



# Neural activity and connectivity are related to food preference changes induced by food go/no-go training

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## ABSTRACT

Simply withholding a response while viewing an appetizing food, over the course of many presentations (i.e., during food go/no-go training) can modify individuals' food preferences—which could, in turn, promote healthier eating behaviors. However, the neural mechanisms underlying this food go/no-go training-induced change in food preferences are still relatively unclear. We addressed this issue in the present functional magnetic resonance imaging (fMRI) study. To this end, we administered a novel passive viewing task before and after food go/no-go training to 91 participants in the scanner. Participants' food preferences were measured with a binary food choice task. At the behavioral level, we found the expected training effect on food preferences: Participants preferred go over no-go foods following training. At the neural level, we found that changes in food preferences were associated with training-related go vs. no-go differences in activity and functional connectivity, such as less activity in the anterior cingulate cortex and superior frontal gyrus but greater functional connectivity between the superior frontal gyrus and middle occipital gyrus. Critically, Dynamic causal modeling showed that this preference change effect was largely driven by top-down influence from the superior frontal gyrus to the middle occipital gyrus. Together, these findings suggest a neural mechanism of the food go/no-go training effect—namely, that the food-viewing-related interplay between prefrontal regions and visual regions might be related to the food preference change following food go/no-go training.

## 1. Introduction

The prevalence of overweight and obesity has risen dramatically in developed and developing nations worldwide (Ng et al., 2014). This fact has far-reaching and costly implications, as a higher body mass index (BMI) is a major risk factor for numerous physical and mental health issues, including cardiovascular diseases (e.g., Lavie et al., 2009), some cancers (e.g., Kyrgiou et al., 2017), and psychiatric disorders (e.g., depression; e.g., Luppino et al., 2010). Consequently, much recent work has aimed to design effective interventions for promoting healthy eating habits and weight loss (Forcano et al., 2018; Jones et al., 2018; Stice et al., 2017; Yang et al., 2019). This study adds to this growing body of literature by examining the neural mechanisms underpinning one such

intervention.

Implicit or explicit preferences for unhealthy foods, coupled with weak executive control, may place individuals at heightened risk for unhealthy eating behaviors and obesity (Shields et al., 2021; Stice and Burger, 2019; Yang et al., 2018, 2021). Because these biased preferences can increase risk, it is possible that, conversely, cognitive training focused on decreasing cognitive bias toward high-calorie foods and enhancing executive control related to these foods could reduce over-eating—which often arises from exposure to obesogenic food environments (Stice et al., 2016; Yang et al., 2019). Nonreinforcement training is one example of cognitive training that has demonstrated notable effects in reducing food liking/wanting or unhealthy food consumption (Schonberg and Katz, 2020; Terenzi et al., 2022; Veling et al., 2022;

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Zahedi et al., 2023). In particular, this form of cognitive training necessitates participants to either respond or withhold their response to specific stimuli without the presence of external reinforcements. The most common paradigms employed in this area are food go/no-go training (e.g., Chen et al., 2019; Veling et al., 2021) and cue-approach training (e.g., Schonberg et al., 2014). In food go/no-go training, participants are instructed to respond quickly to select foods upon sighting a go cue (e.g., a green rectangular frame around the food) and restrain their response to other food items when facing a no-go cue (e.g., a grey rectangular frame around the food). Typically, the go/no-go ratio in this training has been 1:1. Conversely, cue-approach training often features an uneven distribution of go and no-go trials (i.e., only 30% go trials), and only the cue to respond is present on go trials (e.g., Itzkovitch et al., 2022). Exactly why these disparate paradigms can facilitate healthy eating decisions, however, is still somewhat unknown.

To understand the mechanisms underpinning some of the above effects, Schonberg and colleagues conducted series of behavioral and neuroimaging studies investigating the effects of cue-approach training on relevant outcomes (Aridan et al., 2019; Bakkour et al., 2017; Botvinik-Nezer et al., 2020; Salomon et al., 2018, 2019; Schonberg et al., 2014). In this, they discovered that after the cue-approach training, go items were selected more frequently than no-go items in binary choices. More importantly, their neuroimaging studies suggested that the neural mechanisms underpinning cue-approach training benefits involve both reward and perceptual/attention-related systems—referred to as the dorsal value pathway, or DVP (Schonberg and Katz, 2020).

Similar to work on cue-approach training, many studies have investigated the behavioral effects of food go/no-go training (e.g., Lawrence et al., 2022; Moore et al., 2023; van Alebeek et al., 2023). For example, a recent meta-analysis of 36 independent samples, 77 effect sizes, and 3032 participants found that food go/no-go training can lead to statistically significant reductions in the evaluation of no-go foods (Yang et al., 2022). In a series of preregistered experiments, Chen and colleagues demonstrated that after food go/no-go training, participants more frequently selected go foods (compared to no-go foods) for consumption in a binary choice task (Chen et al., 2019, 2021; Chen and Veling, 2022). This preference change effect was replicated by a recent study using similar experimental materials (Wu et al., 2023).

Nonetheless, unlike cue-approach training, the mechanisms underlying food go/no-go training remain relatively unclear. The recently formulated “value updating” theory posits that food go/no-go training updates valuations of items through repeated decisions to act toward go foods and do nothing in response to no-go foods, resulting in the devaluation of no-go items and increased valuation of go items (Veling et al., 2022). Consequently, individuals slowly come to prefer go over no-go foods via changes in valuations of them both. In a related but distinct vein, the stimulus-response account proposes that repeated inhibition of responses towards no-go items and while uninhibitedly responding to go items during training may lead to the formation of stimulus-response associations (e.g., go items become linked to action, and no-go items become linked to stopping) (Best et al., 2016; Johannes et al., 2021; Veling et al., 2017; Verbruggen et al., 2014; Verbruggen and Logan, 2008). Therefore, according to this theory, participants come to choose more go over no-go foods because taking action in response to go foods but inaction in the context of no-go foods becomes a “learned reflex.” These theories, while similar, make competing predictions about the mechanisms underpinning the food go/no-go training effect. However, both theories are consistent with most evidence to date.

Neuroimaging could help to clarify the mechanisms underpinning the effect of food go/no-go training, given the well-mapped reward and cognitive control-related neural circuits and systems. However, unlike cue-approach training, few neuroimaging studies—particularly functional magnetic resonance imaging (fMRI) studies—have examined the neural correlates of food go/no-go training effects. In one such study conducted by Yang et al. (2023), as expected, food go/no-go training led to significant reductions in behavioral no-go food evaluation after food

go/no-go training. More importantly, at the neural level, Yang et al. (2023) observed decreased reward- (e.g., mid-insula) and cognitive-control-related (e.g., middle frontal gyrus) neural responses to these foods in a passive viewing task. In another recent fMRI study, Nakamura et al. (2023) also found that food go/no-go training reduced the ratings of no-go foods, and further found greater reward-related neural activity in response to go foods in a food image task in region of interest (ROI) analysis.

