

The Division of Labor and Cooperative Mechanisms between Cognitive Control and Salience Processing in Categorical Attentional Selection: Evidence from fMRI

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Abstract

Category-based Attentional Selection (CAS) is a core process through which the brain optimizes information filtering via abstract category representations, but the synergistic mechanisms underlying cognitive control and salience processing remain unclear. This study combined the Majority Function Task (MFT, which manipulates cognitive load through symbol category ratios: low load 3:0, high load 2:1) with the Oddball paradigm (which manipulates salience level through stimulus probability: standard stimuli 80%, novel stimuli 20%), and distinguished target relevance (task-relevant: changing category probability; task-irrelevant: changing color probability), to systematically investigate the behavioral and neural modulatory mechanisms of cognitive control and salience processing on CAS. Behavioral results showed: high cognitive load significantly reduced CAS efficiency, and the interference effect of novel stimuli was significant only when task-relevant. The three-way interaction indicated that only when task-relevant, the interference effect of novel stimuli under high load was significantly greater than under low load; fMRI results showed that high cognitive load activated the dorsal attention network (DLPFC, SPL), while novel stimuli activated the ventral attention network (rTPJ, AIC); joint activation analysis revealed co-activation in the cognitive control network (SPL, ACC, AIC); Multi-voxel pattern analysis (MVPA) revealed that the right parieto-occipital junction (rPOJ) and frontal eye fields (FEF) achieved 86.83% decoding accuracy for cognitive load and salience processing, indicating that they can integrate dual-pathway information for dynamic resource allocation. In summary, cognitive control and salience processing consume resources via the dorsal and ventral networks, respectively; when both coexist, the cognitive control network determines CAS efficiency through conflict resolution and resource reallocation.

This study reveals the division of labor and synergistic mechanisms between cognitive control and salience processing at the category level, proposes a dynamic pathway model, providing new neural empirical support for refining the dual-pathway model of attention.

Full Text

Functional Division and Synergy of Cognitive Control and Salience Processing in Category-Based Attentional Selection: Evidence from fMRI

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Abstract

Category-based attentional selection (CAS) is a core process through which the brain optimizes information filtering via abstract category representations, yet the synergistic mechanism by which cognitive control and salience processing jointly regulate CAS remains unclear. This study combined a Majority Function Task (MFT)—which manipulates cognitive load through symbol category ratios (low load: 3:0, high load: 2:1)—with an Oddball paradigm that manipulates salience level through stimulus probability (standard: 80%, novel: 20%), while distinguishing target relevance (task-relevant: altering category probability; task-irrelevant: altering color probability). This design systematically examined the behavioral and neural regulatory mechanisms of cognitive control and salience processing on CAS. Behavioral results showed that high cognitive load significantly reduced CAS efficiency, and the interference effect of novel stimuli was significant only when task-relevant. A three-way interaction revealed that under task-relevant conditions, the interference effect of novel stimuli was significantly greater under high load than low load. fMRI results showed that high cognitive load activated the dorsal attention network (DLPFC, SPL), whereas novel stimuli activated the ventral attention network (rTPJ, AIC). Conjunction analysis demonstrated co-activation in the cognitive control network (SPL, ACC, AIC). Multivariate pattern analysis (MVPA) revealed that the right parieto-occipital junction (rPOJ) and frontal eye fields (FEF) achieved 86.83% decoding accuracy for cognitive load and salience processing, indicating that

these regions can integrate dual-pathway information for dynamic resource allocation. Overall, cognitive control and salience processing consume resources through dorsal and ventral networks, respectively; when both are present, the cognitive control network determines CAS efficiency through conflict resolution and resource reallocation. This study reveals the functional division and synergistic mechanism of cognitive control and salience processing at the category level, proposes a dynamic pathway model, and provides new neural evidence for refining the dual-pathway model of attention.

Keywords: cognitive control, salience processing, category-based attention, cognitive control network, right parieto-occipital junction

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Introduction

Attentional selection is the fundamental mechanism by which information processing systems choose limited information for deeper processing in complex environments, serving as the gateway to cognitive activity (Desimone & Duncan, 1995). In the external world, the diversity of object features and environmental dynamics lead people to organize perceptual experience according to object collections—categories (Rosch et al., 1976). The abstract nature of categories can integrate discrete features into unified representations, significantly reducing information redundancy and enhancing processing efficiency (Reeder & Peelen, 2013; Macé et al., 2009). Category-based attentional selection (CAS) directs the object of attentional selection toward category representations, giving priority to stimuli that match target categories (Peelen & Kastner, 2014; Yang & Zelinsky, 2009; Wyble et al., 2013; Wu et al., 2016; Wu & Fu, 2017). Compared with feature-level attentional selection, CAS exhibits longer processing time windows and stronger involvement of object-selective cortex (Freedman et al., 2003; Ferrera et al., 2009), making it an important process for investigating the dynamic interaction between high-level cognition and perception. However, previous research has focused primarily on the neural mechanisms of CAS itself (activated brain regions and temporal dynamics), leaving unclear how the attention system dynamically regulates cognitive resources during CAS and lacking theoretical basis for applying CAS in complex environments.

On one hand, cognitive control can influence resource allocation for CAS. Cognitive control refers to the ability to monitor, inhibit, and schedule information processing according to current goals in resource-limited situations, representing a core function of high-level attention systems (Wu et al., 2020a; Fan, 2014; Lavie, 2005). The Majority Function Task (MFT) manipulates cognitive load

by changing the entropy of information to be processed. The task requires participants to judge the orientation of the majority of arrows in a set. When the majority-to-minority ratio decreases from 3:0 to 2:1, information conflict increases significantly, requiring participants to recruit more cognitive control resources to coordinate perceptual encoding and decision-making (Wu et al., 2016). When cognitive load increases, functional connectivity between the right temporoparietal junction (rTPJ) and dorsal attention network (DAN) strengthens significantly, facilitating real-time synergy between goal-directed top-down signals and stimulus-driven salience signals in rTPJ, thereby enhancing attentional priority for features such as color and location (Wu et al., 2015). However, how changes in cognitive load regulate CAS selection efficiency and its neural mechanisms for category information remains unclear.

