



Research report

Neural correlates underlying preference changes induced by food Go/No-Go training

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ABSTRACT

Consistently not responding to appetitive foods during food go/no-go training could change individuals' food choices and sometimes even body weight, however, fewer studies have explored the neural pathways underlying the effects of food go/no-go training. In this study, we scanned eighty-six female participants using functional magnetic resonance imaging and investigated the neural bases of preference changes in a binary food choice task following action (e.g., go) or inaction (e.g., no-go) toward distinct foods within a food go/no-go training paradigm. In line with prior behavioral work, we found that participants' food preferences changed as a function of food go/no-go training, with participants choosing more "go" over "no-go" foods for consumption following training. At a neural level, preference changes were inversely associated with frontoparietal and salience network activity when choosing go (vs. no-go) foods. Additionally, task-related functional connectivities from the inferior parietal lobule to the pre-supplementary motor cortex, dorsolateral prefrontal cortex, and dorsal anterior cingulate cortex were related to these preference changes. Together, current work supports that food go/no-go training reliably changes people's preferences. More importantly, our findings suggest that a neural pathway centered on areas traditionally associated with selective attention may interface with prefrontal regions to guide preference changes induced by food go/no-go training, though future studies using other tasks (e.g., passive viewing tasks) are still needed to test this potential neural mechanism.

1. Introduction

Eating healthier was the most commonly reported desired lifestyle change by US consumers last year (Nextbite, 2022; Nutrisystem, 2022). Indeed, many individuals endeavor to resist the approach tendency to appetitive yet unhealthy foods—especially those that contain much sugar and fat (Hall, 2016; Yang et al., 2019). However, food preferences are notoriously difficult to change: About 80% of people who lose weight will have failed to maintain that weight loss one year later (Wing & Phelan, 2005). Although some lab interventions do appear to produce a somewhat lasting effect on food preferences (Aridan et al., 2019; Lawrence et al., 2022; Schonberg et al., 2014), the mechanisms underpinning those effects are largely unknown. Understanding these

mechanisms may help to improve the efficacy of those interventions, which illustrates the importance of that lack of understanding. This study helps to address that gap.

One commonly known method for acquiring or modifying food preferences is reinforcement learning, which involves reinforcing or punishing specific behaviors to increase or decrease their frequencies, respectively (Dayan & Niv, 2008). The principles of reinforcement learning have been applied in many psychosocial interventions that aim to facilitate behavioral changes, such as smoking cessation (e.g., Prochaska et al., 2004) or weight loss (e.g., Petry et al., 2011). However, the beneficial effects of these interventions may fade quickly after the intervention has finished (e.g., Prochaska et al., 2004).

Interestingly, some recent studies have found that simple action

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toward (e.g., responding) or inaction (e.g., not responding) related to stimuli in the absence of external reinforcements may in fact contribute to behavioral and preference changes related to those stimuli (e.g., Chen et al., 2019; Chen et al., 2021; Schonberg et al., 2014; Schonberg & Katz, 2020; Veling et al., 2021; Zoltak et al., 2018). The most prominent paradigms in this work are cue-approach training (Schonberg et al., 2014) and the food go/no-go training (e.g., Veling et al., 2013), both of which manipulate responding versus not responding to foods. In cue-approach training, participants view a series of items (e.g., foods) and are told to respond quickly (e.g., pressing a key on the keyboard) if they hear a tone, which is paired with around 25% of the items. Cue-approach training has been shown to reduce relative preferences for no-go snack foods (compared to go snack foods) in multiple studies (Botvinik-Nezer et al., 2020; Schonberg et al., 2014). It is thought that bottom-up perceptual mechanisms may underpin immediate changes in preferences, and decreases in top-down attention processes may be related to long-lasting preference changes induced by cue-approach training (Botvinik-Nezer et al., 2020; Schonberg & Katz, 2020).

Another paradigm that has been found to modify food preferences is food go/no-go training (Chen et al., 2019). In contrast to cue-approach training, food go/no-go training usually contains an equal number of go and no-go trials (i.e., not the 70%/30% split used by cue-approach training), and the cue to respond or not is present on both types of trials. As such, the influences of food go/no-go on food preferences are thought to be related to repeated decisions of action or inaction (Chen et al., 2019). Importantly, recent studies have found that food go/no-go training can produce desired but more distal real-world outcomes, such as weight loss, especially for individuals with a higher body weight (Forman et al., 2019; Lawrence et al., 2015; Stice et al., 2017; Veling et al., 2014; but see Adams et al., 2021; Carbine et al., 2021; Stice et al., 2022; Yang et al., 2021).

The mechanisms behind food go/no-go training are still a matter of debate. The prevailing theory is that food go/no-go training updates valuations of items via repeated decisions of action or inaction, such that no-go items are devalued and go items are more highly valued (Value-updating account) (Veling et al., 2022). This theoretical view thus posits that food go/no-go training does not modify food preferences by training inhibition of those items per se (Veling et al., 2022). However, this prevailing view of food go/no-go training effects has not yet been tested outside of a behavioral level, and it is difficult to disentangle improved inhibition (e.g., stronger top-down control of a bottom-up signal) from decreased valuation (e.g., a weaker bottom-up signal) at a behavioral level.

Neuroimaging may help to clarify how food go/no-go training modifies food choices and preferences, given well-mapped top-down and bottom-up neural circuits and systems (Baluch & Itti, 2011; Schonberg & Katz, 2020). For example, during a food go/no-go, palatable stimuli elicit activity within regions involved in top-down control as well as regions involved in value-based decision-making, and activity levels in each of these regions during this task are related to body mass index (BMI) (Batterink et al., 2010). Similarly, food go/no-go training produces changes in reported food valuations, and these changes are linked to training-induced differences in insula activity (Yang et al., 2021). As implied by the above, a small but growing body of work has examined neural changes related to (food) go/no-go training. To date, however, no study has examined whether the neural changes related to food go/no-go training or go/no-go food decision-making might relate to training-related preference changes. This study addresses this gap.