In contrast to these two fMRI studies focusing on the effects of food go/no-go training on food evaluation, only one study has used fMRI to examine the neural bases of food preference changes (e.g., preferring go but not no-go foods) induced by food go/no-go training (Wu et al., 2023). This study found that, after training, preference changes were inversely associated with frontoparietal and salience network activity when choosing go (vs. no-go) foods in the binary choice task. Additionally, task-related functional connectivities from the inferior parietal lobule to the pre-supplementary motor cortex (Pre-SMA), dorsolateral prefrontal cortex (DLPFC), and dorsal anterior cingulate cortex (dACC) were positively related to these preference changes. The authors speculated that their results supported the associative account, given that choosing more go (vs. no-go) foods was consistent with the established association (e.g., go foods = response, no-go foods = stop). Furthermore, participants who chose more go foods showed less activation in conflict monitoring (e.g., dACC) or resolution-related brain regions (e.g., DLPFC). However, it should be noted that only linking fMRI data during choices in the binary choice task with preference changes might not be sufficient to reveal the underlying neural mechanisms of preference changes induced by nonreinforcement training, such as food go/no-go training or cue approach training (Botvinik-Nezer et al., 2020).

### 1.1. Current research

The present study aimed to investigate the neural bases underlying preference changes induced by food go/no-go training using a novel passive viewing task. During this task, participants were asked to view pictures of snack food items individually, without making any response. This task was performed and scanned before and after food go/no-go training. By analyzing fMRI activity during the passive viewing task, we aimed to test whether neural activity and task-related functional or effective connectivity to go versus no-go foods after training compared with baseline could be predictors of food preference changes. We calculated task-related functional connectivity via generalized psychophysiological interactions (gPPI) (McLaren et al., 2012). Given that gPPI is a correlational method, we used dynamic causal modeling (DCM) for effective connectivity analysis to further evaluate the directional information flow of the observed significant functional connectivity in gPPI analysis (Friston et al., 2003; Zeidman et al., 2019a). Based on previous findings (Wu et al., 2023; Yang et al., 2023) and the aforementioned accounts (e.g., value-updating account; the DVP pathway), we hypothesized that reward, conflict perception/resolution, and visual attention-related processes are involved in the food preference changes following food go/no-go training.

## 2. Methods

### 2.1. Participants

Only female undergraduate or graduate students were recruited for the study because of the gender differences in eating behavior (Rolls et al., 1991) or metabolism (Blaak, 2001). Participants who reported current mental disorders, eating disorders, and/or head injuries were excluded. A power analysis (e.g., correlation: bivariate normal model) was performed utilizing G\*Power (Version 3.1) (Faul et al., 2007), with  $\alpha = 0.05$ ,  $1 - \beta = 0.95$ , to determine the sample size required to detect an expected effect size of  $r = 0.4$ . This estimate was based on the observed association between behavior changes induced by food go/no-go

training and the corresponding neural activation, as reported in recent studies (Wu et al., 2023; Yang et al., 2023). The power analysis indicated that a total sample size  $N \geq 75$  was required. To mitigate the risk of insufficient statistical power resulting from excessive head movement or participant dropouts during MRI scanning, we strategically recruited a total of 91 participants. Of the 91 participants, one was excluded from imaging analysis due to motion (e.g., displacement of  $>3$  mm in any plane and rotation of  $>3^\circ$  in any direction).

## 2.2. Procedure

Prior to their study session, participants were instructed to fast for the 3 h immediately preceding their arrival at the lab. Upon arriving at the lab, participants first provided informed consent and completed demographic questionnaires. Participants then completed short, practice versions of the food go/no-go training and the food choice task, before completing the five formal experimental tasks, including the food evaluation task, passive viewing task (baseline), food go/no-go training, passive viewing task (post-training), and food choice task (see Fig. 1 for the sequence of main experimental tasks). Prior to task commencement, participants were asked to rate their hunger by moving a mouse cursor along an analog scale that ranged from  $-100$  (not at all) to  $100$  (extremely hungry). Detailed outlines of the entire experimental procedure and individual tasks were provided in Figs. 1 and 2. Ethical approval of all procedures was granted by Southwest University, H22063 (12/2021). The study was carried out in accordance with Declaration of Helsinki.

## 2.3. Measurements

### 2.3.1. fMRI data acquisition

Structural and functional images were acquired on a 3 T Prisma Siemens Trio MRI scanner using a 64-channel brain coil at Southwest University (for the detailed scan parameters, see our prior studies; (Wu et al., 2023; Yang et al., 2023).

### 2.3.2. Pre-training food evaluation

During the evaluation task, 40 color images of candies were presented on the screen one after the other in random order. The pictures were taken from a previously published study (Chen et al., 2019). For each candy picture, participants were asked to indicate how much they wanted to eat this candy at that moment by using a 200-point scale from 0 (*not at all*) to 2 (*very much*) (Chen et al., 2019). The food image remained on the screen until participants pressed a key ('continue') to confirm their rating, after which the task moved on to the next question.

### 2.3.3. Item selection

For each participant, images of candies were rank-ordered from 1 (highest value) to 40 (lowest value) based on their evaluation. Then, 12 pictures (ranked 3–14) were used in the food choice task (Wu et al., 2023). To pair go and no-go pictures with similar initial evaluation, the 12 pictures were divided into 2 subgroups with identical mean rank. Six of the 12 pictures (i.e., pictures 3, 6, 7, 10, 11, 14) were chosen to be paired with the go cue during training (go items), and the other 6 (i.e., pictures 4, 5, 8, 9, 12, 13) were paired with the no-go cue during training (no-go items). These items were also used during go/no-go training and passive viewing tasks. Ensuring that the palatability of foods was matched guaranteed that any observed changes in food preference can

be attributed to the training itself, rather than to inherent differences in food value prior to training.

### 2.3.4. Passive viewing task: baseline

During this task, the 12 go and no-go images were presented to participants using an event-related design in a random order to assess neural response to these food images before and after go/no-go training. Participants were asked to simply view the food images on the screen without taking any action. The task consisted of 2 runs. In each run, each of the 12 images was presented on the screen for a fixed duration of 2 s, followed by a 1–4 s interstimulus interval. Each image was presented one time.

