideration is that hubs of the DMN are not only involved in episodic tasks but also semantic tasks, and drawing on known associations is clearly a semantic task (see Kim, 2016; Krieger-

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<sup>1</sup> Note that this node also includes the precuneus cortex.

Redwood et al., 2022); thus, reinstatement within these DMN hubs strongly implicate the reinstatement of both types of information.

Overall, our results show that the generation and evaluation phases of the creative process can be characterized by the reinstatement of information both between and within nodes of the ECN and DMN. Importantly these results elaborate on the picture of the DMN as a network important for generation and the ECN as a network for evaluation, and strongly suggest—based on the strength of Bayesian evidence—that within-network reinstatement is important for generating and evaluating ideas. We can make sense of this dynamic by considering the roles of network nodes that coordinate information across different sensorimotor and interoceptive modalities (see also Mok, 2014). To the extent that these nodes integrate different types of information then, their roles in generating and evaluating ideas will be shaped by whether novelty or appropriateness is the goal; specifically, ECN prefrontal cortical nodes operate on information that is necessary for novelty and the DMN cortical nodes operate on information necessary for appropriate associations. We can speculate about what the critical information may be in each task. For instance, in the novel task, within-ECN reinstatement may support the need to generate and evaluate abstract action plans in the here and now; when associations are less creative, within-DMN reinstatement is appears crucial, perhaps due to the role of previously learned, self-relevant, episodic and semantic information.

## **4.2. Limitations**

There are a number of important limitations of our present analysis. First, we focused on a subset of cortical regions defined by intrinsic connectivity. Thus, our study does not exhaust the possible contributions of nodes outside the ECN and DMN that may be critical in evaluating and generating ideas. While we focused on the ECN and DMN because they have been

previously implicated in idea generation and evaluation, note that only a subset of the nodes studied here are implicated in informational reinstatement in our task. This suggests that there are differential contributions of nodes within the ECN and DMN to idea generation and evaluation, and not simply that the cortex shows stable (i.e., repeated) patterns over phases; that is, it does not appear that RSA detects unchanging pattern similarity between the generation and evaluation phases across the cortex more generally, which would be expected if the technique was insensitive to task changes or informational content.

Second, we did not find evidence that the strength of reinstatement predicted the creativity of associations that participants generated (i.e., SemDis scores). While this is not surprising in the appropriate task (where participants are generating common associates), we did anticipate that reinstatement would predict creativity in the novel task. There may be a number of explanations for this, including that we had inadequate statistical power to detect such a relationship. However, it may be the strength of reinstatement within the nodes we studied here is not a reliable predictor of semantic distance. If so, this would suggest that the patterns of reinstatement in the DMN and ECN are important for attempting to generate and evaluate creative ideas, though it may not be important for determining the success of these process. Another related possibility is that reinstatement in nodes outside of the network nodes studied here are more important for determining the quality of responses. Finally, we restricted the generation phase to 5 seconds and only a single response. However, in situations where creative output is not time restricted and multiple responses are given creativity tends to increase later in the response period (i.e. the serial order effect in divergent thinking tasks; Christensen, Guilford, & Wilson, 1957; Beaty & Silvia, 2012). While we did show that SemDis was higher under the novelty instruction, these constraining features of our task likely limited the originality of the

responses given. If reinstatement is more important for truly original responses, then we would fail to detect a relationship between SemDis and reinstatement<sup>2</sup>. Future research should investigate the contributions of reinstatement outside of the DMN and ECN or use more unconstrained tasks.

Third, like other fMRI studies of idea generation and evaluation, we explicitly manipulated the phases of the creative process. However, it is clear that these processes are integrated dynamically during ecological creative thinking, and while there are advantages to explicitly manipulating the goals of a task, it is unclear whether these stages can be properly dissociated from each other at a neural level (see Zamani et al., 2022). In this way, our study allows us to make inferences about the reinstatement of neural information under different task demands but we are limited in our ability to target the more integrated dynamics that are occurring in both the generation and the evaluation phases used in the present study.

### 4.3. Conclusion

Overall, across generating and evaluating ideas, the ECN lateral prefrontal cortex and the DMN medial prefrontal cortex are most widely implicated in reinstating information, either within themselves or with other nodes. While the LPFC reinstatement is strongest in the novel association task, and the MPFC reinstatement is strongest in the appropriate association task, these two nodes show evidence of reinstatement in both tasks, suggesting a critical role of both networks in idea generation and evaluation. Given that RSA captures informational content of cortical patterns, our results suggest that accounts of creative thought need to extend beyond accounting for the dual *processes* of generating and evaluation, to considering the relevant

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<sup>2</sup> We thank an anonymous reviewer for this suggestion.

*information* that those processes rely on, and point to the critical role of both networks in the general human capacity for creative thought.

