



Creative Connections: Computational Semantic Distance Captures Individual Creativity and Resting-State Functional Connectivity

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Abstract

Recent studies of creative cognition have revealed interactions between functional brain networks involved in the generation of novel ideas; however, the neural basis of creativity is highly complex and presents a great challenge in the field of cognitive neuroscience, partly because of ambiguity around how to assess creativity. We applied a novel computational method of verbal creativity assessment—semantic distance—and performed weighted degree functional connectivity analyses to explore how individual differences in assembly of resting-state networks are associated with this objective creativity assessment. To measure creative performance, a sample of healthy adults ($n = 175$) completed a battery of divergent thinking (DT) tasks, in which they were asked to think of unusual uses for everyday objects. Computational semantic models were applied to calculate the semantic distance between objects and

responses to obtain an objective measure of DT performance. All participants underwent resting-state imaging, from which we computed voxel-wise connectivity matrices between all gray matter voxels. A linear regression analysis was applied between DT and weighted degree of the connectivity matrices. Our analysis revealed a significant connectivity decrease in the visual-temporal and parietal regions, in relation to increased levels of DT. Link-level analyses showed higher local connectivity within visual regions was associated with lower DT, whereas projections from the precuneus to the right inferior occipital and temporal cortex were positively associated with DT. Our results demonstrate differential patterns of resting-state connectivity associated with individual creative thinking ability, extending past work using a new application to automatically assess creativity via semantic distance. ■

INTRODUCTION

Creative thinking is essential to all human progress and innovation. Recent studies of functional neuroimaging and network neuroscience have revealed interaction between large-scale brain networks associated with creative cognition. The neuroscience of creativity seeks to disentangle these complex brain processes that facilitate the generation of novel ideas. Creativity has been defined as the production of novel and useful ideas to solve problems (Guilford, 1967), and it is often assessed with tasks of divergent thinking (DT), which require the production of multiple solutions to open-ended problems. A classic test of DT, the Alternative Uses Task (AUT), prompts participants to generate alternative uses for a common object. To assess the creative quality of ideas, traditional approaches to DT assessment have largely relied on human raters, a subjective and labor-intensive procedure. Recent developments in creativity assessment have sought to standardize and automate creativity assessment by applying computational measures of semantic distance (Beaty & Johnson, 2020;

Dumas, Organisciak, & Doherty, 2020; Kenett & Faust, 2019; Heinen & Johnson, 2018; Prabhakaran, Green, & Gray, 2014). The application of semantic distance to creativity assessment is based on the associative theory of creativity (Kenett & Faust, 2019; Mednick, 1962), which characterizes creative thought as a novel and useful recombination of semantic knowledge; thus, the integration of more semantically distant concepts is considered more creative. This study applies semantic distance models to automatically and objectively assess DT. Past work has largely focused on human ratings of creativity, so it is unknown whether similar neural mechanisms underlie objective assessments of creative thinking that do not rely on the subjective judgments of human raters. Given high correlations reported between human ratings and semantic distance (Beaty & Johnson, 2020; Dumas et al., 2020), we expect to find similar (though perhaps nonredundant) neural patterns for human ratings and semantic distance measures of DT. We measure semantic distance via a latent semantic distance factor—a combination of computational semantic models that show a high correspondence to human ratings of novelty and creativity (Beaty & Johnson, 2020). Automated assessments of creativity via semantic distance represents a new direction in the field of creativity research, permitting an analysis of the extent to which neural

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correlates of creativity overlap when creativity is assessed by humans versus machines.

Advances in neuroimaging techniques have enabled researchers to study functional networks involved in creative cognition. One approach that has been employed is functional connectivity magnetic resonance imaging, which allows researchers to measure dynamic interactions between brain regions. Resting-state functional connectivity magnetic resonance imaging studies have begun to dissociate large-scale functional networks underlying cognitive and attentional control processes relevant for creative cognition (Beaty, Benedek, Silvia, & Schacter, 2016). Among the most well studied of these functional networks, the Default Mode Network (DMN)—composed of a set of midline and posterior inferior parietal regions—shows increased activation in the absence of an externally presented stimulus (Raichle et al., 2001). DMN activity is associated with self-generated thought, such as mind wandering and imagination (Andrews-Hanna, Smallwood, & Spreng, 2014; Buckner, Andrews-Hanna, & Schacter, 2008). It has been suggested that activity in the DMN contributes to the generation of candidate ideas, whereas executive control networks exert top-down monitoring to meet specific task goals or constraints (Beaty et al., 2016; Beaty, Silvia, Nusbaum, Jauk, & Benedek, 2014). Task-based approaches have helped to uncover the dynamic relationship of these large-scale networks during creative task performance (Beaty, Kenett, et al., 2018; Shi et al., 2018). In addition, resting-state studies have shown that temporal variability of DMN connectivity correlates with DT and frequency of transitions between functional connectivity-states are associated with creative ability (Feng et al., 2019; Sun et al., 2019; Liu et al., 2018; Gao et al., 2017; Li et al., 2017; Takeuchi et al., 2012). Seed-based connectivity analyses in resting-state fMRI data have revealed greater connectivity between inferior pFC and DMN to be associated with idea generation (Vartanian et al., 2018; Wei et al., 2014). The objective of the present work was not necessarily to replicate previous findings of the interaction between default mode and executive control networks; we do not expect to find consistent patterns of such network connectivity previously reported in task-based studies. Rather, we apply novel semantic distance measures and data-driven graph theory methods to resting-state data, exploring the overlap between human- and computationally derived creativity metrics.