On the other hand, salience processing may also influence resource allocation for CAS. Salience refers to the degree of prominence of stimuli in physical or statistical features that can rapidly guide attention (Itti & Koch, 2001). According to whether it matches current task goal selection rules, it can be distinguished as task-relevant salience and task-irrelevant salience (Kim, 2014). The former refers to novel stimuli overlapping with features or categories relied upon for target decision-making, which can be encoded as valid information and accompanied by coordinated activity in frontoparietal networks (including lateral prefrontal cortex LPFC and intraparietal sulcus IPS) (Brass & von Cramon, 2004; Lerebourg et al., 2024). The latter refers to novel stimuli that are prominent in probability or physical attributes but do not meet current target conditions, constituting only external interference (Theeuwes, 2010). This interference effect is associated with enhanced activation in rTPJ (Kucyi et al., 2012; Corbetta & Shulman, 2002). Task-relevant salience may save cognitive control resources and accelerate category filtering (Thayer et al., 2022), whereas task-irrelevant salience lacks active suppression of irrelevant features, creating resource competition (Oxner et al., 2023). In experimental paradigms, the Oddball paradigm makes low-probability novel stimuli statistically salient, thereby triggering attentional capture (Näätänen, 2011). The mismatch negativity (MMN) and subsequent P3 components in EEG directly reflect this salience processing efficiency (Bekinschtein et al., 2009; Garrido et al., 2009). However, previous research has focused primarily on low-level features such as color and location (Chapman & Störmer, 2022; Oxner et al., 2023), and direct evidence for how salience processing affects resource allocation for high-level category information remains lacking. The differences between these two types of salience processing in CAS scenarios remain unclear.

Both cognitive control and salience processing affect cognitive resource allocation, showing functional division in mechanism while also demonstrating synergy under specific conditions. On one hand, they show distinct neural mechanisms involving different brain networks: cognitive control primarily involves core regions of the cognitive control network (CCN) such as dorsolateral prefrontal cortex (DLPFC), frontal eye fields (FEF), and superior parietal lobule (SPL) (Li et al., 2010; Noudoost & Moore, 2011; Wang et al., 2020; De Fockert et

al., 2004; Wu et al., 2015); salience processing primarily involves the ventral attention network (VAN, such as rTPJ, anterior insula AIC) and salience network (SN, such as IPS, superior temporal sulcus STS) to rapidly detect external salient signals (Arcizet et al., 2011; Corbetta & Shulman, 2002; Theeuwes, 2010). The division of these two processing pathways is particularly evident in conflict tasks: when salient distractors conflict with task goals, the prefrontal cortex must enhance control over parietal regions to suppress interference (Broschard et al., 2024), while parietal regions prioritize encoding salience signals (Kroner et al., 2023). In CAS, due to the abstract nature of category targets requiring more cognitive resource investment, stronger cognitive control is needed under higher load conditions to continuously reinforce target templates and better resist irrelevant salient interference (Yang & Zelinsky, 2009); whereas salience processing may rapidly capture salient features within categories through the ventral visual pathway, competing with dorsal pathway spatial orienting (Chen et al., 2012), making the division of labor more prominent. On the other hand, cognitive control and salience processing also show synergy in complex visual tasks. For example, TPJ serves as a multimodal information integration hub, playing a central role in coordinating task goals and salient stimuli (Wu et al., 2015; Corbetta et al., 2008; Kucyi et al., 2012), suggesting that cognitive control and salience processing may achieve information synergy in specific brain regions to enable dynamic attentional resource allocation. Based on this, this paper will focus on the boundaries and patterns of synergy between the two, i.e., under which contexts stronger synergy will be exhibited. These boundary conditions and synergistic patterns still require further testing within the CAS framework.

To investigate the regulatory effects and neural mechanisms of cognitive control and salience processing on CAS, this study employed functional magnetic resonance imaging (fMRI) technology, combining MFT and Oddball paradigms to simultaneously manipulate cognitive load and salience type (task-relevant/irrelevant). By varying cognitive load (3:0 low load vs. 2:1 high load) to manipulate cognitive control levels¹, varying stimulus salience level (80% standard stimuli vs. 20% novel stimuli) to manipulate salience processing, and varying whether stimuli conformed to current task goal selection rules (task-relevant: changing category probability; task-irrelevant: changing color probability) to manipulate salience relevance, we recorded participants' behavioral responses and brain activation. Combining whole-brain activation analysis and multivariate pattern analysis (MVPA), we examined the division of labor and synergy between the two mechanisms from multiple angles, providing systematic support for dynamic resource allocation. Experimental hypotheses were: (1) Behaviorally, high cognitive load would reduce CAS efficiency (decreased accuracy, prolonged RT); novel stimuli would interfere with CAS, with less interference when task-relevant; a three-way interaction would show that under task-relevant conditions, the interference effect of novel stimuli would be more pronounced under high load than low load. (2) In brain imaging, cognitive control would activate DAN (e.g., DLPFC, SPL), salience

processing would activate VAN (e.g., rTPJ, AIC); CCN would participate in the synergy of both processes, with its multivariate patterns distinguishing the two processes with high decoding accuracy.

2. Method

2.1 Participants

Using MorePower 6.0 (Campbell & Thompson, 2012), we calculated the required sample size for a $2 \times 2 \times 2$ within-subjects design with statistical power of 0.80, α level of 0.05, and medium effect size ($p^2 = 0.3$), which yielded 26 participants.

We recruited 29 university students from Tianjin Normal University (age range: 18-27 years; mean age: 20.83 ± 2.60 years; 24 females, 5 males). All participants were right-handed with normal or corrected-to-normal vision and no color blindness or weakness. The experiment was approved by the Tianjin Normal University Ethics Committee (Approval No. 2022030702). Participants signed informed consent before the experiment and received compensation upon completion.

