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Neural Representations of Conceptual Fixation during Creative Imagination

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ABSTRACT

A large body of research has revealed that viewing example image stimuli tends to constrain creative idea generation. However, the neurocognitive mechanisms underlying such visual fixation in creative cognition are unclear. In the present experiment, we explored whether example images impacted creative imagination and patterns of neural activity within brain regions associated with visual object recognition. Participants first viewed example images (ambiguous line drawings) accompanied by high-constraint and low-constraint labels. High-constraint labels resembled the line drawings, whereas low constraint labels did not. Next, participants imagined new labels for the same line drawings, with the initial labels removed. Consistent with our predictions, semantic distance analysis comparing cue labels to newly generated labels showed lower average semantic distance (i.e., less creative ideas) on high-constraint trials compared to low-constraint trials. Using representational similarity analysis, we also demonstrated that neural pattern similarity was anticorrelated (less similar) from object recognition to high-constraint imagination trials within the right inferior temporal gyrus, right middle temporal gyrus, and right superior occipital gyrus. Broadly, these findings suggest that salient visual examples may guide the formation of strong mental representations that constrain creative imagination. This research also offers a first step toward identifying neurocognitive signatures associated with the effortful process of producing new, creative ideas following exposure to fixating examples – particularly at the early level of object recognition/representation in the ventral visual stream.

One of the hallmarks of creative cognition is the ability to form new associations between known concepts. Knowledge and experience are tools for creative expansion and efficient problem-solving but may also confine exploration of diverse alternatives when "novel" ideas are merely reiterations of stored information (Alipour, Faizi, Moradi, & Akrami, 2018). Given that successfully combining information in original and useful ways can yield creative ideas and solutions (Mednick, 1962), it is not surprising that constraining this process via related examples has been shown to impede creativity (Beaty, Christensen, Benedek, Silvia, & Schacter, 2017; Chrysikou, Motyka, Nigro, Yang, & Thompson-Schill, 2016; Chrysikou & Weisberg, 2005; George & Wiley, 2019, 2020; Jansson & Smith, 1991; Lloyd-Cox, Christensen, Silvia, & Beaty, 2020; Smith, 2003; Smith, Ward, & Schumacher, 1993; Storm, 2011; Storm & Angello, 2010; Ward, 1994; Ward, Patterson, & Sifonis, 2004).

Fixation occurs when a source of interference – such as examples or prior knowledge – interferes with one's ability to successfully execute cognitive tasks (Smith, 2003; Storm, 2011). Although much work has examined constraints on associative thought processes in verbal creative cognition tasks, less neuroscientific research has attempted to constrain creative associations through fixation in the visual domain (Lloyd-Cox et al., 2020). In the present research, we experimentally manipulated associative conceptual constraints to explore whether fixation on salient mental representations of visual stimuli impacted neural pattern similarity during divergent creative imagination (i.e., imagining novel labels for ambiguous line drawings; Jankowska & Karwowski, 2015). Exploring distinctions in how conceptual constraints are represented at the neural level may offer fine-grained insights into the role fixation plays in creative cognition.

The impact of fixation on creative cognition

In the context of creative thinking, knowledge may be leveraged to construct unique associations that fit task-relevant goals (Ward & Kolomyts, 2010). For example, musical composers must first learn distinct sounds and positions of notes on a given instrument prior to constructing novel melodies. Similarly, creative cognition

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often involves extending prior knowledge in novel ways and requires controlled representation of task stimuli and goal-maintenance (e.g., a goal to generate unique, uncommon ideas; Benedek, Jauk, Sommer, Arendasy, & Neubauer, 2014). Mentally manipulating knowledge schemas to pursue novel goals is what Sternberg (1999) operationalized as the process of creative redirection. Thus, knowledge is important for generating new conceptual combinations (Mednick, 1962; Ward & Kolomyts, 2010). However, relying too heavily on prior experiences may trap individuals in a semantic network of close, conventional associations that constrain creative cognition (Kenett, 2018; Kenett & Faust, 2019). Despite the intuitive benefits of knowledge and experience, mental fixation in creative cognition may occur when individuals are unable to inhibit salient information to imagine novel response candidates (Chrysikou et al., 2016; Smith et al., 1993).

Researchers have explored the fixating impacts of salient examples on creative cognition in a variety of ways, using divergent (Chrysikou et al., 2016; Chrysikou & Weisberg, 2005; Sio, Kotovsky, & Cagan, 2015; Smith et al., 2003; Ward, 1994; Ward et al., 2004; Wiley, 1998), and convergent thinking assessments (Luft, Zioga, Thompson, Banissy, & Bhattacharya, 2018; Smith & Blankenship, 1991; Storm & Angello, 2010). For example, the verbal Remote Associates Test (RAT) of convergent thinking (Mednick, 1962), requires identifying a common associate that links a triad of words (e.g., print, berry, bird = *blue*). Several studies have shown that participants generate fewer correct solutions after studying example word associates (e.g., "print-cheetah," "berry-straw," "bird-robin"), compared to when examples are not provided (Luft et al., 2018; Smith & Blankenship, 1991; Storm, 2011; Storm & Angello, 2010). However, some evidence suggests that the fixating effects of examples in both convergent and divergent thinking may be diminished by forgetting. Storm and Angello (2010) found that participants who solved more RAT triads also forgot more example associates on a cued-recall task. Additionally, Storm and Patel (2014) observed that more creative alternative uses for common objects were generated among participants who forgot more previously studied example uses. To this end, failing to retrieve example information may help inhibit creative constraints (Lin & Lien, 2013; Storm, 2011; Storm & Angello, 2010; Storm, Angello, & Bjork, 2011; Storm & Patel, 2014).

Conversely, prior exposure to other people's verbal ideas for object uses has been linked to higher subsequent divergent thinking originality than exposure to meaningless words, or reflection on one's own ideas

(Fink et al., 2010, 2012). Similarly, humor production – jokes generated on the spot – are rated as funnier when people are provided with good and bad examples relative to no examples (Shin, Cotter, Christensen, & Silvia, 2018). However, most empirical work in the visual domain points to a detrimental impact of examples on creative divergent thinking, which was the focus of the present experiment. For example, Dahl and Moreau (2002) asked participants to design a novel device that would minimize spill risks during vehicular dining. Before starting their designs, participants were shown a variety of example sketches (e.g., cup holder, tray table, etc.). Relative to a no-example control group, participants exposed to example sketches appeared susceptible to the phenomenon known as "unconscious plagiarism." That is, rather than serving as a springboard for originality, visual examples constrained designs, as participants often replicated features of the examples in their own responses. The constraining effects of visual examples have been shown to hinder original thinking in diverse experimental paradigms. These include imagining novel alien creatures to inhabit a distant planet, toys for a hypothetical company, or a measuring cup to accommodate consumers with visual impairments (George & Wiley, 2020; Jansson & Smith, 1991; Smith et al., 1993; Ward et al., 2004). Reproducing concrete attributes of example images has also been observed even when participants are explicitly instructed to avoid replicating exemplar components or are shown flawed, incorrect examples (Chrysikou et al., 2016; Chrysikou & Weisberg, 2005; Smith et al., 1993), highlighting the dramatic effect of prior knowledge (examples) on idea generation.