Illuminating the specific contributions of DMN connectivity to the production of novel ideas continues to be a topic of great interest in the neuroscience of creativity literature. Internal attention requires the disengagement from immediate sensory information and may reflect a more abstract cognition associated with creativity. Internally directed cognition, which involves the shielding of internal processes from external stimuli, has been associated with extended deactivation of occipital and parietal regions (Benedek et al., 2016). A recent series of neuroimaging studies have focused on the role of internally directed attention in creativity and mental imagery (Fink & Benedek,

2019; Benedek, 2018; Fink et al., 2014). Attenuation of visual input has also been associated with creative insight (Salvi & Bowden, 2016; Salvi, Bricolo, Franconeri, Kounios, & Beeman, 2015). Moreover, occipital and parietal regions, such as the lateral occipital cortex and the inferior parietal lobule, have been critically involved in the integration of sensory perception toward multisensory and association cortices (Diez et al., 2019; Sepulcre, 2014; Sepulcre, Sabuncu, Yeo, Liu, & Johnson, 2012). Creative individuals may exhibit a higher degree of internally directed cognition at rest, reflected in lower connectivity within primary visual systems and increased connectivity to areas of multimodal integration.

Applications of graph theory in neuroscience have emerged as an effective approach to studying functional networks of the brain (van den Heuvel & Hulshoff Pol, 2010). Network analysis offers insight into the structural and functional organization of human brain networks (Sporns, Chialvo, Kaiser, & Hilgetag, 2004), with brain regions represented as nodes and the relationships between nodes (i.e., connectivity) represented as edges (Sepulcre, Sabuncu, & Goñi, 2014; Bullmore & Bassett, 2011; Bullmore & Sporns, 2009). Individual variability in functional network organization provides a lens to study the relationship between brain morphology and cognitive ability. Several network metrics have been developed to quantify different properties of network architecture. One such measure is the *degree* of a node, the number of edges that connects it to the rest of the network (Sepulcre et al., 2012; Bullmore & Bassett, 2011; Buckner et al., 2009). Weighted degree (WD) provides a measure of centrality, quantifying the importance of each node within the whole-brain architecture. In addition, link-level analyses characterize the strength of specific links between discrete brain regions. Although graph theory approaches have been employed in previous studies of creativity—for example, using regions of interest applied to task-based fMRI data and DT assessed with human creativity ratings (Beaty, Benedek, Kaufman, & Silvia, 2015)—the present work contributes new insight, applying a data-driven WD and link-level connectivity analysis to explore resting-state network architecture related to DT assessed objectively via computational semantic distance. Brain graphs provide a powerful model to study the complex organization of the human brain; application of graph theory metrics may deepen our understanding of the network interactions, which facilitate creative thinking.

Present Research

New approaches in network neuroscience have begun to elucidate the cognitive mechanisms that underlie creative thought; however, more work is needed to disentangle the complex network interactions involved in the production of novel ideas and how these interactions relate to objective assessments of creativity. This study applies WD and link-level analysis to represent individual differences in

resting-state networks associated with DT ability. To objectively quantify individual's DT performance, we leverage latent variable modeling and multiple computational models of semantic distance, extracting a latent factor of semantic distance from five semantic models previously shown to have a strong (but non-unity) correlation with human judgments of relatedness, novelty, and creativity (Beaty & Johnson, 2020). Semantic distance has been employed in a task-based fMRI study using a noun-verb generation task, finding that the semantic distance between nouns and verbs tracked increases in frontopolar cortex activity and connectivity (Green, Cohen, Raab, Yedibalian, & Gray, 2015). We do not seek to replicate these findings in our study, given differences in the tasks, semantic distance calculations, and fMRI data; however, this work provides preliminary evidence that semantic distance captures individual variation in task-relevant neural response. To date, it is unknown how such automated assessments relate to individual differences in the brain's intrinsic functional architecture (i.e., during the resting state) and whether similar neural correlates correspond to human versus automated creativity assessment. The present research thus aimed to extend research on the neural basis of creative thinking by combining WD analysis of resting-state fMRI data with both human and automated creativity assessments.

METHODS

The data were collected as part of a larger study on individual differences in creativity and imagination (Beaty, Kenett, et al., 2018). The larger project included a task-based fMRI study of DT; the task fMRI data from this study are not analyzed here but have been published elsewhere (Frith et al., 2020; Adnan, Beaty, Silvia, Spreng, & Turner, 2019; Beaty, Chen, et al., 2018). Here, we analyze resting-state fMRI data from the full sample of the larger project. We have previously published subsets of the resting-state fMRI sample in studies of personality (Beaty, Chen, et al., 2018) and human ratings on the AUT (Kenett, Betzel, & Beaty, 2020), but no study has examined resting-state data in relation to computational semantic distance. The total sample consisted of 186 participants from the University of North Carolina, Greensboro and members of the community; art, music, and science majors were oversampled to broaden the representation of creative backgrounds. From the 177 participants who completed a resting-state scan, two were excluded because of distortion of the structural image. The final sample consisted of 175 participants (127 women, mean age = 22.67 years, $SD = 6.37$ years).

All participants were right-handed with normal or corrected-to-normal vision and reported no history of any neurological disorders, cognitive disabilities, or medications that affect the central nervous system (Beaty, Chen, et al., 2018). All participants provided written informed consent. The study was approved by the University of North Carolina, Greensboro, institutional review board.