### 2.3.5. Go/no-go training

The training task parameters are similar to those used in previously published studies (Chen et al., 2019; Wu et al., 2023; Yang et al., 2023). The evaluated 12 food images were used in the training. During the task, food images were randomly presented individually on the center of a computer screen for up to 1 s, followed by a 1–4 s interstimulus interval. A green or grey rectangular frame appeared around the picture 100 ms after the picture onset, and it was visible for the remainder of the time that the picture was displayed. Participants were instructed to press a button on an MRI-compatible response box as quickly and accurately as possible if the rectangular frame surrounding the picture was green. However, if the rectangular frame surrounding the picture was grey, they were instructed not to respond. The training session consisted of 12 runs with 12 trials per run (i.e., 6 go trials and 6 no-go trials per block; a total of 144 trials across all blocks), and it took approximately 12 min to complete. Participants were allowed a break after finishing half of the training.

### 2.3.6. Passive viewing task: post-training

After the training, participants again viewed the images that were included in the training task, using the same procedure as in the pre-training passive viewing task.

### 2.3.7. Food choice task

The food choice task is similar to those used in previously published studies (Chen et al., 2019; Wu et al., 2023). The evaluated 12 food images were used in the task. In each trial, one go food and one no-go food were presented side by side, and participants had to choose one food they wanted to eat within 1.5 s by pressing the corresponding button on an MRI-compatible response box. After each choice, the chosen item was surrounded by a black rectangle for 500 ms as confirmatory feedback. The task consisted of 2 runs, each with 36 trials, and trials were separated by a fixation cross that lasted on average 2.5 s (range, 1–4 s). The entire task took approximately 7 min to complete. Participants were allowed a break after finishing half of the trials.

## 2.4. Statistical analyses

### 2.4.1. Behavioral data analysis

Food choices were analyzed with a multilevel logistic regression at the participant level (formula: choice  $\sim 1 + (1 | \text{subject})$ ), using the glmer function from the lme4 package in R version 4.2.1 (Bates et al., 2015; R Core TeamR., 2013). Food choice was dummy coded (choosing go food = 1, choosing no-go food = 0).

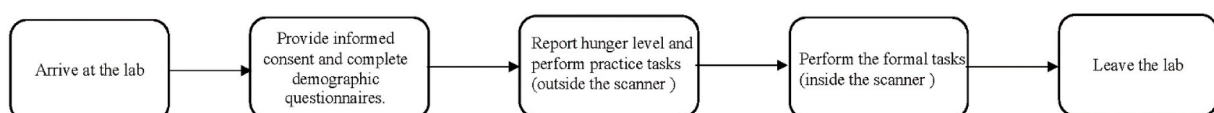
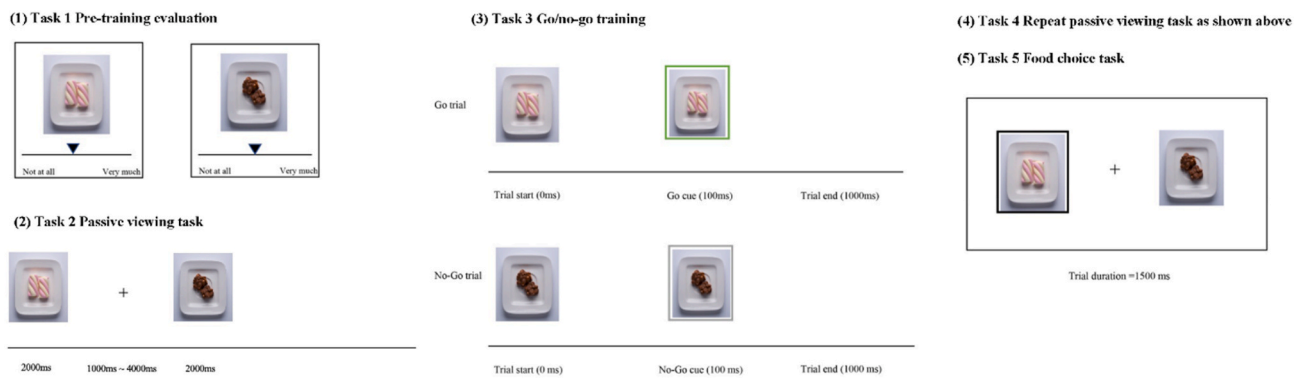


Fig. 1. The entire experimental procedure.



**Fig. 2.** Sequence of the main experimental tasks. (1) Evaluation task; (2) In the passive viewing task, food items were individually presented on the screen; (3) The food go/no-go training; (4) Passive viewing task; (5) Food choice task. (Color figure).

## 2.5. Whole-brain analyses

fMRI data preprocessing was performed using DPBAI toolbox (Yan et al., 2016) in MATLAB (version R2021a, MathWorks). Preprocessing consisted of slice timing and head motion corrections, coregistration, segmentation, normalization to Montreal Neurological Institute space in  $3 \times 3 \times 3 \text{ mm}^3$  voxel sizes, and spatial smoothing with a Gaussian kernel of 8 mm at full width half-maximum (for greater detail, see Wu et al., 2023; Yang et al., 2023).

First-level and second-level analyses were conducted in SPM12. In the first-level analysis (i.e., at the subject level), the four conditions (pre-training go foods, pre-training no-go foods, post-training go foods, and post-training no-go foods) and six motion regressors were modeled using the general linear model, with delta functions convolved with a canonical hemodynamic response function. The critical contrast of interest was within-subject activations during go foods vs no-go foods (post-training vs pre-training). The resulting contrast images were used in second-level analyses, where multiple linear regression was conducted to identify brain activations correlated with changes in food preferences (i.e., the probability of choosing go foods). Significant clusters were identified using a cluster-forming threshold of  $P < 0.001$  (uncorrected) and a cluster-level family-wise error (FWE) rate-corrected threshold  $P < 0.05$ .

### 2.5.1. Generalized psychophysiological interaction analysis (gPPI)

The gPPI analysis was conducted using CONN toolbox (version 22) (Whitfield-Gabrieli and Nieto-Castanon, 2012), which computed seed-to-voxel functional connectivity while participants viewed food images [contrast: (go - no-go) - (post-training - pre-training)], and further allowed us to examine the association of this event-related functional connectivity with preference changes. This analysis was divided into four sequential steps including setup, denoising, first-level, and second-level analyses. By default, the blood-oxygen-level-dependent (BOLD) signal from the white matter and the segmented cerebrospinal fluid (CSF), estimates of motion parameters, and the main task effects (pre-training go, pre-training no-go, post-training go, post-training no-go) were treated as confound regressors in our functional connectivity analysis. We applied a band-pass filter (0.008, inf) to limit the effect of low-frequency drift. Significant clusters from the whole-brain analysis (Section 2.4.2) were used as seed regions, and connectivity measure was calculated as bivariate correlations. All reported results were thresholded at an uncorrected voxel-level  $P < 0.001$  for cluster formation, with cluster-based FWE correction ( $P < 0.05$ ).