One explanation for the robust influence of visual examples on creative thinking performance may be that individuals become fixated on functional object attributes (i.e., functional fixedness; Davidson, 2003; Duncker, 1945), and cannot flexibly access abstract lexical, relational, and/or semantic information (Chrysikou et al., 2016). Functional fixedness has been observed following exposure to visual examples using convergent tasks that are commonly solved with sudden insight, such as the Two Strings Problem (Maier, 1931). For this specific problem, participants are shown two strings, hanging from the ceiling and positioned just far enough apart so that it is impossible to grasp both strings at the same time. A pile of heavy objects is also visible (including a pair of pliers and a chair) in the room. The challenge is to generate one correct solution for tying the two strings together (Maier, 1931). People tend to become constrained by common knowledge of how the example objects are typically used, which may inhibit

using these objects in novel ways to solve the problem successfully (i.e., tying the pliers to one string to create a weighted pendulum that will swing into reach while the other string is grasped; Davidson, 2003).

Similarly, in divergent thinking protocols, picture-based examples (relative to verbal examples) have been shown to provoke top-down retrieval of known object properties that are biased toward the object's canonical *function*, rather than its name or other semantic characteristics (Chrysikou et al., 2016; Marsh, Landau, & Hicks, 1996; Smith et al., 1993). For example, before generating creative uses for a shoe, viewing an example image of a flip flop may reinforce specific function-biased responses (e.g., using the shoe as a fishing bobber, based on the knowledge that rubber materials float) that differ from function-biased responses prompted by viewing the image of a stiletto (e.g., using the heel to dig a hole, based on recalling the challenges of lawn-walking in heels). Overall, image-based stimuli may support mental representations of imagined action and manipulation affordances, but may also constrain memory retrieval strategies, resulting in functional fixedness (Boronat et al., 2005; Chainay & Humphreys, 2002; Chrysikou et al., 2016; Saffran et al., 2003). In summary, fixation on the canonical function of example stimuli, particularly in the visual domain, may be one mechanism underlying creative constraints (Dahl & Moreau, 2002; Ward, 1994).

Neurocognitive mechanisms underlying fixation in creative thinking

One way that individuals may overcome fixating information is through inhibitory control. Inhibitory control is a mental construct positioned within a larger executive function framework for higher-order, goal-directed cognition (Cassotti, Agogué, Camarda, Houdé, & Borst, 2016; Diamond, 2013; Zelazo, Craik, & Booth, 2004). Knowledge-driven constraints may reflect inhibitory control failures, as salient, habituated mental representations impede an effortful exploration of remote ideas (Benedek & Fink, 2019; Chrysikou, 2018; Wiley, 1998). Conversely, successfully inhibiting fixating information may liberate uncommon response candidates (Beaty, Benedek, Silvia, & Schacter, 2016; Beaty et al., 2017; Benedek et al., 2014). For instance, in a series of four experiments, Luft and colleagues (2018) provided evidence indicating that right temporal alpha transcranial alternating current brain stimulation may be a mechanism for successful inhibition of habituated mental sets during convergent and divergent thinking under high goal-directed attention demands (e.g., exposure to misleading associates and/or generating uncommon uses

for common objects; Luft et al., 2018). Some accounts have emphasized that disinhibition likely favors creative thinking performance under conditions of lower task-constraint (e.g., generating as many ideas as possible; Radel et al., 2015; Lin & Lien, 2013). This is because ostensibly irrelevant information is less likely to be flagged as extraneous to the task; thus, failure to inhibit unrelated stimuli may invite access to a repository of remote concepts (Radel et al., 2015; Zabelina, Saporta, & Beeman, 2016).

Most work on the role of inhibitory control in creative cognition highlights a dynamic interplay between spontaneous and controlled cognitive processes (Camarda et al., 2018), particularly when the task-demands for goal-directed cognition are higher (Radel et al., 2015). Neuroscientific research has provided some support for this interplay, contributing to a more clarified understanding of fixation and inhibition in creative cognition paradigms. A meta-analytic examination of 45 neuroscientific studies pointed to consistent activation in frontal brain regions, specifically the anterior cingulate cortex and inferior and middle frontal gyri, in effortful visual and verbal creative thinking (Boccia, Piccardi, Palermo, Nori, & Palmiero, 2015). These regions are involved in error detection, response selection, inhibitory control, and working memory (a strong executive correlate to inhibitory control; Boccia et al., 2015; Diamond et al., 2013), suggesting that the ability to engage controlled cognitive processes may be imperative for successful creative ideation. Though it is well-established that habituated mental sets are not conducive to divergent thinking, such mental sets may be inhibited by controlled executive processes, which strategically guide memory retrieval in search of original ideas (Beaty, Silvia, Nusbaum, Jauk, & Benedek, 2014b; Benedek, Franz, Heene, & Neubauer, 2012).

While executive control network regions tend to be involved in controlled cognitive processes, such as attention regulation and selection of candidate responses that satisfy task demands (Beaty, Benedek, Kaufman, & Silvia, 2015; Beaty et al., 2016; Shen et al., 2020; Spreng, Stevens, Chamberlain, Gilmore, & Schacter, 2010), default network regions are often recruited during spontaneous semantic processing, internally oriented mentation, self-generated thought, and visual creative thinking (De Pisapia, Bacci, Parrott, & Melcher, 2016; Pidgeon et al., 2016; Vatansever, Menon, & Stamatakis, 2017; Zhu et al., 2017). Stronger large-scale brain network interactions between the default network and executive control network have been observed during constrained idea generation (i.e., generating novel verb associates for studied nouns included in an earlier noun-verb associate memory task), compared to less

constrained ideation (i.e., generating novel verbs for new, unstudied nouns; Beaty et al., 2017). This network convergence may therefore be one mechanism underlying effortful rerouting of memory search and retrieval processes (Krieger-Redwood et al., 2016) away from spontaneously activated, known concepts, and toward controlled reconstruction of original ideas (Beaty et al., 2015; Beaty, Thakral, Madore, Benedek, & Schacter, 2018; Benedek & Fink, 2019; Schacter et al., 2012). Therefore, as constraints are incorporated into the problem-space, the requirement for executive control over spontaneous cognitive processes may also be greater to curb conceptual interference.

Recent creativity research has employed representational similarity analysis (RSA) methods to compare neural representation patterns within brain regions between different cognitive tasks (Beaty et al., 2020; Ren et al., 2020). RSA is a multivariate technique that models multi-voxel *patterns* of brain activity across cognitive tasks – for example, comparing the similarity of voxel patterns during memory encoding to voxel patterns during memory retrieval (Kriegeskorte, Mur, & Bandettini, 2008) – extending conventional fMRI analysis that typically models univariate activation of voxel clusters. In one study on divergent thinking, greater neural pattern similarity was identified in the angular gyrus and posterior cingulate cortex regions of the default network between divergent thinking and a semantic (compared to an episodic) induction task, highlighting the involvement of semantic processing and associative combination in creative cognition (Beaty et al., 2020).