2.2 Experimental Design

Stimuli were presented on a 17-inch CRT monitor with a resolution of 1024×768 pixels and a refresh rate of 60 Hz, with a gray background (CIE x/y coordinates: 0.313/0.329). Participants viewed the screen from a distance of approximately 57 cm in a shielded room. The experimental program was compiled using E-Prime 3.0 software.

This experiment used a 2 (cognitive load: high load, low load) $\times 2$ (salience level: novel stimulus, standard stimulus) $\times 2$ (salience relevance: task-relevant, task-irrelevant) within-subjects design. The experimental task combined MFT and Oddball paradigms (Figure 1 [Figure 1: see original paper]). First, a fixation cross “+” was randomly presented at the center of the screen for 100–600 ms. Then a search display appeared for 400 ms, containing three symbols ($0.31^\circ \times 0.31^\circ$) equidistant from the central fixation point (0.86° from center). Symbols could be digits (2–9) or letters (A, B, C, D, E, F, G, H). Symbols appeared at one of 12 possible positions around the central fixation point, with the three symbols presented equidistant from each other (e.g., positions 1, 5, 9) to avoid uneven symbol distribution. Participants’ task was to judge the category (letter or digit) of the majority of the three presented symbols and respond by pressing keys: right index finger for “1” if the majority were digits, right middle finger for “2” if the majority were letters. Response keys were counterbalanced across participants. After a response window of 900–1400 ms and a 100 ms blank screen, the next trial began.

Cognitive load was manipulated by changing the ratio of symbol categories: in the low cognitive load condition, all three symbols belonged to the same cat-

egory (3:0), i.e., all digits or all letters; in the high cognitive load condition, two symbols belonged to one category and the remaining one belonged to the other category (2:1), i.e., two digits and one letter or two letters and one digit. Stimulus salience level was manipulated by stimulus frequency: standard stimuli comprised the majority (80%), while novel stimuli were less frequent salient stimuli (20%). Salience relevance was manipulated by whether stimuli conformed to current task goal selection rules: task-irrelevant salience was implemented by changing the proportion of stimulus colors, i.e., red (CIE x/y: 0.640/0.330) and green (CIE x/y: 0.300/0.600), with one color as standard (80%) and the other as novel (20%), with color salience counterbalanced across experimental blocks and participants; task-relevant salience was implemented by changing the proportion of the majority symbol category, with the majority being digits in most cases (80%) and letters in fewer cases (20%), or vice versa, with majority category proportions counterbalanced across blocks and participants.

The experiment consisted of 4 blocks, each containing 200 trials (160 standard stimulus trials and 40 novel stimulus trials). Participants practiced sufficiently before the formal experiment. They rested for 2 minutes after completing each block, with the entire experiment lasting approximately 35 minutes.

Figure 1. Schematic diagram of experimental design. Note: Cognitive load (low vs. high) was manipulated by changing the majority category ratio of the three symbols (3:0 vs. 2:1). Stimulus salience level (standard vs. novel) was manipulated by changing stimulus frequency (standard 80%, novel 20%). Salience relevance (relevant vs. irrelevant) was manipulated by conformity to current task goal selection rules: in task-relevant conditions, salience was implemented by changing the proportion of task-relevant majority symbol categories; in task-irrelevant conditions, salience was implemented by changing the proportion of task-irrelevant stimulus colors.

2.3 fMRI Data Acquisition and Preprocessing

Brain imaging data were acquired on a Siemens Prisma 3.0T scanner using a 64-channel standard head coil. Blood oxygen level-dependent (BOLD) signals were collected using echo-planar imaging (EPI) sequences with a resolution of $3.8 \times 3.8 \times 4.0 \text{ mm}^3$. Repetition time (TR): 2 s, echo time (TE): 27 ms, echo spacing: 0.4 ms, field of view: $240 \times 240 \text{ mm}^2$, flip angle: 77° , slice thickness: 4.0 mm, slice gap: 0, number of slices: 40, EPI factor: 64, bandwidth: 3126 Hz/Px. After functional imaging, participants completed a 5-minute structural scan with a resolution of $0.9 \times 0.9 \times 0.9 \text{ mm}^3$.

Preprocessing mainly included: slice timing correction, orientation standardization, registration, segmentation, head motion correction, spatial normalization, and smoothing. BOLD functional images first underwent slice timing correction to align the acquisition time of each voxel's time series to the middle slice, then were realigned to the first image to correct for head motion between scans. All images were normalized within a Montreal Neurological Institute

(MNI) template in Talairach space (Talairach & Tournoux, 1988) using bilinear interpolation to a $3 \times 3 \times 3 \text{ mm}^3$ resolution. Functional images were spatially smoothed using a Gaussian filter with a full-width at half maximum (FWHM) of 6 mm.

2.4 fMRI Data Statistical Analysis

Brain imaging data analysis used SPM12 software based on MATLAB for integrated preprocessing and data analysis of task-state fMRI data. At the individual participant level, first-level statistical brain maps of BOLD activation were calculated using the General Linear Model (GLM). Eight regressors were defined corresponding to correct responses under eight experimental conditions: 2 (cognitive load: high load, low load) \times 2 (salience level: novel stimulus, standard stimulus) \times 2 (salience relevance: task-relevant, task-irrelevant). These regressors were convolved with the standard hemodynamic response function (HRF). The model also included six head motion parameters from motion correction as nuisance covariates. Each voxel's time series was high-pass filtered (1/128 Hz) to remove low-frequency noise and signal drift. By setting linear contrast values between trial conditions and completing GLM parameter estimation, contrast activation maps for main effects of cognitive load (high, low), salience level (novel, standard), salience relevance (irrelevant, relevant), and their three-way interactions were obtained for each participant. These contrast maps entered second-level analysis with GLM construction.

AlphaSim program (<http://afni.nimh.nih.gov/pub/dist/doc/manual/AlphaSim.pdf>) was used for Monte Carlo simulation to determine appropriate cluster thresholds. Assuming a single-voxel Type I error of $p < 0.005$, a cluster extent of 46 contiguous voxels was required for correction of multiple voxel comparisons at $p < 0.05$.