### 2.5.2. Dynamic causal modeling analysis (DCM)

Given that gPPI analysis is a correlational method and cannot provide evidence concerning the direction of functional interactions

between brain regions, we further conducted DCM analysis in SPM 12 for effective connectivity analysis to evaluate the directional information flow of the significant functional connectivity observed in gPPI analysis (Section 2.4.3). Three matrices in DCM were used to model the experiment: (1) matrix A, the intrinsic connections within and between brain regions; (2) matrix B, the strength of connection changes due to different experimental conditions (modulatory terms); (3) matrix C, the driving input to the system (Friston et al., 2003). Since our design did not include any modulatory input, we did not model modulatory terms (matrix B). Therefore, in this study, we focused on the effect of viewing food images after food go/no-go training (driving input) on intrinsic connections (matrix A).

The Parametric Empirical Bayes (PEB) method was used to estimate effective connectivity parameters at the group level (Zeidman et al., 2019b). In our study, we were interested in whether effective connectivity was related to the food preference changes induced by training at the group level. To down-weight participants with noisy data and uncertain parameters, PEB used the full posterior density over the parameters (i.e., expected values and covariance) from subject-level (first-level) DCM analysis to inform the group-level (second-level) DCM results. After estimating the PEB model, we then used Bayesian model reduction (BMR)—a “greedy search” approach—to prune parameters that did not contribute positively to the model evidence. Posterior parameter estimates following BMR were averaged using Bayesian model averaging (BMA), and we thresholded averaged model parameters at  $>95\%$  posterior probability. ( $P_p$ ) (i.e., “Strong” evidence of the parameters being present, rather than absent).

## 3. Results

### 3.1. Demographic information and hunger level

Participants were, on average, 20.62 years old [standard deviation ( $SD$ ) = 1.55; range = 18–26 years]. The mean body mass index (BMI) was 20.79 ( $SD$ , 2.81; range, 16.77–31.14; six participants met criteria for overweight). The mean hunger was 48.70 ( $SD$ , 42.85; range, –63.75–99.75).

### 3.2. Behavioral results

#### 3.2.1. Performance during go/no-go training

The training was relatively easy to complete; as such, performance was near-ceiling: the average commission error rate was 0.007 ( $SD$  = 0.01); the average omission error rate was 0.010 ( $SD$  = 0.03). The average go response time was 382.32 ms ( $SD$  = 44.44 ms).

#### 3.2.2. Food evaluation before training

A paired  $t$ -test was conducted to check whether the ratings of go and



no-go foods were matched before the food go/no-go training. In this, there was no significant difference between the average ratings of go foods ( $M = 1.31$ ,  $SD = 0.44$ ) and no-go foods ( $M = 1.31$ ,  $SD = 0.44$ ) before training,  $t(90) = 0.53$ ,  $p = 0.597$ .

### 3.2.3. Probe in food choice task

Although the evaluations of go and no-go foods were matched before training, multilevel logistic regression showed that participants significantly preferred go over no-go foods after the food go/no-go training, with a mean proportion of choosing go foods of 57.83%,  $OR = 1.47$ , 95% CI [1.21, 1.77],  $p < 0.001$  (Fig. 3).

### 3.2.4. Correlation between food go/no-go training performance and preference changes

A notable negative correlation emerged between the proportion of choosing go foods and go response time ( $r = -0.21$ ,  $p = .04$ ). However, there was no significant correlation found in relation to either the commission error rate ( $r = 0.19$ ,  $p = .08$ ) or the omission error rate ( $r = -0.05$ ,  $p = .63$ ).

### 3.3. Brain activations are related to preference changes

To identify brain regions associated with preference changes following food go/no-go training, we examined the association between the probability of choosing go foods and neural activity while passively viewing go (vs. no-go) foods in the after training compared to before. In this, we found that the preference change effect (e.g., the proportion of choosing go foods) was negatively correlated with BOLD activity in response to go vs. no-go foods (post vs. pre-training) in the ACC, superior frontal gyrus (SFG), middle frontal gyrus (MFG), middle temporal gyrus (MTG), and angular gyrus (AG) (Table 1, Fig. 4).

### 3.4. Functional connectivity between SFG and MOG is related to preference changes

Next, to understand how the brain regions with activity related to the passive viewing task interacted with other brain regions, we conducted a gPPI analysis with the ACC (MNI coordinates: 3, 45, 0), SFG (MNI coordinates: 6, 54, 3; 3, 48, 21), MFG (MNI coordinates: 27, 33, 39), MTG

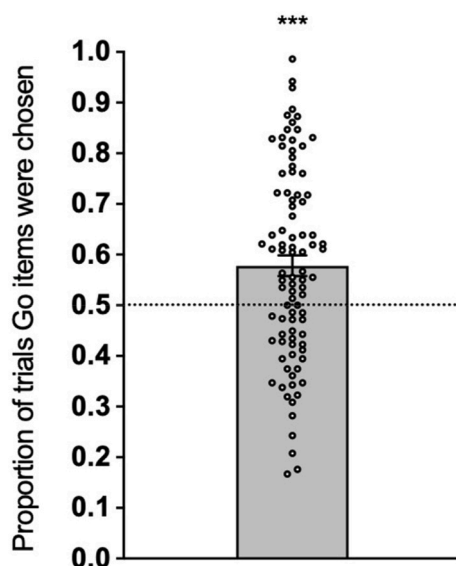


Fig. 3. Probability of choosing go foods during the probe task. The mean proportion of trials in which participants chose go over no-go foods is shown. The dashed line indicates an equal preference level of 50%; error bars represent the standard error of the mean. Asterisks indicate the statistical significance in a repeated-measures logistic regression.  $***p < 0.001$ .

(MNI coordinates: 60, -6, -24; MNI coordinates: 48, 9, -39), and AG (MNI coordinates: 39, -63, 33) as seed ROIs (6 mm sphere centered on the peak cluster) (Table 1). In this, we examined whether whole-brain functional connectivity of seed ROIs during passive viewing of go (vs. no-go) foods after training compared with before training was related to the probability of choosing go foods. Bonferroni tests were used to correct for the number of tests ( $p < .05/7$  seeds = 0.007). The results showed a significant SFG seed-to-voxel middle occipital gyrus (MOG) cluster connectivity that was significantly correlated with preference changes (Fig. 5a, Table 2).

We then extracted activity from the MOG cluster, defined by a 6 mm-radius sphere centered at the MOG cluster's peak, and conducted a correlation analysis between the MOG connectivity changes and preference changes induced by food go/no-go training. Results showed that the functional connectivity change of SFG with MOG while viewing go vs. no-go foods (post-training vs. pre-training) positively correlated with the probability of choosing go foods ( $r = 0.44$ ,  $p < 0.001$ ) (Fig. 5b).

### 3.5. Effective connectivity between SFG and MOG is related to preference changes

We then used DCM models (Figs. 6a and 7a) and PEB to examine whether the effective connectivity (defined as the extent to which a brain region's neural activity directly influences another region) between SFG and MOG was related to the probability of choosing go foods. We focused on connection parameters with a  $P_p$  greater than 0.95, which corresponds to strong evidence.