Other work using RSA examined the neural mechanisms for constructing novel and useful concepts in creative cognition (Ren et al., 2020). Neural patterns were less similar in the middle temporal gyrus between baseline evaluation of familiar, useful object images (e.g., a picture of a pot lid to use while cooking) and evaluation of novel, useful objects (e.g., a picture of an adapted lid, standing upright on a table to prevent contamination), compared to evaluation of familiar, useful objects and novel, useless objects (a picture of a pot lid riddled with holes). Middle temporal gyrus connections to the hippocampus subserved goal-relevant novelty processing, and connections to executive control regions corresponded with successful inhibition of prepotent associates (Ren et al., 2020). Overall, these findings are consistent with other work implicating the middle temporal gyrus in the cognitive process of meaningful, task-relevant concept formation (Karalyn, Nestor, & Rogers, 2007; Tranel, Kemmerer, Adolphs, Damasio, & Damasio, 2003), and may also

suggest that constructing novel associations is reinforced as ordinary concepts are detected and suppressed (Ren et al., 2020). Taken together, different representational patterns of neural activations associated with familiarity discrimination and novelty processing, as well as the unique roles of associative memory and executive function, underscore the importance of using prior knowledge in an adaptive way to offset constraints during creative thinking.

The present research

Although a substantial body of research has shown that visual examples prompt fixation in creative thinking tasks, the neurocognitive mechanisms underlying visual creative constraints are unclear. In the present experiment, we examined visual creative constraints by investigating the impact of fixation on neural activations within visual association regions underlying *object recognition*. We focused on the object recognition system because of its theoretical relevance to fixation: activating a conceptual representation via object recognition may constrain subsequent divergent imagination to the extent that the initial representation "sticks" in mind when generating ideas. During fMRI, participants first viewed images (ambiguous line drawings) and corresponding labels that varied in degree of similarity (high constraint labels resembled the line drawing, while low constraint labels did not); then, the label disappeared, and participants were asked to imagine new, creative labels (cf. Lloyd-Cox et al., 2020).

At the behavioral level, we predicted that high-constraint images would render conceptual knowledge more salient and thus constrain creative imagination. At the neural level, we predicted greater neural pattern similarity in the high-constraint condition, relative to the low-constraint condition. Multivariate RSA (Kriegeskorte et al., 2008) was employed to examine whether neural patterns activated from initial visual object recognition to subsequent creative imagination were similar or dissimilar depending on constraints induced by the experimental manipulations (high versus low). Broadly, this project aimed to advance understanding of the neurocognitive mechanisms of fixation during creative cognition.

Methods

Participants

Thirty-four right-handed adult participants were recruited from The University of North Carolina at Greensboro (UNCG). The experimental procedure

was approved by the UNCG ethics committee and all participants provided written informed consent prior to data collection. Two participants were excluded from analyses due to excessive head motion while in the scanner (> 3 mm across all runs). Therefore, the final sample consisted of 32 individuals (67.7% women, M_{age} = 22.61, SD = 7.14) with normal, or corrected-to-normal, vision and no self-reported history of neurological disorder or use of psychotropic medications.

Experimental protocol

The fMRI experiment included two phases: visual object recognition (high-constraint or low-constraint; Phase 1) and shape identification or imagination (Phase 2). The phases were presented consecutively, with Phase 1 serving as a "priming" manipulation for Phase 2 (see Figure 1).

Phase 1: visual object recognition

Participants were given four seconds to rate how well a label related to an incomplete figure stimulus. Labels were rated on a scale of 1 = *not at all related* to 4 = *highly related*. For all trials, participants were instructed to "imagine the figure as its label" when rating the relatedness of labeled figures. All 54 incomplete figures and labels selected for this task were used in previous research (see Lloyd-Cox et al., 2020), including figural stimuli from the Torrance Test (Torrance, 1965) and the Test of Creative Imagery Abilities (Jankowska & Karwowski, 2015). Label-figure pairs were prespecified as *related* (high-constraint; i.e., ≥20% of English-speaking MTurk pilot participants generated the same label for the figure), or *unrelated* (low-constraint; i.e., related labels from other figures were randomly paired with an alternative incomplete figure, with dissimilarity further confirmed by the research team). Each trial was separated by an interstimulus interval (4–6s). For a complete description of stimuli selection, see Lloyd-Cox et al. (2020), but note that original data was collected for this experiment.
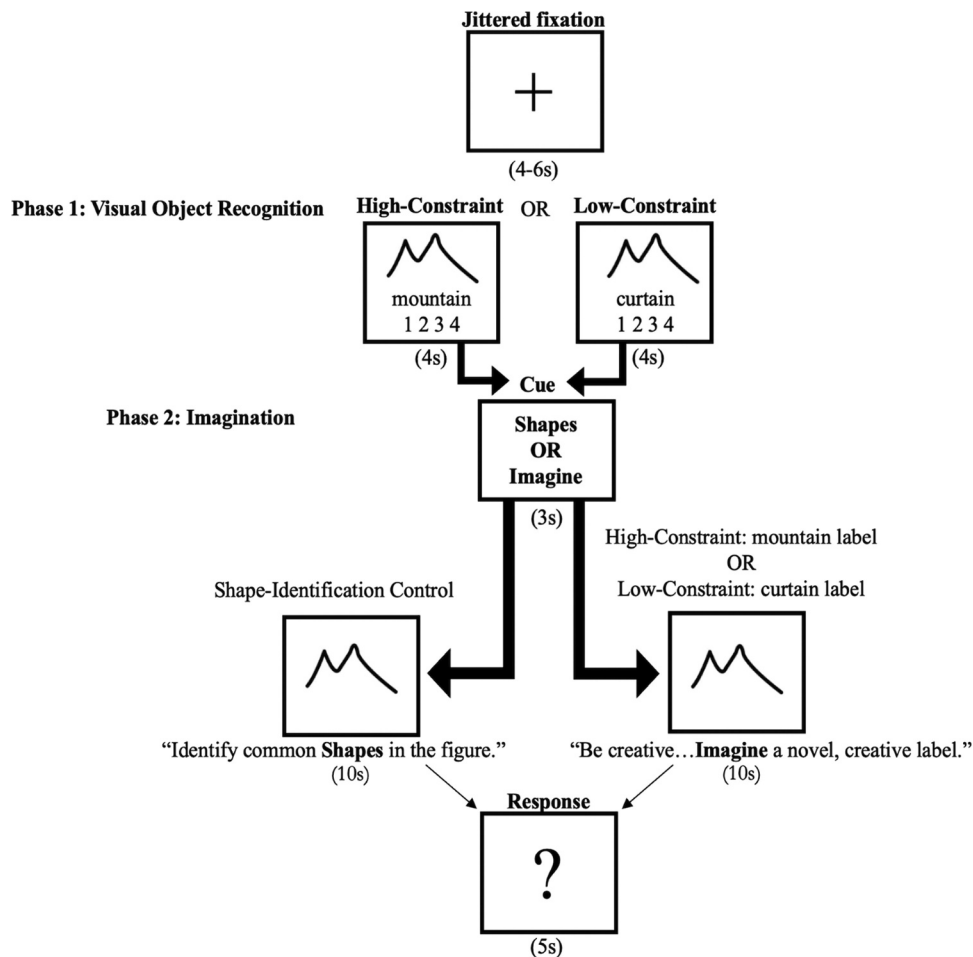

Figure 1. Schematic description of the study design.

