More complex than you might think: Neural representations of food reward value in obesity

Leonardo Pimpini a,7, Sarah Kochs a, Sieske Franssen a,c, Job van den Hurk b,c, Giancarlo Valente c, Alard Roebroeck c, Anita Jansen a, Anne Roefs a

a Department of Clinical Psychological Science, Faculty of Psychology and Neuroscience, Maastricht University, Maastricht, Netherlands
b Scannexus, Maastricht, Netherlands
c Department of Cognitive Neuroscience, Faculty of Psychology and Neuroscience, Maastricht University, Netherlands

ARTICLE INFO

Keywords:
fMRI
Food
Brain
Reward
MVPA
Obesity
Healthy-weight

ABSTRACT

Obesity reached pandemic proportions and weight-loss treatments are mostly ineffective. The level of brain activity in the reward circuitry is proposed to be proportionate to the reward value of food stimuli, and stronger in people with obesity. However, empirical evidence is inconsistent. This may be due to the double-sided nature of high caloric palatable foods: at once highly palatable and high in calories (unhealthy).

This study hypothesizes that, viewing high caloric palatable foods, a hedonic attentional focus compared to a health and a neutral attentional focus elicits more activity in reward-related brain regions, mostly in people with obesity. Moreover, caloric content and food palatability can be decoded from multivoxel patterns of activity most accurately in people with obesity and in the corresponding attentional focus.

During one fMRI-session, attentional focus (hedonic, health, neutral) was manipulated using a one-back task with individually tailored food stimuli in 32 healthy-weight people and 29 people with obesity. Univariate analyses (p < 0.05, FWE-corrected) showed that brain activity was not different for palatable vs. unpalatable foods, nor for high vs. low caloric foods. Instead, this was higher in the hedonic compared to the health and neutral attentional focus. Multivariate analyses (MVPA) (p < 0.05, FDR-corrected) showed that palatability and caloric content could be decoded above chance level, independently of either BMI or attentional focus. Thus, brain activity to visual food stimuli is neither proportionate to the reward value (palatability and/or caloric content), nor significantly moderated by BMI. Instead, it depends on people’s attentional focus, and may reflect motivational salience. Furthermore, food palatability and caloric content are represented as patterns of brain activity, independently of BMI and attentional focus. So, food reward value is reflected in patterns, not levels, of brain activity.

A. More complex than you might think

Imagine Anja, a healthy-weight woman going out for dinner with a few close friends, at the end of an intense week of work. Anja and friends will likely enjoy the food, fully focusing on the taste. Imagine Anja again, this time entering the hall of her gym, full of posters of very fit athletes, after which she goes grocery shopping. Now she will likely be more concerned with health and body weight, focusing on the caloric value of foods. Now imagine Sonja, a woman with overweight, experiencing the exact same two situations. Would Sonja respond similarly to Anja? Or would food palatability and reward strongly and consistently dominate her responses?

The current Western environment is considered obesogenic, as people are constantly surrounded by easy accessible, high caloric palatable foods, jobs nowadays demand more intellectual than physical effort, and limited time is left for fitness activities (Hill et al., 2005; Morland & Evenson, 2009; Small, 2009). According to a recent report (WHO), worldwide, more than 1.9 billion adults are overweight, of whom 650 million have obesity (Bentham et al., 2017). So, it is evident that within this obesogenic environment it is hard to stay or become lean (Wadden et al., 2002). However, despite sharing the same environment, not everyone is overweight. The most common explanation for this

1. Introduction

Imagine Anja, a healthy-weight woman going out for dinner with a few close friends, at the end of an intense week of work. Anja and friends will likely enjoy the food, fully focusing on the taste. Imagine Anja again, this time entering the hall of her gym, full of posters of very fit athletes, after which she goes grocery shopping. Now she will likely be more concerned with health and body weight, focusing on the caloric value of foods. Now imagine Sonja, a woman with overweight, experiencing the exact same two situations. Would Sonja respond similarly to Anja? Or would food palatability and reward strongly and consistently dominate her responses?

The current Western environment is considered obesogenic, as people are constantly surrounded by easy accessible, high caloric palatable foods, jobs nowadays demand more intellectual than physical effort, and limited time is left for fitness activities (Hill et al., 2005; Morland & Evenson, 2009; Small, 2009). According to a recent report (WHO), worldwide, more than 1.9 billion adults are overweight, of whom 650 million have obesity (Bentham et al., 2017). So, it is evident that within this obesogenic environment it is hard to stay or become lean (Wadden et al., 2002). However, despite sharing the same environment, not everyone is overweight. The most common explanation for this

Abbreviations: MVPA, Multivoxel Pattern Analysis.
* Corresponding author.
E-mail address: leonardo.pimpini@maastrichtuniversity.nl (L. Pimpini).