Behavioral Assessment

DT performance was assessed by the AUT, conducted during a separate task-based fMRI scan, as well as on a computer outside scanner. Note that the task-based fMRI data are not presented here (only the verbal responses; see Beaty, Chen, et al., 2018). During the task-based fMRI scan, participants were presented with a series of everyday objects (e.g., brick) and asked to imagine new and unusual uses for each object. Participants had 12 sec to think of a single alternate use for a list of 23 objects and then had 5 sec to verbally report their response via an MRI-compatible microphone (Benedek, Christensen, Fink, & Beaty, 2019; Beaty, Chen, et al., 2018). For the computer-based assessment, consistent with conventional procedures, participants had 3 min to generate as many alternative uses for two objects as possible (box and rope). In addition, participants completed a test of visuospatial intelligence (Gv) to measure the ability to mentally manipulate visual stimuli, assessed via three independent tasks: paper-folding, block-rotations, and cube comparisons (Frith et al., 2020).

The MRI- and lab-based DT responses were pooled and scored for creative quality by 1) trained human raters using the subjective scoring method (Silvia, 2008) and 2) computational models using semantic distance (Beaty & Johnson, 2020). Regarding human ratings, four trained raters independently scored the creative quality of each response using a 1 (*not at all creative*) to 5 (*very creative*) scale (Benedek, Mühlmann, Jauk, & Neubauer, 2013; Silvia, 2008). Raters were instructed to provide a single rating for each response, focusing on uncommonness, remoteness, and cleverness; the scoring rubric and guidance for raters can be found on Open Science Framework (<https://osf.io/vie7s/>).

Regarding semantic distance, we followed the approach described in Beaty and Johnson (2020). We thus computed the semantic distance between each object cue word (e.g., box) and each response using an on-line application called *SemDis*, an open platform developed to automate creativity assessment via semantic distance (semdis.wlu.psu.edu). *SemDis* leverages five compositional vector models to compute the relatedness between inputted texts: three continuous bag of words (CBOW) predict models and two count models. CBOW/predict models were built using a neural network architecture (Mandera, Keuleers, & Brysbaert, 2017) that employs a sliding window to move through text corpora and aims to predict a central word from surrounding context words (cf. *word2vec*); count models, in contrast to predict models, compute the co-occurrence of words within these large text corpora. The three CBOW models included: 1) a concatenation of the ukwac web crawling corpus (~2 billion words) and the subtitle corpus (~385 million words; window size = 12 words, 300 dimensions, most frequent 150,000 words); 2) the subtitle corpus only (window size 12 words, 300 dimensions, most frequent 150,000 words); and 3) a concatenation of the British National Corpus (~2 billion words), ukwac corpus, and the 2009 Wikipedia dump

(~800 million tokens; window size = 11 words, 400 dimensions, most frequent 300,000 words). CBOV models have previously demonstrated high correlations with human relatedness judgments (Mandera et al., 2017) as well as human creativity ratings across a range of common creativity tasks, including the AUT (Beaty & Johnson, 2020). The two count models include: 1) a latent semantic analysis model, Touchstone Applied Science Associates, which computes word co-occurrences within a text corpus (37,000 documents, middle and high school textbooks and literary words, 92,393 different words), followed by a singular value decomposition on the resulting sparse matrix (300 dimensions; cf. Prabhakaran et al., 2014); and 2) the global vectors (Glove; Pennington, Socher, & Manning, 2014) model, which is trained on ~6 billion tokens (300 dimensions, top 400,000 words) and uses weighted least squares to extract global information across a concatenation of the 2014 Wikipedia dump and the Gigaword corpus (news publications from 2009 to 2010).

All five spaces were used to compute the semantic distance between the AUT item (e.g., box) and participants' responses, where the cosine angle between the word vectors represents semantic similarity; semantic distance is then computed by subtracting this similarity from 1 (Kenett & Faust, 2019; Beaty, Christensen, Benedek, Silvia, & Schacter, 2017; Green, 2016; Prabhakaran et al., 2014). Following Beaty and Johnson (2020), we used latent variable modeling to extract the common variance from the five semantic models. This approach has the benefit of reducing the influence of any one model—which has been shown to yield idiosyncratic values specific to the given model and text corpus employed (Mandera et al., 2017)—thus boosting the reliability and generalizability of results.

Using Mplus 8, we specified a confirmatory factor analysis (CFA) that modeled semantic distance, human creativity ratings, and Gv as three latent variables using the full sample of participants with available data ($n = 186$). For semantic distance, the mean values of the five semantic models served as indicators for three lower order latent variables, corresponding to the three AUT tasks (box, rope, and MRI); a higher order variable was indicated by these three lower order variables. For human ratings, the mean values of the four raters served as indicators for three lower order latent variables (box, rope, and MRI); a higher order variable was indicated by these three lower order variables. For Gv, the summed scores of the three tasks were modeled as indicators of a Gv factor. The variance of the latent variables was fixed to one; all indicators were standardized. For the fMRI analyses below, we extracted factor scores from the two higher order semantic distance and human creativity variables.

MRI Acquisition and Preprocessing

Resting-state MRI data were acquired for all participants on a 3 T Siemens Magnetom MRI system using a 16-channel

head coil (Figure 1). High-resolution T1 scans were acquired for anatomical normalization. BOLD T2*-weighted functional images were acquired with gradient EPI sequence with the following parameters: repetition time = 2000 msec, echo time = 30 msec, flip angle = 78°, 192-mm field of view, 32 axial slices, $3.5 \times 3.5 \times 4.0$ mm, interleaved slice ordering, sequence length = 5 min. Participants were instructed to relax awake in the scanner with eyes closed for the duration of the scan.

