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It is a matter of perspective: Attentional focus rather than dietary restraint drives brain responses to food stimuli

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ABSTRACT

Brain responses to food are thought to reflect food's rewarding value and to fluctuate with dietary restraint. We propose that brain responses to food are dynamic and depend on attentional focus. Food pictures (high-caloric/low-caloric, palatable/unpalatable) were presented during fMRI-scanning, while attentional focus (hedonic/health/neutral) was induced in 52 female participants varying in dietary restraint. The *level* of brain activity was hardly different between palatable versus unpalatable foods or high-caloric versus low-caloric foods. Activity in several brain regions was higher in hedonic than in health or neutral attentional focus ($p < .05$, FWE-corrected). Palatability and calorie content could be decoded from multi-voxel activity patterns ($p < .05$, FDR-corrected). Dietary restraint did not significantly influence brain responses to food. So, *level* of brain activity in response to food stimuli depends on attentional focus, and may reflect salience, not reward value. Palatability and calorie content are reflected in *patterns* of brain activity.

1. Introduction

We live in an obesogenic environment, which is characterized by the pervasive presence of cheap, easily obtainable high-caloric palatable food, and a predominantly sedentary lifestyle. This excessive supply of high-caloric food can easily lead to a positive energy balance (Stubbs and Lee, 2004). Consequently, the prevalence of overweight and obesity has increased rapidly (Swinburn et al., 2009; WHO 2020). Given this development, many people attempt to control their body weight by dieting (Slof-Op 't Landt et al., 2017). Chronic dieting attempts to reduce or maintain body weight are referred to as dietary restraint (Herman and Polivy, 1980). However, long-lasting weight reduction by dietary restraint appears to be difficult (Fildes et al., 2015). Restrained eaters tend to struggle with weight gain and often have a higher body-mass-index (BMI) than unrestrained eaters (Snoek et al., 2008). This suggests that restrained eaters are prone to overeating. Their eating behavior is influenced by cognitive processes, like dieting rules, and food cue reactivity, and they appear to be less sensitive to internal ingestion signals, such as hunger and satiety cues, than unrestrained eaters (Jansen et al., 2016; Herman and Polivy, 1984). The current study aims to examine if the responsiveness to high-caloric foods that restrained eaters display, is consistently reflected in brain responses to food.

In the past decade, researchers have examined brain responses to food stimuli in restrained eaters (Coletta et al., 2009; Demos et al., 2011; Ely et al., 2014; Born et al., 2011; Wood et al., 2016; Burger and Stice, 2011; Wang et al., 2016; Su et al., 2019). Several studies tested hypotheses related to the paradoxical eating patterns of restrained eaters that are observed in behavioral experiments. That is, restrained eaters increase their food intake after consumption of a high-caloric preload (e.g., a milkshake), but consume less than unrestrained eaters in a no-preload control condition (Herman and Mack, 1975). Overall, these studies hypothesized that restrained eaters would show increased reward-related brain activity (compared to unrestrained eaters) in a satiated state, that is when a preload was given, but decreased reward-related brain activity (compared to unrestrained eaters) in a hungry state, that is when no preload was given (Coletta et al., 2009; Demos et al., 2011; Ely et al., 2014; Born et al., 2011) However, the results of these studies are inconsistent. For example, Coletta et al. (2009) (Coletta et al., 2009) observed differences in brain activity between restrained and unrestrained eaters with and without pre-load, whereas Ely et al. (2014) (Ely et al., 2014) only with a pre-load.

Other studies on the effect of dietary restraint on brain responses to food generally expected differences in reward sensitivity between restrained and unrestrained eaters, predominantly predicting increased re-

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ward sensitivity in restrained eaters. However, these studies do not provide consistent evidence for increased reward sensitivity in restrained eaters either. For example, Wang et al. (2016) (Wang et al., 2016) observed differences in brain responses to food images between restrained and unrestrained eaters, whereas Burger and Stice (2011) (Burger and Stice, 2011) found no effect of dietary restraint on brain responses to pictures of appetizing food. Taken together, the studies on differences in brain responses to food between restrained and unrestrained eaters do not provide a clear picture. Different studies have tested contradictory hypotheses and the variability between study results is large (Coletta et al., 2009; Demos et al., 2011; Ely et al., 2014; Born et al., 2011; Wood et al., 2016; Burger and Stice, 2011; Wang et al., 2016; Su et al., 2019; Nakamura et al., 2021). The inconsistency in findings in this field may be partly due to small sample sizes (Coletta et al., 2009; Ely et al., 2014; Born et al., 2011; Wood et al., 2016; Burger and Stice, 2011; Wang et al., 2016) and/or lenient thresholding (Coletta et al., 2009; Ely et al., 2014). The divergence in findings resembles the divergence in findings on brain responses to food stimuli in healthy-weight individuals, which have been described as moderately convergent at best by a meta-analysis (van der Laan et al., 2011), as well as the inconsistency in brain responding to food stimuli in obese people (Ziauddeen et al., 2012; Morys et al., 2020).

Divergent findings might partly be caused by differing task instructions and paradigms across studies. In particular, previous neuroimaging studies either employed a passive viewing paradigm, in which participants are asked to look at food stimuli without further instructions, or used simple instructions, such as indicating whether the presented stimulus is a food, to ensure deliberate processing of food stimuli (Demos et al., 2011; Ely et al., 2014; Burger and Stice, 2011; Ziauddeen et al., 2012). In this way, no experimental control is exerted over the mental processes that participants engage in while viewing food stimuli. Instead, the mental processes that participants engage in, like experiencing feelings of reward, are merely assumed or inferred from the repertoire of cognitive functions that the discovered brain regions have been associated with before in the literature. However, the latter logic is based on reverse inference – that is, inferring mental function from brain activity – and is unlikely to be valid (Poldrack, 2006; Poldrack, 2011). Importantly, high-caloric palatable food can evoke ambiguous feelings. Its taste is highly pleasurable, yielding a high hedonic value, yet its consumption is associated with negative health outcomes, like weight gain, yielding a low health value. Depending on the internal state of an individual or on situational factors, an individual might focus on either hedonic or health-related aspects of food stimuli. Therefore, it is likely that mental processes in response to viewing high-caloric palatable food vary within and across individuals, depending on the attentional focus that a person endorses (Roefs et al., 2018; Siep et al., 2012).

Mental processes are reflected in brain responses measured by functional magnetic resonance imaging (fMRI). Recently, it has been shown that specific brain activations crucially depend on the *interpretation* of a stimulus (Yeshurun et al., 2017). Furthermore, it has been demonstrated that the type of task (edibility vs. color judgements) that participants perform, influences the brain response to food stimuli (Pohl et al., 2017). Relatedly, considering the ambivalent nature of high-caloric palatable food, the attentional focus of a person is a crucial factor influencing the brain activation to food stimuli. It has been shown that the attentional focus plays a role in determining brain responses to food stimuli, such that a hedonic attentional focus results in different brain responses to food stimuli than a health attentional focus (Roefs et al., 2018; Siep et al., 2012; Hare et al., 2011; Frankort et al., 2012; Bhanji and Beer, 2012; Hege et al., 2018; Franssen et al., 2020). Effects of attentional focus might even outweigh effects of stimulus characteristics. As such, it has been observed that several regions of the mesocorticolimbic system showed increased activation to food stimuli when participants engage in a hedonic attentional focus compared to a neutral attentional focus, whereas no differential level of activation could be detected between palatable and unpalatable food stimuli (Franssen et al., 2020).

In addition, analysis methods might have a share in ambiguous research results. More commonly used univariate analysis techniques might be less sensitive than multivariate analysis techniques (Haxby, 2012; Kragel et al., 2012). Interestingly, it has been shown that positive and negative valence cannot be significantly distinguished by univariate analysis techniques. However, it is possible to distinguish between positive and negative valence based on multi-voxel activity patterns (Chikazoe et al., 2014), as well as obtain information about value from those patterns in the orbitofrontal cortex (OFC) (Yan et al., 2016; Howard et al., 2015). More specifically, food value could be decoded from multi-voxel activity patterns in the orbitofrontal cortex (Suzuki et al., 2017). In addition, food preference and choice could be predicted from multi-voxel activity patterns (Van der Laan et al., 2012; Pogoda et al., 2016). Similarly, it is possible to decode palatability of food stimuli, especially when participants engage in a hedonic attentional focus (Franssen et al., 2020). So, food characteristics, such as palatability or calorie content might be reflected in patterns of brain activity rather in the level of brain activity.

The current study investigates the effects of attentional focus, palatability, and calorie content on brain responses to food stimuli in healthy-weight women varying in dietary restraint using fMRI. Three attentional foci are employed: a hedonic attentional focus, a health attentional focus, and a neutral attentional focus. The hedonic attentional focus is conceptualized as a focus on taste properties of food. The health attentional focus is conceptualized as a focus on the calorie content, as an example of a health-related property of food. The neutral attentional focus is conceptualized as focus on color, as an example of a neutral, non-ingestion-related property of food. Attentional focus is manipulated by a fast-paced one-back task (comparable to the task used by Franssen et al., 2020) (Franssen et al., 2020), in which participants are asked to compare subsequent food images, either on taste (hedonic attentional focus), calorie content (health attentional focus), or color (neutral attentional focus). The presented food stimuli are individually tailored on palatability and comprise palatable and unpalatable, high-caloric and low-caloric food. The current study builds on the findings of Franssen et al. (2020) (Franssen et al., 2020), and extends their findings by testing the effects in healthy-weight participants and by assessing the effects of calorie content and dietary restraint, and by adding a health attentional focus.

We hypothesize that attentional focus in interaction with dietary restraint determines brain responses to food. We predict that a hedonic attentional focus will lead to more involvement of brain regions like the ventral striatum or the OFC, while a health attentional focus will elicit more involvement in brain regions like the dorsolateral prefrontal cortex (DLPFC) or the anterior cingulate cortex (ACC). Furthermore, we expect that palatability and calorie content are represented in multi-voxel activity patterns. We expect that decoding accuracy of palatability will be higher in the hedonic than in the health attentional focus, and that decoding accuracy of calorie content will be higher in the health than in the hedonic attentional focus. We expect that these effects will be more pronounced in participants scoring high on dietary restraint. We use standard mass-univariate analysis as well as multi-voxel pattern analysis (MVPA) to test these hypotheses.

