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Title: The human brain's intrinsic network architecture is organized to represent diverse cognitive task information

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Abstract

A set of distributed cognitive control networks are known to contribute to diverse cognitive demands, yet it is unclear how these networks gain this domain-general capacity. We hypothesized that this capacity is largely due to the particular organization of the human brain's intrinsic network architecture. Specifically, we tested the possibility that each brain region's domain generality is reflected in its level of global (hub-like) intrinsic connectivity, as well as its particular global connectivity topography. Consistent with prior work, we found that cognitive control networks exhibited domain generality, as they represented diverse task context information covering sensory, motor response, and logic rule domains. Supporting our hypothesis, we found that the level of global intrinsic connectivity (as estimated with task-free fMRI) was correlated with domain generality during tasks. Further, using a novel information fingerprint mapping approach, we found that each brain region's unique cognitive rule response profile could be predicted based on its unique intrinsic connectivity pattern. Together these results suggest that the human brain's intrinsic network architecture supports its ability to represent diverse cognitive task information, largely via the placement of cognitive control networks within the brain's global network organization.

Keywords: Cognitive control, domain general, fMRI, information fingerprint, rule representation

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Introduction

Cognitive control processes allow individuals to intentionally select thoughts and behaviors according to current goals. These processes are particularly important in situations when previously learned rules need to be applied in novel situations. This ability to transfer rules from one context and apply them in a new situation greatly increases cognitive flexibility. Rapid instructed task learning (RITL) is a cognitive ability that has been successfully used to study cognitive control that requires especially flexible cognitive processes (Cole, Laurent, et al., 2013; Liefooghe et al., 2013; Pereg & Meiran, 2019; Ruge et al., 2019). These cognitive control processes are supported by specialized large-scale brain networks (Cole & Schneider, 2007; Niendam et al., 2012), which are thought to contribute to the ability to direct cognition in a goal-directed manner by flexibly reconfiguring domain-specific (e.g., sensory and motor) neural systems (Cole et al., 2017; Cole, Reynolds, et al., 2013; Desimone & Duncan, 1995; Miller & Cohen, 2001; Schneider, 2003).

Historically, there has been a debate between theories emphasizing the localization of brain function and those that emphasize a highly distributed organization in the brain. At the spatial scale of fMRI, evidence for cognitive control networks suggests many cognitive processes are neither fully distributed nor fully localized to a single brain region, since it appears cognitive control processes are distributed across regions within brain networks. Supporting this balanced localized-distributed perspective, it has been proposed that a multiple demand network exists that overlaps with the recently identified cognitive control networks. The proposal for a multiple demand network followed the observation of common patterns of activation during a variety of cognitive tasks including: auditory discrimination, visual divided attention, self-paced response production, task switching, spatial problem solving, and semantic processing of words (Duncan, 2010; Duncan & Owen, 2000). These findings suggest that regions belonging to the multiple demand network are recruited under a large variety of cognitive processes, regardless of the modality of the stimuli or specific cognitive demand. Despite the common patterns of co-activation observed in the multiple demand network, subsequent research has suggested that this network is not homogenous (Camilleri et al., 2018). The multiple demand network can be split into several smaller cognitive control networks characterized by different cognitive specialization (Assem et al., 2020; Cole & Schneider, 2007; Yeo et al., 2015). This suggests that task rule representations show different patterns of localization, and that they aren't homogeneously distributed across regions composing the multiple demand network.

Multivariate activation patterns within cognitive control networks during task performance also provide results regarding the degree of distribution for task rule representations. A number of studies have found that rule identity can be decoded based on multivariate activation patterns, and that the most accurate decoding of these patterns tends to occur in cognitive control network regions (Cole et al., 2011; Pischedda et al., 2017; Reverberi, Görgen, et al., 2012; Reverberi, Gorgen, et al., 2012; Woolgar et al., 2011; Yeo et al., 2015). Electrophysiological studies in monkeys have also identified neurons that code for specific task rules, largely in prefrontal cortical regions (Asaad et al., 2000; Brincat et al., 2018; Wallis & Miller, 2003; White & Wise, 1999). These context-dependent neural representations may contribute to how cognitive control networks increase cognitive flexibility with flexible representations of information.

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Previous studies have shown that multivariate patterns of activation contain information, or can be used to decode rules, across three different domains in the concrete permuted rule operations (C-PRO) paradigm. The C-PRO paradigm consists of a large set of systematically related flexible control tasks (Cocuzza et al., 2020; Ito et al., 2017). We sought to replicate these results and expand on them by exploring how the brain's intrinsic network architecture contributes to diverse task rule representation. Previous studies have found support for both distributed and localized task rule representations in the human brain. This may reflect the possibility that task rule representation occurs on a continuum, from highly distributed to largely localized. We predicted that cognitive control brain regions would contain task rule representations, or task information, across a wide variety of rule domains, consistent with previous research supporting distributed rule representations across the multiple demand network. We also expected to observe a degree of localization in task rule representations. For example, we predicted task rule information largely localized to the motor cortex would be specific to motor rules.

While there is evidence for both localized and distributed rule representations in the brain, this study was designed to evaluate the degree of specialization of task rule representations. We also developed the novel hypothesis that patterns of information content in cognitive control regions could be used to predict patterns of information content in other brain regions by weighting patterns of information content by their unique whole-brain connectivity patterns. If task rule representations across the brain could be predicted based on intrinsic functional connectivity patterns, it would further support the hypothesis that global connectivity plays an important role in task rule representation. Together, these results would provide additional support for the hypothesis that cognitive control networks use their unique intrinsic functional connectivity patterns to integrate domain-specific representations so they can be coordinated for task performance when different combinations of rules are encountered, likely increasing the cognitive flexibility of the human brain.

Methods

Participants

Data were collected at the Rutgers University Brain Imaging Center (RUBIC). The participants were recruited from the Rutgers University-Newark campus and surrounding community. All procedures were approved by the Rutgers University-Newark Institutional Review Board and all participants provided informed consent. The sample consisted of data from 106 participants. Technical error or equipment malfunction during the scanning session resulted in removing six participants from the study. Out of the remaining 100 participants, 56 were female and 44 were male. Participants were between the ages of 18 and 38 (M = 22.24, SD = 4.07). Participants were all right-handed, had not been diagnosed with any psychiatric disorders, and met standard MRI safety criteria.

Behavioral Task

We used the C-PRO paradigm (Ito et al., 2017), which is a variant of the original permuted rule operations task (Cole, Bagic, et al., 2010). The C-PRO task combines specific task rules from three different rule domains (logical, sensory, and motor) to create sixty-four

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unique task sets (Figure 1). Each of the three different rule domains includes four specific rules (Logic: Both, Not Both, Either, Neither; Sensory: Red, Vertical, Constant, High Pitch; Motor: Left Index, Left Middle, Right Index, Right Middle). This task design allowed us to compare task rule information content across three different modalities while controlling for attention, arousal, sensory input, and motor output across tasks. Visual and auditory stimuli were presented simultaneously on each trial with the visual stimuli consisting of red or blue bars that were oriented either horizontal or vertical. The auditory stimuli were either high (3000 Hz) or low (300 Hz) tones that were presented continuously or non-continuously (beeping). Trials were structured as miniblocks. Each miniblock started by presenting instructions for 3925 ms. After the instructions there was a jittered delay that lasted between 1570 and 6280 ms. Three trials were presented. The duration of each trial was 2355 ms. The intertrial interval was 1570 ms. Following the last trial there was another jittered delay between 7850 and 12560 ms. The mean miniblock duration was 28,260 ms. Each of the sixty-four task set miniblocks were presented twice during the experiment, and the same task set was never presented consecutively.

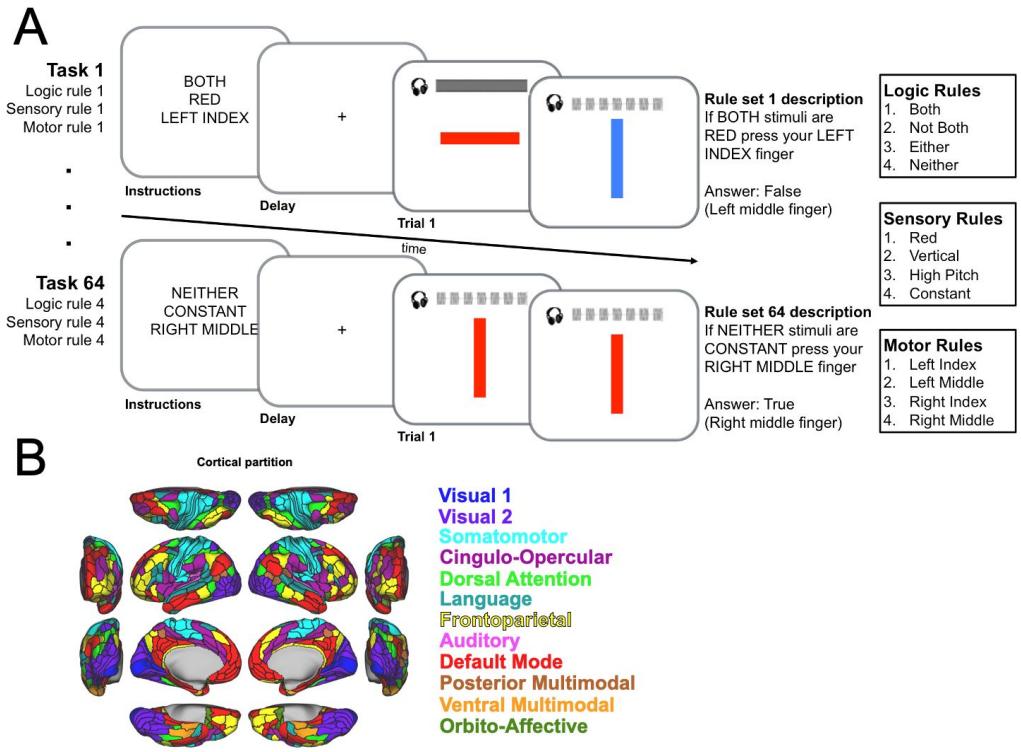

Figure 1. The Concrete Permuted Rule Operations cognitive paradigm and functional network assignments. (A) The cognitive paradigm combines specific task rules from three different rule domains (logical, sensory, and motor) to create sixty-four unique task sets. (B) Functional network assignment for brain regions based on (Ji et al., 2019).