Participants used a Cedrus LSC-400B (San Pedro, California) four-button response box to rate incomplete figure labels. For all trials, black-and-white visual stimuli were presented via E-Prime software on a PC laptop computer. Text labels were always positioned underneath incomplete figures. 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.

Phase 2: imagination

In a subsequent phase, immediately following the label-rating phase, participants were first shown the task cue "Imagine" or "Shapes" for three seconds. "Imagine" experimental trials (36) were equally divided into two experimental conditions, in which participants were explicitly instructed to "be creative," and were given ten seconds to generate creative labels for unlabeled incomplete figures from Phase 1 (Nusbaum, Silvia, & Beaty, 2014; Said-Metwaly, Fernández-Castilla, Kyndt, & Van Den Noortgate, 2019). "Shapes" trials (18) were included as a shape-identification control condition, where participants were given ten seconds to identify common shapes present in the unlabeled/incomplete figures from Phase 1. Though beyond the scope of the present experiment, the shape-identification control condition was included to permit a separate activation analysis.

Additionally, the Imagine condition was further subdivided into "high-constraint" and "low-constraint" trials (equally balanced with the number of control trials). We predicted that the 18 high-constraint trials would induce fixation because incomplete figure stimuli had been paired with related labels in Phase 1. That is, we hypothesized that to successfully generate new, creative labels for figures in Phase 2, participants may need to override conceptual representations stimulated by high-constraint trials (Benedek, Christensen, Fink, & Beaty, 2019). In contrast, we predicted that the 18 low-constraint trials would be unlikely to induce conceptual fixation because incomplete figures had been paired with unrelated labels in Phase 1 (cf. Lloyd-Cox et al., 2020). For both high and low-constraint trials, participants were encouraged to "mentally manipulate the figure" (e.g., modify, expand on, elaborate, etc.) as they thought of creative labels. After the 10 second creative imagination experimental period, or shape-identification control period, participants were given five seconds to speak their responses into an MRI- compatible microphone (Optoacoustics; Mazor, Israel; www.optoacoustics.com).

Brain image acquisition and preprocessing

A 3-T Siemens Magnetom MRI system (Siemens Medical Systems, Erlangen, Germany) was equipped with a 16-channel head coil and used to acquire whole-brain images. A high-resolution T1 scan was acquired for anatomical normalization. Blood-oxygen-level dependent (BOLD)-sensitive T2*-weighted functional images were obtained using interleaved slice-ordering acquisition, with a single shot gradient-echo EPI pulse sequence, a 2000-ms repetition time, a 30-msec echo time, a 192 × 192 mm field of view, a 78° flip angle, 32 axial slices, 3.5 × 3.5 × 4.0 mm, and a distance factor of 0%. All functional images were corrected online for head motion, with the first two acquired volumes removed for T1 equilibration.

Anatomical data preprocessing

Results included in this manuscript come from preprocessing performed using *fMRIPrep* 1.4.1rc1 (Esteban et al. (2018); Esteban, Blair, et al. (2018); RRID: SCR_016216), which is based on *Nipype* 1.2.0 (Gorgolewski et al. (2011); Gorgolewski et al. (2018); RRID:SCR_002502). The T1-weighted (T1w) image was corrected for intensity non-uniformity (INU) with N4BiasFieldCorrection (Tustison et al., 2010), distributed with ANTs 2.2.0 (Avants, Epstein, Grossman, & Gee, 2008, RRID:SCR_004757), and used as T1w-reference throughout the workflow. The T1w-reference was then skull-stripped with a Nipype implementation of the antsBrainExtraction.sh workflow (from ANTs), using OASIS30ANTs as target template. Brain tissue segmentation of cerebrospinal fluid (CSF), white-matter (WM) and gray-matter (GM) was performed on the brain-extracted T1w using fast (FSL 5.0.9, RRID: SCR_002823, Zhang, Brady, and Smith Zhang, Brady, & Smith, 2001). Brain surfaces were reconstructed using recon-all (FreeSurfer 6.0.1, RRID:SCR_001847, Dale, Fischl, and Sereno Fischl, Sereno, & Dale, 1999), and the brain mask estimated previously was refined with a custom variation of the method to reconcile ANTs-derived and FreeSurfer-derived segmentations of the cortical gray-matter of Mindboggle (RRID: SCR_002438, Klein et al. Klein et al., 2017). Volume-based spatial normalization to one standard space (MNI152NLin2009cAsym) was performed through nonlinear registration with antsRegistration (ANTs 2.2.0), using brain-extracted versions of both T1w reference and the T1w template. The following template was selected for spatial normalization: ICBM 152 Nonlinear Asymmetrical template version 2009 c [Fonov, Evans,

McKinstry, Almli, and Collins (2009), RRID: SCR_008796; TemplateFlow ID: MNI152NLin2009 cAsym].

Functional data preprocessing

The following preprocessing was performed for the single BOLD run completed per subject. First, a reference volume and its skull-stripped version were generated using a custom methodology of fMRIPrep. The BOLD reference was then co-registered to the T1w reference using bbregister (FreeSurfer) which implements boundary-based registration (Greve & Fischl, 2009). Co-registration was configured with nine degrees of freedom to account for distortions remaining in the BOLD reference. Head-motion parameters with respect to the BOLD reference (transformation matrices, and six corresponding rotation and translation parameters) were estimated before any spatiotemporal filtering using mcflirt (FSL 5.0.9, Jenkinson, Bannister, Brady, & Smith, 2002). BOLD runs were slice-time corrected using 3dTshift from AFNI 20160207 (Cox & Hyde, 1997). The BOLD time-series were resampled to surfaces on the following spaces: fsaverage5. The BOLD time-series (including slice-timing correction when applied) were resampled onto their original, native space by applying a single, composite transform to correct for head-motion and susceptibility distortions. These resampled BOLD time-series will be referred to as preprocessed BOLD in original space, or just preprocessed BOLD. The BOLD time-series were resampled into standard space, generating a preprocessed BOLD run in ['MNI152NLin2009cAsym'] space. First, a reference volume and its skull-stripped version were generated using a custom methodology of fMRIPrep.