2. Material and methods

2.1. Participants

Participants were recruited via advertisements on university notification boards, social media, and the university's student research participation system. All participants were screened before participating to check study eligibility, excluding participants with MRI safety issues or neurological illnesses. In total, 63 healthy right-handed female volunteers took part in the study. We only recruited female participants because dieting is more prevalent in women than in men (Hill, 2002), and women display different dieting behaviors than men

(Kiefer et al., 2005). Therefore, understanding effects of dieting in women is most relevant. Eleven participants were excluded from analyses due to the following reasons: one participant had to be excluded due to technical problems with the scanning sequence, one participant felt sick in the scanner and quit during the first run, one participant could not enter the scanner due to a not previously reported non-removable metallic object, and eight participants were excluded afterwards due to excessive head movement (exceeding 3 mm/degree in any direction). The final sample consisted of 52 participants (BMI: $M = 22.15$, $SD = 1.91$; age: $M = 22.13$ years, $SD = 3.13$; dietary restraint: $M = 13.92$, $SD = 5.00$). The study was approved by the Ethical Committee of the Faculty of Psychology and Neuroscience of Maastricht University and each participant gave written informed consent prior to participation. The participant either received a gift voucher of €25 or course credits as compensation and were debriefed after the study. The study was pre-registered on AsPredicted (https://aspredicted.org/blind.php?x=/M51_64S).

2.2. Materials and assessments

2.2.1. Restraint scale

Each participant's level of dietary restraint was assessed by an online questionnaire approximately one week before the study. The online questionnaire encompassed the eleven items of the revised restraint scale (Herman and Polivy, 1980), which were intermixed with distractor items to obscure the purpose of the questionnaire. Lifestyle-related questions, like "How many hours do you sleep per night on average?", were used as distractor items. The restraint scale had acceptable internal consistency in the current sample (Cronbach's $\alpha = 0.76$).

2.2.2. Hunger assessment

To standardize hunger level, the participant was asked to eat something small (e.g., a sandwich) 2 h before participation, and thereafter refrain from eating and drinking anything except water. The participant was asked to fill a form about the time of their last meal and to describe what they had eaten. Hunger level was assessed with the question: "How hungry do you feel at this moment?", on a 100 mm visual analogue scale (VAS) ranging from 0 (not hungry at all) to 100 (very hungry).

2.3. Stimuli

2.3.1. Stimulus pool

The total stimulus pool of the study consisted of high-resolution color photographs of 86 food stimuli (43 high-caloric food stimuli, 43 low-caloric food stimuli). To reduce potential biases of a specific picture of a food, each food was portrayed in two versions, yielding a total stimulus set of 172 pictures. Images were obtained from the internet and from the database of the Eating Behavior Laboratory, Salzburg University (Blechert et al., 2014; Blechert et al., 2019).

2.3.2. Stimulus selection

A subset of images from the stimulus pool was presented to each participant. An online questionnaire was used to tailor the stimuli to the food preferences of the participant. In this questionnaire, the participant was asked to select her three most and three least preferred high-caloric and low-caloric foods. According to the selection of the participant, the food stimuli were grouped into four categories: high-caloric palatable food (HC+), high-caloric unpalatable food (HC-), low-caloric palatable food (LC+), and low-caloric unpalatable food (LC-). In this way, 24 different food images, depicting 12 different foods, were selected and presented to the participant during a one-back task.

2.3.3. Stimulus ratings

In the online questionnaire, the participant was asked to rate the palatability (1: absolutely not tasty; 10: extremely tasty) and the estimated caloric content (1: very few kilocalories; 10: very many kilocalories, separately for high-caloric and low-caloric food stimuli.

2.3.4. Stimulus presentation

During the one-back task, the food images were displayed centrally on a light gray background (RGB: 191 191 191) with a size of approximately twelve degrees of visual angle. During rest periods, a black (RGB: 32 32 32) fixation cross (presented in font size: 32) was presented centrally.

2.4. Experimental paradigm

2.4.1. Attentional focus manipulation

Attentional focus was induced using a one-back task while the participant was viewing food pictures in the scanner (see Fig. 1). In this task, food pictures were presented in quick succession and the participant had to compare the currently presented food stimulus with the previously presented one, with focus on a certain aspect of the food stimuli. Stimuli were presented in a blocked fashion, and each block contained stimuli from one of the four categories (HC+, HC-, LC+, LC-). So, in the one-back task, stimuli were compared within category. Within each block, the order of stimuli was randomized, with the constraint that the same food item could not be shown twice in a row to avoid comparisons of a food item with itself.

In this way, three attentional foci were induced: a hedonic focus, a health focus, and a neutral focus. A hedonic attentional focus was induced by having the participant focus on the palatability of food stimuli, using the question: "Is the current food item less or more tasty than the previous one?". A health attentional focus was induced by having participants compare the food stimuli on calorie content, using the question: "Does the current food item contain fewer or more calories than the previous one?". A neutral attentional focus was induced by having the participant compare the presented food stimuli on color, using the question: "Does the current food item contain fewer or more colors than the previous one?". Each of the attentional foci (hedonic focus, health focus, neutral focus) was combined with each of the four categories (HC+, HC-, LC+, LC-), yielding twelve conditions. The order of conditions was randomized.

2.4.2. Task procedure

First, an anatomical scan was conducted. Thereafter, four functional runs were performed.[1] In each functional run, each condition was repeated twice in randomized, mirrored order (e.g., 8 6 10 1 3 7 5 4 9 12 2 11 11 2 12 9 4 5 7 3 1 10 6 8), yielding twenty-four blocks per run. In this way, each condition was presented 8 times during the study. In each block, 6 food pictures (2 versions of 3 different foods) were presented for 1.5 s each, and each followed by a response interval of 1.4 s.[2] During the response interval, a minus and a plus sign were presented on the screen, together with a repetition of the current attentional focus. That is, either the word 'taste', 'calories', or 'color' was displayed. The response was given on a button box, and the participant was instructed to press one button with her index finger to indicate 'less', and to press another button with her middle finger to indicate 'more'. Response latencies were recorded as measure of task difficulty. Each block lasted 16 s and was preceded by an attentional focus instruction text (black font color (RGB: 32 32 32), font size 32) stating either 'Taste', 'Calories' or 'Color', which was presented for 1 s. Each block was preceded by a rest interval during which a fixation cross was presented. The duration of the rest interval was jittered around a mean of 15 s. The task was administered using Presentation software (Version 18.1, Neurobehavioral Systems, Inc., Berkeley, CA, www.neurobs.com).

2.4.3. Visual similarity rating

After scanning, the participant was asked to rate the similarity in shape and color of all possible unique pairs of the twelve foods pre-

[1] For two participants only three functional runs were performed due to technical problems.

[2] With exception of the first image of each block.

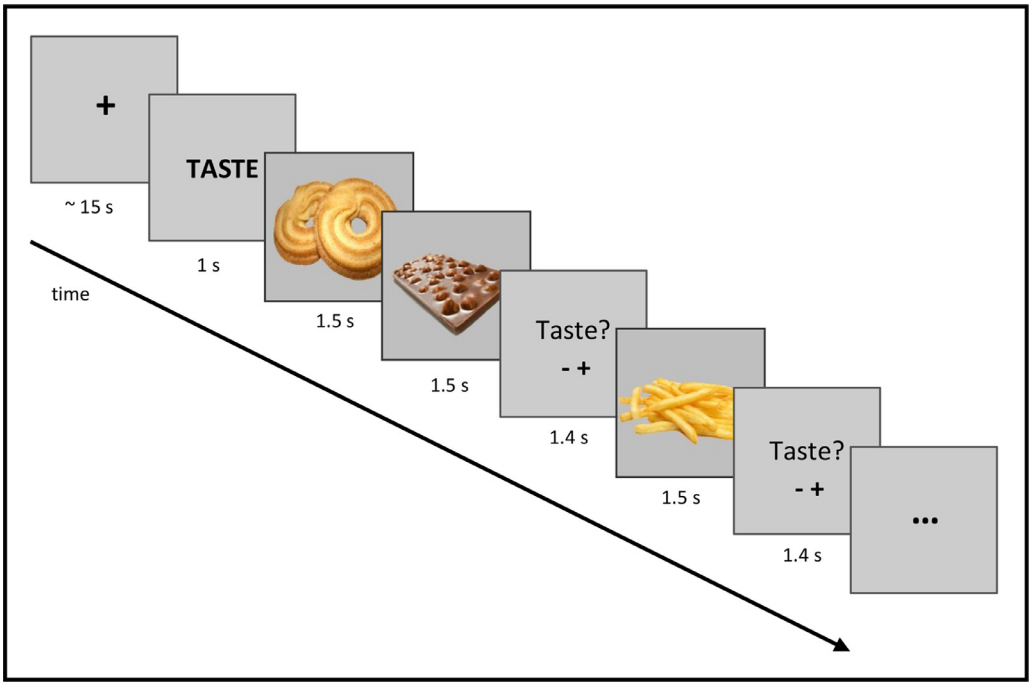

Fig. 1. Schematic depiction of the one-back task used to manipulate attentional focus: here an excerpt of a block with hedonic attentional focus with high-caloric food stimuli is shown; in the hedonic focus "taste", in the health focus "calories", and in the neutral focus "color" was displayed at the start of the block; in each block one category of food stimuli was presented (either HC+, HC-, LC+, or LC-): in each block 6 food stimuli were display and each block had a duration of 16 s.

sented during scanning on a five-point scale (1: not similar at all, 5: highly similar). To do this, the stimuli were presented next to each other on a black background and with a rating scale underneath. The participant was instructed to give her answer by pressing the corresponding button (1 – 5) on the keyboard. Shape and color similarity ratings were done in separate blocks. Only one image version of each food was used during this task, and it was determined randomly which image version was used. This yielded 66 possible pairings of food stimuli. The aim of the visual similarity rating was to check if food stimuli from the same category were not more perceptually similar than food stimuli belonging to different categories based on calorie content or palatability. This was done to be able to exclude the possibility that differences in brain activation can be explained by perceptual properties of the stimuli.

2.4.4. Scanning parameters

The scanning session took place at Scannexus (Maastricht, the Netherlands). A 3 Tesla MRI scanner (Magnetom Prisma Fit, Siemens Medical Systems) with a 64-channel head/neck coil was used to collect the data. Foam cushions were placed at the side of the participant's head to stabilize it. Images were projected to a screen which was viewed through a mirror attached to the head coil. A high-resolution three-dimensional T1-weighted anatomical scan was obtained (MPRAGE pulse sequence, TR = 2250 ms, TE = 2.21 ms, flip angle = 9°, FOV = 256 × 256 mm, voxel size 1 × 1 × 1 mm). T2*-weighted functional images were gathered in an axial interleaved fashion using multiband gradient echo-planar imaging (Feinberg et al., 2010; Moeller et al., 2010; Setsompop et al., 2012) (TR = 2000 ms, TE = 30 ms, flip angle = 77°, FOV = 208 × 208 mm, voxel size of 2 × 2 × 2 mm, 62 slices with multiband factor 2 and GRAPPA2). Slices were acquired with a tilt of approximately fifteen degrees in the sagittal plane to reduce signal dropout near the orbitofrontal cortex. Slices covered the whole brain. During each functional run 386 vol were collected.