Multivariate pattern analysis (MVPA) models were programmed in Python 3.11 using Nilearn, Numpy, Sklearn, and other third-party packages. Based on results from second-level GLM analysis, brain regions with high activation in both cognitive load and salience level conditions were selected to compose feature voxels for that condition. At the individual participant level, data structure consisted of three components: fMRI scan data, condition, and group. The model decoded which condition task participants were performing from brain activation data collected during task performance. fMRI scan data were processed using SPM12's ImCalc function: images for cognitive load conditions were generated by subtracting each low load-standard stimulus condition image from each high load-standard stimulus condition image, and each high load-novel stimulus condition image from each low load-novel stimulus condition image; images for salience level conditions were generated by subtracting each high load-standard stimulus condition image from each high load-novel stimulus condition image, and each low load-standard stimulus condition image from each low load-novel stimulus condition image. Condition and group labels were retained for model input. This study used leave-one-out cross-validation, randomly selecting three

groups as training set (75%) and the remaining group as test set (25%) each time. The model was then tested on the test set to obtain test accuracy. We then calculated each voxel's weight in the model, output individual participants' decoding accuracy for different voxels under that condition, and generate images for further analysis. Finally, output images were spatially smoothed with a Gaussian filter (FWHM = 6 mm) and imported into group-level GLM for further difference testing of decoding accuracy across voxels.

3. Results

3.1 Behavioral Results

We conducted 2 (cognitive load: high load, low load) \times 2 (salience level: novel stimulus, standard stimulus) \times 2 (salience relevance: task-relevant, task-irrelevant) repeated measures ANOVA on accuracy (ACC), correct response reaction time (RT), and inverse efficiency scores (IES = RT/ACC, representing overall performance).

3.1.1 Accuracy The main effect of cognitive load was significant, $F(1, 28) = 209.34$, $p < 0.001$, $p^2 = 0.88$, with higher accuracy in low load than high load. The main effect of salience level was significant, $F(1, 28) = 22.06$, $p < 0.001$, $p^2 = 0.44$, with higher accuracy for standard than novel stimuli.

The cognitive load \times salience level interaction was significant, $F(1, 28) = 24.98$, $p < 0.001$, $p^2 = 0.47$. Simple effects analysis found that accuracy for standard stimuli was significantly higher than for novel stimuli under both low load [$F(1, 28) = 4.35$, $p = 0.046$, $p^2 = 0.13$] and high load [$F(1, 28) = 38.33$, $p < 0.001$, $p^2 = 0.58$]. Further paired t-tests on salience effects ($ACC_{\text{standard}} - ACC_{\text{novel}}$) across cognitive load conditions showed that the salience effect was larger under high load than low load, $t(28) = 5.00$, $p < 0.001$, Cohen's $d = 0.93$, 95% CI [0.49, 1.36]. Additionally, accuracy under low load was significantly higher than under high load for both standard [$F(1, 28) = 193.28$, $p < 0.001$, $p^2 = 0.87$] and novel stimuli [$F(1, 28) = 148.29$, $p < 0.001$, $p^2 = 0.84$]. Paired t-tests on load effects ($ACC_{\text{low load}} - ACC_{\text{high load}}$) across salience levels showed that the load effect was larger for novel than standard stimuli, $t(28) = 5.00$, $p < 0.001$, Cohen's $d = 0.93$, 95% CI [0.49, 1.36].

The salience level \times salience relevance interaction was significant, $F(1, 28) = 24.01$, $p < 0.001$, $p^2 = 0.46$. Simple effects analysis found that when task-relevant, accuracy for standard stimuli was significantly higher than for novel stimuli, $F(1, 28) = 28.06$, $p < 0.001$, $p^2 = 0.50$; when task-irrelevant, accuracy did not differ significantly between standard and novel stimuli, $F(1, 28) = 0.14$, $p = 0.710$.

The three-way interaction of cognitive load \times salience level \times salience relevance was significant, $F(1, 28) = 12.22$, $p = 0.002$, $p^2 = 0.30$. To clarify the three-

way interaction pattern, we conducted separate cognitive load \times salience level two-way ANOVAs under task-relevant and task-irrelevant conditions. Under task-relevant conditions, the cognitive load \times salience level interaction was significant, $F(1, 28) = 37.03$, $p < 0.001$, $p^2 = 0.57$. Standard stimuli accuracy was significantly higher than novel stimuli under both low load [$F(1, 28) = 6.34$, $p = 0.018$, $p^2 = 0.19$] and high load [$F(1, 28) = 51.49$, $p < 0.001$, $p^2 = 0.65$]. The salience effect ($ACC_{\text{standard}} - ACC_{\text{novel}}$) was larger under high than low load, $t(28) = 6.09$, $p < 0.001$, Cohen's $d = 1.13$, 95% CI [0.66, 1.59]. Low load accuracy was significantly higher than high load for both standard [$F(1, 28) = 73.71$, $p < 0.001$, $p^2 = 0.73$] and novel stimuli [$F(1, 28) = 72.50$, $p < 0.001$, $p^2 = 0.72$]. The load effect ($ACC_{\text{low}} - ACC_{\text{high}}$) was larger for novel than standard stimuli, $t(28) = 6.09$, $p < 0.001$, Cohen's $d = 1.13$, 95% CI [0.66, 1.59]. However, under task-irrelevant conditions, the cognitive load \times salience level interaction was not significant, $F(1, 28) = 0.04$, $p = 0.844$.

Figure 2 [Figure 2: see original paper]. Accuracy (%) results across different cognitive load, salience level, and salience relevance conditions. Note: *** indicates $p < 0.001$, * indicates $p < 0.05$, ns indicates $p \geq 0.05$. The same applies below.

3.1.2 Reaction Time The main effect of cognitive load was significant, $F(1, 28) = 404.96$, $p < 0.001$, $p^2 = 0.94$, with faster RTs in low than high load. The main effect of salience level was significant, $F(1, 28) = 72.53$, $p < 0.001$, $p^2 = 0.72$, with faster RTs for standard than novel stimuli. The main effect of salience relevance was significant, $F(1, 28) = 22.16$, $p < 0.001$, $p^2 = 0.44$, with faster RTs for task-relevant than task-irrelevant conditions.