1.1. Current research

The current study aimed to determine the neural bases underlying changes in food preferences after food go/no-go training. To this end, eighty-six participants completed both food go/no-go training and a food choice task in a functional magnetic resonance imaging (fMRI) scanner. We then examined neural activity in both go/no-go training

and the food choice task in relation to food preference changes following training. For the analyses predicting preference changes from go/no-go training imaging data, we examined training-related brain activity (i.e., neural activity differentiating go vs. no-go foods as a function of training phase [late vs. early]) as a predictors of food preference changes. For the food choice imaging results, we examined neural activity differentiating go vs. no-go food choices as predictors of food preference changes. We also examined task-related functional connectivity indicative of training-induced changes in food preferences via generalized psychophysiological interactions (gPPI) (McLaren et al., 2012). Drawing on the work described above (e.g., Yang et al., 2021) and the value-updating account (e.g., Veling et al., 2022), we expected activity and functional connectivity changes in reward network during go/no-go training (contrast of interest: [go foods – no-go foods] – [late training phase – early training phase]) and the food choice task (contrast of interest: [go food chosen – no-go food chosen]) to predict changes in food preferences.

2. Methods

2.1. Participants

Female undergraduate students from Southwest University were recruited via on-campus advertisements. We only recruited female participants because of logistical constraints—it is difficult to find male students (relative to female undergraduate students) willing to participate in psychology studies at Southwest University. We do note, though, that female participants have been historically underrepresented in research, and less is known about them as a result, which highlights the importance of studying women (Holdcroft, 2007; Sugimoto et al., 2019). Participants who reported current mental disorders, eating disorders, and/or head injuries were excluded. We intended to recruit around eighty subjects, based on a previous study which found a preference change effect of food go/no-go training (Chen et al., 2019). Our final sample consisted of $N = 86$ participants with valid behavioral data.

Of the 86 participants, two were excluded from imaging analysis due to scan error. In addition, two participants in the food go/no-go training, and six participants in the food choice task were excluded due to motion (e.g., displacement of >3 mm in any plane and rotation of $>3^\circ$ in any direction). Therefore, our analyses consisted of 86 participants for behavioral data, 82 participants for the food go/no-go training imaging data, and 78 participants for the food choice imaging data.

2.2. Procedure

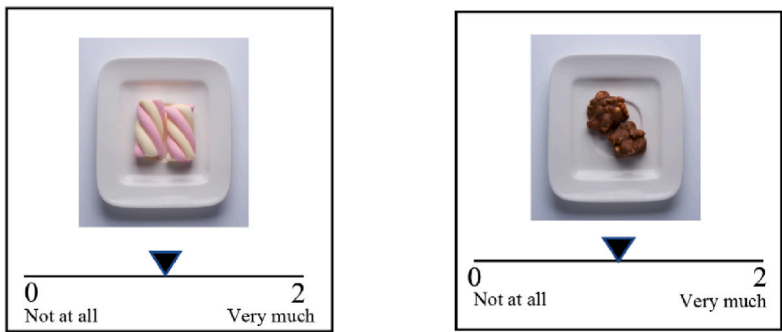
Before coming into the lab, participants were instructed to fast for 3 h (drinking water was allowed). Upon arrival, the participants provided informed consent and completed demographic and fasting questionnaires. Those who did not adhere to the fasting requirement were excluded. Participants then completed short, practice versions of the food go/no-go training and the food choice task, before completing the formal experimental tasks (see Fig. 1 for the sequence of main experimental tasks). A detailed description of each task appears below.