2.4.5. Procedure

Upon initial contact, the participant was screened for neurological illnesses and MRI safety issues. Approximately a week before participation, the participant filled in the online questionnaire to assess dietary restraint and food preferences. On the testing day, the participant was welcomed at the scanning facility. At the beginning of the experiment, the participant was informed about the scanning procedure, signed the informed consent form, filled out a hunger rating questionnaire, and received an offline training of the experimental task, which took approximately thirty minutes. Thereafter, height and weight of the participant were measured. Then, the participant entered the scanner for the anatomical scan and four functional runs. The scanning session took approximately 1.5 h. Afterwards, the visual similarity rating task was performed outside of the scanner. This task took approximately fifteen minutes. At the end of the experiment, the participant was thanked and received compensation.

2.5. Analyses

2.5.1. Analysis response latencies

Response latencies from the one-back task, performed during the functional runs, were analyzed to assess whether the different versions of the task (i.e., different attentional foci) differed in difficulty. First, trials without response (6.55%) and trials with response latency of more than three standard deviations from the mean across participants (i.e., too slow trials (0%) and too fast trials (1.23%)) were excluded from the response latency analysis. Average response latency per block type was calculated and analyzed in a 2 (calorie content: high vs. low) x 2 (palatability: palatable vs. unpalatable) x 3 (attentional focus: hedonic vs. health vs. neutral) repeated measures ANOVA.

2.5.2. Visual similarity rating analysis

Visual similarity ratings were analyzed to assess if within-category perceptual similarity was greater than between-category perceptual similarity. To do so, pairs of food stimuli were categorized once according to calorie content and once according to palatability, each time collapsing over the other factor. Similarity for same category pairs (e.g., high-caloric – high-caloric or palatable – palatable) and different category pairs (e.g., high-caloric – low-caloric or palatable – unpalatable) was calculated. Average similarity of same vs. different category pairs were

compared using paired-samples *t*-tests. This procedure was done separately for shape and color ratings.

2.5.3. fMRI analysis

The analysis of the fMRI data was performed with SPM12 (Statistical Parametric Mapping, London, UK), using MATLAB version 9.6.0.1072779 (R2019a).

2.5.3.1. Pre-processing. Before performing analyses, the data were pre-processed. Firstly, slice-timing correction was applied, with middle slice as reference. Next, small head movements were corrected by three-dimensional motion correction using second degree B-spline interpolation. Translation (x, y, and z direction) and rotation (roll, pitch, and yaw) parameters were estimated, and volumes were aligned to the mean for each functional run. Movement was considered excessive if it exceeded 3 mm in translation or 3° in rotation in any direction. Runs with excessive movements were excluded from further analysis (resulting in the exclusion of 5 runs across 5 subjects). If two or more runs of a participant contained excessive movement, all data of the participant was excluded from the analysis, resulting in 8 participant exclusions. Following motion correction, co-registration between anatomical and functional data was performed by warping the anatomical scan to the mean functional data space, to align anatomical and functional images. A unified segmentation procedure was performed on the images to derive deformation fields. These deformation fields were used to perform spatial normalization to transform the images to MNI space (Montreal Neurological Institute, Montreal, Canada). The functional data were temporally filtered using a high-pass filter with a cut-off period of 128 s (= 0.008 Hz) to remove low-frequency drifts. Finally, spatial smoothing was performed with Gaussian Kernel of 6 mm full width half-maximum (FWHM).

2.5.3.2. Univariate analysis.

2.5.3.2.1. Frequentist analysis. During first-level whole-brain analysis, a general linear model (GLM) was estimated for each participant. In the GLM, a predictor was defined for each condition, yielding 12 predictors of interest per run. To obtain the time-courses for the predictors of interest, a box-car shaped function was convolved with a canonical two-gamma hemodynamic response function (HRF). The six motion parameters that were estimated during pre-processing were added as nuisance regressors. This was done for each of the four runs separately. For each run, a mean intensity regressor was added to the GLM as predictor of no interest. Contrasts for the main effect of calorie content and the main effect of palatability were computed from the GLM for each participant. To test the main effect of attentional focus, the calorie content by attentional focus interaction, and the palatability by attentional focus interaction, two t-contrast vectors were defined for each participant, covering further vectors needed to test the effects in second-level analysis by linear combination.

During second level analysis, a whole-brain random effects analysis was performed. Contrast images from the first-level analysis were used as input and dietary restraint was entered as covariate in all second-level analyses, to test if dietary restraint moderated any of the effects of interest. *t*-contrasts were used to test the main effect of calorie content and the main effect of palatability at group-level. *F*-contrasts, which used two *t*-contrast vectors per participant as input, were used to test the main effect of attentional focus, the calorie-content-by-attentional focus interaction, and the palatability-by-attentional focus interaction at group-level. Resulting statistical maps were thresholded at an alpha of 0.05 using voxel-level family-wise error (FWE) correction to adjust for multiple testing (Eklund et al., 2016; Han and Glenn, 2018). To also consider the risk of false negatives, the analyses were repeated with a more lenient cluster-level FWE correction, at a cluster-defining threshold of $p < .001$, and cluster-extent threshold determined per analysis in SPM12. Follow-up analyses were performed for the significant main effect of attentional focus. To do this, functional regions of interest (fROIS) were created from significantly activated clusters using the MarsBar toolbox (http://marsbar.sourceforge.net/) in SPM. From these fROIS, average beta values were extracted for each attentional focus. Differences in beta values between attentional foci (i.e., hedonic vs. health, hedonic vs. neutral, health vs. neutral) were analyzed using paired samples *t*-tests in Microsoft Excel (2016).

Table 1
ROIs used in the part of the Bayesian analysis assessing the interaction between calorie content, palatability, attentional focus and dietary restraint, respectively.

ROI	Center coordinates	Size
Left inferior frontal gyrus	-26 32 -14	8.35
Left middle insular cortex	-26 32 -14	6.71
Left posterior fusiform gyrus	-30 -56 -10	9.00
Right posterior fusiform gyrus	38 -74 -14	8.52

2.5.3.2.2. Bayesian analysis. A whole-brain Bayesian second level analysis was performed using a MATLAB toolbox (https://doi.org/10.5281/zenodo.4394423) (Krekelberg, 2020). The analysis was based on the GLM estimates per participant that were used in the frequentist analysis. A Bayesian one-sample *t*-test was performed to compare the plausibility of the alternative hypothesis and the null hypothesis regarding the effects of calorie content and palatability. For palatability, the alternative hypothesis states that the level of brain activity will be increased for palatable food compared unpalatable food. The null hypothesis states that the level of brain activity will not differ between palatable and unpalatable food. For calorie content, the alternative hypothesis states that level of brain activity will be increased for high-caloric food compared to low-caloric food. The null hypothesis states that the level of brain activity will not differ between high-caloric and low-caloric food. To assess the meaning of the observed distribution of Bayes Factors, a Bayesian *t*-test was also performed on simulated null hypothesis data. We used the prior specification for the null and alternative hypothesis as suggested by Rouder and colleagues (Rouder et al., 2012) and implemented by Krekelberg (Krekelberg, 2020), with a Cauchy prior on the mean (under H1) and a Jeffrey's uninformative prior on the variance of the population (both under H0 and H1).

To test if effects of palatability, calorie content, or attentional focus depends on dietary restraint, a Bayesian ANCOVA (Analysis of Covariance) was performed. Due to high computational requirements, the analysis of these interaction effects was performed only in four regions of interest (ROIs): left inferior frontal gyrus, left middle insular cortex, left posterior fusiform gyrus, and right posterior fusiform gyrus. The ROIs were based on results of a meta-analysis (van der Laan et al., 2011) and were created as spheres around the center coordinates in SPM12 (see Table 1). For each ROI, a model containing only main effects of factors palatability, calorie content, attentional focus, and dietary restraint was compared to a model containing those main effects and an interaction between either palatability, calorie content, or attentional focus and dietary restraint. So, a separate model for each interaction was computed. Next, the distribution of Bayes factors was examined to assess the plausibility of an interaction with dietary restraint. In these analyses, we also used the priors proposed by Rouder and colleagues (Rouder et al., 2012), with a non-informative prior on mean and residual variance, and a G-prior with independent Cauchy distributions.

2.5.3.3. Multivariate analysis. Whereas univariate analyses of fMRI data are mainly informative of the *involvement* of certain brain regions in certain tasks, MVPA of fMRI data decodes *representational content* in the brain (Haxby et al., 2001; Norman et al., 2006). A whole-brain MVPA was conducted to test if calorie content and palatability of food stimuli can be decoded above chance from multi-voxel activity patterns. Decoding analysis of calorie content and palatability were carried out across attentional foci as well as for each attentional focus separately. It was tested if decoding accuracy differed significantly between attentional foci.

MVPA was performed using the CoSMoMVPA toolbox (Oosterhof et al., 2016) in MATLAB. Functional images that were pre-processed as described earlier except for spatial smoothing were used input for the analysis (Mur et al., 2009). The design matrix was set in the same way as for the univariate analysis except that it contained one predictor for each block, yielding 24 predictors per run. This was done to have more training examples as input for the classification procedure. Whole-brain classification was performed using a 100-voxel spherical searchlight (Kriegeskorte et al., 2006) with a linear support-vector machine as classification algorithm.

Decoding accuracy was computed for each participant individually. For decoding calorie content, data were partitioned into high-calorie blocks and low-calorie blocks, thereby collapsing across palatability. For decoding palatability, data were partitioned into palatable and unpalatable blocks, thereby collapsing across calorie content. This was done for each attentional focus individually and across attentional foci. Data of three runs were used to train the classifier while the data of the remaining run were used for testing classification accuracy.[3] This procedure was repeated four times, following a leave-one-run-out cross validation procedure.

Afterwards, decoding accuracies were analyzed across participants. Therefore, subject-level classification accuracy maps were spatially smoothed with a Gaussian kernel of 6 mm FWHM before group analysis. Group analysis included only voxels that showed 90% overlap across participants to exclude voxels with poor group overlap. Mean decoding accuracies for decoding calorie content and palatability were non-parametrically tested, using Wilcoxon signed-rank tests, against chance level (0.5) for within and across attentional focus decoding, and against zero for testing differences in decoding between attentional foci. All results were false discovery rate (FDR)-corrected on voxel-level (Benjamini and Hochberg, 1995; Genovese et al., 2002).