Several confounding time-series were calculated based on the preprocessed BOLD: framewise displacement (FD), DVARS and three region-wise global signals. FD and DVARS are calculated for each functional run, both using their implementations in Nipype (following the definitions by Power et al., 2014). The three global signals are extracted within the CSF, the WM, and the whole-brain masks. The head-motion estimates calculated in the correction step were also placed within the corresponding confounds file. The confound time series derived from head motion estimates and global signals were expanded with the inclusion of temporal derivatives and quadratic terms for each (Satterthwaite et al., 2013). Frames that exceeded a threshold of 0.5 mm FD or 1.5 standardized DVARS were annotated as motion outliers. All re-samplings can be performed with a single interpolation step by composing all the pertinent transformations (i.e., head-motion transform matrices, susceptibility distortion correction when available, and co-registrations to anatomical and output spaces). Gridded (volumetric) re-samplings were performed using antsApplyTransforms (ANTs), configured with Lanczos interpolation to minimize the smoothing effects of other kernels (Lanczos, 1964). Non-gridded (surface) re-samplings were performed using mri_vol2surf (FreeSurfer).

Semantic distance analyses

For all analyses statistical significance was set at $p < .05$. Behavioral analyses were conducted in R (version 3.6.0; R Core Team, 2019) and RStudio (v.1.2.1335; www.rstudio.com; RStudioTeam, 2019). To evaluate the novelty of labels generated during the Imagine condition, average semantic distance values were computed using the open, automated scoring platform SemDis semdis.wlu.psu.edu; (Beaty & Johnson, 2021). Prior to SemDis analysis, participants' generated labels were screened by a member of the research team who cleaned the data for spelling errors, inappropriate responses, and responses containing the incomplete figure label shown in Phase 1. For example, if a stimulus image was accompanied with the label "table" in Phase 1, and the participant responded "table" during the Imagine condition in Phase 2, a valid semantic distance score could not be rendered using SemDis (i.e., zero distance), thus any repeated label words were manually removed from responses.

Average semantic distance scores were computed via the additive compositional model, which combines word vectors within a response to form a single vector (Mitchell & Lapata, 2010). We specifically compared how distantly-associated each participant's newly generated label was from the initial high-constraint (18 trials) and low-constraint labels (18 trials) shown in Phase 1. Higher average semantic distance values represent more creative responses (i.e., more distantly associated with the Phase 1 label; Beaty & Johnson, 2021). Thus, 36 average semantic distance scores were computed for each individual (18 high-constraint and 18 low-constraint values). Next, we conducted paired samples t-tests to compare whether average semantic distance values differed between the high- and low-constraint trials.

Representational similarity analyses

To compare neural patterns during the object recognition and imagination conditions, we used RSA. Here, we evaluated whether cognitive states were similar between object recognition (label rating in Phase 1) and novel label generation in the Imagine condition (further classified into high-constraint and low-constraint trials). We predicted that object recognition regions would be recruited when participants judged the relatedness of labels to incomplete figures in Phase 1, and that these "object recognition" neural representations could be detected during the subsequent imagination period – and more so for the high constraint condition compared to the low constraint condition. We thus operationalized fixation/constraint at the neural level by examining whether high-constraint neural representations "stick in mind" during subsequent imagination.

Given these *a priori* predictions, we entered the search term "object recognition" (Yarkoni, Poldrack, Nichols, Van Essen, & Wager, 2011) into the Neurosynth database (http://neurosynth.org). This approach meta-analyzes relevant neuroimaging studies to create an object recognition mask for download and subsequent analysis. In total, 17 ROIs were derived from this Neurosynth mask using xjView (http://www.alivelearn.net/xjview/xjview97/) for anatomical localization and labeling. Three of the 17 ROIs were removed due to high possibility of yielding a false positive (< 5 voxel extent threshold; Woo, Krishnan, & Wager, 2014) – therefore, 14 ROIs were retained for subsequent analyses (see Table 1 and Figure 2).

To estimate neural activity associated with individual trials, we ran separate general linear models defining one regressor for each trial at object recognition (Phase 1) and imagination (Phase 2) in SPM12. Six additional

Table 1. Object recognition regions of interest.

Region of Interest (ROI)	H	X	Y	Z	k
		MNI Coordinates		
Calcarine fissure and surrounding cortex	R	14	−100	−4	11
Cerebellum	L	−52	−46	−42	14
Fusiform gyrus	L	−14	−4	−44	21
Fusiform gyrus	L	−40	−48	−22	162
Fusiform gyrus	R	44	−46	−26	217
Inferior occipital gyrus	L	−38	−78	−8	369
Inferior temporal gyrus	L	−34	−6	−48	57
*Inferior temporal gyrus	L	−40	−26	−28	5
Inferior temporal gyrus	R	52	−66	−14	675
Middle occipital gyrus	L	−24	−80	36	6
Middle temporal gyrus	R	52	−24	−18	5
Superior occipital gyrus	R	30	−80	34	17
Superior parietal gyrus	L	−24	−74	44	5
Postcentral gyrus	L	−40	−42	58	19
Postcentral gyrus	R	30	−42	74	9
*Temporal pole: middle temporal gyrus	L	−20	18	−36	7
*Ventral anterior cingulate	L	−4	8	−30	10

Note. H = hemisphere: L = left; R = right; MNI coordinates: X, Y, and Z represent peak MNI; k indicates cluster extent; * ROIs not retained for analyses.
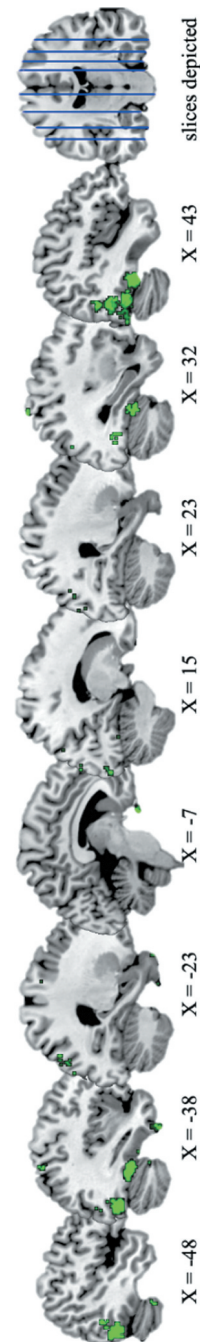

Figure 2. Regions in object recognition mask downloaded from the neurosynth database (green). 14 regions from this mask were retained for analysis.

nuisance regressors were included in each run corresponding to motion (x, y, z, pitch, roll, and yaw). Whole-brain parameter maps were generated for each trial at each phase for all participants. In any given parameter map, the value in each voxel represents the regression coefficient for that trial's regressor in a multiple regression containing all other trials in the run and motion parameters. These beta parameter maps were next concatenated across runs and submitted to custom-coded scripts using the CoSMoMVPA toolbox (Oosterhof, Connolly, & Haxby, 2016) for pattern similarity analysis.

To examine whether constraint level (high vs. low) influenced the similarity of representations, we directly compared neural patterns of activation between Phase 1 and Phase 2. Given our *a priori* hypothesis that constraint level would impact neural similarity, low- and high-constraint conditions were analyzed separately. Specifically, beta estimates extracted from the single trial models described above for each individual trial for a given condition during label rating were correlated with every trial of the same type during imagination (e.g., objects during label rating that were considered high-constraint were correlated with all high-constraint objects presented during the imagination phase). This resulted in neural similarity scores, as operationalized by Pearson's *r* correlation values, for each trial. The correlations were then transformed to Fisher's *z*, averaged within condition, and converted back to Pearson's correlations for each participant. Group-level results were generated from averaging within-condition similarity across all participants.