## 5. Appendix

### *Word lists and psychologicistic features for the word association task*

#### List 1

| <b>Word</b> | <b>Semantic Diversity</b> | <b>Imageability</b> | <b>Concreteness</b> | <b>Frequency</b> | <b>QSS</b> | <b>Valence</b> |
|-------------|---------------------------|---------------------|---------------------|------------------|------------|----------------|
| coin        | 1.66                      | 6.5                 | 4.89                | 497              | 12         | 6.55           |
| hat         | 1.65                      | 6.7                 | 4.88                | 3273             | 12         | 5.69           |
| statue      | 1.46                      | 6.5                 | 4.93                | 540              | 17         | 5.95           |
| alley       | 1.51                      | 6.4                 | 4.82                | 831              | 18         | 4.17           |
| subway      | 1.48                      | 6.7                 | 4.86                | 546              | 17         | 5.44           |
| sword       | 1.33                      | 6.8                 | 4.93                | 1335             | 18         | 5.27           |
| rock        | 1.49                      | 6.4                 | 4.91                | 4394             | 13         | 5.72           |
| plant       | 1.56                      | 6.3                 | 4.76                | 1408             | 14         | 7.05           |
| palace      | 1.46                      | 6.5                 | 4.57                | 979              | 14         | 6.1            |
| branch      | 1.82                      | 6                   | 4.9                 | 514              | 11         | 5.15           |
| bath        | 1.7                       | 6                   | 4.85                | 1587             | 10         | 7              |
| plane       | 1.58                      | 6.8                 | 4.92                | 4872             | 12         | 5.72           |
| seat        | 1.74                      | 6.2                 | 4.78                | 4018             | 10         | 5.22           |
| match       | 1.71                      | 5.1                 | 4.14                | 2521             | 18         | 5.61           |
| log         | 1.66                      | 6.3                 | 4.96                | 610              | 9          | 4.94           |
| church      | 1.56                      | 6.7                 | 4.9                 | 3553             | 15         | 5.21           |
| rocket      | 1.63                      | 6.4                 | 4.73                | 604              | 18         | 5.8            |
| pet         | 1.39                      | 6.4                 | 4.71                | 1029             | 11         | 7.05           |
| purse       | 1.81                      | 6.5                 | 4.9                 | 1008             | 12         | 5.95           |
| leather     | 1.55                      | 6.5                 | 4.82                | 693              | 20         | 5.84           |
| ladder      | 1.76                      | 6.4                 | 5                   | 472              | 14         | 5.32           |
| robot       | 1.45                      | 6.6                 | 4.65                | 621              | 15         | 6.18           |
| brass       | 1.62                      | 5.8                 | 4.7                 | 618              | 19         | 5.05           |
| shell       | 1.76                      | 6                   | 4.8                 | 674              | 17         | 6.05           |
| mail        | 1.7                       | 6.3                 | 4.69                | 1879             | 15         | 6.28           |
| dock        | 1.55                      | 6.1                 | 4.64                | 497              | 10         | 5.05           |
| coat        | 1.58                      | 6.7                 | 4.97                | 2146             | 17         | 5.29           |
| pocket      | 1.64                      | 6                   | 4.68                | 1821             | 18         | 5.67           |
| screen      | 1.51                      | 6.2                 | 4.6                 | 1193             | 16         | 5.55           |
| hotel       | 1.51                      | 6.7                 | 4.93                | 5264             | 16         | 6.6            |

*Notes.* QSS = cue set size (Nelson et al., 2004).