MRI Parameters

Multiband whole-brain echo-planar imaging (EPI) data was collected using a 32-channel head coil on a 3T Siemens Trio MRI scanner with the following parameters: TR = 785 ms, TE = 34.8 ms, flip angle = 55°, Bandwidth 1924/Hz/Px, in-plane FoV read = 208 mm, 72 slices, 2.0 mm isotropic voxels, with a multiband acceleration factor of 8. Whole-brain high-resolution

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T1-weighted and T2-weighted anatomical scans with 0.8 mm isotropic voxels were also collected. Spin echo field maps were collected in both the anterior to posterior direction and the posterior to anterior direction consistent with the Human Connectome Project preprocessing pipelines (Glasser et al., 2013). Resting state fMRI was collected as described previously (Schultz et al., 2018). The resting state scan was 14 minutes in duration (1070 TRs). Eight runs of task fMRI data were collected while participants performed the C-PRO task. Each task run had a duration of 7 minutes and 36 seconds (581 TRs). Task runs were run sequentially with a short break between each run. A resting state scan was also collected prior to the task fMRI scans.

fMRI Preprocessing

We minimally preprocessed the fMRI data using the publicly available Human Connectome Project minimal preprocessing pipeline (version 3.5.0). This included anatomical reconstruction and segmentation, EPI reconstruction, segmentation, normalization to a standard template, intensity normalization, and motion correction (Glasser et al., 2013). Subsequent processing was conducted on CIFTI 64k gray ordinate space. A standard general linear model (GLM) was fit to the task time series with a convolved canonical hemodynamic response function from SPM using the sixty-four task sets as regressors. Task regressors represented the entire duration of each miniblock. We also included 12 motion parameters (6 motion estimates and their derivatives), mean signal from the ventricles and white matter (and their derivatives) which were defined anatomically via Freesurfer (Fischl et al., 2002) as nuisance regressors. Motion scrubbing as described by Power and colleagues (2012) was implemented with a frame-wise displacement threshold of 0.3 mm. Frame-wise displacement estimates were temporally filtered prior to thresholding to reduce the influence of respiration on FD estimates (Siegel et al., 2016). Resting state data was processed in the same way as task data with the exception of excluding the task based regressors. Functional connectivity was estimated by calculating Pearson's correlation of the mean timeseries for each pair of regions in the brain. Brain regions were defined by the Glasser et al. (2016) parcellation which consists of 360 cortical regions.

fMRI Data Analysis

Information estimates

Information estimates were computed for each brain region. The calculation of information estimates was conducted within each participant using a cross-validated multivariate pattern analysis. Task beta estimates were created for each vertex and for each of the sixty-four unique task sets. A representational analysis using a minimum-distance metric (using Pearson correlation as the distance measure) was then calculated for each of the 360 cortical regions. Information estimates were calculated on multiple levels (Mur et al., 2009). First, we calculated information estimates for each domain (Logic, Sensory, Motor). For each of the sixty-four task sets we calculated the similarity between the vertex-level pattern of activation with the vertex-level pattern of activation in the remaining sixty-three task sets that shared the rule of the domain being examined with a Spearman correlation (fifteen other task sets). Next we calculated the similarity between the vertex-level pattern of activation with the vertex-level

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pattern of activation for each of the sixty-three remaining tasks which did not share the rule of the domain being examined (we excluded the task sets that shared off-domain rules with the held out task set, 45 task sets). We calculated the mean similarity for task sets with shared rules and the mean similarity for task sets without a shared rule in the same domain. The mean of these values across the sixty-four task sets was calculated. Then we subtracted the non-shared rule similarity from the shared rule similarity. Thus, positive information estimates indicate that the vertex-wise pattern of activation is more similar to the vertex-wise pattern of activation for trials in which shared rules for each domain were present relative to the pattern of activation for trials in which non-shared rules for each domain were present. This results in an information estimate for each domain (Logic, Sensory, Motor) for each brain region. We used a similar procedure to calculate information estimates for each individual task rule. Rather than comparing all tasksets that shared any rule in a particular domain, we calculated the information estimates for only tasksets that shared a specific rule in each domain. This process results in an information estimate for each individual task rule for each brain region (Logic: Both, Not Both, Either, Neither; Sensory: Red, Vertical, Constant, High Pitch; Motor: Left Index, Left Middle, Right Index, Right Middle). Statistical comparisons were made for each region by using a *t*-test against zero. The p-values from these tests were corrected for multiple comparisons using permutation tests (Nichols & Holmes, 2002) and a FWE corrected threshold of $p < 0.05$ was used.

Information fingerprint mapping

Information fingerprints were defined for each brain region as the pattern of the information estimates for each of the 12 task rules. We used a modified version of activity flow mapping (Cole et al., 2016) to predict information fingerprints. For each participant we predicted the information estimate for each task rule by weighting the information estimate for every other region in the brain by the strength of the functional connectivity between the two regions. Importantly, the functional connectivity estimates were based on an independent resting state scan. After calculating the predicted information estimates, we combined the 12 individual task rule information estimates into information fingerprints and correlated the predicted information fingerprints with the actual information fingerprints. The resulting Pearson's r values were Fisher's Z transformed, and group statistical comparisons were made using a *t*-test against zero. The p-values from these tests were corrected for multiple comparisons using permutation tests and a FWE corrected threshold of $p < 0.05$ was used.

Results

Participants learned the C-PRO paradigm

Cross-subject average accuracy on the C-PRO task was 84.86%. Participants performed well above chance level performance (25%) on all 12 rules: Both (*M(SD)*, 91.2%(0.07%)); Either (89.1(0.09)); Neither (81.4(0.11)); Not Both (72.6(0.14)); Constant (78.2(0.15)); High Pitch (83.8(0.10)); Red (86.7(0.08)); Vertical (85.7(0.09)); Left Index (83.2(0.10)); Left Middle (84.0(0.10)); Right Index (83.5(0.10)); Right Middle (83.6(0.10)). No participants performed at less than chance level on any of the rules.

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Task domain information is present in numerous brain regions

We tested whether the activation pattern within any brain region contained information about each of the three task domains (Logic, Sensory, Motor). This allowed us to map task rule information and determine the degree of distribution for each rule. We calculated the information estimate for each region on each of the task domains.

The information estimate measure has previously been validated using a computational model and a portion of the same data analyzed here (Ito et al., 2017). Briefly, the information estimate compares the similarity in activation pattern (Pearson correlation) for a given task (e.g., Both, Red, Left Index) with the activation pattern from other tasks with a matching rule. That value is compared to the similarity in activation pattern between the same starting task (Both, Red, Left Index) and the activation pattern from the other tasks that do not share the same rule for each participant. An information estimate value greater than zero suggests that the pattern of activity for a particular rule is more similar to tasks that share a rule than it is for tasks that do not share a rule. If the information estimate value is significantly greater than zero we conclude that the activation pattern in that particular brain region contains information related to the rule.

First we tested whether brain regions contained general information about the three different modalities (Logic, Sensory, Motor). For example, a region contained information regarding the Logic rule domain if the pattern of activity was more similar on tasks that shared any Logic rule. We found that widespread regions of the brain contained information regarding the Logic and Sensory rules. We found that the brain regions containing information about the Motor rules were largely located in the somatomotor network, with several adjacent regions from other networks containing information (Figure 2).

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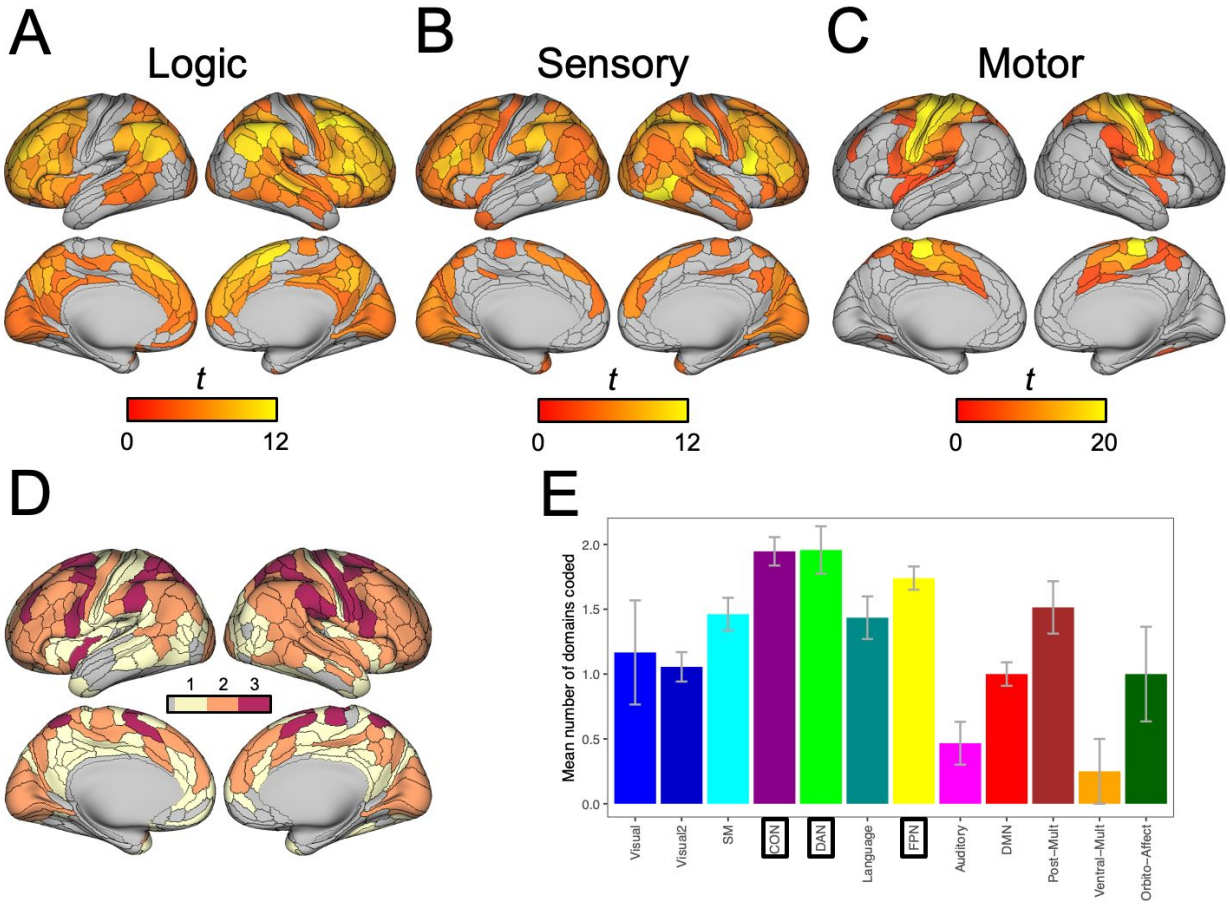