Results

Semantic distance

First, we examined the occurrence of extreme outliers for average semantic distance (Q1 – 3 * IQR or Q3 + 3 * IQR) in the Imagine condition, with no outliers detected. Paired-samples *t*-tests were then conducted to evaluate the difference between average ratings for how related the assigned labels were to the incomplete figures for high-constraint and low-constraint trials, average response times for those ratings, and average semantic distance of novel labels generated for the high-constraint and low-constraint experimental trials. The average relatedness ratings for the high-constraint condition ($M = 3.58$, $SD = 0.73$) were significantly higher, $t(1107) = 46.41$, $p < .001$, $d = 2.78$, than the low constraint condition ($M = 1.42$, $SD = 0.81$). Participants were significantly faster, $t(1107) = -10.64$, $p < .001$, $d = 0.64$, when rating the relatedness of the high-constraint label ($M = 1863.40$ ms, $SD = 600.42$ ms) compared to the low-constraint label ($M = 2276.10$ ms, $SD = 690.00$ ms). For semantic distance of generated labels, results revealed that, in the Imagine condition, average semantic distance was *lower* on high-constraint trials ($M = 0.876$, $SD = 0.02$) compared to low-constraint trials ($M = 0.894$, $SD = 0.016$). The difference in average semantic distance between trial types was statistically significant, $t(31) = -3.877$, $p < .001$, Cohen's $d = 0.68$ (see Figure 3).
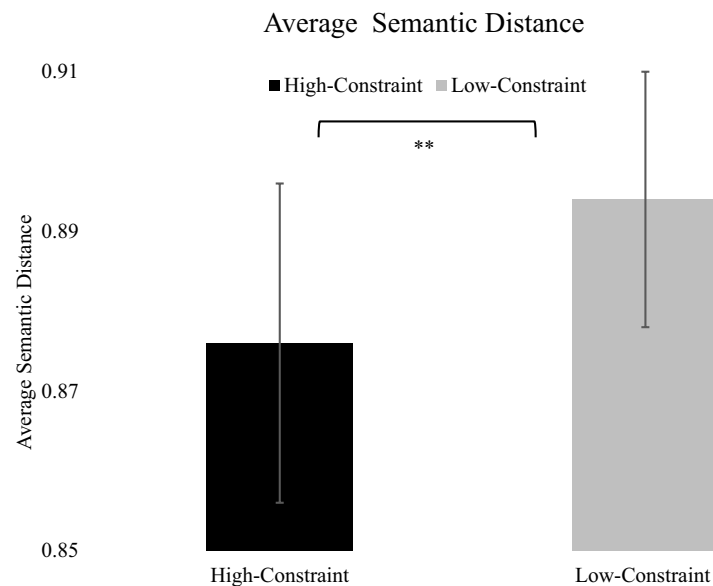
Average Semantic Distance

Figure 3. Average semantic distance scores. *Note.* Figure 3. displays the average semantic distance performance in the high and low-constraint trials (error bars represent standard deviation); ** = $p < .001$.

Table 2. Descriptive statistics for neural similarity in the imagine condition.

| ROI | H | Imagine Condition Trial Type | |
		High Constraint Trials M(SD)	Low Constraint Trials M(SD)
Calcarine fissure	R	−0.001(0.03)	−0.006(0.02)
Cerebellum	L	−0.007(0.04)	−0.023(0.04)
Fusiform gyrus	L	−0.042(0.06)	−0.022(0.03)
Fusiform gyrus	L	−0.012(0.01)	−0.008(0.01)
Fusiform gyrus	R	−0.016(0.02)	−0.008(0.01)
Inferior occipital gyrus	L	−0.008(0.02)	−0.009(0.01)
Inferior temporal gyrus	L	−0.017(0.01)	−0.015(0.02)
Inferior temporal gyrus	R	−0.012(0.01)	−0.005(0.01)
Middle occipital gyrus	L	−0.011(0.04)	0.004(0.03)
Middle temporal gyrus	R	−0.025(0.02)	0.001(0.03)
Postcentral gyrus	L	−0.01(0.02)	−0.003(0.02)
Postcentral gyrus	R	−0.009(0.03)	−0.022(0.02)
Superior occipital gyrus	R	−0.011(0.02)	−0.002(0.02)
Superior parietal gyrus	L	−0.016(0.03)	−0.004(0.03)

Note. ROI = region of interest; H = hemisphere; R = right; L = left; M = mean; SD = standard deviation

Neural pattern similarity

First, we examined the occurrence of extreme outliers for neural pattern similarity (Q1 – 3 * IQR or Q3 + 3 * IQR) across each ROI. Participants were excluded from subsequent analyses if they met outlier criteria. Thus, reduced degrees of freedom in several of the ROI models are indicative of outlier exclusion and/or missing data for neural similarity. Descriptive statistics for neural pattern similarity across the 14 retained ROIs, with outliers excluded, are displayed in Table 2.

We next conducted paired-samples t-tests to examine differences in neural pattern similarity between object recognition (label rating in Phase 1) and novel label generation in the Imagine condition, separated by high-constraint and low-constraint trials.

Contrary to our predictions, we found that neural patterns were more anticorrelated (less similar) from object recognition to high-constraint imagination trials, relative to low-constraint imagination trials in three regions. Neural patterns were less similar from object recognition to high-constraint imagination trials ($X = -0.012$, SD = 0.01), relative to low-constraint imagination trials ($X = -0.005$, SD = 0.01) within the right inferior temporal gyrus. The difference in neural pattern similarity between the two trial types was statistically significant, $t(26) = -3.348$, $p = .002$, 95% confidence interval (CI) [−0.011, −0.003], Cohen's $d = 0.64$. Neural patterns were also less similar from object recognition to high-constraint imagination trials ($X = -0.025$, SD = 0.02), relative to low-constraint imagination trials ($X = 0.001$, SD = 0.03) within the right middle temporal gyrus. The difference in neural pattern similarity between the two trial types was statistically significant, $t(25) = -3.448$, $p = .002$, 95% CI [−0.041, −0.01], Cohen's $d = 0.68$. Lastly, neural patterns were less similar from object recognition to high-constraint imagination trials ($X = -0.011$, SD = 0.02) relative to low-constraint imagination trials ($X = -0.002$, SD = 0.02) in the right superior occipital gyrus. The difference in neural pattern similarity between the two trial types was statistically significant, $t(27) = -2.196$, $p = .04$, 95% CI [−0.018, −0.001], Cohen's $d = 0.42$ (see Figure 4). Differences in neural pattern similarity between the imagination trial types were not statistically significant for the remaining 11 ROI models (all ps > .05).