2.3. Measurements

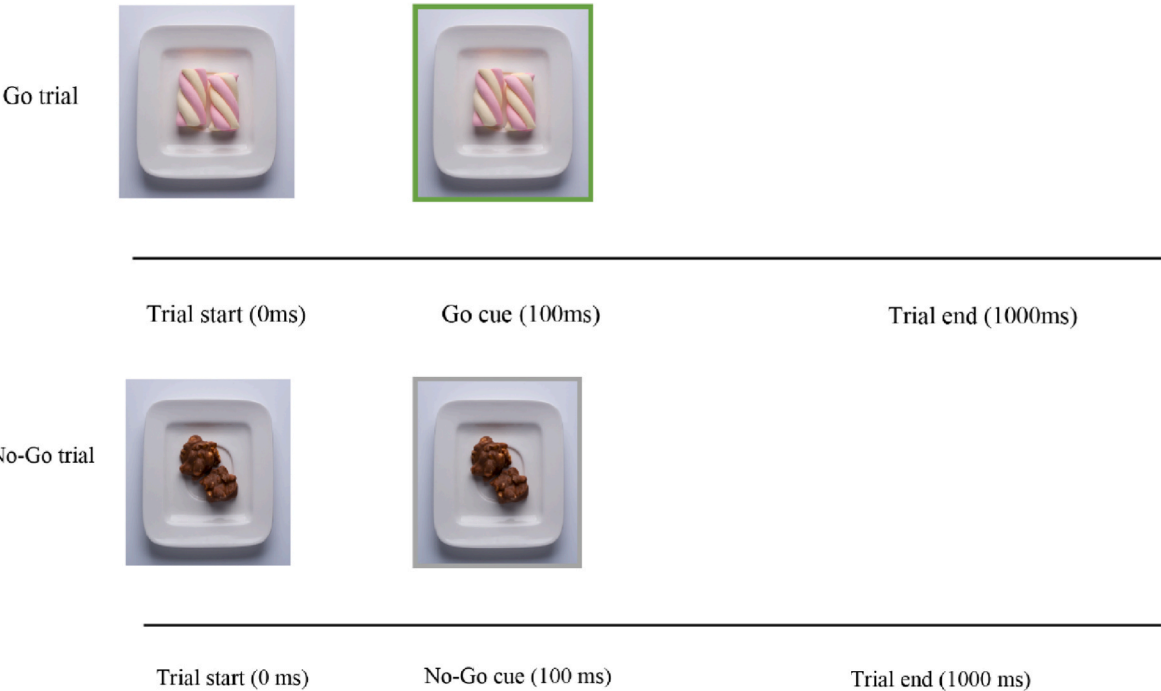
2.3.1. fMRI data acquisition

Structural and functional images were acquired on a 3T Prisma Siemens Trio MRI scanner using a 64-channel brain coil at Southwest University. High-resolution T1-weighted structural images were acquired using a magnetization prepared rapid acquisition gradient-echo (MPRAGE) sequence: TR = 2530 ms, TE = 2.98 ms, FOV = 224×256 mm², resolution matrix = 448×512 , flip angle = 7° , slices = 192, thickness = 1.0 mm, inversion time = 1100 ms, voxel size = $0.5 \times 0.5 \times 1$ mm³. During the functional task, blood oxygen level dependent (BOLD) imaging was performed using a single shot echo-planar imaging

(1) Task 1 Pre-training evaluation



(2) Task 2 Go/no-go training In scanner



(3) Task 3 Food choice task In scanner

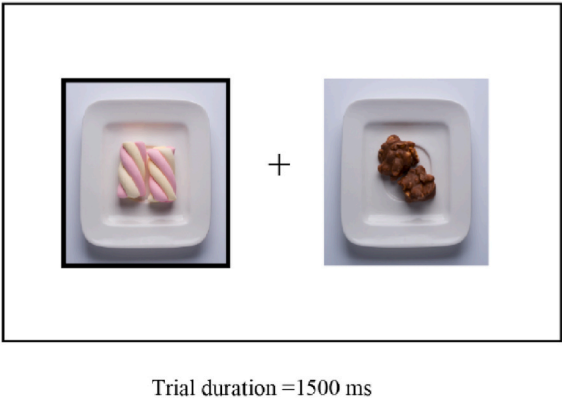


Fig. 1. The sequence of main experimental tasks. (1) Evaluation task; (2) The go/no-go training; (3) Food choice task.

(EPI) sequence (TR = 2000 ms; TE = 30 ms; flip angle = 90°; FOV = 224 × 224 mm²; matrix size = 64 × 64; voxel size = 2.0 × 2.0 × 2.0 mm³; Slices = 62; thickness = 2.0 mm). Resting-state data were not collected.

2.3.2. Pre-training food evaluation

The participants were randomly presented with 40 color images of candies (e.g., gummies, chocolates) one by one. Images were presented in the center of the screen, with the question, ‘how much do you want to eat this candy right now?’ presented at the bottom of the screen. Participants responded to each image prompt by clicking on a 200-point visual analogue scale, with the range 0 (not at all) to 2 (very much) displayed to participants (Chen et al., 2019). The food image remained on the screen until participants pressed a key (‘continue’) to confirm their rating and moved on to the next question.

2.3.3. Item selection

For each participant, candy pictures were rank-ordered from 1 (highest value) to 40 (lowest value) based on their evaluations. Then, 12 items (ranked 3–14) were selected for the GNG and food choice task. Six of the 12 items (i.e., items 3, 6, 7, 10, 11, 14) were chosen to be go items, and the remaining six were no-go items (i.e., items 4, 5, 8, 9, 12, 13).

2.3.4. Go/no-go training

The training task was similar to previous published studies (e.g., Chen et al., 2019; Yang et al., 2021). The 12 selected pictures (described above) were used for training. During the task, each picture was pseudo-randomly presented individually on the middle of a computer screen for up to 1000 ms, followed by a 1000–4000 ms inter-stimulus interval. A green or grey rectangular frame appeared around the picture 100 ms after picture onset, and it was visible for the remainder of the time that the picture was displayed. If the rectangular frame surrounding the picture was green, participants were asked to press a button on an MRI-compatible response box as quickly and accurately as possible to respond. However, if the rectangular frame surrounding the picture was grey, they were told that they should not respond. The training session consisted of six blocks with 24 trials per block (i.e., 12 go trials and 12 no-go trials per block; total of 144 trials across all blocks), and it took approximately 12 min to complete. The participants were allowed a break after finishing half of the training.

2.3.5. Food choice task

Participants also completed the food choice task in the scanner. On each trial, a pair of foods that had similar initial rankings (i.e., one go food, one no-go food) were pseudo-randomly presented side by side. Participants were told that they should choose the item they want within 1.5 s by pressing the corresponding one of two buttons on an MRI-compatible response box. After each choice, the chosen item was surrounded by a black rectangle for 500 ms as confirmation. A 1–4 s intertrial interval occurred between each trial during which a blank screen with a fixation cross was presented. The whole task consisted of two blocks of 36 trials each (72 total trials) and took approximately 7 min to complete. Participants were allowed a break after finishing half of the task.

2.4. Statistical analyses

2.4.1. Behavioral data analysis

Behavioral data were analyzed using R version 3.6.2. Multilevel logistic regression was conducted at the participants level as the main analysis (Formula: choice = 1 + (1 | subject)) (Bates et al., 2015). The probe in the food choice task was coded as: choosing go food = 1, choosing no-go food = 0.

2.4.2. Neuroimaging analyses

fMRI data preprocessing was performed using data processing and analysis for brain imaging (DPABI) (Yan et al., 2016), in the following

manner. First, slice timing and head motion corrections. Subsequently, each participant's structural images were co-registered to the mean functional image functional images. Then functional images were normalized to the standard Montreal Neurological Institute space. Finally, spatial smoothing was performed with a Gaussian kernel of 8 mm at full width half-maximum.