3. Results

Fifty-two normal weight women (BMI: $M = 22.15$, $SD = 1.91$, range: 18.08 – 25.94) with varying levels of dietary restraint ($M = 13.92$, $SD = 5.00$, range: 4 - 26) participated in the current fMRI study. Dietary restraint was measured with the revised restraint scale (Herman and Polivy, 1980). The food images presented during scanning were individually tailored to the taste-preferences of each participant, yielding the following four food categories: high-caloric palatable food (HC+), high-caloric unpalatable food (HC-), low-caloric palatable food (LC+), and low-caloric unpalatable food (LC-). The attentional focus of the participant was manipulated with a one-back task, in which successive food stimuli were compared on palatability to induce a hedonic attentional focus, on calorie content to induce a health attentional focus, or on color to induce a neutral attentional focus. The food categories were combined with the attentional foci in a blocked design, yielding twelve block types. Perceived similarity in color and shape of the presented food stimuli was rated after the scan session (see Material and methods for a full description).

3.1. Manipulation checks

3.1.1. Stimulus ratings

To check if the individually tailored food stimuli were perceived as intended, two separate 2 (calorie content: high vs. low) x 2 (palatability: palatable vs. unpalatable) repeated measures ANOVAs were performed, on palatability ratings and on calorie content ratings.

[3] For five participants only data of three functional runs were available (due to technical problems during scanning or excessive head movement during a run). For those participants, data of two runs were used to train the classifier.

3.1.1.1. Palatability ratings. There was no significant main effect of calorie content on palatability ratings ($F_{1,51} = 0.005$, $p = .942$, $\eta_p^2 < 0.001$). As expected, palatable food was rated as more palatable than unpalatable food, as evidenced by a significant main effect of palatability ($F_{1,51} = 384.991$, $p < .001$, $\eta_p^2 = 0.881$). Also, there was a significant interaction between calorie content and palatability on palatability ratings ($F_{1,51} = 5.703$, $p = .021$, $\eta_p^2 = 0.099$), indicating that the difference between palatable and unpalatable high-caloric food was slightly larger than for low-caloric food. See Table 2 for relevant means and SDs.

3.1.1.2. Caloric content ratings. As expected, the caloric content of high-caloric food was estimated to be higher than that of low-caloric food, as evidenced by a significant main effect of calorie content ($F_{1,51} = 329.860$, $p < .001$, $\eta_p^2 = 0.864$). In addition, palatable food was estimated to be higher in calories than was unpalatable food, as evidenced by a significant main effect of palatability ($F_{1,51} = 71.499$, $p < .001$, $\eta_p^2 = 0.579$). The calorie content x palatability interaction was significant as well, ($F_{1,51} = 14.306$, $p < .001$, $\eta_p^2 = 0.216$), suggesting that the difference in calorie content ratings between palatable and unpalatable food was larger for high caloric than for low caloric food. See Table 2 for relevant means and SDs.

Taken together, these analyses indicate that individual tailoring of food stimuli was successful, and that the four stimulus categories were rated as intended (see Table 2).

3.1.2. Hunger rating

We attempted to standardize hunger level by instructing participants to refrain from eating and drinking anything except water for two hours before the experiment. To check if this instruction was successful, we assessed time passed since the last eating moment and self-reported hunger level by means of a questionnaire at the beginning of the experiment. The time passed since the last eating moment was on average slightly longer than instructed ($M = 151.06$ min, $SD = 39.25$ min). On average, participants reported moderate hunger levels ($M = 41.33$, $SD = 26.12$). Hunger level was not significantly correlated with dietary restraint ($r_{50} = -0.167$, $p = .237$).

3.2. Behavioral data

3.2.1. Response latencies

Response latencies were recorded during the one-back task as measure of task difficulty. Mean reaction times per block type were analyzed in a 2 (calorie content: high vs. low) x 2 (palatability: palatable vs. unpalatable) x 3 (attentional focus: hedonic vs. health vs. neutral) repeated measures ANOVA. There was a significant main effect of attentional focus ($F_{1.960,99.979} = 6.419$, $p = .003$, $\eta_p^2 = 0.112$). Participants responded slightly faster in the neutral attentional focus condition (color comparison; $M = 442.167$, $SD = 85.463$) than in the hedonic ($M = 454.686$, $SD = 81.837$; $t_{51} = 2.927$, $p = .005$) or health condition ($M = 457.201$, $SD = 81.228$; $t_{51} = 3.134$, $p = .003$), whereas there was no significant difference in response latency between the hedonic and health condition ($t_{51} = 0.572$, $p = .570$). This could indicate that the neutral attentional focus condition was slightly easier than the other two conditions. None of the other main or interaction effects reached significance, all $F < 2.844$, all $p > .067$.

3.2.2. Visual similarity rating

To be able to exclude the possibility that differences in brain response to different food types could be explained by perceptual properties of the stimuli, we tested whether food stimuli from the same category were more perceptually similar than food stimuli from different categories based on either calorie content or palatability. Food stimuli matching on calorie content (color: $M = 2.21$, $SD = 0.53$; shape: $M = 1.93$, $SD = 0.47$) were on average more similar in color and shape than food stimuli differing in calorie content (color: $M = 1.82$, $SD = 0.38$;

Table 2
Overview of means and standard deviations of palatability and calorie content ratings of the individually tailored food stimuli.

	HC+		HC-		LC+		LC-	
	M	*SD*	*M*	*SD*	*M*	*SD*	*M*	*SD*
Palatability rating	9.19	1.34	2.71	1.34	8.96	1.32	2.95	1.66
Calorie content rating	8.72	0.95	6.90	1.37	3.85	1.66	3.29	1.48

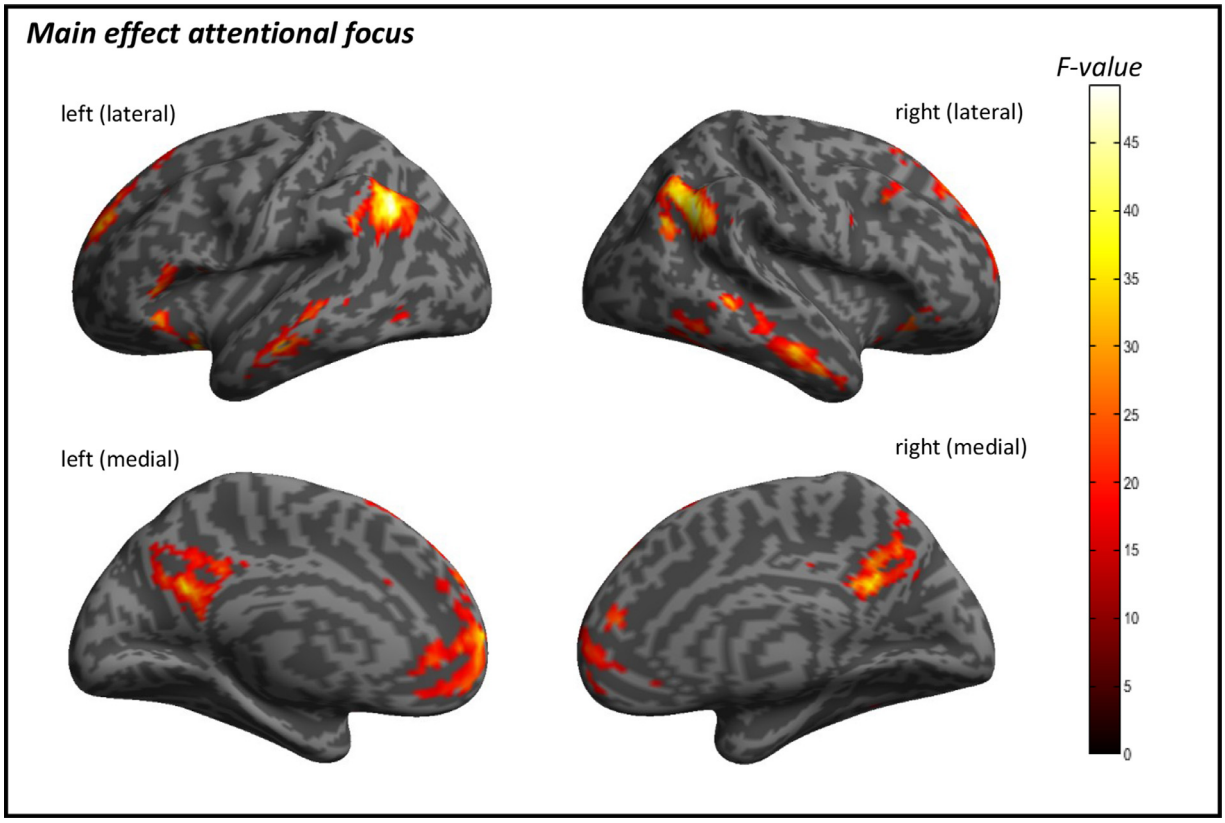

Fig. 2. Significant clusters from univariate analysis (p 0.05, FWE-corrected, displayed are clusters > 10 voxels) for the main effect of attentional focus; visualizations were created in SPM12.

shape: $M = 1.62$, $SD = 0.40$) (color: $t_{51} = 6.04$, $p < .001$, $d = 0.838$; shape: $t_{51} = 6.61$, $p < .001$, $d = 0.917$). Food stimuli matching on palatability (color: $M = 2.05$, $SD = 0.39$; shape: $M = 1.79$, $SD = 0.42$) were on average slightly more similar in color than food stimuli differing in palatability (color: $M = 1.95$ $SD = 0.44$; shape: $M = 1.74$, $SD = 0.41$) (color: $t_{51} = 2.43$, $p = .019$, $d = 0.337$) but not in shape (shape: $t_{51} = 1.67$, $p = .101$, $d = 0.232$). However, the low mean similarity ratings (range: 1.62 – 2.21 on a scale of 1 (not similar at all) to 5 (highly similar)) showed that stimuli were perceived as rather dissimilar, and differences in observed similarity were numerically small (range: 0.05 – 0.39 on a 5-point scale).

3.3. Univariate analysis

3.3.1. Frequentist analysis

In a whole-brain univariate analysis with voxel-level FWE correction, the main effect of calorie content, the main effect of palatability, the main effect of attentional focus, the calorie content x attentional focus interaction, and the palatability x attentional focus interaction were examined. The palatability x attentional focus interaction and the calorie content x attentional focus interaction did not result in significant clusters of brain activity. The main effect of calorie content resulted in four clusters (inferior temporal gyrus and parahippocampal gyrus), with more activity in response to high- than to low-caloric foods (see Table 3). No clusters with a significantly stronger response to low-caloric than to high-caloric food images were found. No significant activation was found for the main effect of palatability, meaning that no regions could be detected that responded significantly stronger to palatable food than to unpalatable food, or the other way around. The main effect of attentional focus yielded 28 significantly activated clusters (see Table 4 & Fig. 2), which among others were located in several regions of the mesocorticolimbic system. Several regions, which were mostly located in the prefrontal cortex, responded significantly stronger in the hedonic attentional focus than in the health or neutral attentional focus, while a few regions responded significantly stronger in the neutral attentional focus than in the health or hedonic attentional focus. All observed patterns of effects can be found in Table 4.