Discussion

The present research examined whether the induction of visual conceptual constraints influenced creative imagination and patterns of neural activity within brain regions associated with object recognition. While much experimental work has shown that viewing example images tends to compromise creative thinking (Chrysikou et al., 2016; Chrysikou & Weisberg, 2005; Dahl & Moreau, 2002; Fink et al., 2010, 2012; Jansson & Smith, 1991; Smith et al., 1993; Ward, 1994; Ward et al., 2004), the neurocognitive mechanisms underlying visual fixation in creative cognition are poorly understood. Behaviorally, participants' newly generated incomplete figure labels were of lower average semantic distance (i.e., less creative) following exposure to high-constraint, related labels, relative to low-constraint, unrelated labels.

Manipulating constraint level also impacted neural patterns underlying conceptual representations. Specifically, using RSA to compare neural pattern similarity from visual object recognition in Phase 1 to subsequent creative label imagination in Phase 2, we found the relationship between phases to be negatively related (anticorrelated). Examining the specific impact of constraint condition on this relationship, we identified more
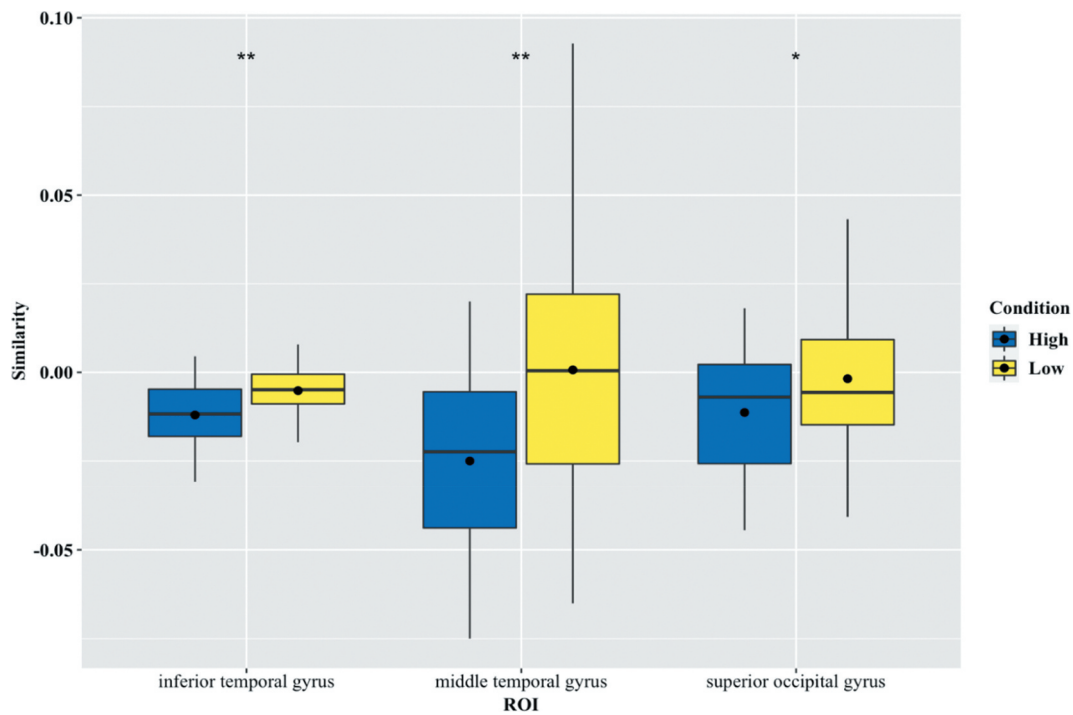
Figure 4. Differences in neural pattern similarity between high-constraint and low-Constraint trials. *Note.* **p < .001; *p < .05; = mean value; ROI = region of interest.

dissimilar neural patterns in the right inferior temporal gyrus, right middle temporal gyrus, and right superior occipital gyrus for high- compared to low-constraint trials. We will discuss and interpret each of these findings in the context of the broader literature in the following sections.

Consistent with our predictions, and the large body of related literature that has elucidated the fixating effects of visual exemplars (Boronat et al., 2005; Chainay & Humphreys, 2002; Chrysikou et al., 2016; Dahl & Moreau, 2002; Saffran et al., 2003; Ward, 1994), we found that examples constrained creative imagination. Overall, after viewing related labels paired with incomplete line drawings, new labels that participants generated for the same line drawings were less creative. Conversely, viewing unrelated labels did not negatively impact subsequent creative thinking relative to related labels. Showing participants related labels may have guided the formation of strong mental representations that disambiguated incomplete figure stimuli, but at a cost to creativity. Viewing labels that closely resembled incomplete figures may have primed a more "rigid" conceptual context, thereby preventing individuals from flexibly separating primed visual associations as they were attempting to produce their own creative labels (Lloyd-Cox et al., 2020; Marsh et al., 1996).

This explanation is aligned with work exploring functional fixedness. As previously described, visual examples may constrain creativity via promoting functional fixation on an object's attributes (Chrysikou et al., 2016; Duncker, 1945; Marsh et al., 1996; Smith et al., 1993). Because individuals have a propensity to solve problems using heuristic information (Borst, Aïte, & Houdé, 2015; Cassotti et al., 2016;, Houde & Borst, 2014), the activation of automatized mental representations via high-constraint visual examples (e.g., a "mountain" label assigned to the example image depicted in Figure 1) may have amplified fixation on information provided by proscriptive labels in this study. It is also possible that the significant neural pattern anticorrelations we observed in visual object recognition regions reflected cognitive processes involved in effortful conceptual expansion. Though we did not submit specific predictions regarding constraint-driven differences in neural pattern similarity from visual object recognition in Phase 1 to creative label imagination in Phase 2, our findings may be a preliminary step toward revealing neurocognitive signatures associated with effortfully changing strong mental representations of highly related stimuli in service of new, creative ideas – particularly at the early level of object recognition/representation in the ventral visual stream.

Compared to low-constraint trials, neural patterns were less similar from object recognition to creative label imagination in the right inferior and middle temporal gyri and superior occipital gyrus during high-constraint imagination trials. Inferior and middle temporal gyri are largely involved in both recognizing and classifying meaningful visual stimuli (Arkin, Przysinda, Pfeifer, Zeng, & Loui, 2019; Tanaka, 2001) as part of the "what" pathway of the ventral visual stream, which facilitates identifying objects' color, shape, and texture (Goodale & Milner, 1992; Milner & Goodale, 1993, 2008). The superior occipital gyrus is part of the "where" pathway of the dorsal visual stream, which enables processing objects' movement, position, and orientation (Galletti & Fattori, 2018). Together, the inferior and middle temporal gyri and superior occipital gyrus may have supported mental representation of visuospatial features (e.g., discrimination of object shape and direction; Rankin et al., 2007; Shi, Cao, Chen, Zhuang, & Qiu, 2017; Xu, 2009) during early object recognition in this experiment.