https://doi.org/10.1016/j.appet.2022.106164
Received 4 November 2021; Received in revised form 1 July 2022; Accepted 8 July 2022
Available online 19 July 2022
0195-6663/© 2022 The Authors. Published by Elsevier Ltd. This is an open access article under the CC BY license (http://creativecommons.org/licenses/by/4.0/).
individual variability is that high caloric foods are more attractive for people with overweight than for healthy-weight people, which is supposed to be reflected in a highly responsive brain-reward circuitry, leading to food overconsumption and weight gain (Berthoud, 2012; Haahr et al., 2012; Kenny, 2011; Leigh & Morris, 2018; Meule, 2015; Murdaha et al., 2012; Scharmüller et al., 2012; Schulte et al., 2016; Stice et al., 2013; Volkow et al., 2011, 2013; Zhang et al., 2015). This view assumes that a highly responsive reward circuitry is a rather durable, inflexible, and unavoidable condition in people with obesity. The present study challenges this view. We propose that food-induced brain reward activity depends on the current attentional focus, which can alternate frequently between a hedonic and a health focus, depending on someone’s current situation or emotional state (Roefs et al., 2015, 2018).

The prevailing view in the literature is that obesity is associated with imbalances in the reward and self-control circuits of the brain (Burger & Berner, 2014; Leigh & Morris, 2018; Volkow et al., 2011, 2013). It is argued that, for people with obesity, anticipatory food responses in the reward circuit of the brain are increased, whereas consummatory brain responses are reduced (Dimitropoulos et al., 2012; Nummenmaa et al., 2012; Stice et al., 2008, 2013), as compared to people with a healthy weight. So, when viewing (high caloric) palatable foods, people with obesity would show an increased anticipatory brain response, whereas they would show a reduced brain response upon actual consumption of high caloric food. It is therefore suggested that people with obesity would need to consume more food to reach the same level of reward-related brain activity compared to healthy-weight people (Small, 2009; Verdejo-Román et al., 2017; Volkow et al., 2011; Volkow & Wise, 2005).

To date, a considerable number of neuroimaging studies have investigated anticipatory brain responses in people with obesity (e.g., Cornier et al., 2013; Mehl et al., 2019; Ochner et al., 2012; Scharmüller et al., 2012; Spepper et al., 2017). It is assumed that the brain activity in reward-related regions (i.e., the mesocorticolumbic circuitry) is proportionate to the palatability (reward value) of the presented food stimuli (Berthoud, 2012; Leigh & Morris, 2018; Meule, 2015; Scharmüller et al., 2012; Schulte et al., 2016; Stice et al., 2013; Volkow et al., 2013; Zhang et al., 2015). This effect is hypothesized to be stronger in people with obesity than in healthy-weight people (Volkow et al., 2011, 2013). However, disappointmentingly, the empirical evidence for this hypothesis is highly inconsistent. Accordingly, a review of studies in the field fittingly concluded: “The pattern emerging from studies comparing people with obesity and binge-eaters with controls is most remarkable for its variability and inconsistency” (Ziauddeen et al., 2012, p. 283), and point at the inconsistent contribution and involvement of the dopaminergic brain circuit as a neuro-cognitive marker of obesity (Janssen et al., 2019). So, although the theory that durable imbalances in the reward vs. self-control circuits of the brain as a cause for obesity makes intuitive sense, the empirical support for this is highly inconsistent (Heather et al., 2018; Ziauddeen et al., 2012).

A reason for the inconsistency could be that in studies with a passive viewing paradigm (e.g., Martin et al., 2010; Rothemund et al., 2007; Stoeckel et al., 2008), it has been tacitly assumed that people – especially people with obesity – firstly and automatically focus on the taste of palatable foods (hedonic attentional focus) when these are presented during neuroimaging studies. The interpretation of findings in these studies often relied on reverse inference, meaning that a mental state was inferred from brain activity (Poldrack, 2006, 2014). For example, if brain activity in the insula was observed upon visual presentation of (high caloric) palatable food stimuli, the conclusion was drawn that this activity reflects pleasant taste, because the insula has been associated with pleasant taste in previous research (Pelchat et al., 2004; Siep et al., 2009; Yokum et al., 2011). However, not only has activity in the insula also been associated with unpleasant taste (Caldar et al., 2007; Schiene et al., 2002), it has in fact been associated with a vast range of cognitive functions, with its activation being present in almost one third of all neuroimaging studies (Chang et al., 2013). So, to avoid falling into the trap of reverse inference, researchers should control – as much as possible – the mental process of the participant. Researchers should engage in forward inference, that is, infer brain activity from known mental processes. To gain more certainty about the ongoing mental process, tight experimental control over the way participants look at the presented visual food stimuli is needed. That is, it needs to be clear if participants in the MRI scanner are evaluating the palatability, the caloric value, or other aspects of the presented food stimuli. Only then can valid conclusions be drawn, based on forward inference, from mental process to brain activity (Poldrack, 2006, 2011).