The cognitive load \times salience relevance interaction was significant, $F(1, 28) = 6.54$, $p = 0.016$, $p^2 = 0.19$. Simple effects analysis found that RTs were significantly faster under low than high load for both task-relevant [$F(1, 28) = 298.04$, $p < 0.001$, $p^2 = 0.91$] and task-irrelevant conditions [$F(1, 28) = 390.17$, $p < 0.001$, $p^2 = 0.93$]. The load effect ($RT_{\text{high}} - RT_{\text{low}}$) was larger for task-irrelevant than task-relevant conditions, $t(28) = 2.56$, $p = 0.016$, Cohen's $d = 0.48$, 95% CI [0.09, 0.86].

The salience level \times salience relevance interaction was significant, $F(1, 28) = 88.90$, $p < 0.001$, $p^2 = 0.76$. Simple effects analysis found that when task-relevant, RTs for standard stimuli were significantly faster than for novel stimuli, $F(1, 28) = 100.78$, $p < 0.001$, $p^2 = 0.78$; when task-irrelevant, RTs did not differ significantly between standard and novel stimuli, $F(1, 28) = 0.00$, $p = 0.959$.

The three-way interaction of cognitive load \times salience level \times salience relevance was not significant, $F(1, 28) = 0.71$, $p = 0.405$.

Figure 3 [Figure 3: see original paper]. Reaction time (ms) results across different cognitive load, salience level, and salience relevance conditions.

3.1.3 Inverse Efficiency Scores IES = RT/ACC was used to correct for speed-accuracy trade-offs, representing participants' overall performance across conditions (Townsend & Ashby, 1983). Lower IES values indicate better overall performance.

The main effect of cognitive load was significant, $F(1, 28) = 250.56$, $p < 0.001$, $p^2 = 0.90$, with better performance in low than high load. The main effect of salience level was significant, $F(1, 28) = 35.11$, $p < 0.001$, $p^2 = 0.56$, with better performance for standard than novel stimuli. The main effect of salience relevance was significant, $F(1, 28) = 6.94$, $p = 0.014$, $p^2 = 0.20$, with better performance for task-relevant than task-irrelevant conditions.

The cognitive load \times salience level interaction was significant, $F(1, 28) = 21.72$, $p < 0.001$, $p^2 = 0.44$. Simple effects analysis found that performance for standard stimuli was better than for novel stimuli under both low load [$F(1, 28) = 20.75$, $p < 0.001$, $p^2 = 0.43$] and high load [$F(1, 28) = 36.51$, $p < 0.001$, $p^2 = 0.57$]. The salience effect (IES_{novel} - IES_{standard}) was larger under high than low load, $t(28) = 4.66$, $p < 0.001$, Cohen's $d = 0.87$, 95% CI [0.43, 1.28]. Additionally, performance under low load was significantly better than under high load for both standard [$F(1, 28) = 353.98$, $p < 0.001$, $p^2 = 0.93$] and novel stimuli [$F(1, 28) = 164.35$, $p < 0.001$, $p^2 = 0.85$]. The load effect (IES_{high} load - IES_{low} load) was larger for novel than standard stimuli, $t(28) = 4.66$, $p < 0.001$, Cohen's $d = 0.87$, 95% CI [0.43, 1.28].

The salience level \times salience relevance interaction was significant, $F(1, 28) = 40.27$, $p < 0.001$, $p^2 = 0.59$. Simple effects analysis found that when task-relevant, performance for standard stimuli was better than for novel stimuli, $F(1, 28) = 43.48$, $p < 0.001$, $p^2 = 0.61$; when task-irrelevant, performance did not differ significantly between standard and novel stimuli, $F(1, 28) = 0.00$, $p = 0.973$.

The three-way interaction of cognitive load \times salience level \times salience relevance was significant, $F(1, 28) = 10.48$, $p = 0.003$, $p^2 = 0.27$. To clarify the three-way interaction pattern, we conducted separate cognitive load \times salience level two-way ANOVAs under task-relevant and task-irrelevant conditions. Under task-relevant conditions, the cognitive load \times salience level interaction was significant, $F(1, 28) = 19.07$, $p < 0.001$, $p^2 = 0.41$. Simple effects analysis found that performance for standard stimuli was significantly better than for novel stimuli under both low load [$F(1, 28) = 28.12$, $p < 0.001$, $p^2 = 0.50$] and high load [$F(1, 28) = 39.90$, $p < 0.001$, $p^2 = 0.59$]. The salience effect (IES_{novel} - IES_{standard}) was larger under high than low load, $t(28) = 4.37$, $p < 0.001$, Cohen's $d = 0.81$, 95% CI [0.39, 1.23]. Performance under low load was significantly better than under high load for both standard [$F(1, 28) = 285.55$, $p < 0.001$, $p^2 = 0.91$] and novel stimuli [$F(1, 28) = 73.54$, $p < 0.001$, $p^2 = 0.72$]. The load effect (IES_{high} load - IES_{low} load) was larger for novel than standard stimuli, $t(28) = 4.37$, $p < 0.001$, Cohen's $d = 0.81$, 95% CI [0.39, 1.23]. However, under task-irrelevant conditions, the cognitive load \times salience level interaction was not significant, $F(1, 28) = 0.00$, $p = 0.965$.

Figure 4 [Figure 4: see original paper]. IES (ms) results across different cognitive load, salience level, and salience relevance conditions.