MRI data for both anatomical and functional images were preprocessed using FMRIB Software Library v5.0.7 and MATLAB 2017a (The MathWorks Inc.). The anatomical and functional preprocessing pipelines were adapted from previous work (Diez et al., 2019). The anatomical T1 preprocessing included: reorientation to right-posterior-inferior; alignment to anterior and posterior commissures; skull stripping; gray matter, white matter, and cerebrospinal fluid segmentation; and computation of nonlinear transformation between individual skull-stripped T1 and 2-mm resolution Montreal Neurological Institute (MNI) 152 template images. The fMRI preprocessing pipeline included: slice time correction, reorientation to right-posterior-inferior, realigning functional volumes within runs with a rigid body transformations (six parameters linear transformation), computation of the transformation between individual skull-stripped T1 and mean functional images, intensity normalization, and removal of confounding factors from the data using linear regression—including 12 motion-related covariates (rigid motion parameters and its derivatives), linear and quadratic terms, and five components each from the lateral ventricles and white matter. Global signal regression was not applied because of the negative correlations this can introduce. Transformation of resting-state data to MNI space was performed, concatenating the transformation from functional to structural and from structural to MNI, spatial smoothing with an isotropic Gaussian kernel of 6-mm FWHM, and band-pass filtering (0.01–0.08 Hz) to reduce low-frequency drift and high-frequency noise were also applied. Head motion was quantified using realignment parameters obtained during image preprocessing, including three translation and three rotation estimates. Scrubbing of time points with excess head motion interpolated all time points with a frame displacement > 0.2 mm was applied. No participants demonstrated excessive head motion; thus, none was removed from the study based on these criteria. The distributions of the correlations across time series were reviewed for possible contamination; no outliers were observed from the whole-brain connectivity distributions.

Weighted-Degree Functional Connectivity Analysis

Pearson correlation coefficients were used to calculate the connectivity matrices of each participant using the time series of all cortical gray matter voxels (Figure 1). A r -to- z Fisher transformation was applied to the resulting

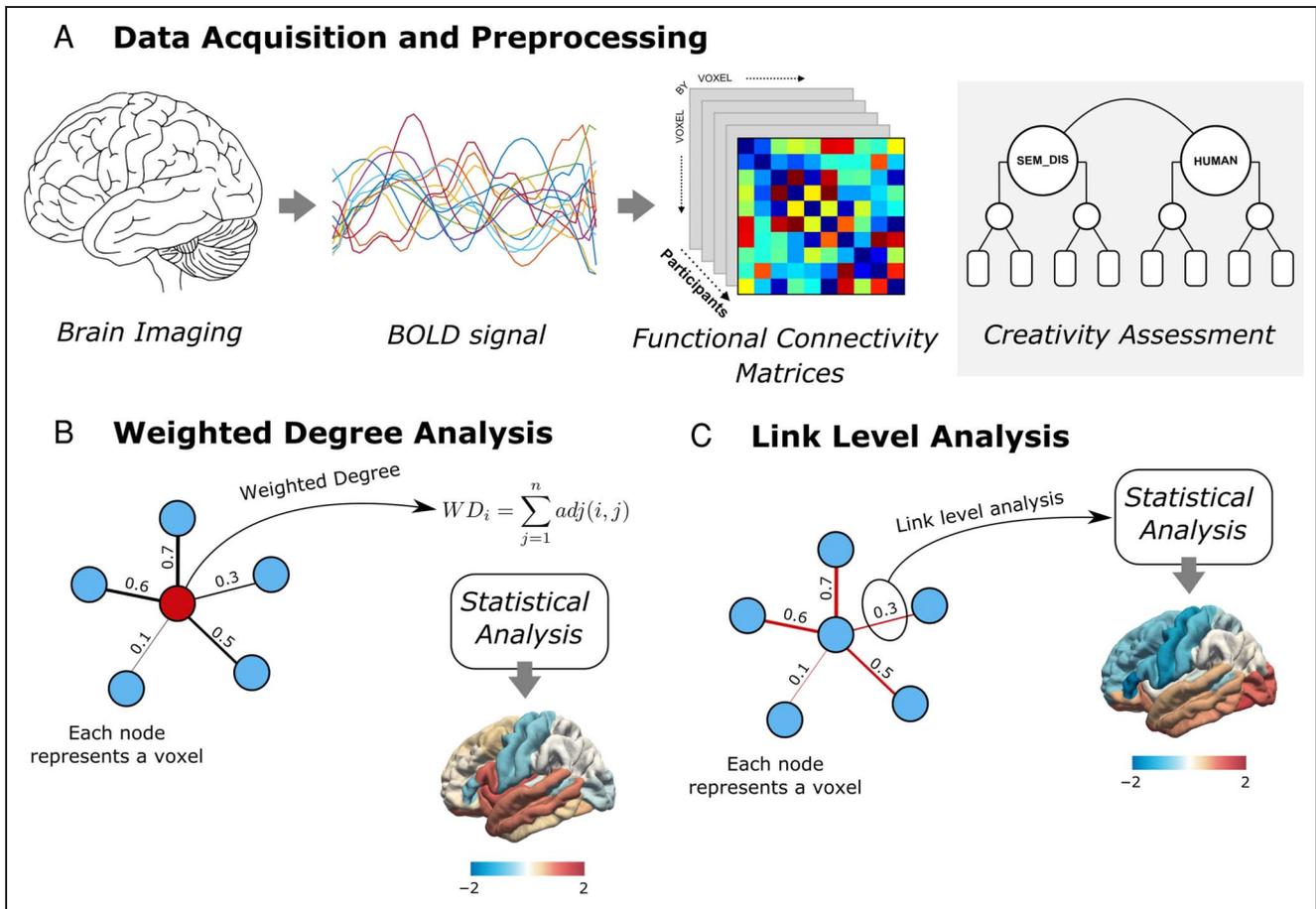


Figure 1. Methods. A sample of healthy adults underwent resting-state fMRI scans, from which we computed voxel-wise connectivity matrices between all gray matter voxels. Behavioral assessment enabled the analysis of individual differences in functional connectivity associated with creative performance.