Repeating the analysis with a more lenient cluster-level FWE correction at cluster-defining threshold of $p < .001$, and cluster-extent threshold determined per analysis in SPM12, we observed four clusters with a significantly higher activity level for high-caloric food than for low-caloric food (cluster-extent threshold: 240 voxels), located in infe-

Table 3
Significant clusters from univariate analysis contrasting high-caloric > low caloric food ($p < .05$, FWE-corrected voxel level).

Cluster	Region	H	Cluster size	Peak coordinates (MNI)	Peak F/t value	Cluster p-value
Contrast: high-caloric > low-caloric						
2	Inferior Frontal Gyrus	L	9	-24 30 -12	5.96	.004
1	Parahippocampal Gyrus	L	4	-22 -34 -14	5.61	.011
3	Parahippocampal Gyrus	L	1	-24 -28 -12	6.02	.027
4	Temporal Lobe	L	2	-48 -52 -6	5.55	.019

rior/medial frontal gyrus, parahippocampal gyrus, and inferior/middle temporal gyrus. In addition, we observed 2 clusters with a significantly higher activity level for low-caloric food than for high-caloric food (cluster-extent threshold: 232 voxels), located in cuneus, lingual gyrus, and middle occipital gyrus. However, with this more lenient multiple comparison correction approach, we did not find any significant effects of palatability or dietary restraint on brain responses to food.

3.3.1.1. Effect of dietary restraint. In all analyses, dietary restraint was added as covariate. No significant effects of dietary restraint were observed in any of the analyses.

3.3.2. Bayesian analysis

A whole-brain mass-univariate Bayesian *t*-test was used to compare the evidence in favor of an effect of palatability (palatable > unpalatable) against the evidence in favor of no effect of palatability on brain activity level in response to food. Overall, the observed Bayes Factors were small, suggesting evidence for no effect of palatability. Only 4.8% of voxels showed evidence in favor of an effect of palatability, with 3.58% of voxels showing anecdotal evidence and 1.22% of voxels showing moderate evidence (Fig. 4; range of $\log_{10}$ of Bayes Factors: -1.67 – 3.13; for reference values see (Kass and Raftery, 1995)). Because the Bayes Factors were computed independently on each voxel, we observed a distribution of values, which we compared with a distribution of Bayes Factors computed on simulated null data. This comparison suggests that the observed data support the null hypothesis (Fig. 4). Overall, the analysis supports the notion that there is no effect of palatability in the univariate results.

Similarly, a whole-brain mass-univariate Bayesian *t*-test was used to compare the evidence in favor of an effect of calorie content (high-calorie > low-calorie) against the evidence in favor of no effect of calorie content on brain activity level in response to food. Most voxels showed no evidence in favor of an effect of calorie content. However, 11.7% of voxels showed evidence in favor of an effect of calorie content. More specifically, 6.92% of voxels showed anecdotal evidence for the alternative hypothesis, and 4.77% of voxels showed moderate evidence for the alternative hypothesis (Fig. 5; range of $\log_{10}$ of Bayes Factors: -1.77 – 5.28. for reference values see (Kass and Raftery, 1995)). So, some voxels showed evidence for an increased brain activity level in response to high-caloric than to low-caloric food, whereas most voxels showed no effect of calorie content. Comparing the distribution of Bayes factors on actual data with a distribution of Bayes Factors on simulated null data suggest that the observed data indeed support that some regions showed increased activity for high-caloric compared to low-caloric food (Fig. 5), confirming the frequentist univariate results.

A region-of-interest (ROI) analysis was used to check for possible interactions with dietary restraint, using a Bayesian ANOVA. In none of the tested ROIs (Table 1), evidence in favor of an interaction between dietary restraint and a factor (palatability, calorie content, attentional focus) was observed. Instead, in all regions evidence in favor of the null hypothesis of no interaction was found (Fig. 6; for reference values see (Kass and Raftery, 1995)).

3.4. Multivariate analysis

We carried out MVPA using a whole-brain searchlight approach (Kriegeskorte et al., 2006) to test if calorie content and palatability of food stimuli could be decoded above chance from multi-voxel activity patterns. This was done across attentional foci (see Fig. 3) and for each attention focus separately (see Supplementary figure 1 & Supplementary figure 2). We also tested if decoding accuracy differed significantly between attentional foci. All results were FDR-corrected for multiple comparisons on the voxel-level (Benjamini and Hochberg, 1995; Genovese et al., 2002). Palatability and calorie content could be decoded significantly above chance in several regions of the mesocorticolimbic system within each attentional focus and across attentional foci (see Table 5 & 6). We did not find any significant differences in decoding accuracies between attentional foci when decoding palatability or calorie content.

3.4.1. Effect of dietary restraint

For all analyses, correlations between dietary restraint and decoding accuracy were calculated. No significant correlations between dietary restraint and decoding accuracy were observed in any of the analyses.

4. Discussion

The current study investigated the effects of attentional focus, food palatability and caloric content on brain responding to visual food stimuli in healthy-weight women, and how these effects are moderated by dietary restraint, using univariate as well as multivariate fMRI analyses. Univariate analyses revealed no brain regions that responded significantly differently to palatable than to unpalatable food stimuli. In addition, only four small clusters, located in the inferior frontal gyrus and parahippocampal gyrus, displayed a significantly higher level of activity for high-caloric than for low-caloric food stimuli. In contrast, a large difference in brain activation levels between attentional foci was detected. A higher level of activity was observed in several regions of the mesocorticolimbic system in the hedonic attentional focus than in health and neutral attentional focus, while the reverse pattern was observed in a few other regions of the mesocorticolimbic system. Multivariate analysis revealed that, by using whole-brain searchlight classification analysis, it was possible to decode palatability and calorie content from several brain regions of the mesocorticolimbic system, across and within attentional foci. Decoding accuracies for palatability and calorie content did not differ significantly between attentional foci. Unexpectedly, none of the effects from univariate or multivariate analysis were significantly moderated by dietary restraint.

A striking finding of the current study is that no differential activity level between palatable and unpalatable food stimuli was detected. Importantly, the lack of differential activation between palatable and unpalatable food stimuli cannot be attributed to a lack of difference in perceived palatability of the presented food stimuli, as the presented food stimuli were individually tailored on palatability and subjective palatability ratings for unpalatable versus palatable food stimuli were highly and significantly different. The lack of differential activation was

Table 4
Significant clusters from univariate analysis of the main effect of attentional focus ($p < .05$, FWE-corrected on voxel-level); significant clusters are grouped according to beta value pattern.

Cluster	Region	H	Cluster size	Peak coordinates (MNI)	Peak *F*-value	Cluster *p*-value	Beta value			*p*-value		
							hedonic	health	neutral	hedonic vs health	hedonic vs neutral	health vs neutral
Contrast: Main effect attentional focus												
beta value pattern: hedonic > health > neutral												
18	Precuneus/ Cingulate gyrus	B	1580	6 -50 32	44.57	< 0.001	0.04	-1.44	-3.03	< 0.001	< 0.001	< 0.001
26	Middle Frontal Gyrus	L	1	-32 24 34	16.16	.029	2.42	1.84	1.11	.008	< 0.001	< 0.001
1	Cerebellum Posterior Lobe	R	489	22 -88 -42	29.37	< 0.001	-0.12	-2.14	-3.30	< 0.001	< 0.001	.011
2	Cerebellum Posterior Lobe	R	139	46 -70 -38	26.95	< 0.001	3.53	1.86	0.53	< 0.001	< 0.001	.001
3	Cerebellum Posterior Lobe	R	14	6 -52 -40	19.05	.002	0.62	-0.01	-0.65	.002	< 0.001	.005
5	Cerebellum Posterior Lobe	L	54	-48 -66 -38	22.23	< 0.001	2.42	0.85	-0.28	< 0.001	< 0.001	.013
25	Cingulate Gyrus	L	6	-2 -14 36	18.28	.008	0.72	-1.22	-2.21	.036	< 0.001	.001
beta value pattern: hedonic > (health = neutral)												
8	Frontal Lobe: Superior Frontal Gyrus/ Medial Frontal Gyrus/ Cingulate Gyrus	B	4443	-2 62 10	41.52	< 0.001	-2.74	-5.30	-5.83	< 0.001	< 0.001	.126
10	Inferior Frontal Gyrus	L	704	-28 14 -18	50.25	.005	2.75	0.94	0.36	< 0.001	< 0.001	.057
11	Inferior Frontal Gyrus/ Insula	R	173	44 22 -10	27.97	< 0.001	0.28	-1.52	-1.80	< 0.001	< 0.001	.324
16	Superior Frontal Gyrus/ Inferior Frontal Gyrus	L	2	-22 54 -6	16.59	.021	3.60	1.65	1.11	< 0.001	< 0.001	.262
19	Anterior Cingulate	L	5	-4 36 18	18.31	.010	-1.46	-2.46	-2.90	< 0.001	< 0.001	.067
21	Anterior Cingulate	L	1	-8 40 18	16.21	.029	-1.42	-2.55	-2.67	< 0.001	< 0.001	.636
27	Middle Frontal Gyrus	L	19	-32 30 48	18.85	.001	-1.45	-3.71	-3.74	< 0.001	< 0.001	.938
28	Superior Frontal Gyrus/ Middle Frontal Gyrus	L	17	-42 12 52	18.35	.001	6.65	4.00	4.21	< 0.001	< 0.001	.672
4	Cerebellum Posterior Lobe	L	452	-32 -86 -36	30.10	< 0.001	0.52	-2.96	-3.50	< 0.001	< 0.001	.219
6	Middle Temporal Gyrus/ Inferior Temporal Gyrus	R	920	56 0 -32	35.27	< 0.001	0.66	-1.65	-1.61	< 0.001	< 0.001	.905
7	Middle Temporal Gyrus/ Inferior Temporal Gyrus	L	429	-62 -16 -18	32.89	< 0.001	-0.32	-2.38	-2.46	< 0.001	< 0.001	.815
17	Superior Temporal Gyrus/ Middle Temporal Gyrus	L	9	-56 -46 4	18.11	.004	0.62	-1.68	-1.74	< 0.001	< 0.001	.889
22	Supramarginal Gyrus/ Inferior Parietal Lobule/ Angular Gyrus/ Superior Temporal Gyrus	R	1155	52 -62 34	49.20	< 0.001	-0.06	-4.12	-4.39	< 0.001	< 0.001	.620
23	Supramarginal Gyrus/ Inferior Parietal Lobule/ Superior Temporal Gyrus/ Middle Temporal Gyrus	L	1085	-50 -64 34	49.27	< 0.001	2.99	-1.20	-1.68	< 0.001	< 0.001	.371
beta value pattern: neutral > (health = hedonic)												
9	Fusiform Gyrus	R	7	30 -40 -18	17.52	.006	4.94	4.83	5.98	.464	< 0.001	< 0.001
13	Fusiform Gyrus	R	13	32 -50 -14	20.36	.002	8.49	8.44	9.76	.792	< 0.001	< 0.001
20	Inferior Frontal Gyrus	R	2	46 36 16	16.50	.021	4.28	4.27	6.82	.984	< 0.001	< 0.001
24	Inferior Frontal Gyrus	R	14	48 4 30	18.30	.002	3.56	3.44	5.33	.634	< 0.001	< 0.001
12	Middle Temporal Gyrus/ Inferior Temporal Gyrus	R	211	50 -52 -14	24.97	< 0.001	7.19	6.93	9.76	.429	< 0.001	< 0.001
15	Middle Temporal Gyrus/ Inferior Temporal Gyrus/ Middle Occipital Gyrus	L	53	-46 -64 -6	25.74	< 0.001	13.58	14.05	16.21	.191	< 0.001	< 0.001
beta value pattern: (neutral = health) > hedonic												
14	Lingual Gyrus	L	8	-18 -88 -6	19.15	.005	35.31	37.35	37.55	< 0.001	< 0.001	.635