Notably, the inferior temporal gyrus is also encompassed within a larger divergent thinking network composed of frontal, parieto-temporal, and temporal regions (Gonen-Yaacovi et al., 2013; Perchtold et al., 2018). The middle temporal gyrus may subserve word production (Indefrey & Levelt, 2004), understanding language, and facilitating lexical-semantic retrieval and selection (Acheson, Hamidi, Binder, & Postle, 2011; Whitney, Kirk, O'Sullivan, Lambon Ralph, & Jefferies, 2011). This region also appears to play a prominent role in new concept construction, as well as meaning and novelty detection (Karalyn et al., 2007; Ren et al., 2020; Tranel et al., 2003). Related evidence suggests that right middle temporal gyrus activity may mediate the cognitive process of inhibiting distracting, obvious semantic associations during novel idea generation (Luft et al., 2018). Here, it is plausible that significant neural pattern anticorrelation outcomes may be associated with cognitive processes operating to change or restructure constraining mental representations (informed by visually recognizing and interpreting related label-figure pairs), to effectively develop task-appropriate, original ideas.

In the present study, we paired unrelated labels with incomplete figures in the low-constraint condition; therefore, changing early visual representations may have been a) less effortful, or b) unnecessary, if the conceptual link between the label and incomplete figure was not strongly formed. However, in the high-constraint condition, successfully imagining creative labels may have required avoiding the path of least resistance by changing one's mental representations of label-figure pairs to subvert salient conceptual knowledge. Although preliminary, it is possible that less dissimilar neural patterns may represent an effortful cognitive process of successfully adapting visual representations of stimuli to destabilize constraining information and permit the imagination of original responses. In contrast, greater dissimilarity may indicate stronger mental representations that are resistant to change.

Notably, we hypothesized that high-constraint neural patterns would be *more* similar (compared to low), reflecting the high-constraint object representation "sticking" in mind during subsequent generation. Contrary to our hypothesis, low-constraint neural patterns were indeed more similar between object recognition and generation. In hindsight, the results are consistent with the idea that neural patterns require less reorganization in the low-constraint condition, i.e., given that the image and label were not obviously related – and a strong association was not likely formed between the two (corresponding to activation of object recognition regions) – one might expect the neural patterns for "object recognition" and idea generation to be more similar. In the high-constraint condition, in contrast, neural patterns required greater restructuring during generation to override the salient activation of existing object representations. In other words, there is "more to change" in the initial object representation when subsequently imagining alternative labels, so the neural patterns should be more different from each other. This interpretation remains speculative and post hoc, however.

Another possibility is that, although evidence in the visual domain indicates that viewing example images may constrain creative divergent thinking (Chrysikou et al., 2016; Dahl & Moreau, 2002; George & Wiley, 2020; Jansson & Smith, 1991; Marsh et al., 1996; Smith et al., 1993; Ward et al., 2004), exposure to example images may provide a template for generating novel ideas. In the context of this experiment, perhaps high-constraint images were viewed as a clear starting-point for adaptive restructuring, relative to fuzzier low-constraint images. Currently, no experimental work has explicitly addressed this possibility; however, the Repeated Closed Figures Test, a classic task included in the Torrance Test of Creative Thinking battery (Torrance, 1990), presents repeating shapes (e.g., circles, triangles, etc.), from which participants must use their imaginations to overcome fixed structures and draw something new. Repeating shapes may therefore activate common knowledge and experience that constrains individuals from iterating beyond obvious responses, or these stimuli may represent a foundation that supports expansion of perspectives and novel ideas. We encourage future research to further examine neural mechanisms of fixation during visual tasks that involve creative imagination.

Limitations and future research directions

One limitation of this study is that we did not employ a baseline creative imagination task. Future research may benefit from the inclusion of a baseline, or control, creativity assessment prior to showing participants related or unrelated labels. This is because asking participants to imagine labels for incomplete images that have yet to be paired with any verbal identifier will offer an opportunity to measure *changes* in divergent thinking performance that are driven by conceptual interference. That is, a baseline comparison would help answer the directional question, "Do examples in the visual domain *impair* or *enhance* individuals' creative imagination performance?" A baseline task would also facilitate a fine-grained examination of individual differences in behavioral and neurocognitive responses to fixating example stimuli. Subsequent work may also consider using semantic distance with other scoring methods, such as subjective rater evaluations of creative quality, to offer additional analytic precision (Silvia et al., 2008). Another potential limitation is that, following the visual object recognition phase of the experiment, some participants in the low-constraint condition generated the common high-constraint labels. That is, the semantic distance from the low-constraint label to the response may have been higher, but not necessarily more creative, relative to the high-constraint label.

Once a constraining mental representation is stimulated, does the threat of fixation remain constant, or does successful cognitive control take time? We assessed the impact of visual creative constraints in a neuroimaging environment, which is essential for discovering neural mechanisms underlying conceptual interference, but the abbreviated nature of the assessment protocol (i.e., each trial lasted <30 seconds, from initial object recognition to creative label generation) may not fully capture the time course of constraint saliency. Complimentary behavioral research should examine whether the constraining effects of image-based examples degrade or persist over time, and continued work is also needed to investigate individual differences (such as personality, intelligence, attention, etc.), which may regulate the lability of mental representations in the face of creative constraints.

Lastly, the present experiment took an innovative, yet exploratory approach to identifying patterns of neural activation that emerge under visual conceptual constraints. We evaluated creative cognition using visual stimuli; however, our paradigm also included a verbal component (i.e., related/unrelated labels). A purely visual measure may provide a clarified understanding of how and when visual constraints impact creative thinking behavior and neural outcomes. For example, two images could be paired, with one pair prespecified as highly related and the other unrelated. Consider the image depicted in Figure 1. Researchers may couple this figure with a related image containing similar angles or line orientations, or an unrelated image that is more curved, composed of disconnected lines. Researchers may also consider presenting a related, complete version of the stimulus image with no label (e.g., a full drawing of a mountain), or a complete version of a different, unrelated image. Next, participants would draw their own creative figure. Participants could become fixated, replicating features of both images, irrespective of constraint level (see Smith et al., 1993; Ward et al., 2004), but variability in the unrelated image pairs could also facilitate conceptual combination that serves to connect information in original ways (Gick & Holyoak, 1983).

Conclusion

Findings from the present experiment indicated that manipulating conceptual interference in the visual domain impacted creative label imagination. Consistent with a wealth of prior research, we demonstrated that visual examples (i.e., related label-incomplete figure pairs) constrained creative idea generation, suggesting that salient conceptual stimuli may evoke strong mental representations of visual associations that are resistant to change. However, the ability to change or remove the cognitive imprint of fixating information may help individuals shift perspectives in order to think creatively (Cassotti et al., 2016). It is possible that less dissimilar neural patterns identified from object recognition to creative label imagination may represent attempts to change constraining mental representations in order to generate original responses. This preliminary evidence contributes to the body of work on fixation in creative cognition as this is the first experiment to identify differences in neural pattern similarity as one potential mechanism underlying the impact of conceptual constraints on creative thinking. From this foundation, continued empirical efforts are needed to further our understanding of the neurocognitive bases of visual fixation in creative thinking. Extending this line of inquiry will also contribute to the larger goal of identifying strategies to overcome constraints and enhance creative cognition.

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