Neuroimaging data were analyzed using statistical parametric mapping (SPM12) (<https://www.fil.ion.ucl.ac.uk/spm/>). For the training image analyses, four regressors of interest—namely, go foods in the first two blocks (i.e., early training phase), no-go foods in the first two blocks, go foods in the last two blocks (i.e., late training phase), no-go foods in the last two blocks—and six motion regressors were modeled in the first-level using the general linear model, with delta functions convolved with a canonical hemodynamic response function (HRF). Next, we modeled for each participant the interaction contrast between Go > No-go and Late phase > Early phase. These 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). For the food choice task image analyses, two regressors of interest (chose go, chose no-go) and six motion regressors were modeled in the first-level. Next, we modeled for each participant the contrast of chose go > chose no-go. These 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). We used a cluster-level family wise error rate (FWE)-corrected threshold of $p < .05$, and a voxel-wise threshold of $p < .001$ to identify significant clusters.

2.5. Task-modulated connectivity predicts preference change

We conducted generalized psychophysiological interaction (gPPI) analyses (McLaren et al., 2012) to examine event-related functional connectivity. The gPPI model consisted of a physiological term (the time series of a seed region), psychological terms (HRF convolved the main effect of the condition of interest, e.g., go and no-go), and PPI terms (deconvolved raw time series of the seed multiplied by the main effect of the condition of interest, and then convolved with HRF). The significant brain activations that emerged from whole-brain analyses mentioned above were used as regions of interests (ROIs) for gPPI analyses. In the analysis, one of the ROIs was used as a seed, the rest were used as targets, and gPPI describes the task related change in influence of a seed on a target region; the outcome is an asymmetrical effective connectivity matrix. To test whether task-modulated connectivity was related to the preference change, we extracted the gPPI parameters (e.g., contrast of interest, go versus no-go). This procedure resulted in a task-modulated functional connectivity matrix for each participant, and we performed a Pearson's correlation analysis between the functional connectivity matrices and the preference change scores. These statistics were false discovery rate (FDR)-corrected for multiple comparisons. We also used another statistic to correct for multiple comparisons (network-based statistic, NBS) (Zalesky et al., 2010), please see supplementary materials for these results.

2.6. Ethics

All participants gave written informed consent for their participation. The study was approved by the local ethics committees of Southwest University.

3. Results

3.1. Demographic information

The mean age of this sample was 20.5 years (SD, 1.60; range, 18–25 years). The mean BMI was 20.6 (SD, 2.22; range, 16.1–26.0; three

participants were overweight).

3.2. Behavioral results

3.2.1. Performance during go/no-go training

Participants made very few errors during training: for accuracy on go trials, mean (M) = 98.34%, standard deviation (SD) = 3.64%; for accuracy on no-go trials, M = 99.06%, SD = 1.09%. Go reaction time was M = 380.05 ms, SD = 46.23 ms.

3.2.2. Stimulus evaluation

A paired t -test showed that the average ratings of go (M = 1.351, SD = 0.37) and no-go (M = 1.348, SD = 0.37) pictures were matched before the training, $t(85) = 1.13$, $p = .263$.

3.2.3. Probe in food choice task

Multilevel logistic regression showed that participants chose go foods significantly more often over no-go foods, mean proportion of go foods = 57.92%, $OR = 1.49$, 95% $CI [1.20, 1.84]$, $p = 3.21 \times 10^{-4}$ (Fig. 2).

3.3. Neural activity

To probe the neural signature of preference changes following food go/no-go training, we examined neural activity during choices of go (vs. no-go) foods following training in relation to the probability of choosing “go” foods (Table 1, Fig. 3). We found that activities in the right pre-supplementary motor cortex (Pre-SMA), right dorsal anterior cingulate cortex (dACC), bilateral anterior insula (AI), left inferior frontal gyrus (IFG), left middle frontal gyrus (MFG), bilateral inferior parietal lobule (IPL), bilateral superior parietal lobule (SPL), left inferior temporal gyrus (ITG), right middle temporal gyrus (MTG), and left cerebellum to go versus no-go choices were negatively correlated with the probability of choosing go foods (or positively correlated with the probability of choosing no-go foods).

To determine the magnitudes of the above associations, we extracted activity from each of these clusters as defined by 6 mm-radius spheres centered at each cluster's peak. FDR-correction was used to correct for the number of tests. Results revealed that greater probability of choosing go foods was significantly associated with lower activities in the Pre-SMA ($r = -0.53$, $p_{\text{corrected}} = 7.5 \times 10^{-6}$), dACC ($r = -0.52$, $p_{\text{corrected}} = 7.5 \times 10^{-6}$), AI (r 's = -0.48 , -0.39 , p 's $_{\text{corrected}} = 3.8 \times 10^{-5}$, $8.3 \times$

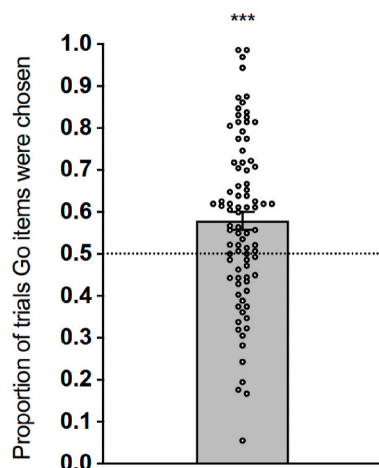


Fig. 2. The behavioral results of Go choices during probe task: the mean proportion of trials in which participants chose Go over No-Go foods are presented. The dashed line indicates the equal preference level of 50%; error bars represent standard error of the mean. The asterisks reflect the statistical significance in a repeated-measures logistic regression. ***: $p < .001$.

10^{-4}), IFG ($r = -0.48$, $p_{\text{corrected}} = 3.8 \times 10^{-5}$), MFG (r 's = -0.35 , -0.43 , p 's $_{\text{corrected}} = 0.003$, 2.5×10^{-4}), IPL (r 's = -0.41 , -0.44 , -0.40 , p 's $_{\text{corrected}} = 4.3 \times 10^{-4}$, 1.8×10^{-4} , 5.6×10^{-4}), SPL (r 's = -0.35 , -0.33 , p 's $_{\text{corrected}} = 0.003$, 0.004), ITG ($r = -0.34$, $p_{\text{corrected}} = .004$, MTG ($r = -0.33$, $p_{\text{corrected}} = .004$), and cerebellum ($r = -0.26$, $p_{\text{corrected}} = .019$) (Fig. 4).