3.2 fMRI Results

3.2.1 Brain Activation Results Whole-brain contrast analysis (Figure 5 [Figure 5: see original paper] and Table 1) revealed no significant brain activation regions for salience relevance. Extracting task-relevant brain regions, the main effect of cognitive load was significant: compared with low load, high load activated bilateral superior parietal lobule, bilateral insula, left middle frontal gyrus, bilateral calcarine fissure, and other regions; compared with high load, low load activated right cuneus, right lingual gyrus, right superior frontal gyrus, left angular gyrus, right inferior parietal lobule, right medial superior frontal gyrus, left middle temporal gyrus, left parahippocampal cortex, left inferior frontal gyrus, and other regions. The main effect of salience level was significant: compared with standard stimuli, novel stimuli activated left precentral gyrus, right angular gyrus, bilateral insula, bilateral caudate nucleus, and other salient activations.

Figure 5. Main effects of cognitive load and salience level. (a) Brain regions related to cognitive load (high load > low load). (b) Brain regions related to salience level (novel stimulus > standard stimulus). Red indicates voxels with increased activation. Blue indicates voxels with decreased activation.

Table 1 . Brain activation regions for main effects of cognitive load and salience level (FDR, $p < 0.05$, $k \geq 46$)

The salience level \times salience relevance interaction mainly showed significant positive activation in left postcentral gyrus, bilateral precentral gyrus, bilateral insula, right superior parietal lobule, and other regions (Figure 6 [Figure 6: see original paper] and Table 2). When task-relevant, novel stimuli compared with standard stimuli significantly activated left precentral gyrus, left pars opercularis of inferior frontal gyrus, right inferior angular gyrus, left insula, and other regions; standard stimuli compared with novel stimuli significantly activated left posterior cingulate cortex, right precuneus, left anterior and paracingulate gyri, left dorsolateral superior frontal gyrus, right middle occipital gyrus, left central operculum, left middle temporal gyrus, left orbital part of inferior frontal gyrus, and other regions. However, when task-irrelevant, novel stimuli compared with standard stimuli only significantly activated left fusiform gyrus and right lingual gyrus. No significant activation regions were found for cognitive load \times salience level, cognitive load \times salience relevance, or three-way interactions.

Figure 6. Interaction between salience level and salience relevance. (a) Brain regions showing interaction effect, $(\text{novel} - \text{standard})\{\text{task}\}\text{-relevant} > (\text{novel} - \text{standard})\{\text{task}\}\text{-irrelevant}$. (b) Simple effects analysis: brain regions activated by different salience level contrasts when task-relevant (novel task-relevant > standard task-relevant). (c) Simple effects analysis: brain regions activated by different salience level contrasts when task-irrelevant (novel task-irrelevant >

standard task-irrelevant). Red indicates voxels with increased activation. Blue indicates voxels with decreased activation.

Table 2 . Interaction between salience level and salience relevance and simple effects analysis (uncorrected, $p < 0.001$, $k \geq 46$)

3.2.2 Joint Activation of Cognitive Control and Salience Processing

To explore the synergy between cognitive control and salience processing, we conducted conjunction analysis on the main effects of task load and salience level. As shown in Figure 7 [Figure 7: see original paper] and Table 3 , left superior parietal lobule, left inferior occipital gyrus, right angular gyrus, right precentral gyrus, bilateral insula, right caudate nucleus, and other regions were jointly involved in cognitive control and salience processing.

Figure 7 [Figure 7: see original paper]. Brain regions showing joint activation of cognitive control and salience processing. Red indicates voxels with increased activation.

Table 3 . Brain regions showing joint activation of cognitive control and salience processing (FDR, $p < 0.05$, $k \geq 46$)

3.2.3 Predictive Effects of Brain Activation Patterns on Cognitive Control and Salience Processing

To identify key hubs for the synergy of cognitive control and salience processing, we used a classifier to predict brain regions that significantly distinguished cognitive load and salience level conditions based on conjunction analysis results. The classifier achieved an average decoding accuracy of 86.83% for predicting cognitive load and salience level conditions, significantly above chance level (50%) [$t(28) = 73.57$, $p < 0.001$, Cohen's $d = 27.81$]. Further difference analysis of brain region weights showed that the right parieto-occipital junction (rPOJ) and right precentral gyrus/FEF contributed significantly to the classifier's predictive power (Figure 8 [Figure 8: see original paper] and Table 4).

Figure 8 [Figure 8: see original paper]. MVPA results distinguishing cognitive control and salience processing. Red indicates brain regions with significant contribution to decoding.

Table 4 . Brain regions distinguishing cognitive control and salience processing (uncorrected, $p < 0.005$, $k \geq 46$)

4. Discussion

This study combined MFT and Oddball tasks to systematically investigate the division of labor and synergistic mechanism between cognitive control and salience processing in category-based attentional selection (CAS). Behavioral results showed that high load significantly reduced CAS efficiency (increased

IES); task-relevant novel stimuli showed a facilitatory effect under low load that switched to interference under high load, while task-irrelevant novel stimuli showed interference that amplified with increasing load. This pattern supports a dynamic category priority map where target enhancement dominates when resources are abundant, but salience weighting exceeds target enhancement when resources are scarce. Brain imaging results revealed that the dorsal attention network (DAN, including DLPFC, SPL) activated under high load, while the ventral attention network (VAN, including rTPJ, AIC) activated for novel stimuli, showing clear functional division. However, conjunction analysis showed that core CCN regions including SPL, ACC, and AIC participated in both processes, suggesting that CCN coordinates cognitive control and salience through global resource regulation. rPOJ and FEF decoded both processes with ~87% accuracy, indicating they serve as synergistic hubs. This finding not only extends the category priority map to higher-order parieto-occipital regions but also validates the applicability of the multiple resource competition framework at the semantic level, injecting a dynamic perspective into the dual-pathway model of attention.