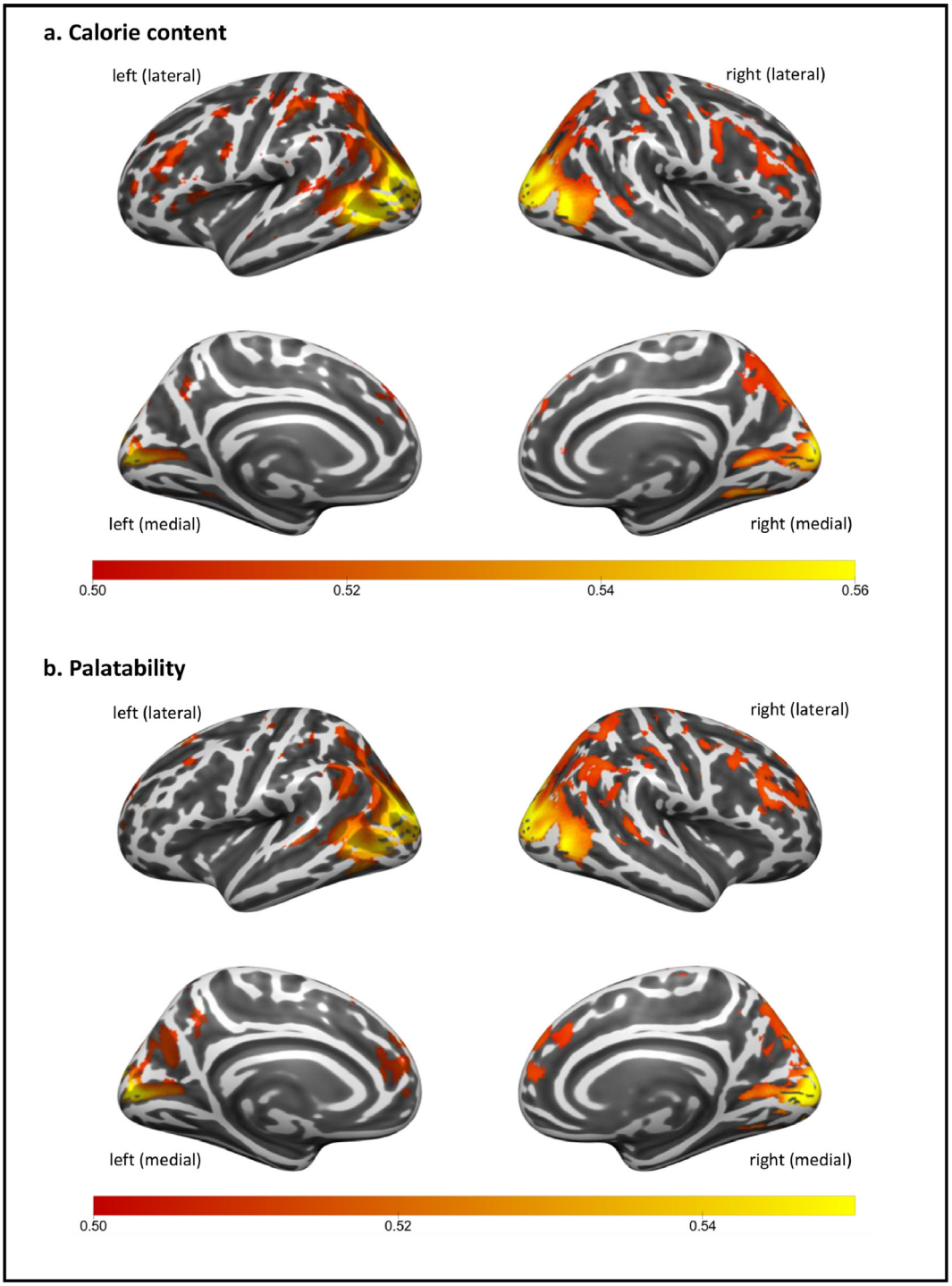

Fig. 3. Clusters with decoding accuracy significantly above chance ($p < .05$, FDR-corrected); a: for decoding calorie content (across attentional foci), b: for decoding palatability (across attentional foci); visualizations were created using FreeSurfer (https://surfer.nmr.mgh.harvard.edu/) and Surf Ice (https://www.nitrc.org/projects/surfice/).

also observed with a lenient statistical threshold and the absence of an effect of palatability was also supported by Bayesian analysis. This finding contradicts results from several previous studies (LaBar et al., 2001; Rothemund et al., 2007; Martin et al., 2010), which observed widespread activation in the mesocorticolimbic system in response to food stimuli and interpreted this activation as evidence that the presented food stimuli are rewarding.

However, most previous studies did not directly contrast palatable and unpalatable food stimuli, but rather contrasted high-caloric palatable food stimuli against neutral non-food stimuli. In these studies, reward value and salience could therefore not be disentangled, as salience and reward value of each stimulus category coincided. That is, positive/salient stimuli were contrasted against neutral/non-salient stimuli. Reward value is high for very positive stimuli and low for very negative stimuli, whereas salience is high for both very positive and very negative stimuli (Kahnt, 2018; Kahnt and Tobler, 2017). Therefore, it is important to include negative stimuli to truly understand the meaning of brain activation in the meso-

Table 5
Brain regions related to food decision making in previous literature with decoding accuracy significantly above chance ($p < .05$, FDR-corrected) for decoding calorie content; H = hemisphere, L = left, R = right, B = Bilateral, MNI = Montreal Neurological Institute.

Cluster	Region	H	Cluster size	Peak coordinates (MNI)	Percentage accuracy
Decoding calorie content: across attentional foci					
6	Inferior Frontal Gyrus/ Middle Frontal Gyrus/ Insula/ Precentral Gyrus	R	1293	44 28 20	51.74
7	Middle Fontal Gyrus/ Inferior Frontal Gyrus/ Superior Frontal Gyrus/ Medial Frontal Gyrus/ Precentral Gyrus/ Insula / Anterior Cingulate	L	2235	-36 42 16	51.83
8	Anterior Cingulate	L	14	-8 40 -2	50.86
9	Middle Frontal Gyrus/ Superior Frontal Gyrus	R	69	30 52 2	51.28
10	Anterior Cingulate	R	104	18 38 12	51.37
11	Insula	L	20	-32 8 8	51.02
13	Inferior Frontal Gyrus	L	2	-50 20 10	50.86
15	Superior Frontal Gyrus	R	5	20 60 18	51.01
26	Middle Frontal Gyrus	R	277	34 -2 46	51.37
27	Cingulate Gyrus	L	5	-4 -40 42	50.99
28	Middle Frontal Gyrus	R	39	26 32 44	51.20
29	Medial Frontal Gyrus/ Superior Frontal Gyrus	R	6	8 32 48	51.08
30	Superior Frontal Gyrus	R	63	10 40 50	51.63
33	Superior Frontal Gyrus	R	79	12 24 58	51.34
35	Medial Frontal Gyrus	R	2	16 -16 60	50.79
36	Superior Frontal Gyrus	L	54	-8 8 66	51.05
37	Medial Frontal Gyrus/ Precentral Gyrus	L	55	-8 -22 70	51.18
38	Middle Frontal Gyrus	L	5	-26 -2 62	50.93
39	Superior Frontal Gyrus	L	2	-12 16 64	50.78
41	Middle Frontal Gyrus/ Superior Frontal Gyrus	L	6	-18 -6 68	50.92

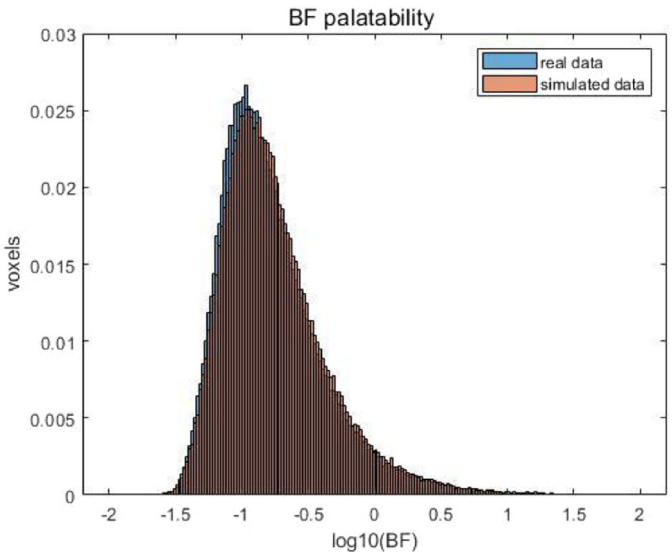

Fig. 4. Distribution of $\log_{10}$ of Bayes Factors assessing the contrast palatable > unpalatable for real and simulated data. Both distributions largely overlap and show evidence predominately in favor of the null hypothesis.