3.4. Food choice task-related functional connectivity

Next, we aimed to understand whether and how preference changes might be reflected by food choice task-related functional connectivity. To do so, we performed gPPI analysis using significant activations that emerged from the whole brain univariate analyses (Table 1) as ROIs. The results indicated that probability of choosing go foods was significantly and positively correlated with the functional connectivities from IPL to Pre-SMA ($r = 0.49$, $p_{\text{corrected}} = .002$) (Fig. 5 A & B), MFG ($r = 0.39$, $p_{\text{corrected}} = .047$) (Fig. 5 A & C) and dACC ($r = 0.38$, $p_{\text{corrected}} = .047$) (Fig. 5 A & D) during choices of go compared with choices of no-go foods.

3.5. Go/no-go training phase

We also examined whether BOLD activities toward go foods in comparison to no-go foods during the late phase compared with early phase of go/no-go training was correlated with the probability of choosing go foods during the food choice task. Contrary to expectations, no effects survived after the FWE-correction.

4. Discussion

To the best of our knowledge, our study is the first to use fMRI to examine the neural bases of the preference changes induced by food go/no-go training. Behaviorally, we found that food go/no-go training resulted in a preference change, in that participants chose more go than no-go foods following training. On a neural level, we found that reduced activations in the network and the salience network, but increased functional connectivities from the IPL to the pre-SMA, MFG/dorsolateral frontal cortex (DLPFC), and dACC during the binary choice phase were associated with these preference changes. Taken together, the present study suggests that a neural pathway centered on areas traditionally associated with selective attention may interface with prefrontal regions to guide preference changes induced by food go/no-go training.

These results are promising from a clinical perspective, as food go/no-go training is simple: It does not rely on self-control, but on basic action or inaction. This simplicity should help to make food go/no-go training more easily applicable to populations with relatively lower executive control, such as those with obesity (e.g., Yang et al., 2018; Yang et al., 2023), whereby food go/no-go training could be used to enhance preferences towards certain stimuli, such as healthy foods. For example, Chen et al., 2019 (Experiment 7) used healthy foods as go items and unhealthy foods as no-go items, and they found that food go/no-go training can promote healthy food choices in comparison with when both items were untrained, suggesting that food go/no-go training can work with less appetitive stimuli (e.g., healthy food).

The behavioral choice results obtained in the current study are in line with those obtained by prior studies using food go/no-go training (Chen et al., 2019, 2021) or cue-approach training (e.g., Itzkovitch et al., 2022; Schonberg et al., 2014), in that participants showed enhanced preferences towards go compared to no-go foods. Taken together, the existing body of literature supports the idea that simple training of action or inaction to certain stimuli can change individuals' preferences related to these stimuli. Indeed, the behavioral effect we observed (i.e., a probability of go over no-go of 57%) was similar in magnitude to previous work using food go/no-go training or cue-approach training (see Carbine & Larson, 2019, and Itzkovitch et al., 2022 for overviews of similar studies), indicating that the food preference change effect is

Table 1
All Choose Go > Choose No-Go activity 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	Right Pre-supplementary motor cortex	2614	6	21	45	6.83
		Right Dorsal anterior cingulate cortex		3	27	33	
		Right Anterior insula		30	24	3	
2	Negative	Left Inferior frontal gyrus	616	-45	12	-3	6.23
		Left Anterior insula		-33	15	-12	
		Left Middle frontal gyrus		-42	45	12	
	Negative	Left Middle frontal gyrus	388	-45	27	33	5.34
4	Negative	Right Inferior parietal lobe	221	-48	12	30	5.19
				36	-54	45	
				48	-45	42	
5	Negative	Left Inferior parietal lobe	213	51	-36	39	5.56
				-30	-51	36	
				-27	-66	39	
6	Negative	Left Cerebellum	171	-36	-72	-45	4.41
				-30	-66	-33	
				-33	-69	-9	
	Negative	Left Inferior temporal gyrus	168	-42	-51	-12	4.87
8	Negative	Right Superior parietal lobule	164	-51	-60	-15	5.18
				6	-69	42	
				-3	-66	36	
	Negative	Left Superior parietal lobule	117	-6	-72	45	4.97
9	Negative	Right Inferior parietal lobe	117	60	-60	30	4.97
				57	-45	27	
				66	-51	21	
	Negative	Right Middle temporal gyrus	91	63	-33	-18	4.40
10	Negative	Right Middle temporal gyrus	91	66	-33	-6	4.40
				66	-33	-6	