Figure 2. Brain regions contain information across content domains. Vertex activity within each brain region can be used to decode rules. (A) Widespread cortical regions from many networks contain information for the logic rules. (B) Significant sensory rule information is also evident in a large number of regions and many networks. (C) Sensorimotor network brain regions contain the most information for the motor rules. The degree of information content in the sensorimotor network is also greater than that observed in either the logic or sensory rules. (D) Conjunction between panels A, B, and C showing how many domains each brain region represents. (E) Summarizing the mean number of domains that are represented in each functional network. Cognitive control networks (marked by black boxes) contain information about the highest number of domains. Error bars indicate standard error.

Next, we used the same process to evaluate whether any brain regions contained information for each of the twelve individual rules (Both, Not Both, Either, Neither, High, Constant, Red, Vertical, Left Index, Left Middle, Right Index, Right Middle). For example, the similarity in the pattern of activation between a particular task (Both, Red, Left Index) and other tasks containing the Both rule relative to tasks containing other Logic rules. This resulted in twelve FWE-corrected maps, one for each individual rule (Figure 3).

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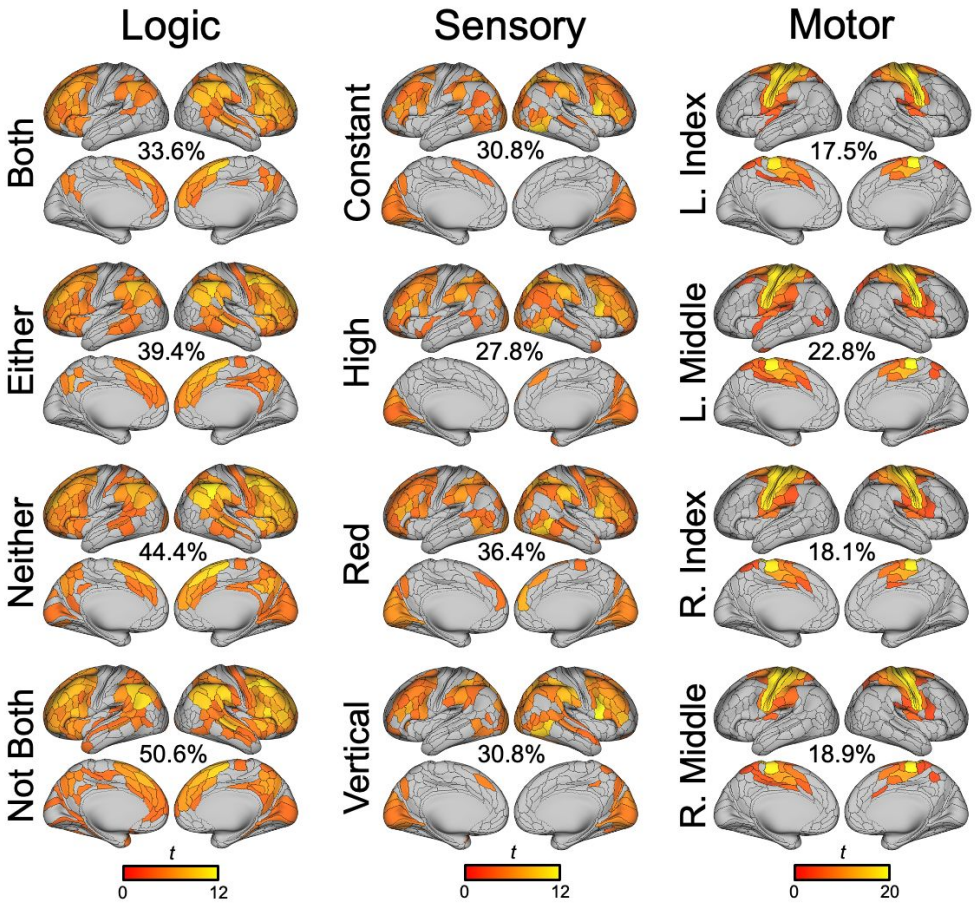

Figure 3. Information estimates for each of the individual rules are largely consistent within each modality. Significant information estimates (FWE corrected $p < 0.05$) are shown for each of the twelve rules. Each column represents a rule domain and rows are the four rule variants within each domain. The information estimates for each individual rule are also consistent with the more general information estimates calculated at the domain level. The percentage of cortical regions (out of 360) showing significant information estimates is provided for each rule.

Cognitive control networks contain domain general information

Next, we assessed whether any brain regions contained domain general information. The brain maps for each individual rule (Figure 3) were binarized, and if a brain region contained a significant degree of information (FWE-corrected) it was coded as a 1. If a brain region did not contain a significant degree of information it was coded as a 0. Then we determined the mean number of rules that were coded for each domain in each brain region. The mean across the three domains was calculated for each region providing an estimate of the degree of domain generality. A truly domain general brain region would contain information for all rules across all domains. Based on our metric this brain region would get a score of 4. A brain region that contained information about all four rules in one domain, but no rules in the other two domains would get a score of 1.33. We found that cognitive control networks (DAN, FPN, CON) had the largest values suggesting that they contained information from a wide

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variety of rules and domains (Figure 4). The cognitive control networks coded for a larger number of rules per domain than other brain regions, $t(358) = 3.61$, $p = 0.00035$.

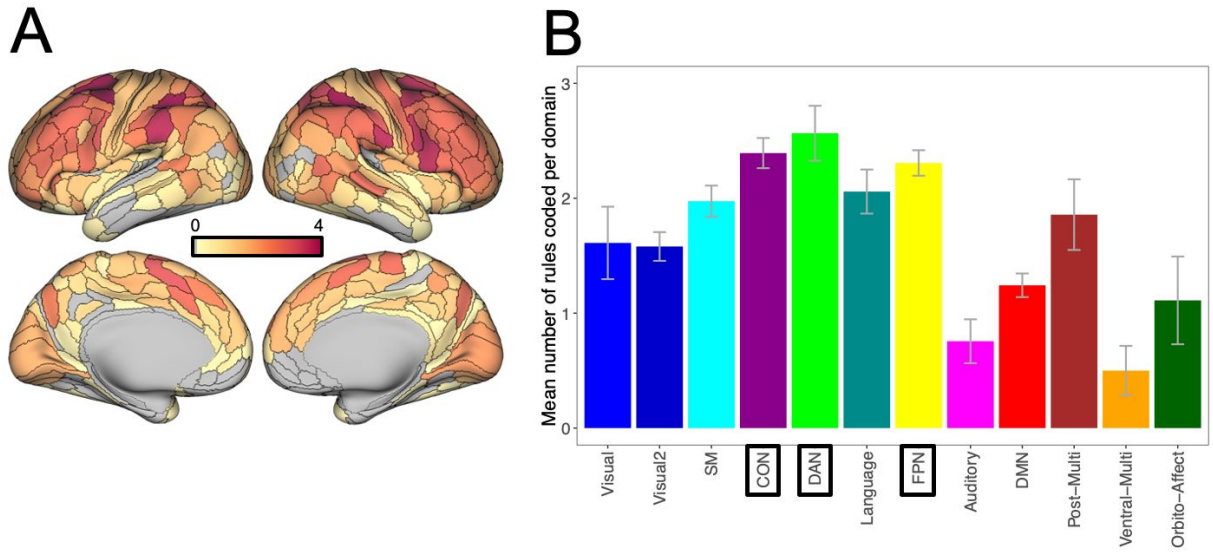

Figure 4. Cognitive control networks show domain general properties. (A) The mean number of rules coded across domains for each brain region. Brain regions colored in red contain information for all four rules in each domain. Brain regions depicted in white may only code for one specific rule in one particular domain. (B) Summarizing the mean number of rules coded per domain across the functional networks reveals that cognitive control networks (marked by black boxes) are domain general meaning they contain information for a larger number of rules than other brain networks. Error bars indicate standard error.