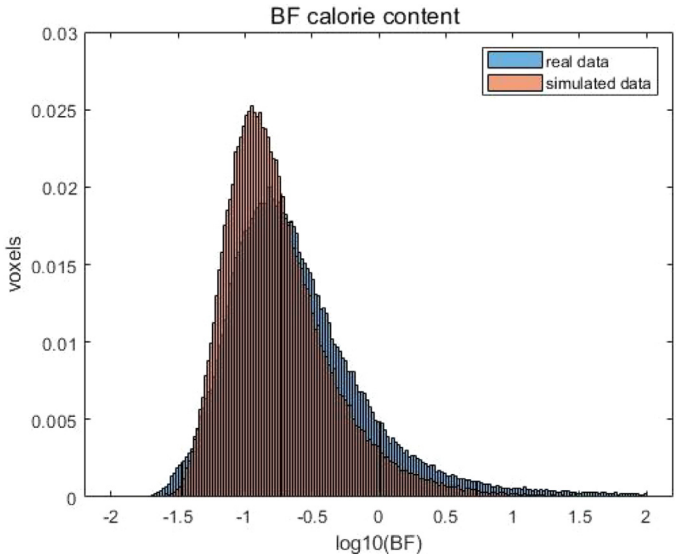

Fig. 5. Distribution of $\log_{10}$ of Bayes Factors assessing the contrast high-calorie > low-calorie unpalatable for real and simulated data. Overlap between both distribution is large, and most voxels show evidence in favor of the null hypothesis. However, some voxels show evidence in favor of the alternative hypothesis.

corticolimbic system. When contrasting very palatable and very unpalatable stimuli, salience is kept constant across these stimulus categories, enabling the researcher to study the pure effect of stimulus valence.

Interestingly, the current results fit with the results from a recent study (Chikazoe et al., 2014), which also showed that positive and negative valence could not be distinguished in univariate fMRI analyses. Furthermore, the current results are in line with the results from two studies from our lab (Franssen et al., 2020; Pimpini et al., 2022) that used stimuli that were individually tailored on palatability and contrasted palatable and unpalatable high-caloric food stimuli. Also in these studies, no differential level of activation between palatable and unpalatable food stimuli was observed. The current findings extend the previous findings (Franssen et al., 2020; Pimpini et al., 2022) testing the effect in healthy-weight participants with varying levels of dietary restraint.

Similarly, very little significant differential brain activity was observed between high-caloric and low-caloric food stimuli in univariate analysis. Higher brain responding to high-caloric food stimuli compared to low-caloric food stimuli was observed in only four small clusters (max. cluster size < 10 voxels) located in the inferior frontal gyrus and parahippocampal gyrus. Notably, the small amount of significant differential activation between high- and low-caloric food stimuli cannot be attributed to a lack of perceived difference in calorie content of the presented food stimuli, as calorie content ratings confirmed that high-caloric and low-caloric items were perceived as highly and significantly different in calorie content. Using a more lenient multiple comparison correction yielded slightly more differences in brain activity level (e.g., located in inferior/medial frontal gyrus, parahippocampal gyrus, and inferior/middle temporal gyrus) between high-caloric and low-caloric food, and Bayesian analysis detected some voxels that show an effect

Table 6
Brain regions related to food decision making in previous literature with decoding accuracy significantly above chance ($p < .05$, FDR-corrected) for decoding palatability; H = hemisphere, L = left, R = right, B = Bilateral, MNI = Montreal Neurological Institute.

Cluster	Region	H	Cluster size	Peak coordinates (MNI)	Percentage accuracy
Decoding palatability: across attentional foci					
6	Medial Frontal Gyrus/ Superior Frontal Gyrus/ Anterior Cingulate/ Inferior Frontal Gyrus	B	2987	-28 46 28	51.94
7	Inferior Frontal Gyrus	L	24	-48 18 4	51.04
8	Superior Temporal Gyrus	R	1	52 -42 14	50.55
9	Inferior Frontal Gyrus/ Middle Frontal Gyrus	R	125	50 30 18	51.21
11	Insula	R	13	38 -20 20	50.89
17	Medial Frontal Gyrus/ Superior Frontal Gyrus	R	22	24 36 30	50.94
20	Middle Frontal Gyrus/ Precentral Gyrus/ Inferior Frontal Gyrus	L	322	-38 2 52	51.41
21	Middle Frontal Gyrus/ Superior Frontal Gyrus/ Cingulate Gyrus	R	322	24 22 48	51.70
22	Superior Frontal Gyrus	R	2	24 44 34	50.95
24	Middle Frontal Gyrus	R	12	42 24 40	51.04
30	Middle Frontal Gyrus	L	72	-28 22 48	51.36
31	Postcentral Gyrus/ Inferior Parietal Lobule	R	17	44 -36 52	51.08
32	Postcentral Gyrus/ Precentral Gyrus	L	73	-38 -28 52	51.01
33	Superior Frontal Gyrus	R	3	10 28 52	50.78
34	Superior Frontal Gyrus	L	10	-4 28 52	50.98
35	Medial Frontal Gyrus	L	3	-8 -24 56	50.70
36	Medial Frontal Gyrus	L	2	-8 -20 56	50.82
38	Medial Frontal Gyrus/ Frontal Lobe White Matter	L	7	-18 -14 56	51.03
39	Superior Frontal Gyrus	L	6	-26 12 56	51.01
40	Superior Frontal Gyrus	L	51	-4 24 56	51.10
41	Superior Frontal Gyrus	R	1	16 26 56	50.90
43	Middle Frontal Gyrus	R	84	22 -14 62	51.24
46	Middle Frontal Gyrus/Precentral Gyrus	L	85	-18 -16 62	51.41
48	Middle Frontal Gyrus	L	1	-20 8 64	50.77
51	Superior Frontal Gyrus	R	1	8 -6 68	50.70

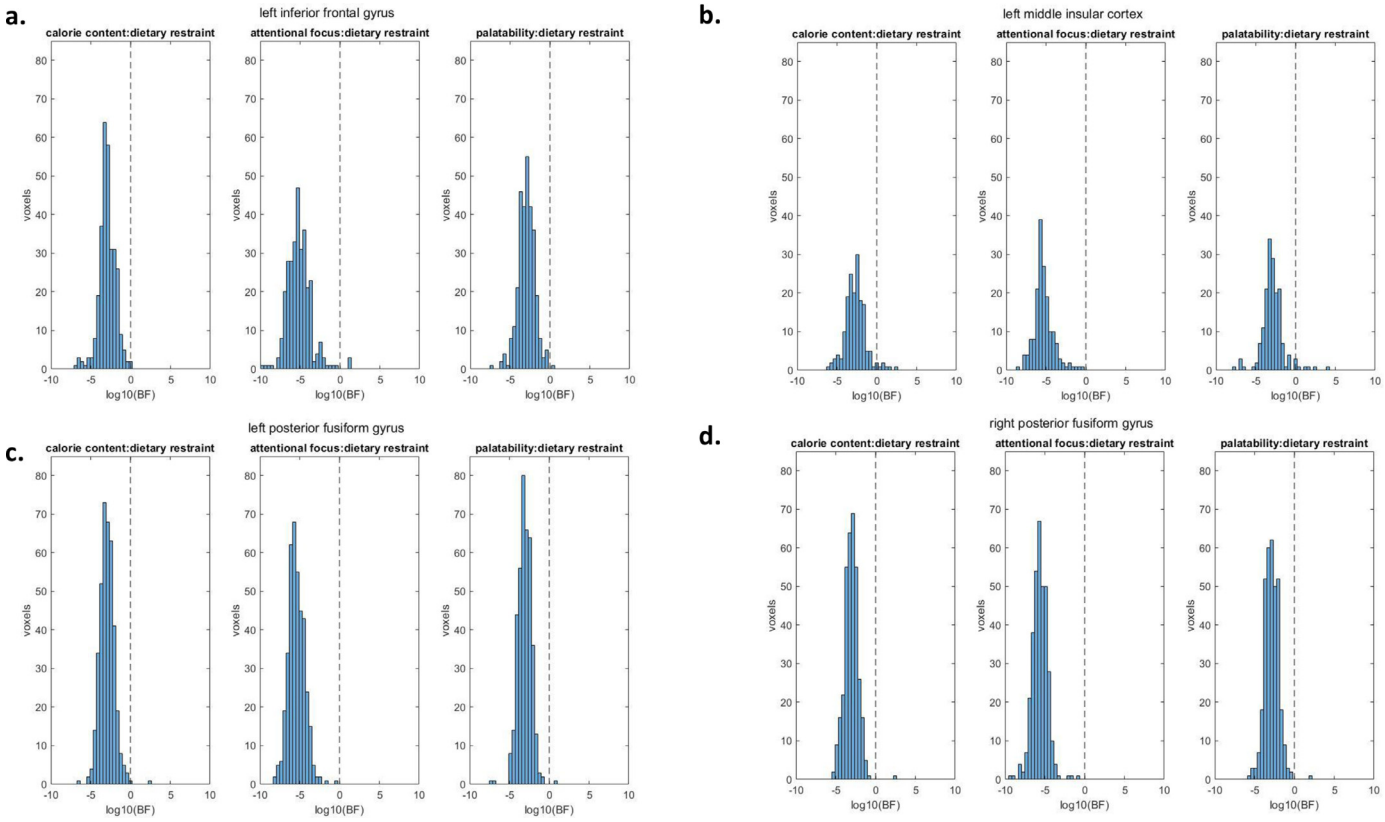

Fig. 6. Log_{10} of Bayes factors for the interactions between calorie content, attentional focus, palatability and dietary restraint respectively; a: in left inferior frontal gyrus ROI; b: in left middle insular cortex ROI; c: in left posterior fusiform gyrus ROI; d: in right posterior fusiform gyrus ROI; in all ROIs, most of the observed Bayes factors (log_{10}) are smaller than zero, indicating support for the null hypothesis.

of calorie content on brain activity level. However, most of the regions showing differential activity for high versus low caloric food stimuli have not been associated with food reward processing in previous studies. The inferior frontal gyrus has been associated with control processes in food perception (Giuliani et al., 2018). Overall, this result is not congruent with some previous studies that reported higher brain activity in several regions of the mesocorticolimbic system, like OFC and insula (Killgore et al., 2003; Frank et al., 2010). In contrast to those studies, which observed differential activation in regions of the mesocorticomlimbic system, the current study employed a much larger sample size and applied a stringent multiple comparison correction. However, the current results fit with another previous study, which did not find differential activation between high- and low-caloric food stimuli (Siep et al., 2009).

Compellingly, the current study found that brain activity depended on attentional focus. The main effect of attentional focus was mainly driven by increased activity levels in the hedonic attentional focus compared to the health or neutral attentional focus. In several regions belonging to the mesocorticolimbic system, like the cingulate gyrus, middle frontal gyrus, and superior frontal gyrus, brain responding to food stimuli was stronger in the hedonic attentional focus than in the neutral or health attentional focus. In a few regions, like the fusiform gyrus, brain activity was stronger in the neutral attentional focus than in the hedonic or health attentional focus. No regions were detected in which the level of activity was strongest in the health attentional focus. It is unlikely that the observed differences between attentional foci resulted from differences in task difficulty (assessed by response latency), as there were no differences in task difficulty between the hedonic and health attentional focus, but there were significant differences in brain activity between these foci. Moreover, differences in task difficulty between the neutral focus and the other two attentional foci were small.