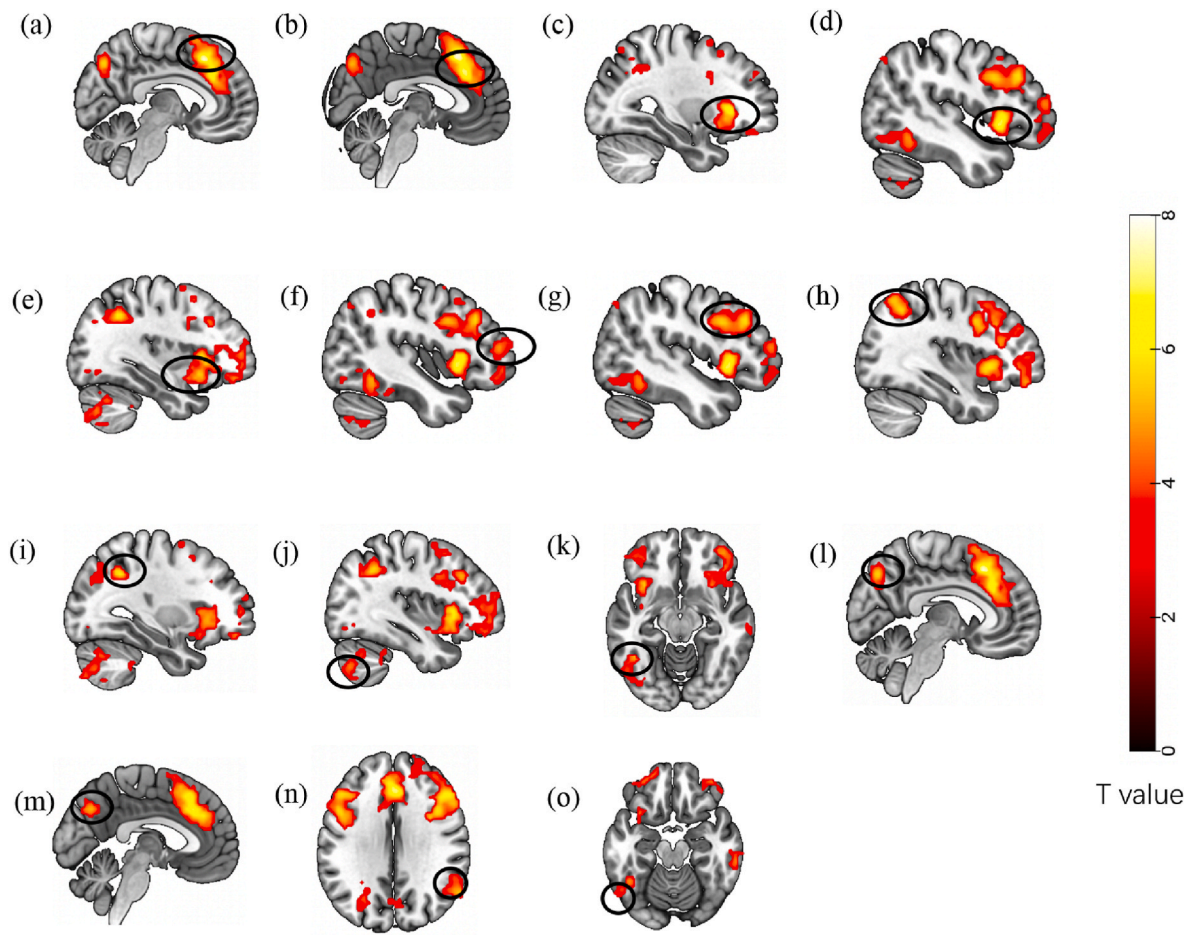


Fig. 3. Food choice imaging results. After training, the probability of choosing go (vs. no-go) foods correlated with the BOLD response to go foods over no-go foods in several regions, including (a) right pre-supplementary motor cortex, (b) right dorsal anterior cingulate cortex, (c&e) bilateral anterior insula, (d) left inferior frontal gyrus, (f&g) left middle frontal gyrus, (h&i&n) bilateral inferior parietal lobule, (l&m) bilateral superior parietal lobule, (k) left inferior temporal gyrus, (o) right middle temporal gyrus, and (j) left cerebellum.