Mapping domain specific information

We next sought to contrast with domain generality, identifying brain regions that preferentially contained information for a specific rule modality. For each rule modality we identified brain regions that contained information for a larger number of rules than the remaining modalities. Within these regions we calculated the difference between the number of rules coded for the modality of interest and subtracted the mean number of rules coded of the remaining modalities. A larger number would indicate a greater imbalance in task rule information suggesting that the region preferentially contained task rule information pertaining to the modality of interest (Figure 5). Qualitatively, we found that the DMN contained domain specific information related to the Logic rules. We also observed that the visual and auditory networks contained domain specific information related to the Sensory rules. Additionally, the somatomotor network appeared to contain domain specific information related to the Motor rules.

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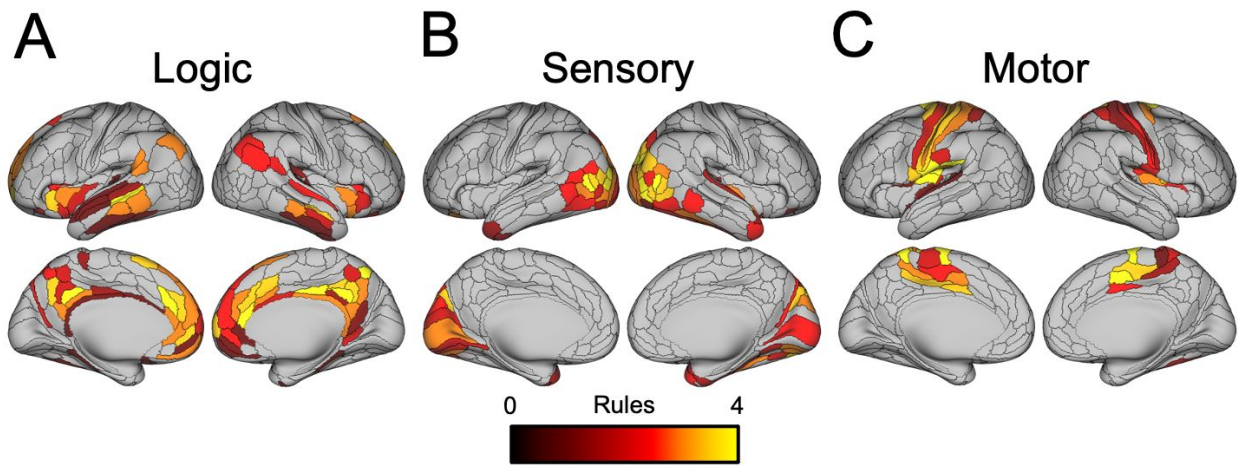

Figure 5. Some regions contain domain specific information. Panels reflect the difference of rules coded for each domain from the mean number of rules coded for the other two domains. (A) Some regions contain more information for the logic domain than the sensory and motor domains. Many of the regions containing logic domain specific information are in the DMN. (B) Some regions contain more information for the sensory rules than the logic and motor rules. The stimuli presented were visual and auditory. Domain specific information for the sensory rules is primarily located in the visual and auditory networks. (C) Some regions contain more information for the motor rules than the logic and sensory rules. Domain specificity for the motor rules is primarily observed in the somatomotor network.

Domain general regions are active during many task contexts and are more hub-like

We ran a standard GLM using 64 task regressors (one for each possible rule combination) and tested which brain regions showed a significant (FWE-corrected) level of activation for each of the 64 unique rule combinations. Then we calculated a summary statistic for each region reflecting what percentage of the 64 tasks showed significant positive activation (Figure 6A). Finally, we compared the percentage of activation for the unique rule combinations in domain general brain regions (mean rules coded per domain > 3) and the rest of the brain. The probability of a brain area showing significant activity during the task was not normally distributed so we used the Wilcoxon signed rank test to evaluate the difference in the probability of activation during the task for domain general regions and the rest of the brain. Domain general regions are more likely to be active during different task rule combinations than the rest of the brain, $Z = 4.73$, $p = 0.0000021$ (Figure 6B). The mean number of rules coded per domain was positively correlated with the percentage of activation, Spearman's rho = 0.3754, p = 0.0000000000001719.

Domain general brain regions were more likely to be activated during the performance of the task. One possible explanation for this result is that cognitive control network regions are well connected to the rest of the brain and different types of information regarding the task may converge in these areas allowing them to represent more complex aspects of the task. Using resting state data that was collected independent of task performance, we evaluated how well each brain region was connected to across-network brain regions. We used the between network global connectivity measure, which computes the average functional connectivity (weighted) of a region excluding within network connections (Ito et al., 2017; Schultz et al., 2018). We found that between network global connectivity values were significantly higher in domain general brain regions, $t(99) = 18.99$ (Figure 6C). This suggests that domain general

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brain regions are more likely to serve as between network hubs in the brain. Between network global connectivity was positively correlated with the mean number of rules coded per domain, Spearman's rho = 0.3908, p = 0.00000000000001399 (Figure 6D).

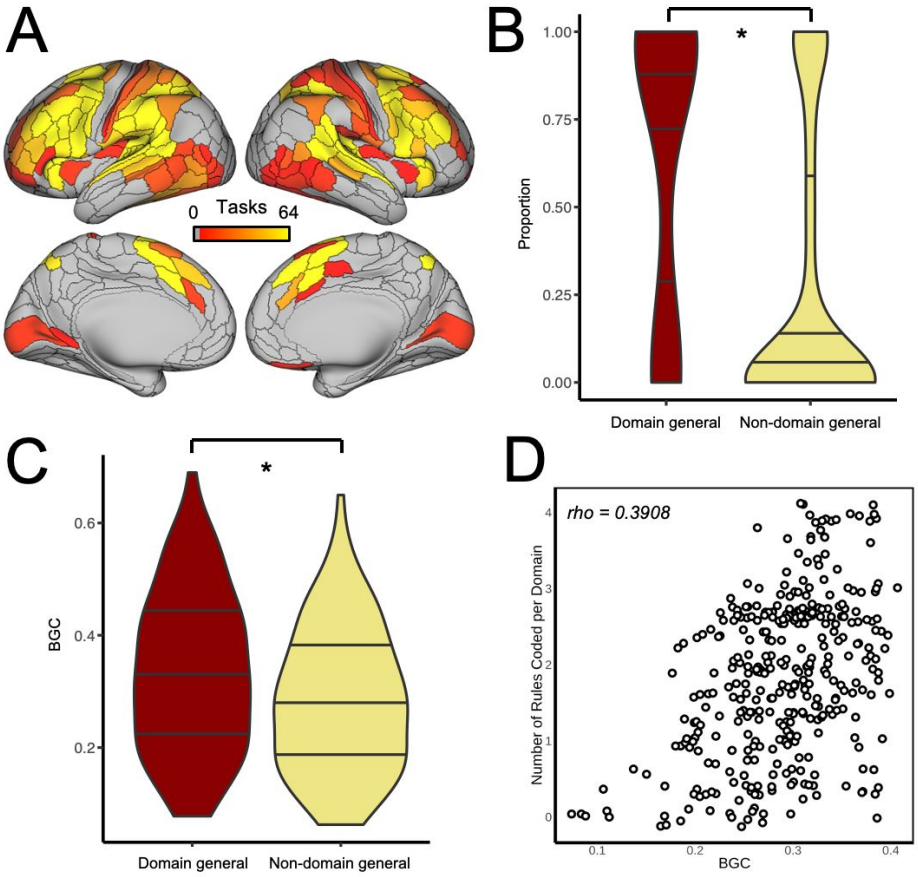

Figure 6. Domain general brain regions are active during the task and serve as hubs. (A) The proportion of task sets showing significant activation during the task. (B) Domain general regions, those brain areas containing information for > 3 rules per domain, have a higher probability of activation across task contexts. The lines on the violin plots represent quartiles. Asterisks indicate p < 0.05. (C) Domain general regions also have significantly greater between-network global connectivity during resting state. The lines on the violin plots represent quartiles. (D) Between-network global connectivity shows a significant positive rank correlation with their degree of domain generality.

Region specific information fingerprints are predicted by connectivity fingerprints

We hypothesized that the pattern of task rule coding in a particular region would be related to the pattern of task rule coding in the brain and the degree to which those regions share information. To evaluate this hypothesis we used the concept of activity flow mapping (Cole et al., 2016) which found that activation in a held out region of the brain could be predicted by the activity in the rest of the regions of the brain weighted by the strength of the functional connections between these regions. We used a similar concept to predict information fingerprints in brain regions using the information fingerprints from other brain regions and the functional connectivity between them (Figure 7A). Here we refer to information fingerprints as the pattern of information content across all twelve of the task rules for each region of the brain.

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This can be visualized with a radar plot where each arm of the plot represents one of the task rules and the farther the point is from the center of the plot the more information for that rule is contained in the brain region. We also calculated the mean information fingerprint for each functional network. The somatomotor network contains the most information about the Motor rules, the visual 2 network contains the most information about the Sensory rules, and the FPN and language networks contain the most information about the Logic rules. A similar radar plot was created for predicted information fingerprints. There was a significant correlation between the network level actual information fingerprints and the predicted information fingerprints, *rho* = 0.319, *p* = 0.0001. We found that we could predict information fingerprints significantly better than chance for every region in the brain (mean correlation between predicted and actual information fingerprints of r = 0.42, Figure 7C).