We found that the effective connectivity from SFG to MOG (estimate = 0.77,  $P_p = 1$ ), MOG to SFG (estimate = 0.57,  $P_p = 1$ ), and SFG to SFG (estimate = 0.80,  $P_p = 1$ ) were related to the probability of choosing go foods when using post-training go foods as model inputs (Fig. 6b). The positive sign of these effective connectivity estimates suggests that larger bidirectional connectivity between MOG and SFG (SFG to MOG,  $r = 0.59$ ,  $p < 0.001$ ; MOG to SFG,  $r = 0.73$ ,  $p < 0.001$ ) or greater self-inhibition of SFG ( $r = 0.76$ ,  $p < 0.001$ ) when viewing go foods was associated with choosing more go foods for consumption after go/no-go training. This association was clearer when plotting the individual connectivity estimates against the probability of choosing go foods (Fig. 6c and d). In contrast, when using post-training no-go foods as model inputs, the effective connectivity from SFG to MOG was negatively related to the probability of choosing go foods (estimate = -0.42,  $P_p = 0.99$ ) (Fig. 7b), suggesting that weaker connectivity strength or greater inhibitory influence from SFG to MOG ( $r = -0.29$ ,  $p = 0.006$ ) when viewing no-go foods was associated with choosing more go foods (or choosing against no-go foods) for consumption after go/no-go training. This association was clearer when plotting the individual connectivity estimates against the probability of choosing go foods (Fig. 7c).

### 3.6. Sensitivity analysis

Considering that BMI and hunger levels may potentially influence the brain's responses to food stimuli, we conducted a sensitivity analysis to account for these variables. Importantly, after adjusting for both BMI and hunger, none of our primary results were altered. Please refer to the supplementary material for a detailed description of these results.

## 4. Discussion

In this study, we examined the neural mechanisms underlying preference changes following food go/no-go training. Unlike our previous study, which analyzed fMRI data from a binary choice task (Wu et al., 2023), we introduced a novel passive viewing task to examine whether the neural changes in response to go (vs. no-go) foods before and after food go/no-go training were related to training-induced preference changes in a relatively large sample ( $N = 91$ ). We predicted that the

**Table 1**

Go &gt; No-Go activity (Post training &gt; Pre training) correlated with the probability of choosing go foods.

Cluster index	Correlation direction	Region	Cluster Size	X	Y	Z	Peak Z-value
1	Positive	None	None				
	Negative	Anterior cingulate cortex	279	3	45	0	4.39
		Superior frontal gyrus		-6	54	3	
2	Negative	Superior frontal gyrus	49	12	45	-6	4.37
				3	48	21	
				-3	57	30	
3	Negative	Middle temporal gyrus	80	-60	-6	-24	4.22
				-57	-21	-15	
				-27	33	39	
4	Negative	Middle frontal gyrus	39	48	9	-39	4.13
5	Negative	Middle temporal gyrus	50	48	18	-30	3.95
6	Negative	Angular gyrus	38	-39	-63	33	3.91

Notes: Peaks within the regions were considered significant at  $p < 0.001$  and corrected for multiple comparisons at the cluster level,  $p < 0.05$ .

underlying neural mechanisms would involve value, conflict perception/resolution, and visual attention-related brain regions. We found a significant negative association between individual differences in preference changes during the binary choice task and activity in the ACC, SFG, MFG, MTG, and AG while passively viewing food images. In addition, we provided evidence for enhanced SFG functional connectivity with MOG associated with the probability of choosing go foods. Furthermore, DCM and PEB analysis showed that this food preference change effect was primarily modulated by top-down influence from the SFG to the MOG.

The behavioral choice results of our study align with the results of previous work on food go/no-go training (Chen et al., 2019, 2021; Veling et al., 2021; Wu et al., 2023) and cue-approach training (Bakkour et al., 2017; Botvinik-Nezer et al., 2020; Itzkovitch et al., 2022; Salomon et al., 2019; Schonberg et al., 2014). Although the evaluations of go foods and no-go foods were matched before training, participants chose more go than no-go foods following training. Taken together, our results add to the body of work that suggests that the preference modification effect of nonreinforcement training, via either food go/no-go training or cue-approach training, is robust and reproducible. This stable training effect may be relevant to clinical interventions: Nonreinforcement training is simple, relying only on simple action or inaction. Future studies are needed to test whether food go/no-go training or cue-approach training can promote healthy food choices in individuals with obesity or eating disorders.

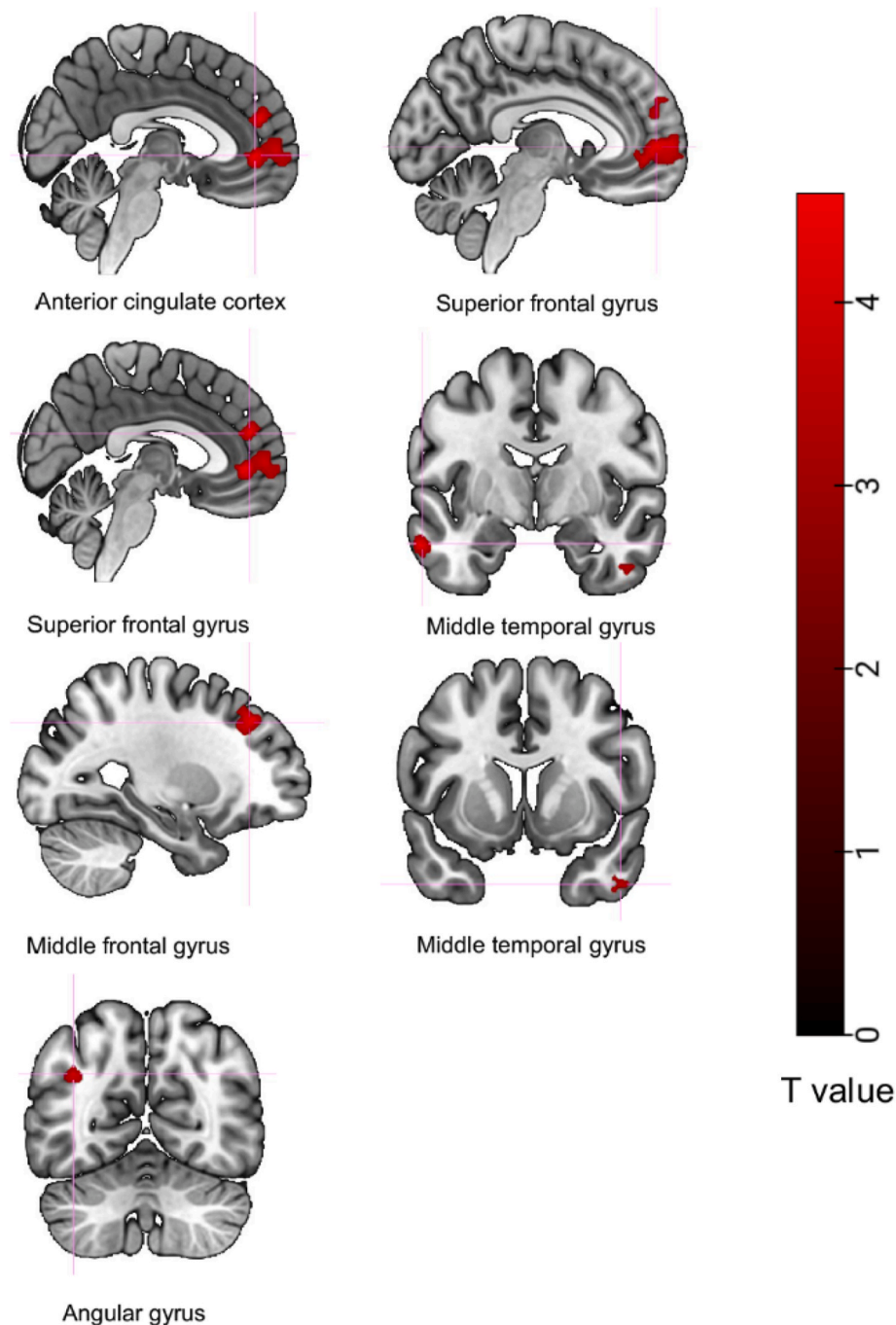
To further explore the neural correlates of preference changes induced by food go/no-go training, we employed fMRI. Participants who chose more go foods over no-go foods demonstrated changes in responses while passively viewing go foods vs. no-go foods (post vs. pre-training) in the ACC, SFG, MFG, MTG, and AG (i.e., activities were negatively correlated with the probability of choosing go foods). The ACC is related to conflict monitoring and error detection (Ham et al., 2013), and the MFG/DLPFC and SFG play a crucial role in executive control (Li et al., 2013; Menon & D'Esposito, 2022). In addition, AG and MTG are respectively involved in attention (Seghier, 2012) and visual perception/memory (Murray et al., 2007).