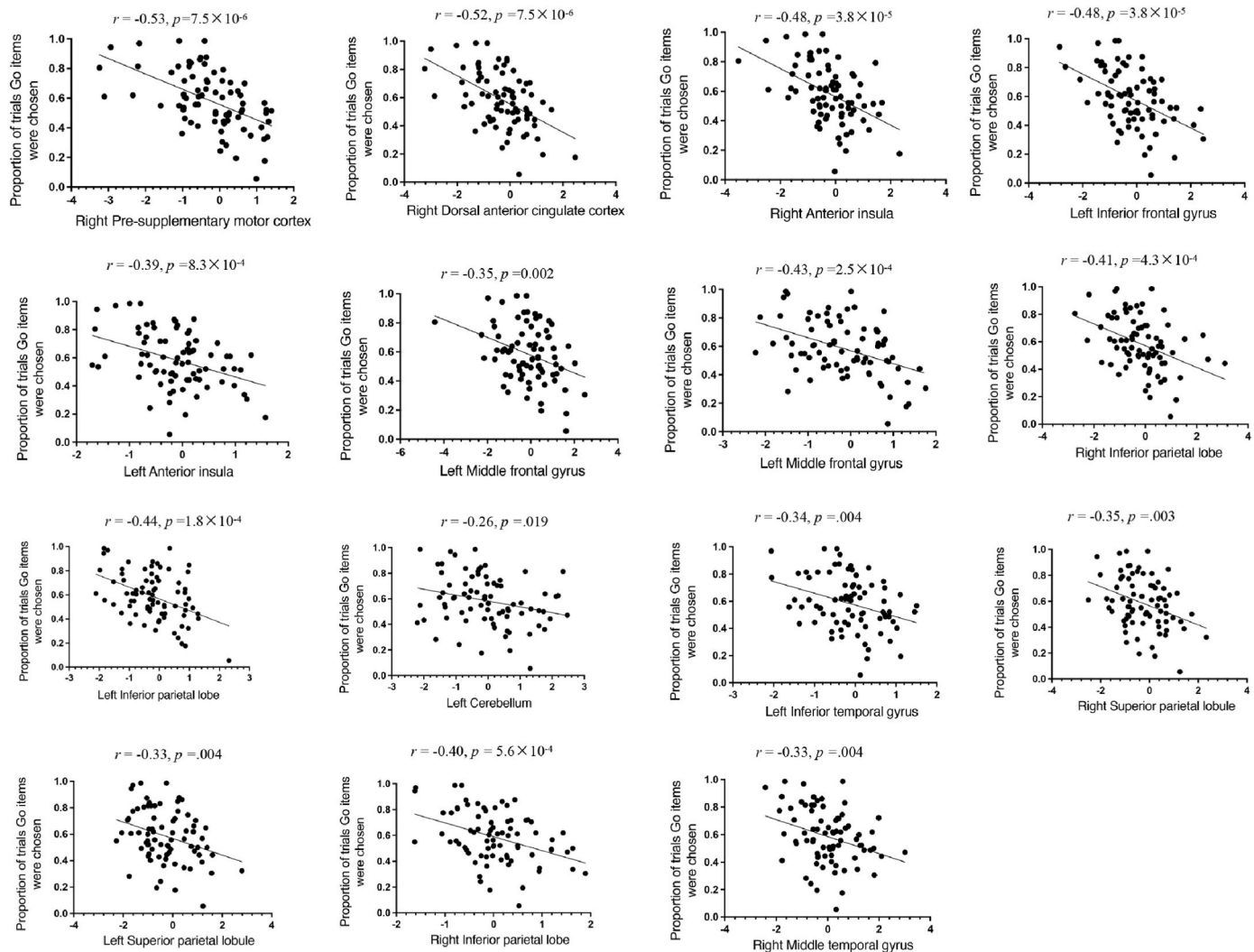


Fig. 4. Greater probability of choosing go foods was significantly associated with lower activities in the right pre-supplementary motor cortex, right dorsal anterior cingulate cortex, bilateral anterior insula, left inferior frontal gyrus, left middle frontal gyrus, bilateral inferior parietal lobule, bilateral superior parietal lobule, left inferior temporal gyrus, right middle temporal gyrus, and left cerebellum.

reproducible.

Several explanations have been offered for why food go/no-go training might contribute to preference changes (Chen et al., 2018; Johannes et al., 2021; Stice et al., 2016; Veling et al., 2017, 2022). For example, training may alter evaluations of go and no-go items, increasing valuations of go items (Chen et al., 2016) but decreasing valuations of no-go items (Yang et al., 2022). As a result, when given a choice between go and no-go items, participants might favor go over no-go items. Alternatively, repeatedly inhibiting responses toward no-go items and responding to go items during training may lead to the formation of stimulus-response associations (e.g., go items with the response of action, no-go items with the response of stopping) (Johannes et al., 2021; Veling et al., 2017; Verbruggen et al., 2014). Participants therefore may more easily respond to go vs. no-go items in a binary choice task after food go/no-go training.

On a neural level, we found negative correlations between go (vs. no-go) activities in the pre-SMA, dACC, AI, IFG, MFG, IPL, SPL, and other regions during the food choice task and individual differences in the preference change effect. The dACC and AI/IFG are core areas within the salience network, which plays a crucial role in conflict monitoring or error detection (Botvinick & Carter, 2001; Koban & Pourtois, 2014). The pre-SMA, MFG/DLPFC, and posterior parietal cortex (e.g., IPL, SPL) belong to the frontoparietal network and are known to be involved in

executive control or behavioral adjustment following the experience of conflict (Mansouri et al., 2007, 2009).

The pattern of results we observed differs from neuroimaging work with cue-approach training, which has primarily found that activities in regions related to encoding reward (e.g., striatum) are related to preference changes. In particular, both Salomon et al. (2020) and Schonberg et al. (2014) found that, after cue-approach training, individual differences in ventromedial prefrontal cortex activity during go (vs. no-go) choices were positively correlated with the individual differences in the number of go stimuli choices. However, another study with cue-approach training (Botvinick-Nezer et al., 2020) failed to replicate this result, instead finding that BOLD activity in the striatum was negatively correlated with the preference change effect across participants. Taken together, it seems that, although both cue-approach and food go/no-go training involve responding and not responding to certain stimuli, the neural mechanisms underlying these two training effects may be different.

The associations of the salience and frontoparietal networks with the preference change effect we observed within current study could be explained by the stimulus-response account. As described above, this account proposed that food go/no-go training could establish an association of go items with the action of responding, and an association of no-go items with not responding (Johannes et al., 2021; Veling et al.,