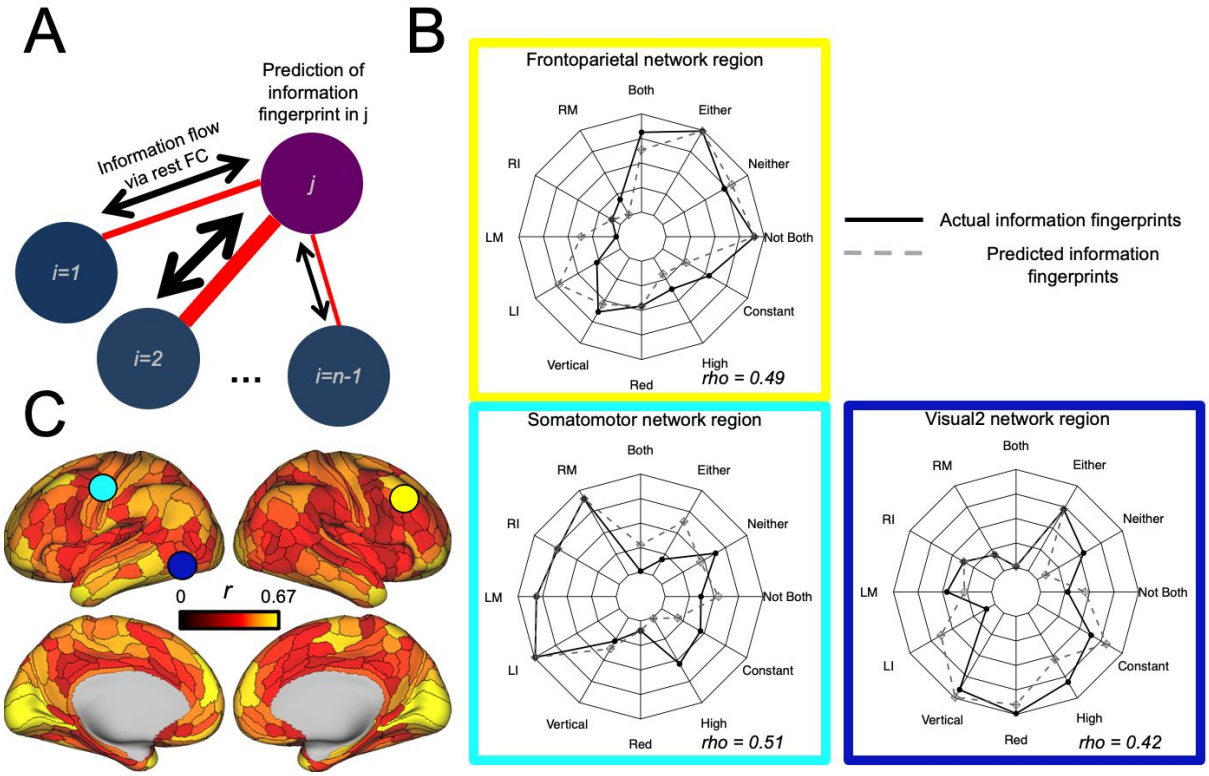

Figure 7. Information fingerprint mapping can predict patterns of task rule information content across the brain. (A) Information fingerprints were computed for each region of the brain. Using a simple computation principle, information fingerprints for a held out region can be predicted by weighting the information fingerprints from all other brain regions by the strength of their resting state functional connectivity to the held out region. Information fingerprints are variable across brain regions. (B) Group average actual and predicted information fingerprints for three representative brain regions. Radar plots depict rank ordered information estimates with the highest information estimates at the perimeter and the lowest information estimates near the center. (C) Information fingerprints can be predicted for every region in the brain. Correlations between actual and predicted information fingerprints for each brain region (FWE corrected p < 0.05). Colored circles indicate the location of the regions depicted in the radar plots in Figure 7B.

Information fingerprints could be predicted for every brain region when we used the information fingerprints from all other regions to make the prediction. However, cognitive control regions tended to show more domain general information coding so we hypothesized that information fingerprints from cognitive control regions would be especially important for making

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information fingerprint predictions. To evaluate this hypothesis we again attempted to predict information fingerprints, but rather than using data from the entire brain to make these predictions we used the information from regions within each functional network as input. We found that first, information fingerprints could be predicted with information from each network, and second, information from cognitive control networks generally outperformed information from other functional networks (Figure 8A). A *t*-test for each network was calculated against the median as a measure of central tendency because the somatomotor network value skewed the distribution. The three cognitive control networks were part of a group of five networks that showed significantly better predictions than the median. Because every network contains a different number of regions we wanted to control for the amount of information being used to make these predictions. We dealt with this issue by permuting network membership for each region randomly, while holding the number of regions assigned to each functional network constant in the next analysis. We compared the information fingerprint prediction accuracy against the prediction accuracy calculated based on random network assignment and extended the analysis to compare mean information fingerprint prediction accuracy to each target functional network. This provided us with more details regarding where in the brain these predictions were more or less accurate. Building on the previous results showing that information from cognitive control networks was more predictive of information fingerprints, we focused our analyses on the cognitive control networks. We found that information fingerprints from each network could accurately predict information fingerprints to other regions in the same network (Figure 8B). We found that information fingerprint data from the CON could make accurate predictions in the visual, somatomotor, DAN, and auditory networks. Information fingerprint data from the DAN could make accurate predictions in the visual, somatomotor, CON, and auditory networks, and information fingerprint data from the FPN could make accurate predictions in the visual, DAN, language, and DMN networks.

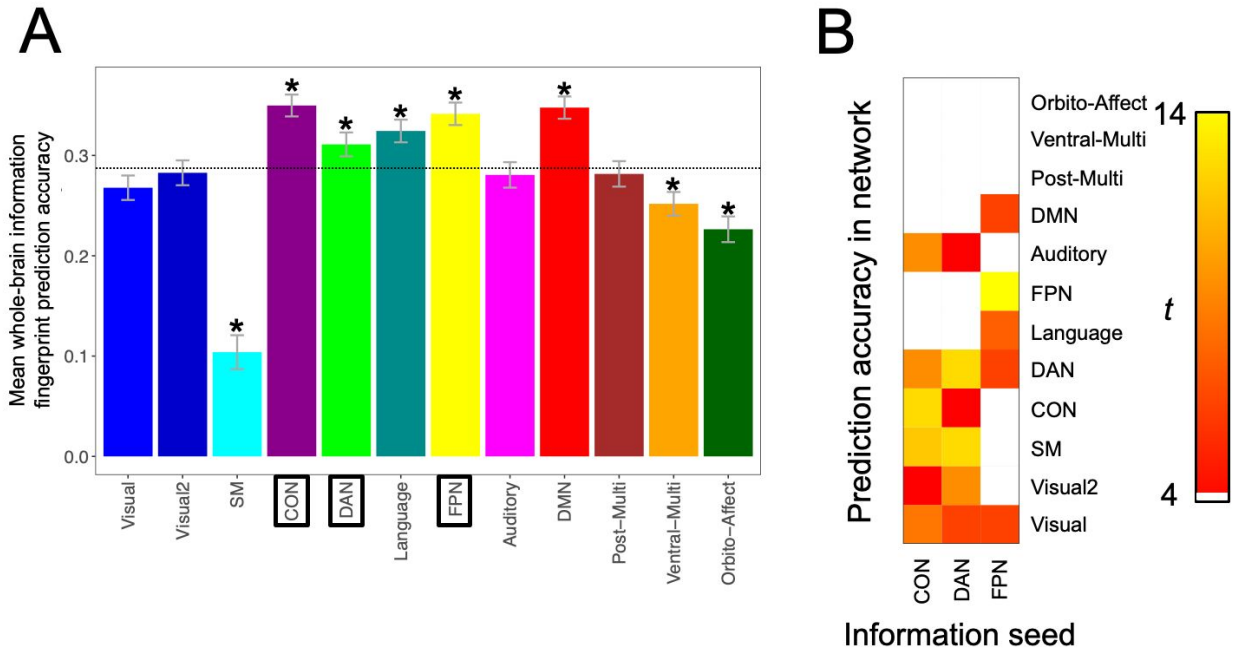

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Figure 8. Global information fingerprint predictions are more accurate when cognitive control networks serve as the source. Information fingerprint predictions were calculated by only using information from regions in one functional network as input. (A) Information fingerprints from each functional network could significantly predict information fingerprints in the rest of the brain. The dash line represents the median and asterisks indicate a FDR-corrected $p < 0.05$ difference from the median. Error bars indicate standard error. Information fingerprints from cognitive control network regions provided the most accurate predictions. (B) Follow-up analyses focused on these cognitive control networks and suggest that information from the CON and DAN could accurately predict information fingerprints in largely sensory networks. Information fingerprints in the FPN could accurately predict fingerprints in a mix of sensory and multimodal functional networks.

Discussion

We found that task rule representations vary in how distributed they are across the cortex. While task rule representations were distributed, they tended to be represented in a core of domain-general cognitive control networks. This is consistent with these regions being classified as hubs and showing a high degree of task activation. Furthermore, we found that the pattern of information content, or information fingerprint, for each of the rules in a brain region could be predicted using the intrinsic functional connectivity properties of each region in conjunction with the information fingerprints derived in the rest of the brain. Finally, we showed that the information fingerprints in cognitive control networks could predict the information fingerprints in other brain networks.

Previous research has suggested that task rule representation in the brain occurs somewhere on a continuum between localized and highly distributed. Consistent with this framework, we found that task rule representations varied in how distributed they were across the brain. Logic and sensory rule information was widely distributed across the brain while motor rule information was more localized to largely somatomotor network regions. We found that regions belonging to the frontoparietal, cingulo-opercular, and dorsal attention network contained domain general task rule information. These results support previous work that has identified a multiple demand network that is involved in a wide variety of cognitive tasks (Duncan & Owen, 2000). While these results support the hypothesis that task rule representation in the brain occurs on a continuum, it is important to note that this conclusion is based on the spatial limitations of fMRI data. It will be important for future studies to evaluate this hypothesis using methods capable of examining the brain on different scales.