The pattern of results in the current study shows some consistency with the studies related to cue-approach training, which is another well-studied nonreinforcement training task. Similar to our results, Botvinik-Nezer et al. (2020) also found that reduced activity in the attention brain areas (e.g., superior parietal lobule, SPL) was associated with (long-term) food preference changes induced by cue-approach training. In addition, the brain activation pattern in the current study is also consistent with our previous study, which linked neuroimaging data from the binary choice task with the preference change effect following food go/no-go training (Wu et al., 2023). Specifically, Wu et al. (2023) found that decreased (rather than increased) activity in the executive control (e.g., DLPFC), conflict monitoring (e.g., dACC) and attention/-visual (e.g., SPL)-related brain regions during the choice of go foods (vs.

no-go foods) was related to choosing more go over no-go foods. However, different from cue-approach training-related work (Salomon et al., 2019; Schonberg et al., 2014), we did not find neural activities in brain regions associated with encoding value (e.g., ventromedial prefrontal cortex, vmPFC) were related to the probability of choosing go foods. This inconsistency can be explained from at least two perspectives. Firstly, there exist differences in the task design between the cue-approach training and the go/no-go training. The ratio of go-to-no-go trials in cue-approach training is typically presented as 3:7, whereas in go/no-go training, the ratio tends to be 1:1. Additionally, both types of trials in go/no-go training are accompanied by cues; this contrasts with cue-approach training, where no-go trials are not prompted by cues. Secondly, the cue-approach training research, led by Schonberg and colleagues (Botvinik-Nezer et al., 2020; Itzkovitch et al., 2022; Salomon et al., 2019; Schonberg et al., 2014), has a broader scope - it focuses not only on the immediate effects of training but also on the long-term effects, and these effects have been explored using both high-value and low-value food items. In contrast, our study is narrower in scope, focusing solely on the immediate impact of go/no-go training on high-value food items.

As mentioned within the introduction, the value updating account and the stimulus-response account have been proposed to explain the effect of food go/no-go training on food evaluation or choices. It seems that the associations of the executive control and conflict monitoring-related brain regions with the preference modification effect we observed in the current work could be explained by the stimulus-response account. Specifically, this account suggests that participants might form an "automatic reflex" (e.g., go foods = respond, no-go foods = stop) following food go/no-go training, leading to the consistent choice of go foods and rejection of no-go foods. Consequently, participants who perceived less conflict or uncertainty when viewing go over no-go foods after training might further develop stronger stimulus-response associations and choose more go over no-go foods. At the neural level, this reduced conflict or uncertainty was reflected by decreased activations in the conflict perception (e.g., ACC) and resolution (e.g., SFG) regions for them. In addition, our findings that participants may learn a specific automatic response to food cues after go/no-go training align with a recently developed computational model of motor response patterns during cue-approach training. By using Bayesian modeling to analyze meta-data from 864 participants across 29 different cue-approach training experiments, Salomon et al. (2024) showed that the attention and motor learning components of the training were correlated with preference changes elicited by the training.

The value updating account proposes that the value of go items (e.g., foods) increases and the value of no-go items decreases after go/no-go training, influencing individuals' choices. Supporting this account, Johannes et al. (2021) found that go/no-go training influences evaluations of smartphone apps, and that these evaluations mediate the effect



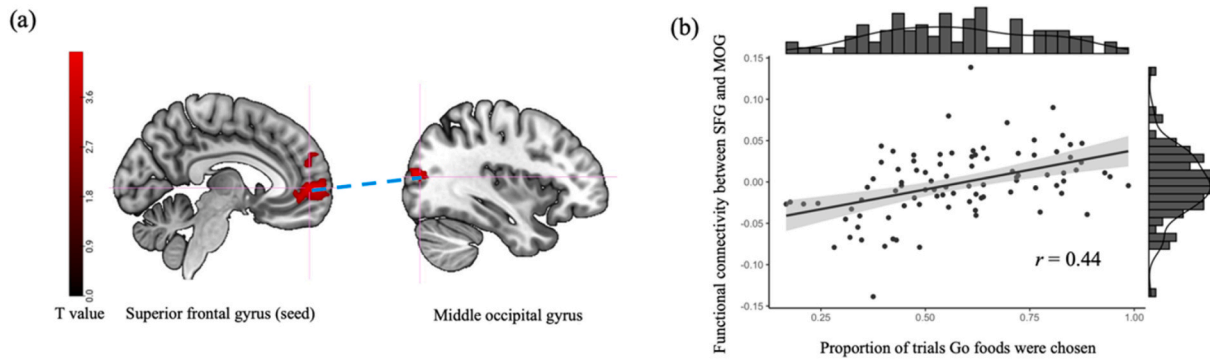
**Fig. 4.** Imaging results from the passive viewing task after, compared to before, food go/no-go training. The probability of choosing go foods negatively correlated with the BOLD response during passive viewing of go (vs. no-go) foods after, compared to before, training in several regions, including the anterior cingulate cortex, superior frontal gyrus, middle temporal gyrus, middle frontal gyrus, and angular gyrus. (Color figure).

of the training on behavioral choices. However, we did not find a significant link between any value-related brain regions (e.g., vmPFC) and the preference change effect. We argue that this was mainly caused by the passive viewing task used in the current study. This task might not be ideal for testing the value updating account, as it does not measure the evaluation process. Therefore, future work should directly use an evaluation task in the fMRI scanner to test the value updating account.