correlation matrix, and negative values were removed. To minimize noise, we considered only the most significant links using a false discovery rate at q -level < 0.005 (Benjamini & Hochberg, 1995). To evaluate the relative prominence of each voxel in the whole-brain architecture of each individual, voxel-level WD values were computed (Figure 1). After obtaining a high-resolution $52,769 \times 52,769$ connectivity matrix for each participant, we summed all the weighted connections of each voxel to generate a WD map showing the extent to which each voxel is functionally connected to the rest of the brain (Ortiz-Terán et al., 2017). A general linear model was used to compute the association between WD and DT score. All statistical analyses were corrected for participant age, sex, and Gv. Whole-brain correction for multiple comparisons was computed using Monte Carlo simulation with 10,000 iterations to estimate the probability of false-positive clusters with a two-tailed $p < .05$ (3dClustSim; afni.nimh.nih.gov).

Link-Level Functional Connectivity Strength Analysis

To further investigate relationships between DT and cortical regions identified in the WD analysis, we evaluated if DT

performance correlated with link-level connectivity strength values across brain areas. To evaluate link-level functional connectivity strength, MRI data were down-sampled to 6-mm isotropic voxels to reduce dimensionality, resulting in a 6620×6620 connectivity matrix for each participant. A general linear model was used at every link of the network to evaluate the association of the link weight and the DT scores (separately for semantic distance and human ratings). Whole-brain correction for multiple comparisons was computed adapting the Monte Carlo simulation method to networks. Ten thousand random networks were generated with the same smoothing properties, to compute a false-positive cluster size with a two-tailed $p < .001$. Compared to WD maps, where clusters were defined as contiguous voxels, here, clusters were defined as links that connect contiguous voxel groups. We reduced the dimensionality of the surviving links for visualization purposes. The statistically significant links positively/negatively associated with DT were then represented in a connectogram in Neuromarvl (<https://immersive.erc.monash.edu/neuromarvl/>). Cortical surfaces were visualized using the population-average landmark and surface-based projections of CARET software. We used Caret v5.65 software to represent the

results in a three-dimensional Population-Average Landmark and Surface-based surface using the “enclosing voxel algorithm” and “fiducial and flat mapping” settings. Surface images were displayed using a color scale based on T-scores.

RESULTS

Correlation between Semantic Distance and Human Creativity Ratings

Before moving to the fMRI analysis, we examined the relationship between semantic distance and human creativity ratings. The CFA showed good fit: χ^2 (396 *df*) 643.242, $p < .001$; comparative fit index = .945; root mean square error of approximation = .058 (90% CI [0.05, .066]); standardized root means square residual = .074 (Figure 2). We found a large latent correlation between semantic distance and human creativity ratings, $r = .81$ ($p < .001$), consistent with the large effect reported in Beaty and Johnson (2020) using only the laboratory-based AUT data. This result indicates a high degree of overlap between semantic distance and human ratings (see Figure 3). Gv correlated significantly with human creativity ratings ($r = .46$, $p < .001$)—as previously reported (see Frith et al., 2020)—but not semantic distance ($r = .11$, $p = .29$), indicating that human ratings share more variance with general cognitive ability than with automated assessments of creativity (cf. Beaty & Johnson, 2020).

Brain Hubs Associated with DT

Our first WD analysis aimed to identify cortical hubs related to individual differences in DT assessed via semantic distance. Results showed that DT semantic distance was negatively correlated with WD of voxels in the occipital cortex, along with parietal-occipital and temporal regions (Figure 3A). WD across lateral occipital and superior parietal regions was negatively correlated with DT. Similarly, lower WD along the temporo-parietal junction and right middle temporal gyrus was associated with higher DT performance. WD of the left inferior parietal sulcus was negatively associated with DT. There were no positive associations between WD and DT.

In addition, we performed WD analysis with human ratings of DT (Figure 3B). WD maps generated with human ratings of DT shared similar cortical distributions to the semantic distance measure, with 51% of voxels shared between the two maps. Results showed that human ratings of DT were negatively correlated with WD of voxels in the occipital cortex and right temporal regions. WD of the right temporal pole was negatively associated with DT. There were no positive associations between WD and human ratings of DT.

Individual Connectivity Patterns and DT

Link-level analysis revealed individual links between brain regions negatively associated with semantic distance of