Multivariate activation patterns have also been used to decode task rule representations. Several studies have suggested that the most accurate rule decoding using multivariate activation patterns occurs in cognitive control regions (Cole et al., 2011; Esterman et al., 2009; Reverberi, Görgen, et al., 2012; Reverberi, Gorgen, et al., 2012). If cognitive control regions can decode a larger number of different rules as we observed, it would be consistent with more accurate rule decoding in these regions as well. Electrophysiological recordings have provided additional evidence that cells in the prefrontal cortex can code for specific task rules (Asaad et al., 2000; Brincat et al., 2018; Wallis & Miller, 2003; White & Wise, 1999). The concept of mixed selectivity – the representation of multiple pieces of information by single neurons – has been used as a model to understand how cognitive control brain regions can contribute to flexible cognition (Rigotti et al., 2013). Analyses of multi-unit recordings of non-human primates have identified mixed selectivity cells in some prefrontal neurons, demonstrating that single prefrontal neurons can respond to several aspects and combinations of task variables at once (Asaad et al., 1998; Warden & Miller, 2010). This type of context-dependent neural representation is one

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possible mechanism for how cognitive control networks achieve their "multiple demand" status, potentially increasing cognitive flexibility via flexible representation of information.

Some brain regions exhibited domain general characteristics, but other regions coded for more domain specific information. The logic rules were preferentially represented in the default mode network. We expected that logic rules would be preferentially coded in the frontoparietal network. It is important to note that the logic rules were represented there, but that the FPN regions also contained information from the other domains which led to more balanced coding and therefore less of a preference for the logic rules. The default mode network containing information more specific to the logic domain is consistent with previous studies showing task rule decoding in the default mode network related to; the level of self-reported detail during the performance of a working memory task (Sormaz et al., 2018), representing task-related information during task switching (Crittenden et al., 2015), or covert attention during a free selection task (Haynes et al., 2007). We found that sensory networks, specifically the visual and auditory networks, preferentially coded for sensory rules. Previous research has also found evidence of coding in visual cortex for orientation (Boynton, 2005; Haynes & Rees, 2005; Kamitani & Tong, 2005) and for color (Brouwer & Heeger, 2009; Parkes et al., 2009). Multivariate patterns of activity in the auditory network can also decode auditory stimuli including human speech (Formisano et al., 2008) and decode several other categories of auditory stimuli (Staeren et al., 2009; Zhang et al., 2015). Finally, we found that the motor rules were preferentially coded in the somatomotor network. Previous studies have found that intended motor actions can be decoded from activity patterns in the motor network (Ariani et al., 2015; Gallivan et al., 2015; Gertz et al., 2017).

We observed that domain general brain regions also had a higher probability of activation during the task. This finding is consistent with descriptions of a multiple demand network (Duncan, 2010) which overlaps with cognitive control networks. We also found that domain general brain regions had higher between-network global connectivity, a measure of how well a brain region is connected to other out-of-network regions, during a resting state scan. Other studies suggest that cognitive control networks have a high degree of connectivity (Cole, Pathak, et al., 2010; Power et al., 2011), specifically for between network connections (Schultz et al., 2018). Along with a high degree of connectivity, cognitive control networks can also adaptively update these connections based on current goals (Cole, Reynolds, et al., 2013). Cognitive control networks have a high degree of connectivity and the ability to rapidly update these connections which are characteristics of flexible hubs. This is one possible explanation for why cognitive control networks show domain general characteristics.

The pattern of task rule information in each brain region could be predicted by weighting the task rule information patterns in the rest of the brain by its resting-state functional connectivity strength. Additional analyses indicated that information fingerprints from cognitive control networks played a disproportionate role in predicting patterns of task rule information in other networks. While these cognitive control networks appeared to contain domain general information, these domain general regions can be subdivided into smaller networks that specialize in different cognitive functions. The FPN is thought to be involved in the initiation of control and for adjusting control in response to feedback or instructions (Braver et al., 2003; Cocuzza et al., 2019; Cole, Reynolds, et al., 2013; Dosenbach et al., 2007). The function of the

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CON has been more difficult to characterize with some suggesting it has a role in task-set maintenance (Dosenbach et al., 2007; Sadaghiani & D'Esposito, 2015), arousal or alertness (Coste & Kleinschmidt, 2016), or conflict monitoring (Braem et al., 2019; Neta et al., 2014). The DAN is thought to be involved in the top-down control of attention (Buschman & Kastner, 2015; Corbetta & Shulman, 2002) and eye movement control (Corbetta et al., 1998). The heterogeneity of these components of the multiple demand network has been supported by resting-state functional connectivity data demonstrating that these components are characterized by distinct functional connectivity profiles (Ji et al., 2019; Power et al., 2011; Yeo et al., 2011). Additionally, changes in functional connectivity patterns during the performance of cognitive tasks also supports functional specialization across cognitive control networks (Cohen & D'Esposito, 2016). Other task activation studies have found evidence for domain specificity within the multiple demand network (Crittenden et al., 2016; Yeo et al., 2015), and even between portions of the FPN (Badre & D'Esposito, 2007; Nee & D'Esposito, 2016).

We found that information fingerprints in the CON could predict the pattern of task rule information in the DAN and vice versa. In addition to predicting information fingerprints between themselves, the cingulo-opercular and dorsal attention network information fingerprints could predict task rule information patterns in sensory networks. The relationship between both the CON and DAN with sensory and motor networks is consistent with a recent report suggesting that CON and DAN possess a large number of "control processing" hubs which aid in the transfer of information between these networks (Gordon et al., 2018). Another recent study found that during the performance of a task the CON can disband to some degree, potentially to provide resources to other task-relevant networks under certain demands (Cocuzza et al., 2019). Alternatively, information fingerprints in the frontoparietal network could predict task rule information patterns in more transmodal networks including the DAN, language, and default mode networks. This result is also consistent with previous work suggesting that the FPN contains more "control default" hubs which aid in the communication between the FPN and DMN potentially allowing for regulation of internally generated processes like planning (Gordon et al., 2018). This result may also be related to the FPN serving as a "flexible coordinator" by maintaining within network connections, but altering connections between the FPN and other networks during tasks which would allow the FPN to serve as a coordinator of information flow (Cocuzza et al., 2019).

There are some limitations of this study which impact how generalizable the results are to other situations. One limitation is that although the C-PRO task allows us to compare many different rule combinations, the task structure is relatively rigid. Participants view instructions, are presented with stimuli, and make a response. The instructions are text presented visually. Future studies may want to consider presenting instructions with auditory stimuli, or using a non-text based visual presentation. Additionally, the stimuli used in the study were simple auditory and visual. It will be important for future studies to examine how information content is represented for other stimulus modalities, or with more complex auditory and visual stimuli. While we balanced the numerous task rules as well as possible, there were some differences in task accuracy across the rules. Ideally, participants would demonstrate equivalent accuracy on the various task rules to rule out the possibility that task accuracy was contributing to the decoding analyses we conducted. Although we cannot conclude that differences in task

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accuracy are not contributing to our results to some degree, we did observe largely consistent decodability across different rules within the same domain even in situations where there were task accuracy differences.

Together, our results support our hypothesis that task rule representations exist on a continuum between distribution and localization. We also found that patterns of task rule information in cognitive control networks could predict patterns of task rule representation in other networks. This prediction used functional connectivity estimated via an independent resting state scan which suggests that intrinsic whole-brain connectivity patterns help shape the way that task activation patterns from different brain regions are combined during task performance. These results support the hypothesis that cognitive control networks use their unique intrinsic functional connectivity patterns to integrate domain-specific representations. These representations can then be coordinated during task performance in situations when novel combinations of rules are encountered. This likely increases the cognitive flexibility of the human brain.

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References

Ariani, G., Wurm, M. F., & Lingnau, A. (2015). Decoding Internally and Externally Driven Movement Plans. *Journal of Neuroscience*, *35*(42), 14160–14171. https://doi.org/10.1523/JNEUROSCI.0596-15.2015

Asaad, W. F., Rainer, G., & Miller, E. K. (1998). Neural Activity in the Primate Prefrontal Cortex during Associative Learning. *Neuron*, *21*(6), 1399–1407. https://doi.org/10.1016/S0896-6273(00)80658-3

Asaad, W. F., Rainer, G., & Miller, E. K. (2000). Task-Specific Neural Activity in the Primate Prefrontal Cortex. *Journal of Neurophysiology*, *84*(1), 451–459. https://doi.org/10.1152/jn.2000.84.1.451

Assem, M., Glasser, M. F., Van Essen, D. C., & Duncan, J. (2020). A Domain-General Cognitive Core Defined in Multimodally Parcellated Human Cortex. *Cerebral Cortex*, *30*(8), 4361–4380. https://doi.org/10.1093/cercor/bhaa023

Badre, D., & D'Esposito, M. (2007). Functional Magnetic Resonance Imaging Evidence for a Hierarchical Organization of the Prefrontal Cortex. *Journal of Cognitive Neuroscience*, *19*(12), 32.

Boynton, G. M. (2005). Imaging orientation selectivity: Decoding conscious perception in V1. *Nature Neuroscience*, *8*(5), 541–542. https://doi.org/10.1038/nn0505-541

Braem, S., Bugg, J. M., Schmidt, J. R., Crump, M. J. C., Weissman, D. H., Notebaert, W., & Egner, T. (2019). Measuring Adaptive Control in Conflict Tasks. *Trends in Cognitive Sciences*, *23*(9), 769–783. https://doi.org/10.1016/j.tics.2019.07.002

Braver, T. S., Reynolds, J. R., & Donaldson, D. I. (2003). Neural mechanisms of transient and sustained cognitive control during task switching. *Neuron*, *39*(4), 713–726.