An intriguing brain signature found in the current study is the functional connectivity between the SFG and MOG and its modulation by preference changes. This connectivity remained significant even survived after Bonferroni correction. As the strength of this connectivity increased, participants chose more go foods. The MOG plays an

important role in visual processing (Tong, 2003), and, as mentioned earlier, the SFG is involved in executive control. Therefore, the significant SFG-MOG connectivity might suggest that the functional integration between executive control and visual processing is critical for the preference change effect following food go/no-go training.

Importantly, we used DCM models and PEB to examine the information flow of the significant SFG-MOG connectivity. We found that the preference change effect of food go/no-go training was primarily modulated by top-down influence from the SFG to the MOG. Critically, our data revealed dissociated associations for the directed influences between the SFG and MOG on preference changes. Specifically, when using post-training go foods as DCM model inputs, both the bottom-up



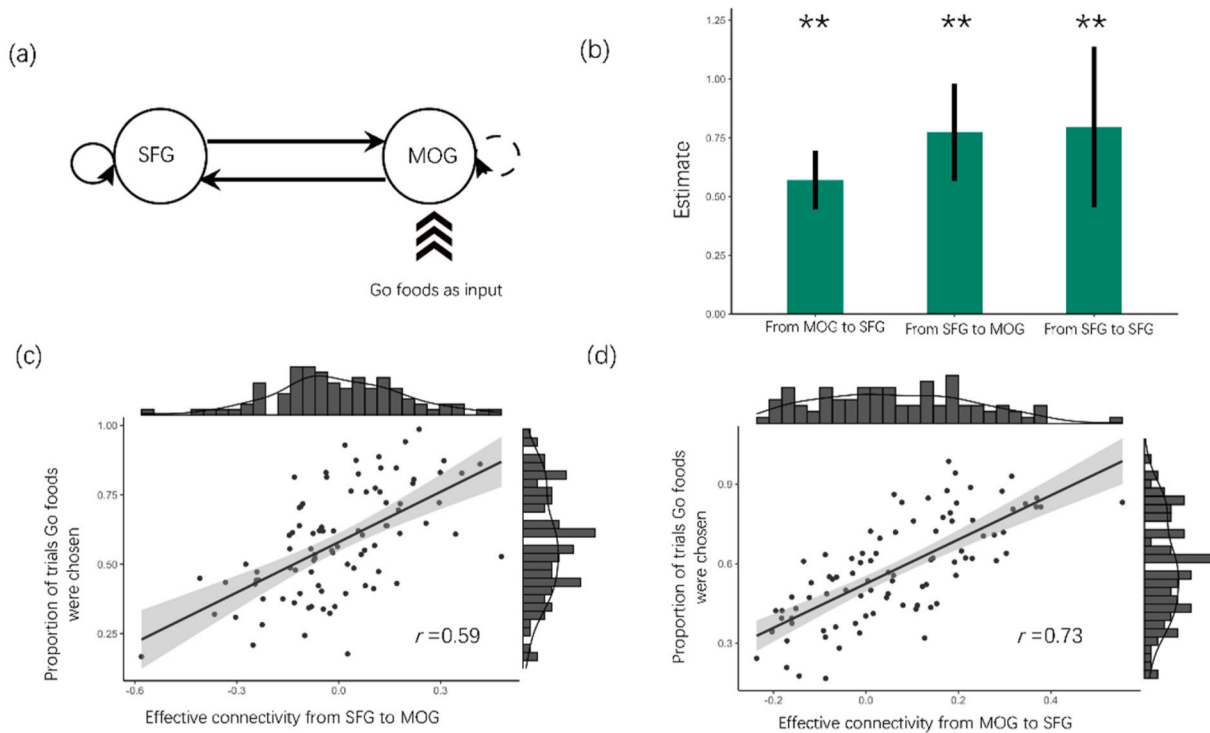
**Fig. 5.** Results from the seed-based ROI superior frontal gyrus (SFG) gPPI functional connectivity analysis. (a) SFG-middle occipital gyrus (MOG) connectivity during passive viewing of go (vs. no-go) foods after, compared to before, training significantly related to the probability of choosing go foods. (b) Specifically, the correlation between SFG-MOG connectivity and the probability of choosing go foods was positive. In other words, across participants, the larger the connectivity, the greater the probability of choosing go foods was observed. Scatter plot is for data visualization purposes only. (Color figure).

**Table 2**

Results of the functional seed-to-voxel connectivity analysis [Go > No-Go (Post-training > Pre-training)] correlated with the probability of choosing go foods.

Seed	Region	Correlation direction	Anatomical Region	Cluster Size	X	Y	Z	Peak Z-value	$P_{FWE-corr}$
1	Superior frontal gyrus	Positive	Middle occipital gyrus	181	-36	-84	12	4.28	< 0.001

Notes: Peaks within the regions were considered significant at  $p < 0.001$  and corrected for multiple comparisons at cluster level,  $p < 0.05$ . In addition, Bonferroni tests were used to correct for the number of tests ( $p < .05/7$  seeds = 0.007). FWE = family-wise error.