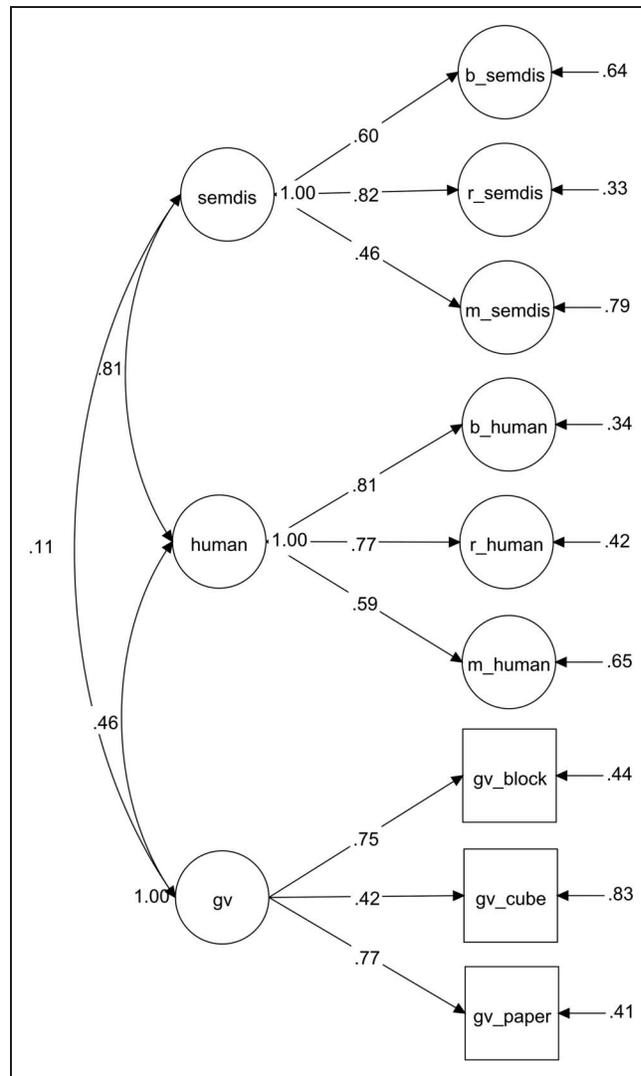


Figure 2. CFA of semantic distance, human creativity ratings, and visuospatial intelligence. Observed variables are depicted as squares, and latent variables are depicted as circles. For interpretability, the observed variables for semantic distance and human creativity ratings are not shown in the diagram. b_semdis = box task, semantic distance; r_semdis = rope task, semantic distance; m_semdis = MRI tasks, semantic distance; b_human = box task, human ratings; r_human = rope task, human ratings; m_human = MRI tasks, human ratings; gv_block = visuospatial intelligence, block rotation; gv_cube = visuospatial intelligence, cube comparison; gv_paper = visuospatial intelligence, paper folding. $n = 186$.

DT, corrected for multiple comparisons (Figure 4A). Strength of connectivity within the primary visual cortex was negatively correlated with DT. In other words, high local connectivity within the visual area was associated with lower DT performance. Projections from bilateral V1 and V2 to the precuneus were negatively associated with DT. Strength of connectivity between primary visual areas and precuneus was negatively associated with DT.

In addition, we identified links positively associated with DT semantic distance (Figure 4B). The strength of the connection between the precuneus and right inferior temporal

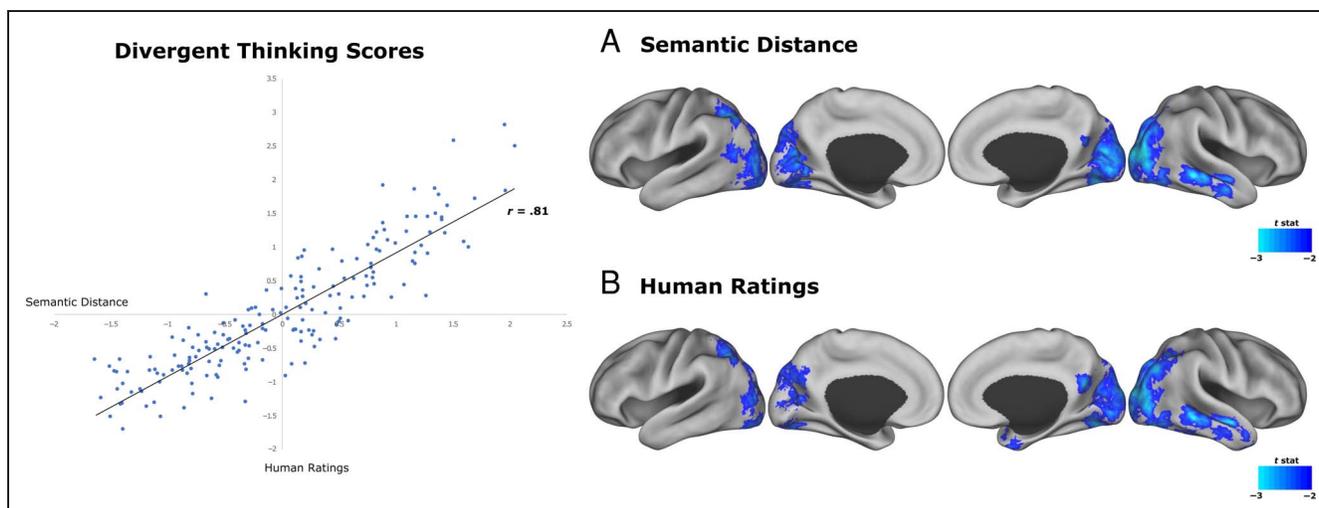


Figure 3. Weighted degree, WD across the lateral occipital and superior parietal cortex was negatively associated with DT. WD along the right middle temporal gyrus negatively correlated with DT. Semantic distance and human ratings of DT were consistent in these findings.

gyrus was positively correlated with DT. Projections from the precuneus to right inferior occipital cortex (fusiform), right inferior temporal, and occipital cortices were positively correlated with DT semantic distance. Link-level analysis with human ratings of DT revealed a negative association similar to that of semantic distance measures. Connectivity across the occipital cortex and projection to

the right primary motor and somatosensory areas were negatively associated with human ratings of DT. We did not find any positive association with human ratings of DT. Despite the similar negative associations between the two measures, semantic distance reveals a positive association between individual connectivity strength and DT, which human ratings do not capture.