**List 2**

| <b>Word</b> | <b>Semantic Diversity</b> | <b>Imageability</b> | <b>Concreteness</b> | <b>Frequency</b> | <b>QSS</b> | <b>Valence</b> |
|-------------|---------------------------|---------------------|---------------------|------------------|------------|----------------|
| bench       | 1.79                      | 6.5                 | 4.87                | 493              | 14         | 5.5            |
| train       | 1.57                      | 6.3                 | 4.79                | 4848             | 19         | 6.36           |
| steam       | 1.4                       | 5.6                 | 4.5                 | 686              | 18         | 5.4            |
| page        | 1.81                      | 5.9                 | 4.9                 | 1912             | 10         | 6.09           |
| sink        | 1.67                      | 5.4                 | 4.74                | 863              | 18         | 4.62           |
| fence       | 1.63                      | 6.6                 | 4.82                | 819              | 20         | 5.05           |
| belt        | 1.78                      | 6.5                 | 4.9                 | 1242             | 11         | 4.44           |
| tea         | 1.56                      | 6.4                 | 4.69                | 2990             | 11         | 6.56           |
| net         | 1.65                      | 5.9                 | 4.53                | 793              | 14         | 5              |
| earth       | 1.72                      | 6.5                 | 4.8                 | 5074             | 12         | 6.83           |
| tray        | 1.43                      | 5.8                 | 4.74                | 410              | 19         | 5.14           |
| barn        | 1.38                      | 6.9                 | 4.79                | 693              | 13         | 6.16           |
| wheel       | 1.49                      | 6.5                 | 4.86                | 1380             | 14         | 5.9            |
| drill       | 1.38                      | 6                   | 4.4                 | 701              | 19         | 4.73           |
| carpet      | 1.49                      | 6.4                 | 4.96                | 594              | 17         | 5.95           |
| circus      | 1.77                      | 6.5                 | 4.43                | 870              | 13         | 5.85           |
| costume     | 1.48                      | 6.5                 | 4.57                | 721              | 18         | 6.05           |
| gym         | 1.5                       | 6.5                 | 4.83                | 927              | 17         | 5.84           |
| rain        | 1.57                      | 6.3                 | 4.97                | 2494             | 18         | 6.58           |
| bar         | 1.66                      | 6.1                 | 4.67                | 4385             | 13         | 5              |
| engine      | 1.33                      | 6.3                 | 4.86                | 1626             | 16         | 5.48           |
| grass       | 1.56                      | 6.9                 | 4.93                | 856              | 14         | 6.47           |
| shadow      | 1.78                      | 6.5                 | 4.54                | 1080             | 18         | 5.07           |
| glove       | 1.69                      | 6.2                 | 4.97                | 515              | 9          | 6.11           |
| bucket      | 1.59                      | 6.4                 | 4.96                | 511              | 11         | 4.55           |
| gum         | 1.68                      | 6.4                 | 4.89                | 683              | 9          | 5.89           |
| sea         | 1.67                      | 6.4                 | 4.79                | 3052             | 15         | 6.56           |
| map         | 1.65                      | 5.9                 | 4.93                | 1623             | 16         | 5.81           |
| pole        | 1.69                      | 5.8                 | 4.66                | 642              | 14         | 5.6            |
| drum        | 1.54                      | 6.4                 | 4.96                | 432              | 16         | 6.05           |

*Notes.* QSS = cue set size (Nelson et al., 2004).

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## Appendix A

### GENERATION INSTRUCTIONS

In Phase 1, you will see a common noun on the screen (e.g., desk) and be asked to think of another noun that can be associated with it. You will come up with two types of noun associations: APPROPRIATE and NOVEL.

APPROPRIATE nouns are clearly related to the noun on the screen. APPROPRIATE associations would probably come to most everyone's mind when they read the noun. For example, an appropriate association to "desk" could be "chair."

Your associations should only be concrete nouns, i.e., things that exist physically and can be touched, seen, smelled, etc. Your associations should *\*not\** be proper nouns (e.g. people's names), verbs, or other parts of speech. Also, your association should only be *\*one word\**.

It is important for you to try to think of the *\*most appropriate\** noun that you can.

For example, other nouns could be considered appropriate when associated with "desk" (such as "computer"). Your task is to think of the *\*most appropriate\** noun that you can.

You will also be asked to think of NOVEL associations.

NOVEL associations are *\*not\** usually related to the noun on the screen. NOVEL associations are unusual, meaning that they are unrelated to the noun. NOVEL associations would probably not come to anyone else's mind when they read the noun. For example, a novel association to "book" could be "cloud."

Your associations should only be concrete nouns, i.e., things that exist physically and can be touched, seen, smelled, etc. Your associations should *\*not\** be proper nouns (e.g. people's names), verbs, or other parts of speech. Also, your association should only be *\*one word\**.

It is important for you to try to think of the *\*most novel\** noun that you can. For example, other nouns could be considered novel when associated with "book" (such as "tire"). Your task is to think of the *\*most novel\** noun that you can.

### EVALUATION INSTRUCTIONS

In Phase 2, you will evaluate your associations from Phase 1. You will see the nouns and your associations and evaluate them on either NOVELTY or APPROPRIATENESS.

To recap, APPROPRIATE associations are clearly related to the noun on the screen. APPROPRIATE associations would probably come to most everyone's mind when they read the noun. Your task is to evaluate the appropriateness of your association in relation to this noun.

When evaluating the appropriateness of your association, it is important that you consider whether it is the \*most appropriate\* possible noun. Some of your associations will be more appropriate than others.

You will evaluate the appropriateness of your associations using a 3-point scale: 1 = not at all appropriate, 2 = somewhat appropriate, and 3 = very appropriate.

You will also be asked to evaluate the NOVELTY of your associations.

To recap, NOVEL associations are \*not\* usually related to the noun on the screen. NOVEL associations are unusual, meaning they are unrelated to the noun. NOVEL associations would probably not come to anyone else's mind when they read the noun. Your task is to evaluate the novelty of your association in relation to this noun.

When evaluating the novelty of your association, it is important that you consider whether it is the \*most novel\* possible noun. Some of your associations will be more novel than others.

You will evaluate the novelty of your associations using a 3-point scale: 1 = not at all novel, 2 = somewhat novel, and 3 = very novel.