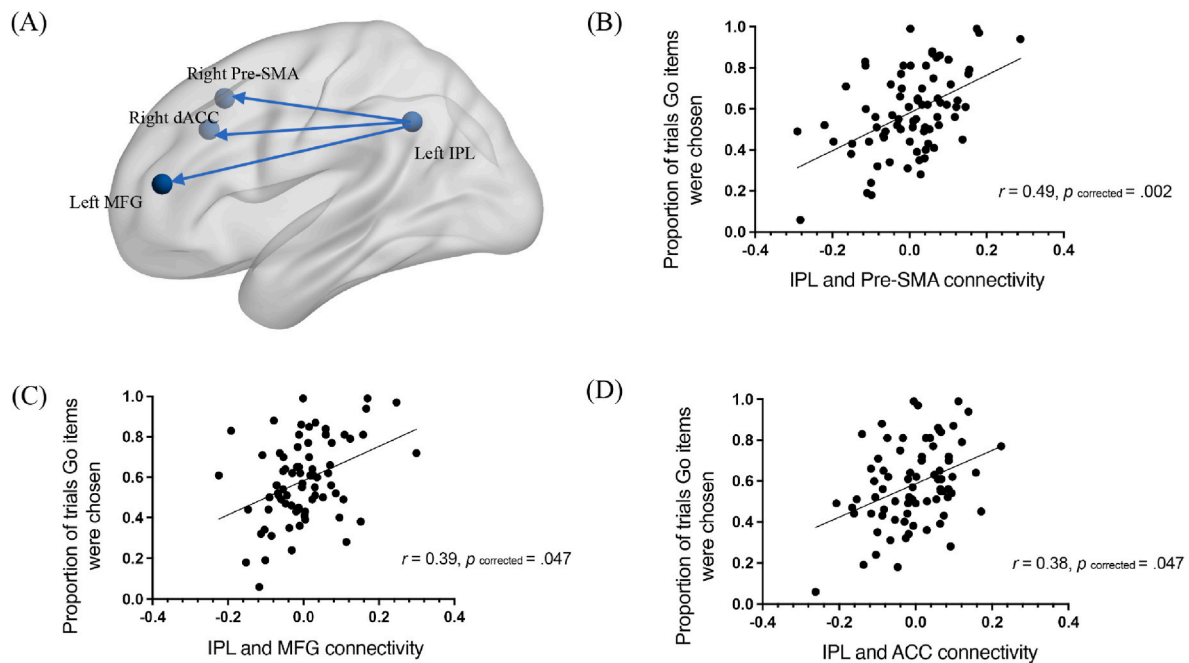


Fig. 5. Results from the generalized psychophysiological interaction (gPPI) functional connectivity analysis. (A) The functional connectivities from the left inferior parietal lobule (IPL) to the right pre-supplementary motor cortex (pre-SMA), right dorsal anterior cingulate cortex (dACC), and left middle frontal gyrus (MFG) during go choices versus no-go choices significantly related to preference change scores. (B) Specifically, the correlations between the connectivities and preference change scores were positive. These statistics were false discovery rate-corrected for multiple comparisons. Scatter plots are for the purpose of data visualization only. Times series data in regions of interest were missing in two participants, in turn, seventy-four participants were included in the gPPI analysis.

2017; Verbruggen et al., 2014). Therefore, choosing go foods over no-go foods is consistent with participants' already "learned reflex" (e.g., go foods = respond, no-go foods = stop). Furthermore, the proportion of trials go foods were chosen was higher for participants who developed stronger contingencies for go and no-go foods and consequently they might precepted less conflict or uncertainty (Stojić et al., 2020) when choosing go foods and rejecting no-go foods for consumption, which was reflected by less activations in the conflict perception (e.g., salience network) and resolution (frontoparietal network) regions for them.

In contrast, the value-updating account suggests that food go/no-go training influences preferences by decreasing liking of no-go items, and/or increasing liking of go items (Chen et al., 2018a; Johannes et al., 2021; Veling et al., 2022; Yang et al., 2022). We did not find significant correlations between the preference change effect and the brain regions related to reward processing (e.g., striatum) during the training or the food choice task. Therefore, the training and food choice imaging results of current study did not support the value-updating account. However, it should be noted that the present experimental setup may not be ideal for testing the theoretical predictions of the value-updating account, and it is possible that other tasks could produce striatal activity indicative of dis/liking that our study was unable to detect. Future studies could use other tasks, such as a passive viewing task (e.g., pictures of snack food items are individually presented on the screen) (e.g., Botvinik-Nezer et al., 2020; Yang et al., 2021), and examine correlations between preference changes and neural changes to go versus no-go items pre-to post-training.

A further interesting neural signature of preference changes observed in current study was the functional connectivities from the IPL to the pre-SMA, DLPFC, and dACC in relation to preference changes. In contrast to the negative univariate effects, the functional connectivities observed in current study were positively related to relatively more choices for go than no-go foods, suggesting that both brain activations and functional couplings contributed to the 'successful' food go/no-go training-induced preference changes. The IPL plays an important role in mediating the automatic allocation of attention to task/behavior-

relevant information (Corbetta & Shulman, 2002; Seghier, 2013). As mentioned earlier, the frontal regions including pre-SMA, DLPFC, and dACC are commonly implicated in cognitive control processes such as conflict detection and response inhibition (Botvinick & Braver, 2015), as well as in selecting appropriate motor/behavioral responses (Kouneiher et al., 2009; Vassena et al., 2020). Thus, one possibility is that connectivities from the IPL to the pre-SMA, DLPFC, and dACC may indicate selective-attention-driven behavioral effects. That is, in the food choice phase, the go foods (compared to the no-go foods) may have been deemed more behaviorally relevant, given that they were frequently acted upon in the food go/no-go training phase (Schonberg & Katz, 2020). Therefore, successful selective attention-based behavioral preference toward the go foods, reflected by increased modulation from IPL to the prefrontal regions, may have led to the relatively greater preference for go foods. Our connectivity result is in accordance with the dorsal value pathway (DVP) model of nonreinforced preference change (Schonberg & Katz, 2020), which proposes that higher perceptual and attentional regions might play an important role in the effect induced by nonreinforced training tasks. Taken together, our results show that, similar to the (neural) mechanisms of other nonreinforcement trainings, such as cue-approach training, a neural pathway centered on areas traditionally associated with selective attention may interface with prefrontal regions to guide preference changes induced by food-go/no-go training.

4.1. Limitations

Our study has several limitations. First, we recruited a sample of female participants, which limits generalizability to male samples. Second, we only assessed immediate training effects. Future studies could examine the long-term changes (e.g., 1-month follow-up) after food go/no-go training. Third, the study sample was not based on power analysis, but on the sample size of a previous study which found changes in food preferences following go/no-go training, and our study was not preregistered. In addition, we did not assess participants' dieting

statuses. Finally, the training used foods with a relatively high value. Future studies are needed to examine the potential neural mechanisms of food go/no-go training-induced preference changes for low-value items (e.g., healthy food items).

5. Conclusion

To summarize, dovetailing with previous studies, current work supports that food go/no-go training reliably changes people's preferences. On the neural level, we found for the first time that less activity within frontoparietal and salience network regions, but greater functional connectivities from the IPL to the pre-SMA, DLPFC, and dACC during go (vs. no-go) food choices is related to individuals' preference changes. Together, these findings suggest that bottom-up neural mechanisms may underpin changes in food preferences following go/no-go training.

Author contributions

Qian Wu and Haishuo Xia: Data curation, Formal analysis, Writing – original draft. Grant S. Shields: Writing – review & editing. Haoyu Nie and Jiwen Li: Methodology. Hong Chen and Yingkai Yang: Project administration, Supervision, Writing – review & editing.

Ethics approval statement

Approval for this study was provided by Southwest University, H22063.

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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.appet.2023.106578>.

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