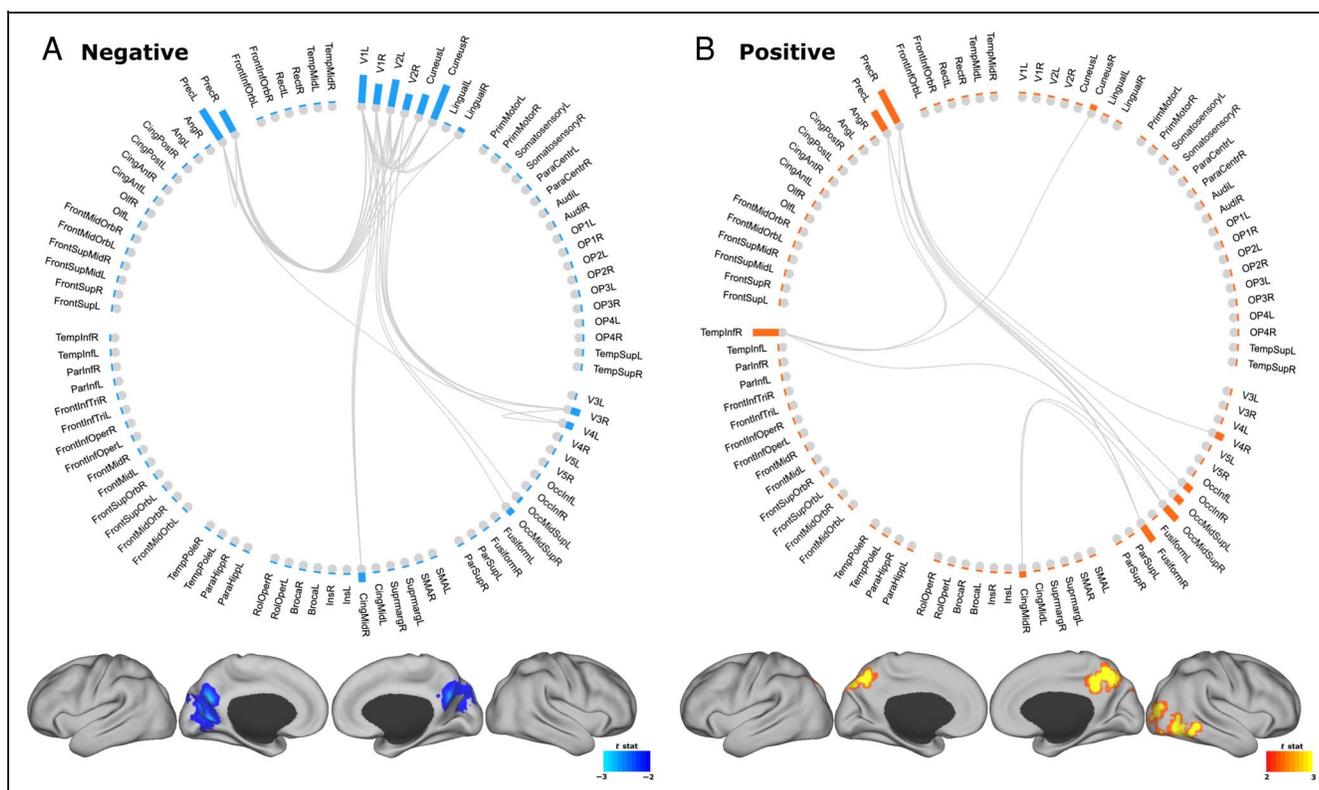


Figure 4. Link level. Strength of connectivity within the primary visual cortex was negatively correlated with DT. Projections from the precuneus to the right inferior occipital and temporal cortices were positively correlated with DT.

DISCUSSION

This study applies graph theory techniques in resting-state functional connectivity MRI data to explore how individual differences in assembly of resting-state networks are related to creativity, using a new application to automatically assess creativity via semantic distance. Critically, WD results from the semantic distance measure were largely consistent with human ratings—producing similar functional connectivity maps—further validating this objective assessment as a viable measure of creative performance. The findings thus contribute to the growing neuroscience literature on individual differences in creative thinking and demonstrate the utility of automated scoring approaches to capture variance in creativity at the neural level.

Lateral Visual Cortex Centralizes the Emergence of DT

Among the most salient findings, our analysis revealed a negative association between DT and WD across lateral occipital, inferior parietal, and right middle temporal areas. Secondary link-level analyses revealed that functional connectivity between the left precuneus and right lateral visual pathway was positively associated with DT, whereas strength of connections within primary visual regions were negatively associated with DT. These results indicate that there is less integration of visual information during resting state in individuals with higher DT scores. High local connectivity within the primary visual system represents a high degree of segregation. One interpretation of these results could be that creative people are more prone to engage in internally directed cognition (such as mind wandering) in the absence of an external task. Schooler et al. (2011) describe the phenomenon of perceptual decoupling, the capacity to disengage attention from perception, during episodes of mind wandering. Perceptual decoupling during resting-state may indicate engagement in more abstract, internally directed attention, which characterizes creative individuals. Internally directed attention has been associated with extended deactivation in occipital and inferior parietal cortices (Benedek et al., 2016). In addition, Sepulcre (2014) identifies the lateral occipital cortex and the inferior parietal lobule as integrators of sensory information, toward more high-level cognition. One possibility is that participants with reduced functional connectivity to the primary visual system are engaged in more creative, self-generated cognitive processes during resting state.