The overall higher level of activity in response to food stimuli in the hedonic attentional focus points towards a higher motivational salience of food or increased reward sensitivity elicited by focusing on hedonic properties of food compared to non-indulgent properties of food, like calorie content or color. In addition, we observed no significant differences in brain activity level between palatable and unpalatable food and almost no significant differences between high-caloric and low-caloric food. Taken together, this combination of findings suggests that the activity level in the mesocorticolimbic system reflects the salience of stimuli or reward sensitivity rather than reward value. That is, if level of brain activity reflected reward value (either defined as palatability or as caloric value), then a significant difference in brain activity between these food categories should have been observed. The results are in line with theory and studies that suggest that both positive and negative stimuli are more salient than neutral stimuli (Kahnt, 2018; Kahnt and Tobler, 2017; Kahnt et al., 2014).

The findings are in line with previous research showing that attentional focus influences brain responding to food stimuli (Siep et al., 2012; Hare et al., 2011; Frankort et al., 2012; Bhanji and Beer, 2012; Hege et al., 2018; Franssen et al., 2020). Especially, the current findings provide a replication of the results of two previous studies from our lab (Franssen et al., 2020; Pimpini et al., 2022), showing that specifically a hedonic attentional focus leads to an increased level of activation in the mesocorticolimbic system. The findings on the effect of a health attentional focus differ from previous studies that found strong effects of an attentional focus on health (Hare et al., 2011; Bhanji and Beer, 2012), but this might be explained by differing conceptualization of the health attentional focus and differing analysis approaches. In general, the significant main effect of attentional focus shows that the brain response to food stimuli depends on the attentional focus of a person, and that brain responses to food stimuli are influenced by cognitive states rather than being automatic reactions that are always the same.

The current findings underline the importance of having a clear mental task when investigating brain responses to food stimuli. It seems that attentional focus can only be manipulated successfully with tasks that meet certain characteristics. That is, like the current study, studies that were successful in detecting effects of attentional focus (Franssen et al., 2020; Bhanji and Beer, 2012; van Rijn et al., 2018; Hare et al., 2011) used a manipulation of attentional focus that was centrally embedded in the experimental task. Also, the use of cognitive strategies to manipulate the focus on food stimuli appears to be effective (Siep et al., 2012; Miedl et al., 2018). It seems crucial that the cognitive strategies are emphasized throughout the task with frequent repetition of instructions. In contrast, more task-independent manipulations of attentional focus, like presenting participants with video messages about attentional focus, appear to be ineffective (Franssen et al., 2022; Kochs et al., 2022). Possibly, messages that only frame the experimental tasks are not sufficiently important to task performance, and participants might forget about them quickly in an artificial laboratory environment. Therefore, the nature of the experimental task is a crucial factor in research on the effects of attentional focus in brain responses to food.

Multivariate analysis showed that it was possible to decode food palatability and calorie content from numerous brain regions, among which several regions of the mesocorticolimbic system. It is unlikely that decoding was driven by visual properties of stimuli, as stimuli were individualized, were perceived as rather dissimilar, and differences in perceptual similarity between categories were small. The current findings parallel the findings of two studies from our lab (Franssen et al., 2020; Pimpini et al., 2022) that observed significant decoding of food palatability in a multitude of brain regions, which largely overlapped with the regions observed in the current study. Similarly, the current findings are in line with the observations that information about valence and food value could only be revealed by multivariate analysis techniques (Chikazoe et al., 2014; Suzuki et al., 2017).

Decoding of palatability and calorie content was possible across and within attentional foci, and there were no significant differences in decoding accuracy for palatability or calorie content between attentional foci. This finding differs from the results of Franssen et al. (2020) (Franssen et al., 2020) who observed brain regions in which palatability could be decoded significantly better in the hedonic attentional focus than in the neutral attentional focus but are in line with Pimpini et al. (2022) (Pimpini et al., 2022) who observed no differences in decoding accuracy between attentional foci neither for palatability nor for calorie content. Overall, the current results suggest that food characteristics, like palatability and calorie content, are barely reflected in the level of brain activation, while distributed patterns across voxels contain information about these food characteristics, as revealed by multivariate analysis techniques.

Interestingly, no significant moderation of brain activity related to palatability or calorie content by dietary restraint was detected, suggesting that palatable or high-caloric food is not generally more salient or represented differently in healthy-weight people scoring high on dietary restraint. This lack of findings cannot be attributed to a lack of variation in dietary restraint scores, as the measured range of dietary restraint scores was large. Also, Bayesian analysis results indicate the absence of any interaction with dietary restraint. The current findings are not in line with findings of several previous studies (Coletta et al., 2009; Demos et al., 2011; Ely et al., 2014; Born et al., 2011; Wood et al., 2016; Hollmann et al., 2012) in which dietary restraint was associated with increased activity to visual food stimuli in diverse brain regions, like as the DLPC or striatum. However, previous studies mostly had small sample sizes (Coletta et al., 2009; Ely et al., 2014; Born et al., 2011; Wang et al., 2016) and some studies used lenient multiple comparison corrections (Coletta et al., 2009; Ely et al., 2014), which is problematic as the probability of false positives is not properly controlled this way (Eklund et al., 2016). In contrast to most previous studies, the current study had a large sample size and employed a stringent multiple comparison correction.

Furthermore, some previous studies did not restrict their sample to participants without obesity. However, dietary restraint and BMI are typically quite correlated (Ramírez-Contreras et al., 2021). So possibly,

effects of dietary restraint have been mixed with effects of BMI in previous studies, as effects of non-experimental correlated factors are hard to disentangle statistically (Miller and Chapman, 2001). To make sure to study the pure effect of dietary restraint – not confounded by BMI – we selected participants in the healthy-weight BMI range. Moreover, some previous studies that observed differences in brain responses to food between restrained and unrestrained eaters, manipulated hunger with a preload/no preload condition. In the current study, it was not our aim to assess how preloads affect brain responses to food in restrained compared to unrestrained eaters. Instead, we wanted to investigate how attentional focus affects brain responses to visual food stimuli in relation to dietary restraint. Therefore, we decided to keep hunger level as constant as possible between participants, at a moderate hunger level, because we think that under moderate hunger food and food characteristics, that is palatability and calorie content, are most relevant to all participants.

In addition, most previous studies did not control attentional focus during food viewing (Roefs et al., 2018). However, as high-caloric palatable food is highly tasty but unhealthy, restrained eaters are unlikely to consistently focus on hedonic aspects of food, but rather alternate between a hedonic and a health attentional focus frequently. Inconsistencies in the literature might partly result from uncontrolled alternation in attentional focus. The current study controlled attentional focus with task instructions, which involved frequent switching between hedonic, health, and neutral attentional foci. Thereby, the current manipulation of attentional focus might have subsumed the effect of dietary restraint, which presumably involves frequent switching of attentional focus between hedonic and health-related aspects of food stimuli. Taken together, it appears that, under tight control of attentional focus, dietary restraint does not significantly influence brain responses to food stimuli, and suggest that transient cognitive states might be more influential in determining brain responses to food than relatively stable characteristics, like dietary restraint.

The current study has several strengths. Firstly, tight control over mental processes was achieved by having participants perform a one-back task to manipulate attentional focus, and the study was well-powered, especially for detecting within-subject effects. Furthermore, we used mass-univariate as well as multivariate analyses to not only assess involvement of brain regions but also consider information reflected in multi-voxel patterns of brain activity (Mur et al., 2009). In addition, we used food stimuli that were individually tailored on palatability and used high-caloric as well as low-caloric food stimuli. Nevertheless, the current study has some limitations. The health attentional focus was conceptualized as calorie content comparisons. This conceptualization might be an oversimplification, as there are likely other important characteristics of food stimuli that determine healthiness considerations.

Future research could use a larger set of food stimuli to test generality of findings across a larger range of food stimuli and might use representational similarity analysis techniques (Kriegeskorte et al., 2008), in addition to classification analysis, to assess the neural representation of food characteristics more closely. Furthermore, it might also be interesting to utilize a broader conceptualization of a health attentional focus to assess its effects on neural representations of food. This might be done by assigning a subjective health score, by having participants rate food stimuli on several health aspects, depending on how important they are to them individually.

5. Conclusion

The current study showed that the *level* of brain activity is not proportionate to the palatability of food stimuli and hardly proportionate to the caloric content. Instead, palatability and calorie content of food stimuli could be significantly decoded from *patterns* of brain activity using MVPA. The *level* of brain activity did depend strongly on attentional focus, and was generally largest with a hedonic attentional focus. These findings – that is, the combination of a lack of significant effects of palatability and caloric value and a robust effect of attentional focus – suggest that the *level* of brain activity does not reflect stimulus valence or reward value (i.e., palatability and caloric content), but may reflect motivational salience (Roefs et al., 2018; Salamone and Correa, 2012) or reward *sensitivity*. Importantly, and contrary to hypothesis, we observed no significant correlations between brain responding and dietary restraint in healthy-weight women. This suggests that dynamic cognitive states (i.e., attentional focus) might be more influential in determining brain responses to food stimuli than relatively stable characteristics, like chronic dietary restraint. Therefore, it is highly important to exert experimental control over mental processes that participants engage in when viewing food stimuli in fMRI studies. Without clearly knowing the mental state of the participant in the different experimental conditions, drawing clear conclusions from brain activity is impossible (Poldrack, 2006; Poldrack, 2011) Taken together, univariate analyses of brain activity elicited by visual food stimuli is not sufficient to truly understand how our brain responds to food. Information about food palatability and calorie content is contained in *patterns* of brain activity. Importantly, the distinction between valence and salience was only possible by including palatable as well as unpalatable food stimuli.

Declaration of Competing Interest

The authors declare no competing financial interest.

Credit authorship contribution statement

Sarah Kochs: Conceptualization, Software, Formal analysis, Investigation, Visualization, Writing – original draft, Writing – review & editing. **Sieske Franssen:** Formal analysis, Writing – review & editing. **Leonardo Pimpini:** Investigation, Writing – review & editing. **Job van den Hurk:** Formal analysis, Software, Writing – review & editing. **Giancarlo Valente:** Formal analysis, Software, Visualization, Writing – review & editing. **Alard Roebroeck:** Software, Writing – review & editing. **Anita Jansen:** Supervision, Writing – review & editing. **Anne Roefs:** Conceptualization, Funding acquisition, Supervision, Writing – original draft, Writing – review & editing.

Data availability

Data will be made available on request.

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Supplementary materials

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