Brincat, S. L., Siegel, M., von Nicolai, C., & Miller, E. K. (2018). Gradual progression from sensory to task-related processing in cerebral cortex. *Proceedings of the National*

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Academy of Sciences, *115*(30), E7202–E7211. https://doi.org/10.1073/pnas.1717075115

Brouwer, G. J., & Heeger, D. J. (2009). Decoding and Reconstructing Color from Responses in Human Visual Cortex. *Journal of Neuroscience*, *29*(44), 13992–14003. https://doi.org/10.1523/JNEUROSCI.3577-09.2009

Buschman, T. J., & Kastner, S. (2015). From Behavior to Neural Dynamics: An Integrated Theory of Attention. *Neuron*, *88*(1), 127–144. https://doi.org/10.1016/j.neuron.2015.09.017

Camilleri, J. A., Müller, V. I., Fox, P., Laird, A. R., Hoffstaedter, F., Kalenscher, T., & Eickhoff, S. B. (2018). Definition and characterization of an extended multiple-demand network. *NeuroImage*, *165*, 138–147. https://doi.org/10.1016/j.neuroimage.2017.10.020

Cocuzza, C. V., Ito, T., Schultz, D., Bassett, D. S., & Cole, M. W. (2019). *Flexible coordinator and switcher hubs for adaptive task control* [Preprint]. Neuroscience. https://doi.org/10.1101/822213

Cocuzza, C. V., Ito, T., Schultz, D., Bassett, D. S., & Cole, M. W. (2020). Flexible coordinator and switcher hubs for adaptive task control. *The Journal of Neuroscience*, JN-RM-2559-19. https://doi.org/10.1523/JNEUROSCI.2559-19.2020

Cohen, J. R., & D'Esposito, M. (2016). The Segregation and Integration of Distinct Brain Networks and Their Relationship to Cognition. *Journal of Neuroscience*, *36*(48), 12083–12094. https://doi.org/10.1523/JNEUROSCI.2965-15.2016

Cole, M. W., Bagic, A., Kass, R., & Schneider, W. (2010). Prefrontal Dynamics Underlying Rapid Instructed Task Learning Reverse with Practice. *Journal of Neuroscience*, *30*(42), 14245–14254. https://doi.org/10.1523/JNEUROSCI.1662-10.2010

Cole, M. W., Braver, T. S., & Meiran, N. (2017). The task novelty paradox: Flexible control of

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inflexible neural pathways during rapid instructed task learning. *Neuroscience & Biobehavioral Reviews*, *81*, 4–15. https://doi.org/10.1016/j.neubiorev.2017.02.009

Cole, M. W., Etzel, J. A., Zacks, J. M., Schneider, W., & Braver, T. S. (2011). Rapid Transfer of Abstract Rules to Novel Contexts in Human Lateral Prefrontal Cortex. *Frontiers in Human Neuroscience*, *5*. https://doi.org/10.3389/fnhum.2011.00142

Cole, M. W., Ito, T., Bassett, D. S., & Schultz, D. H. (2016). Activity flow over resting-state networks shapes cognitive task activations. *Nature Neuroscience*, *19*(12), 1718–1726. https://doi.org/10.1038/nn.4406

Cole, M. W., Laurent, P., & Stocco, A. (2013). Rapid instructed task learning: A new window into the human brain's unique capacity for flexible cognitive control. *Cognitive, Affective, & Behavioral Neuroscience*, *13*(1), 1–22. https://doi.org/10.3758/s13415-012-0125-7

Cole, M. W., Pathak, S., & Schneider, W. (2010). Identifying the brain's most globally connected regions. *NeuroImage*, *49*(4), 3132–3148. https://doi.org/10.1016/j.neuroimage.2009.11.001

Cole, M. W., Reynolds, J. R., Power, J. D., Repovs, G., Anticevic, A., & Braver, T. S. (2013). Multi-task connectivity reveals flexible hubs for adaptive task control. *Nature Neuroscience*, *16*(9), 1348–1355. https://doi.org/10.1038/nn.3470

Cole, M. W., & Schneider, W. (2007). The cognitive control network: Integrated cortical regions with dissociable functions. *NeuroImage*, *37*(1), 343–360. https://doi.org/10.1016/j.neuroimage.2007.03.071

Corbetta, M., Akbudak, E., Conturo, T. E., Snyder, A. Z., Ollinger, J. M., Drury, H. A., Linenweber, M. R., Petersen, S. E., Raichle, M. E., Van Essen, D. C., & Shulman, G. L. (1998). A Common Network of Functional Areas for Attention and Eye Movements. *Neuron*, *21*(4), 761–773. https://doi.org/10.1016/S0896-6273(00)80593-0

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Corbetta, M., & Shulman, G. L. (2002). CONTROL OF GOAL-DIRECTED AND STIMULUS-DRIVEN ATTENTION IN THE BRAIN. *Nature Reviews Neuroscience*, *3*(3), 215–229. https://doi.org/10.1038/nrn755

Coste, C. P., & Kleinschmidt, A. (2016). Cingulo-opercular network activity maintains alertness. *NeuroImage*, *128*, 264–272. https://doi.org/10.1016/j.neuroimage.2016.01.026

Crittenden, B. M., Mitchell, D. J., & Duncan, J. (2015). Recruitment of the default mode network during a demanding act of executive control. *ELife*, *4*, e06481. https://doi.org/10.7554/eLife.06481

Crittenden, B. M., Mitchell, D. J., & Duncan, J. (2016). Task Encoding across the Multiple Demand Cortex Is Consistent with a Frontoparietal and Cingulo-Opercular Dual Networks Distinction. *The Journal of Neuroscience*, *36*(23), 6147–6155. https://doi.org/10.1523/JNEUROSCI.4590-15.2016

Desimone, R., & Duncan, J. (1995). *Neural Mechanisms of Selective Visual Attention*. 30.

Dosenbach, N. U., Fair, D. A., Miezin, F. M., Cohen, A. L., Wenger, K. K., Dosenbach, R. A., Fox, M. D., Snyder, A. Z., Vincent, J. L., Raichle, M. E., & others. (2007). Distinct brain networks for adaptive and stable task control in humans. *Proceedings of the National Academy of Sciences*, *104*(26), 11073–11078.

Duncan, J. (2010). The multiple-demand (MD) system of the primate brain: Mental programs for intelligent behaviour. *Trends in Cognitive Sciences*, *14*(4), 172–179. https://doi.org/10.1016/j.tics.2010.01.004

Duncan, J., & Owen, A. M. (2000). Common regions of the human frontal lobe recruited by diverse cognitive demands. *Trends in Neurosciences*, *23*(10), 475–483. https://doi.org/10.1016/S0166-2236(00)01633-7

Esterman, M., Chiu, Y.-C., Tamber-Rosenau, B. J., & Yantis, S. (2009). Decoding cognitive

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control in human parietal cortex. *Proceedings of the National Academy of Sciences*, *106*(42), 17974–17979. https://doi.org/10.1073/pnas.0903593106

Fischl, B., Salat, D. H., Busa, E., Albert, M., Dieterich, M., Haselgrove, C., Van Der Kouwe, A., Killiany, R., Kennedy, D., Klaveness, S., & others. (2002). Whole brain segmentation: Automated labeling of neuroanatomical structures in the human brain. *Neuron*, *33*(3), 341–355.

Formisano, E., De Martino, F., Bonte, M., & Goebel, R. (2008). "Who" Is Saying "What"? Brain-Based Decoding of Human Voice and Speech. *Science*, *322*(5903), 970–973. https://doi.org/10.1126/science.1164318

Gallivan, J. P., Johnsrude, I. S., & Flanagan, J. R. (2015). Planning Ahead: Object-Directed Sequential Actions Decoded from Human Frontoparietal and Occipitotemporal Networks. *Cerebral Cortex*, bhu302. https://doi.org/10.1093/cercor/bhu302

Gertz, H., Lingnau, A., & Fiehler, K. (2017). Decoding Movement Goals from the Fronto-Parietal Reach Network. *Frontiers in Human Neuroscience*, *11*. https://doi.org/10.3389/fnhum.2017.00084

Glasser, M. F., Coalson, T. S., Robinson, E. C., Hacker, C. D., Harwell, J., Yacoub, E., Ugurbil, K., Andersson, J., Beckmann, C. F., Jenkinson, M., Smith, S. M., & Van Essen, D. C. (2016). A multi-modal parcellation of human cerebral cortex. *Nature*, *536*(7615), 171–178. https://doi.org/10.1038/nature18933

Glasser, M. F., Sotiropoulos, S. N., Wilson, J. A., Coalson, T. S., Fischl, B., Andersson, J. L., Xu, J., Jbabdi, S., Webster, M., Polimeni, J. R., Van Essen, D. C., & Jenkinson, M. (2013). The minimal preprocessing pipelines for the Human Connectome Project. *NeuroImage*, *80*, 105–124. https://doi.org/10.1016/j.neuroimage.2013.04.127

Gordon, E. M., Lynch, C. J., Gratton, C., Laumann, T. O., Gilmore, A. W., Greene, D. J., Ortega,

bioRxiv preprint doi: https://doi.org/10.1101/2021.01.25.428141; this version posted January 25, 2021. The copyright holder for this preprint (which was not certified by peer review) is the author/funder, who has granted bioRxiv a license to display the preprint in perpetuity. It is made available under aCC-BY-NC-ND 4.0 International license.