Link-level analyses showed that strength of connections within the primary visual cortex was negatively associated with DT, whereas connectivity from the right lateral and ventral occipital cortex to the precuneus was positively associated with DT. At first glance, these results may appear to be in conflict, as we see projections from the precuneus both positively and negatively associated

with DT. This differential connectivity reflects the attenuation of primary visual areas, with higher connectivity between lateral inferior occipital regions and multimodal integration areas being positively associated with DT. The precuneus is a core hub of the DMN and is thought to play a role in multimodal integration. In a study examining gray matter density and verbal creativity, it was found that increased gray matter density in precuneus was positively associated with DT (Benedek, 2018). Our results suggest that regions of the precuneus may be differentially involved in creative problem solving. Stronger connectivity between visual regions and precuneus may reflect tighter coupling between perception and generation systems, whereas decreased connectivity between the visual cortex and semantic regions may reflect weaker communication between perception and object representation along the ventral stream. Differential pathways for the integration of visual information may elucidate the neural mechanisms involved in DT, although further research is needed to support this claim.

Previous studies of task-based and resting-state data have described consistent patterns of network interaction between DMN and executive control networks in relation to creative cognition (Christensen, Benedek, Silvia, & Beaty, 2019; Beaty, Kenett, et al., 2018; Beaty et al., 2015). DMN activity is thought to contribute to the generation of candidate ideas, whereas executive control networks exert top-down monitoring to meet external constraints (Beaty et al., 2016). Notably, our results do not reflect this interaction between default mode and executive control networks, suggesting that the novel semantic distance measures and graph theory analyses reported here capture variance in creative thinking that is distinct from these network dynamics.

The finding of a negative association between WD in the right middle temporal gyrus and DT raises questions regarding the involvement of this region in verbal creativity. Task-based studies of DT have applied dynamic causal modeling to describe unidirectional control from the pFC over the middle temporal gyrus (Vartanian et al., 2018). Other studies have implicated the middle temporal gyrus in idea generation (Ellamil, Dobson, Beeman, & Christoff, 2012) and semantic integration (Jung-Beeman, 2005). It has been suggested the right hemisphere is preferentially involved in the processing of distantly related “coarse” semantic information (Beeman et al., 1994). The negative association between DT performance and WD of right middle temporal areas demonstrate that, at rest, these regions are less functionally connected to the rest of the brain in participants who scored higher on the AUT. Link-level connectivity strength between inferior temporal areas and the precuneus was positively associated with DT, which may reflect more coupling of semantic processing and multimodal-integration areas. In summary, our findings extend past research by identifying neural correlates of individual creative thinking using objective and automated assessments of creativity based on semantic distance.

Limitations and Future Directions

An important consideration in cognitive and neuroscience studies of creativity concerns the operationalization of creativity. Many studies focus on the creative quality of ideas (assessed via human creativity ratings or semantic distance) as the primary dependent outcome, but this outcome alone can only provide a modest window into the cognitive basis of idea generation. Viewed as a high-level cognitive ability, creative thought (or the output from creativity tasks and their assessed quality) likely results from the complex interplay of multiple “lower level” cognitive processes, such as memory retrieval, cognitive control, and attention. We encourage future research to further identify the cognitive processes that give rise to creative ideas.

The observed overlap between WD maps generated from human ratings and semantic distance measures showed 51% of voxels common between the two maps. Currently, there is no clear benchmark for determining the magnitude or significance between these maps. Although the cortical distributions appear visually similar (see Figure 3), we cannot explain what is reflected by the nonoverlapping regions. Speculatively, the distinction may be because of features of ideas that humans consider when rating creative responses that are not captured by computational semantic distance (e.g., utility or cleverness of an idea). These unique neural features should be more deeply explored in future work (cf. Vartanian et al., 2020). The present research uses resting-state fMRI data to examine functional networks of the brain at rest. Given the nature of resting-state data, there is a considerable amount noise. In collecting the data, we are not able to control for the participant’s mood or state of mind during the resting-state scan and there is known to be high variability between scans of the same individual. Although this measure is subject to noise, the size of our sample ($n = 175$) allows us to be confident that these findings are not simply the result of noise and do provide new insight into individual differences in the creative brain.

Future studies may explore the causal relationship between identified regions and DT performance. For example, transcranial magnetic stimulation to the right middle temporal gyrus before completion of the AUT may provide further clarification into the role of this brain region in the integration of semantically distant concepts (Luft, Zioga, Thompson, Banissy, & Bhattacharya, 2018). In addition, future work in the field may explore cortical gene expression related with patterns of functional connectivity to describe how specific genetic pathways may be related to individual variability in creativity.

Conclusions

This study applied graph theory techniques to resting-state fMRI data to measure individual differences in functional connectivity associated with DT. Computational semantic models were applied to calculate the semantic distance

between objects and responses to obtain an automated measure of DT performance. This automated measure of DT provided results consistent with (but not identical to) those of human ratings, highlighting the potential of semantic distance as a reliable metric of creativity. The finding of a negative association between resting-state connectivity in the occipital cortex and DT may be explained by perceptual decoupling, reflecting a higher degree of internally directed cognition in participants who scored higher on the AUT. In addition, our findings suggest a positive association between DT and connectivity from the precuneus to right inferior temporal regions. More work is needed to validate these findings and further characterize the complexities of the creative brain.

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Author Contributions

William Orwig: Conceptualization; Formal analysis; Visualization; Writing – original draft; Writing – review & editing. Ibai Diez: Formal analysis; Methodology. Patrizia Vannini: Writing – review & editing. Roger Beaty: Data curation; Supervision; Writing – review & editing. Jorge Sepulcre: Supervision; Writing – review & editing.

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