Behavioral results revealed a dual modulation pattern of cognitive load and salience processing on CAS, providing key evidence for understanding the dynamics of attentional resource allocation (Lavie, 2005). Specifically, high load increased information processing costs (worse performance under high load), while task-irrelevant novel stimuli only significantly amplified interference under high load. In contrast, task-relevant novel stimuli showed slight facilitatory effects under low load (relatively small difference from standard stimuli) but switched to clear interference under high load (relatively large difference from standard stimuli). This pattern supports the priority map theory of attentional selection (Fecteau & Munoz, 2006; Itti & Koch, 2001; Mo et al., 2018), which posits that the brain's resource allocation priority values are flexibly regulated by both stimulus-driven salience and goal-driven relevance. When cognitive resources are sufficient (low load), target templates (i.e., abstract representations of category semantics) can be adequately maintained, allowing the system to actively utilize task-relevant salience (such as novel stimuli) as additional cues to enhance filtering efficiency through positive modulation of the priority map. At this point, task-relevant novel stimuli, matching the target template, are considered beneficial signals, producing facilitatory effects. However, under high load, target template maintenance is weakened, forcing the attention system to rely on externally input stimulus-driven processing (Geng & Mangun, 2011). Any novel stimulus (regardless of task relevance) then consumes residual resources, especially task-relevant novel stimuli that partially overlap with target features—these are amplified in the priority map, causing their interference effect to switch from facilitation under low load to significant inhibition under high load. By comparison, task-irrelevant novel stimuli always lack target template constraints, with interference magnitude primarily determined by remaining resources: under low load with abundant resources, interference from irrelevant novel stimuli is minimal; under high load with scarce resources, interference from irrelevant

novel stimuli becomes prominent due to intensified resource competition. This difference further validates the selective amplification mechanism (Lavie, 2005), which posits that when attentional resources are limited, the cognitive system does not equally suppress all salience processing but rather sacrifices fine-tuned control for target-matching features, creating differential interference patterns across relevance types (task-relevant/irrelevant). Overall, cognitive load dynamically changes the neural resource allocation strategy for salience processing by modulating target template maintenance strength: under low load, the system actively processes relevant salience to optimize filtering; under high load, it passively responds to resource competition from all novel stimuli. This mechanism provides direct behavioral evidence for dynamic resource allocation in CAS and extends priority map theory into the semantic domain and dynamic resource framework.

The role patterns of cognitive control and salience processing in CAS reflect the dialectical unity of functional division and neural synergy. Their division is manifested in the separation of neural pathways: cognitive control primarily relies on the DAN (including DLPFC, FEF, SPL) to strengthen target templates (such as semantic categories of digits) and suppress interference (Li et al., 2010; Broschard et al., 2024), while salience processing automatically captures salient features (such as color contrast of green letters) through the SN (including ACC and AIC) (Harsay et al., 2012; Kumaran et al., 2009; Corbetta & Shulman, 2002; Kroner et al., 2023). This separation is particularly evident in conflict tasks: when salient distractors conflict with task goals under high cognitive load, DLPFC activation increases to maintain target representations while TPJ prioritizes salience signals, leading to decreased behavioral response efficiency (Bouvier et al., 2023; Geng & Mangun, 2011). This resource competition phenomenon indicates that the two processes differ fundamentally in resource allocation: cognitive control is a capacity-limited, goal-directed process, whereas salience processing is a stimulus-driven, automatic process (Theeuwes, 2010).

However, synergy between the two is achieved through dynamic functional coupling in CAS. fMRI conjunction analysis showed that left superior parietal lobule, left inferior occipital gyrus, right precentral gyrus, right ACC, bilateral AIC, right caudate nucleus, and other regions participated in both processes, indicating that CCN coordinates goals and salience through global resource regulation to complete cognitive control processing (Keller et al., 2022; Li et al., 2010; Noudoost & Moore, 2011; Wang et al., 2020; Wu et al., 2015). For example, when task-relevant salience appears, functional connectivity between DLPFC and LOC strengthens, thereby synergistically encoding salience signals into target templates to enhance search efficiency (Oxner et al., 2023). This synergistic mechanism received further support from neural decoding results: multivariate activation patterns in rPOJ and FEF could significantly distinguish cognitive control from salience processing. rPOJ is located at the high-order visual-spatial association cortex at the occipito-parietal junction, participating in attentional selection, integrating visual and motor information, and having visuomotor co-

ordination functions (Chen et al., 2012; Collignon et al., 2011; Zhang et al., 2024). Therefore, rPOJ may serve as a key region for conflict monitoring, dynamically adjusting dorsal-ventral pathway resource allocation by real-time assessing conflict strength between task demands and stimulus salience. On the other hand, FEF is located in the premotor-attention hub of the precentral gyrus, serving as a key region for translating synergistically encoded priority maps into specific orienting commands (Noudoost & Moore, 2011). Thus, FEF can act as an output conversion hub from priority map to action commands, feeding back selective gain to visual cortex and synchronously regulating eye-hand orienting networks to synergistically encode goal-driven enhancement and salience-driven signals into executable orienting and response plans. Overall, these results are consistent with Katsuki and Constantinidis' s (2014) adaptive control model, which posits that parietal-frontal networks can dynamically regulate goal-directed enhancement and stimulus salience processing according to priority maps. This study further speculates that CAS efficiency depends on CCN' s capacity for processing complex information and flexible allocation, with rPOJ and FEF serving as key nodes for synergistic processing. In summary, this study pioneeringly reveals the division-synergy balance between cognitive control and salience processing within the category attention framework. Unlike simple feature attention (Chapman & Störmer, 2022), the abstract nature of category targets in CAS requires higher-level semantic processing, which amplifies CCN' s regulatory demands. This indicates that rapid target recognition depends not only on explicit feature definition but also on dynamic coordination of conflicts between task goals and environmental salience.