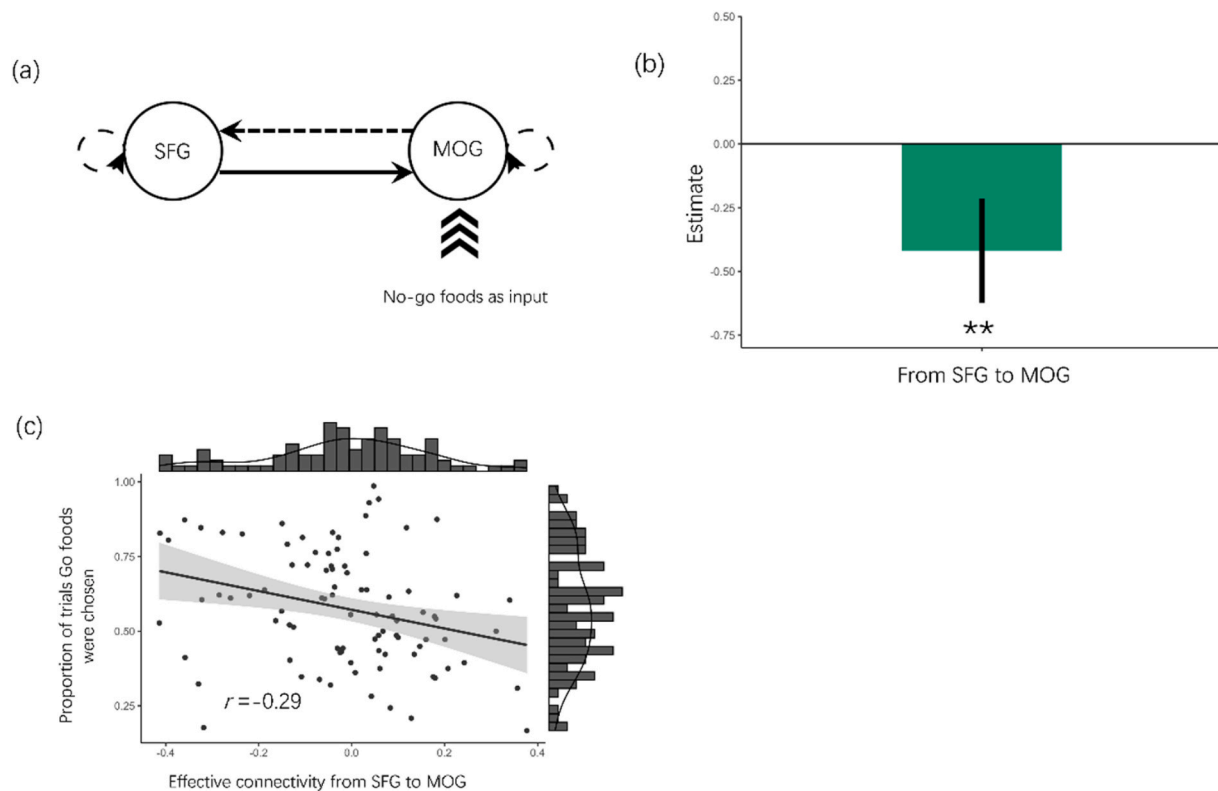


**Fig. 6.** Association between the probability of choosing go foods and effective connectivity using post-training go foods as inputs. (a) The schematic network presentation of the DCM model. The solid lines represent connections surviving the 95% posterior probability ( $P_p$ ) threshold based on free energy; (b) The posterior parameter estimates of connections surviving the 95%  $P_p$ . Error bars indicate standard error; (c) The association between the probability of choosing go foods and effective connectivity from the superior frontal gyrus (SFG) to the middle occipital gyrus (MOG); (d) The association between the probability of choosing go foods and effective connectivity from MOG to SFG. \*\*:  $P_p > 95\%$ . (Color figure).

connectivity from MOG to SFG and the top-down connectivity from SFG to MOG were positively related to preference changes. In contrast, when using post-training no-go foods as DCM model inputs, the top-down connectivity from SFG to MOG showed an inverse association with

preference changes. The top-down MOG to SFG connectivity could be taken to suggest that when processing go foods, a stronger excitatory influence from the visual processing region to the executive control region underpins choices for go foods, whereas the influence of the





**Fig. 7.** Association between the probability of choosing go foods and effective connectivity using post-training no-go foods as inputs. (a) The schematic network representation of the DCM model. The solid lines represent connections surviving the 95% posterior probability ( $P_p$ ) threshold based on free energy; (b) The posterior parameter estimates of connections surviving the 95%  $P_p$ . Error bars indicate standard error; (c) The association between the probability of choosing go foods and effective connectivity from the SFG to the MOG. \*\*:  $P_p > 95\%$ . (Color figure).

executive control region on the visual processing region (top-down connectivity) depends on the visual input (go or no-go foods). In line with the stimulus-response account, when the visual input was go foods, the executive control region exerted more excitatory influence on the visual processing region, potentially prompting participants to choose more go foods (go foods = respond). Conversely, when the visual input was no-go foods, the executive control region exerted more inhibitory influence on the visual processing region, potentially prompting participants to reject no-go foods (no-go foods = stop) and, subsequently, choose more go foods. Our functional/effective connectivity results are thus consistent with the DVP model of nonreinforced preference change (Schonberg and Katz, 2020), which proposes that prefrontal regions interface with visual, attention regions to guide preference modification following nonreinforcement training (e.g., cue-approach training).

#### 4.1. Limitations

Despite its strengths, such as a relatively large fMRI sample and using a novel passive viewing task, our study has some limitations. First, we recruited a sample of female undergraduate or graduate students, mostly with normal weight. More studies are needed to examine the generalizability of our results in other samples (e.g., individuals with obesity). Second, our study was not preregistered. Third, our investigation was restricted to the immediate effects of training on neural responses. Future studies should extend this line of inquiry to explore the neural correlates associated with long-term effects of such training, thereby unveiling whether these immediate changes translate into more sustained modifications in neural activity and behavior. Additionally, the absence of control tasks, such as a non-food related go/no-go task, in our experimental setup represents a limitation. Finally, we used high-calorie or high-value foods (e.g., candy) as training materials; future studies should investigate the potential neural mechanisms of training effects on

low-calorie foods (e.g., healthy foods).

## 5. Conclusion

Nonreinforcement training, such as food go/no-go training, may reduce overeating and promote healthy eating behaviors. We examined the neural mechanisms underlying the effect of food go/no-go training in the present study. At the behavioral level, consistent with prior work, we found the food go/no-go training effect on preference changes, indicating that this effect appears to be robust. At the neural level, we found that less activity in the ACC, SFG, MFG, MTG, and AG, but greater functional connectivity between the SFG and MOG during viewing of go (vs. no-go) food is related to individuals' preference changes from pre- to post-training. Critically, we found that this food preference change effect was primarily modulated by the top-down influence from the SFG to the MOG. Together, these findings suggest that prefrontal regions might interface with visual regions to guide preference modification following nonreinforcement training.

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#### CRediT authorship contribution statement

**Haishuo Xia:** Writing – original draft. **Qian Wu:** Writing – original draft. **Grant S. Shields:** Writing – review & editing. **Haoyu Nie:** Data curation. **Xin Hu:** Data curation. **Shiyu Liu:** Data curation. **Zhehan Zhou:** Data curation. **Hong Chen:** Conceptualization. **Yingkai Yang:**

Writing – review & editing, Conceptualization.

## Declaration of competing interest

None.

## Data availability

Data will be made available on request.

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## Appendix A. Supplementary data

Supplementary data to this article can be found online at <https://doi.org/10.1016/j.neuropsychologia.2024.108919>.

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