M., Nguyen, A. L., Schlaggar, B. L., Petersen, S. E., Dosenbach, N. U. F., & Nelson, S. M. (2018). Three Distinct Sets of Connector Hubs Integrate Human Brain Function. *Cell Reports*, *24*(7), 1687-1695.e4. https://doi.org/10.1016/j.celrep.2018.07.050

Haynes, J.-D., & Rees, G. (2005). Predicting the orientation of invisible stimuli from activity in human primary visual cortex. *Nature Neuroscience*, *8*(5), 686–691. https://doi.org/10.1038/nn1445

Haynes, J.-D., Sakai, K., Rees, G., Gilbert, S., Frith, C., & Passingham, R. E. (2007). Reading Hidden Intentions in the Human Brain. *Current Biology*, *17*(4), 323–328. https://doi.org/10.1016/j.cub.2006.11.072

Ito, T., Kulkarni, K. R., Schultz, D. H., Mill, R. D., Chen, R. H., Solomyak, L. I., & Cole, M. W. (2017). Cognitive task information is transferred between brain regions via resting-state network topology. *Nature Communications*, *8*(1). https://doi.org/10.1038/s41467-017-01000-w

Ji, J. L., Spronk, M., Kulkarni, K., Repovš, G., Anticevic, A., & Cole, M. W. (2019). Mapping the human brain's cortical-subcortical functional network organization. *NeuroImage*, *185*, 35–57. https://doi.org/10.1016/j.neuroimage.2018.10.006

Kamitani, Y., & Tong, F. (2005). Decoding the visual and subjective contents of the human brain. *Nature Neuroscience*, *8*(5), 679–685. https://doi.org/10.1038/nn1444

Liefooghe, B., De Houwer, J., & Wenke, D. (2013). Instruction-based response activation depends on task preparation. *Psychonomic Bulletin & Review*, *20*(3), 481–487. https://doi.org/10.3758/s13423-013-0374-7

Miller, E. K., & Cohen, J. D. (2001). An integrative theory of prefrontal cortex function. *Annual Review of Neuroscience*, *24*(1), 167–202.

Mur, M., Bandettini, P. A., & Kriegeskorte, N. (2009). Revealing representational content with

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pattern-information fMRI—an introductory guide. *Social Cognitive and Affective Neuroscience*, *4*(1), 101–109. https://doi.org/10.1093/scan/nsn044

Nee, D. E., & D'Esposito, M. (2016). The hierarchical organization of the lateral prefrontal cortex. *ELife*, *5*, e12112.

Neta, M., Schlaggar, B. L., & Petersen, S. E. (2014). Separable responses to error, ambiguity, and reaction time in cingulo-opercular task control regions. *NeuroImage*, *99*, 59–68. https://doi.org/10.1016/j.neuroimage.2014.05.053

Nichols, T. E., & Holmes, A. P. (2002). Nonparametric permutation tests for functional neuroimaging: A primer with examples. *Human Brain Mapping*, *15*(1), 1–25. https://doi.org/10.1002/hbm.1058

Niendam, T. A., Laird, A. R., Ray, K. L., Dean, Y. M., Glahn, D. C., & Carter, C. S. (2012). Meta-analytic evidence for a superordinate cognitive control network subserving diverse executive functions. *Cognitive, Affective, & Behavioral Neuroscience*, *12*(2), 241–268. https://doi.org/10.3758/s13415-011-0083-5

Parkes, L. M., Marsman, J. B. C., Oxley, D. C., Goulermas, J. Y., & Wuerger, S. M. (2009). Multivoxel fMRI analysis of color tuning in human primary visual cortex. *Journal of Vision*, *9*(1), 1–1. https://doi.org/10.1167/9.1.1

Pereg, M., & Meiran, N. (2019). Rapid instructed task learning (but not automatic effects of instructions) is influenced by working memory load. *PLOS ONE*, *14*(6), e0217681. https://doi.org/10.1371/journal.pone.0217681

Pischedda, D., Görgen, K., Haynes, J.-D., & Reverberi, C. (2017). Neural Representations of Hierarchical Rule Sets: The Human Control System Represents Rules Irrespective of the Hierarchical Level to Which They Belong. *The Journal of Neuroscience*, *37*(50), 12281–12296. https://doi.org/10.1523/JNEUROSCI.3088-16.2017

bioRxiv preprint doi: https://doi.org/10.1101/2021.01.25.428141; this version posted January 25, 2021. The copyright holder for this preprint (which was not certified by peer review) is the author/funder, who has granted bioRxiv a license to display the preprint in perpetuity. It is made available under aCC-BY-NC-ND 4.0 International license.

Power, J. D., Barnes, K. A., Snyder, A. Z., Schlaggar, B. L., & Petersen, S. E. (2012). Spurious but systematic correlations in functional connectivity MRI networks arise from subject motion. *NeuroImage*, *59*(3), 2142–2154. https://doi.org/10.1016/j.neuroimage.2011.10.018

Power, J. D., Cohen, A. L., Nelson, S. M., Wig, G. S., Barnes, K. A., Church, J. A., Vogel, A. C., Laumann, T. O., Miezin, F. M., Schlaggar, B. L., & Petersen, S. E. (2011). Functional Network Organization of the Human Brain. *Neuron*, *72*(4), 665–678. https://doi.org/10.1016/j.neuron.2011.09.006

Reverberi, C., Görgen, K., & Haynes, J.-D. (2012). Compositionality of Rule Representations in Human Prefrontal Cortex. *Cerebral Cortex*, *22*(6), 1237–1246. https://doi.org/10.1093/cercor/bhr200

Reverberi, C., Gorgen, K., & Haynes, J.-D. (2012). Distributed Representations of Rule Identity and Rule Order in Human Frontal Cortex and Striatum. *Journal of Neuroscience*, *32*(48), 17420–17430. https://doi.org/10.1523/JNEUROSCI.2344-12.2012

Rigotti, M., Barak, O., Warden, M. R., Wang, X.-J., Daw, N. D., Miller, E. K., & Fusi, S. (2013). The importance of mixed selectivity in complex cognitive tasks. *Nature*, *497*(7451), 585–590. https://doi.org/10.1038/nature12160

Ruge, H., Schäfer, T. A., Zwosta, K., Mohr, H., & Wolfensteller, U. (2019). Neural representation of newly instructed rule identities during early implementation trials. *ELife*, *8*, e48293. https://doi.org/10.7554/eLife.48293

Sadaghiani, S., & D'Esposito, M. (2015). Functional Characterization of the Cingulo-Opercular Network in the Maintenance of Tonic Alertness. *Cerebral Cortex*, *25*(9), 2763–2773. https://doi.org/10.1093/cercor/bhu072

Schneider, W. (2003). Controlled & automatic processing: Behavior, theory, and biological

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mechanisms. *Cognitive Science*, *27*(3), 525–559. https://doi.org/10.1016/S0364-0213(03)00011-9

Schultz, D. H., Ito, T., Solomyak, L. I., Chen, R. H., Mill, R. D., Anticevic, A., & Cole, M. W. (2018). Global Connectivity of the Frontoparietal Cognitive Control Network is Related to Depression Symptoms in the General Population. *Network Neuroscience*, 1–46. https://doi.org/10.1162/NETN_a_00056

Siegel, J. S., Mitra, A., Laumann, T. O., Seitzman, B. A., Raichle, M., Corbetta, M., & Snyder, A. Z. (2016). Data Quality Influences Observed Links Between Functional Connectivity and Behavior. *Cerebral Cortex*. https://doi.org/10.1093/cercor/bhw253

Sormaz, M., Murphy, C., Wang, H., Hymers, M., Karapanagiotidis, T., Poerio, G., Margulies, D. S., Jefferies, E., & Smallwood, J. (2018). Default mode network can support the level of detail in experience during active task states. *Proceedings of the National Academy of Sciences*, *115*(37), 9318–9323. https://doi.org/10.1073/pnas.1721259115

Staeren, N., Renvall, H., De Martino, F., Goebel, R., & Formisano, E. (2009). Sound Categories Are Represented as Distributed Patterns in the Human Auditory Cortex. *Current Biology*, *19*(6), 498–502. https://doi.org/10.1016/j.cub.2009.01.066

Wallis, J. D., & Miller, E. K. (2003). Neuronal activity in primate dorsolateral and orbital prefrontal cortex during performance of a reward preference task. *European Journal of Neuroscience*, *18*(7), 2069–2081. https://doi.org/10.1046/j.1460-9568.2003.02922.x

Warden, M. R., & Miller, E. K. (2010). Task-Dependent Changes in Short-Term Memory in the Prefrontal Cortex. *Journal of Neuroscience*, *30*(47), 15801–15810. https://doi.org/10.1523/JNEUROSCI.1569-10.2010

White, I. M., & Wise, S. P. (1999). Rule-dependent neuronal activity in the prefrontal cortex. *Experimental Brain Research*, *126*(3), 315–335. https://doi.org/10.1007/s002210050740

bioRxiv preprint doi: https://doi.org/10.1101/2021.01.25.428141; this version posted January 25, 2021. The copyright holder for this preprint (which was not certified by peer review) is the author/funder, who has granted bioRxiv a license to display the preprint in perpetuity. It is made available under aCC-BY-NC-ND 4.0 International license.

Woolgar, A., Thompson, R., Bor, D., & Duncan, J. (2011). Multi-voxel coding of stimuli, rules, and responses in human frontoparietal cortex. *NeuroImage*, *56*(2), 744–752. https://doi.org/10.1016/j.neuroimage.2010.04.035

Yeo, B. T. T., Krienen, F. M., Eickhoff, S. B., Yaakub, S. N., Fox, P. T., Buckner, R. L., Asplund, C. L., & Chee, M. W. L. (2015). Functional Specialization and Flexibility in Human Association Cortex. *Cerebral Cortex*, *25*(10), 3654–3672. https://doi.org/10.1093/cercor/bhu217

Yeo, B. T. T., Krienen, F. M., Sepulcre, J., Sabuncu, M. R., Lashkari, D., Hollinshead, M., Roffman, J. L., Smoller, J. W., Zollei, L., Polimeni, J. R., Fischl, B., Liu, H., & Buckner, R. L. (2011). The organization of the human cerebral cortex estimated by intrinsic functional connectivity. *Journal of Neurophysiology*, *106*(3), 1125–1165. https://doi.org/10.1152/jn.00338.2011

Zhang, F., Wang, J.-P., Kim, J., Parrish, T., & Wong, P. C. M. (2015). Decoding Multiple Sound Categories in the Human Temporal Cortex Using High Resolution fMRI. *PLOS ONE*, *10*(2), e0117303. https://doi.org/10.1371/journal.pone.0117303