Based on evidence that cognitive control and salience processing are functionally divided yet interconnected, we propose a concise dynamic pathway model: First, division is reflected in relatively distinct neural pathways and functional roles—cognitive control is dominated by DAN (e.g., DLPFC, FEF, SPL), which preferentially activates and maintains target categories, representing capacity-limited, goal-directed processing (Li et al., 2010; Awh et al., 2012); salience processing is dominated by VAN and SN (e.g., rTPJ, ACC, AIC), which automatically detect and capture physically or statistically salient features, with the two pathways anatomically and initiatorily separate (Corbetta et al., 2002; Arcizet et al., 2011). Second, under complex task contexts, the two show conditional synergy: when task-irrelevant salient distractors appear under high cognitive load, the attention system often exhibits resource competition and coupling reallocation, where DAN enhances target representations via DLPFC to maintain control while VAN prioritizes salience signals via TPJ (Geng & Mangun, 2011; Wu et al., 2015). Finally, hubs such as ACC/AIC coordinate resource allocation between the two with assistance from rPOJ and FEF, achieving suppression of irrelevant salience and enhancement of relevant salience to enable dynamic attentional resource configuration (Chen et al., 2012; Katsuki & Constantinidis, 2014). This resource reallocation process also explains the behavioral effects of facilitation under low load and interference under high load, consistent with the salience-goal weight competition mechanism emphasized by priority map theory

(Fecteau & Munoz, 2006). Overall, the dynamic pathway model emphasizes that cognitive control and salience processing are not opposing but achieve functional division through separate pathways and synergy under specific boundary conditions to simultaneously satisfy goal-directed and stimulus-driven demands in complex environments.

Notably, CCN' s interaction with salience processing depends on task relevance. The study found that only when salient stimuli were task-relevant did core CCN regions (e.g., DLPFC, SPL) show significantly enhanced activation, with functional connectivity strength to visual cortex (e.g., LOC) positively correlating with behavioral efficiency. This phenomenon can be explained by a goal-salience synergy mechanism: CCN is responsible not only for maintaining goal direction but also for dynamically evaluating the task relevance of salience signals and synergistically encoding qualifying salient features into target representations. This synergy is crucial in conflict tasks: when multiple stimuli share category attributes, CCN must prioritize salient stimuli that are spatially or semantically consistent with task goals through SPL' s spatial orienting function (Kroner et al., 2023). This finding challenges the traditional view that CCN is responsible only for pure cognitive control (Desimone & Duncan, 1995), demonstrating more flexible function: in task-relevant salience processing, CCN acts as an adaptive filter that both suppresses irrelevant interference and actively enhances salient signals matching target templates. For example, Wu et al. (2015) proposed that after TPJ (SN core) detects salient stimuli, it communicates their task relevance to CCN through functional connectivity with prefrontal cortex, which then decides whether to allocate attentional resources. In this study, task-relevant novel stimuli elicited synergistic activation of rPOJ and DLPFC, further supporting this cross-network collaboration model. Therefore, CCN' s involvement in task-relevant salience is essentially goal-directed adaptive selection rather than passive response. In complex category processing, this dynamic monitoring mechanism can balance conflicts between abstract semantic representations and concrete perceptual features.

Interestingly, reviewers noted that while behavioral results showed a main effect of salience relevance, brain imaging results revealed no significant activation. This discrepancy may be explained in two ways. First, behavioral main effects reflect macroscopic performance after cross-regional synergy, whereas fMRI only captures average signal intensity at the voxel level (Haxby et al., 2001). Neural representation of task relevance (relevant/irrelevant) may not rely on activation magnitude changes in single brain regions but rather on distributed activity patterns across multiple regions or network-level synergy (Bressler & Menon, 2010). Second, task relevance modulation of attention may occur in a pre-activation phase before stimulus onset, whereas GLM analysis only captures average BOLD signals 4–6 seconds after stimulus presentation (Logothetis, 2008). For example, target template (category semantics) matching may influence subsequent processing through pre-activation of visual cortex before stimulus onset (Miao et al., 2023); task-irrelevant stimuli, lacking attentional templates, rely more on stimulus-driven processing. If core effects of task relevance concentrate

in the pre-stimulus period, fMRI may fail to detect behavioral-level differences due to incomplete temporal window coverage. Therefore, the discrepancy between behavioral and brain imaging results is not a measurement conflict but rather a combined product of measurement dimension differences (macroscopic synergy vs. local averaging) and analysis time window differences (pre-activation vs. post-stimulus response). Future research could combine high temporal resolution techniques (e.g., EEG/MEG) to capture full-time neural dynamics from pre- to post-stimulus periods and use MVPA to uncover distributed neural coding features, thereby more comprehensively revealing how task relevance modulates attentional processing through spatiotemporal synergy mechanisms.

Additionally, several issues remain unresolved. First, the semantic clarity of digits/letters may underestimate processing difficulty for ambiguous categories in natural scenes (e.g., diversity of tool categories); future research should introduce prototype gradient materials (Miao et al., 2023) to test category boundary modulation effects. Second, fMRI's low temporal resolution limits parsing of early perceptual windows (e.g., N1/P1); combining EEG technology (Wu & Fu, 2017) could more precisely capture the temporal dynamics of category representation. Furthermore, individual differences (e.g., prefrontal decline in older adults) may amplify salience interference effects (Zhang et al., 2024), requiring inclusion of age and clinical variables in future studies. For clinical interventions, TMS targeting rPOJ and FEF activity may improve patients' target-distractor inhibition capacity (Kucyi et al., 2012). In summary, optimizing CAS efficiency requires balancing task goal clarity with dynamic environmental salience, a principle with important value for both theoretical construction and practical applications.

This study combined MFT and Oddball paradigms to systematically examine the roles of cognitive control and salience processing in category-based attentional selection (CAS). Behavioral results showed that both cognitive control and salience processing independently affect attentional selection, showing synergistic effects under high load and task-relevant novel conditions. Brain imaging results further revealed that cognitive control primarily activated DAN, while salience processing relied on VAN/SN. Within CCN, rPOJ and FEF synergistically connected the two processes: rPOJ evaluated the match between task demands and stimulus salience, while FEF translated this into executable orienting commands. Overall, CAS involves both division of labor and synergy between cognitive control and salience processing under specific conditions.

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¹ Previous studies typically used flanker, Simon, or Stroop tasks to investigate cognitive control, but in these tasks conflict information is irrelevant to target processing (e.g., flanking arrows in flanker tasks are distractors), making them susceptible to confounding by bottom-up stimulus-response congruency effects. In contrast, in the MFT task, all presented stimuli are potential targets with no fixed distractors, excluding bottom-up confounding factors (Fan et al., 2008; Wang et al., 2011).

Note: Figure translations are in progress. See original paper for figures.

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