So, researchers should be aware of the double-sided nature of (high caloric) palatable foods. That is, these foods are highly palatable, but have a low health value due to their high caloric content (Roefs et al., 2015, 2018). In our view, it is a matter of attentional focus whether the hedonic value of (high caloric) palatable food takes precedence. Attentional focus can fluctuate between a hedonic and a health focus, depending on for example participants’ emotional or physiological state. Critically, attentional focus may switch—unbeknown to the researchers—within and across participants as well as within and across studies, complicating the interpretation of results. Previous studies have indeed shown that task demands, expectations, context and attentional focus affect brain responses to visual food stimuli (e.g., Bhanji & Beer, 2012; Frankort et al., 2012; Gravenhorst et al., 2008; Hare et al., 2011; Hege et al., 2018; Kaisari et al., 2019; Pohl et al., 2017; Schroder et al., 2014; Siep et al., 2012; Yokum et al., 2011). Interestingly, the level of brain activity in response to food stimuli was higher in people with obesity compared to healthy-weight when their attentional focus was on taste evaluation, but not without control of attentional focus (Frankort et al., 2012). Furthermore, it was found that brain responses to visual food stimuli decreased by the active suppression of food craving-related thoughts (Siep et al., 2012).

Another relevant factor is that most previous studies used only mass-univariate analyses for their fMRI-data, which only inform on where in the brain the level of brain activity is relatively high. However, empirical studies have shown that the level of brain activity in the mesocorticolumbic system is actually unlikely to reflect the reward value of the presented visual food stimuli (Chikazoe et al., 2014a; Janssen et al., 2019; Kahnt, 2018; Salamone & Correa, 2012; Suzuki et al., 2017). Brain activity in this system, instead, may reflect salience. More specifically, two of these recent studies (Chikazoe et al., 2014a; Suzuki et al., 2017) showed that the level of brain activity was not significantly different for positive versus negative food stimuli. Instead, food value could be decoded from multivoxel patterns of brain activity. In multivoxel pattern analysis (MVPA), a classifier is trained to distinguish between multivoxel patterns of brain activity associated with different classes of stimuli. In a test-dataset, the classification accuracy is computed and it is statistically tested if classes of stimuli can be decoded above chance from these patterns of brain activity (Haxby, 2012; Haxby et al., 2014; Norman et al., 2006; Oosterhof et al., 2016).

In a recent study (Franssen et al., 2020), participants’ ongoing mental process was tightly controlled by having the participants perform a fast-paced one-back task (Kane et al., 2007; Kirchner, 1958). Data were analyzed using both mass-univariate as well as multivoxel pattern analyses (MVPA). By means of this 1-back task, participants attention was either focused on palatability (hedonic attentional focus) or on the color of the presented food stimuli (neutral attentional focus). Participants were presented with individually tailored highly palatable and highly unpalatable high caloric food stimuli. The mass-univariate analysis showed that the level of brain activity in the mesocorticolumbic system was not significantly different between highly palatable and highly unpalatable foods, which is in line with previous studies showing that the level of neural activity does not reflect food reward value (Chikazoe et al., 2014; Suzuki et al., 2017). Note that the majority of previous studies did not include unpalatable food stimuli in their design, which makes it impossible to disentangle salience from valence, as both high
and low valence stimuli are considered salient (Born et al., 2010; Dimitropoulos et al., 2012; Ely et al., 2014; Ho et al., 2012; Lawrence et al., 2012; Luo et al., 2013; Murdaugh et al., 2012; Passamonti et al., 2009; Pursey et al., 2014; Scharrmüller et al., 2012; Schur et al., 2009; Tryon et al., 2013). MVPA showed that food palatability (high vs. low) could be decoded above chance from multivoxel patterns of brain activity, most accurately with the hedonic attentional focus, which is again in line with earlier studies showing that food value is reflected in patterns of brain activity, not level of brain activity (Chikazoe et al., 2014; Franssen et al., 2020; Roefs et al., 2018; Suzuki et al., 2017).

The present study extends this work (Franssen et al., 2020), by including also low-caloric food stimuli, a health attentional focus, and a group of participants with a healthy weight. The hypothesis is tested that a hedonic attentional focus, as compared to a health and neutral attentional focus, is associated with more involvement of the mesocorticolimbic system in response to high caloric palatable foods, most strongly in people with obesity. In addition, the hypothesis is tested that caloric value and food palatability can be decoded above chance from multivoxel patterns of activity, most accurately in the corresponding attentional focus and in people with obesity.

2. Method

2.1. Participants

Seventy female participants (n = 36 healthy-weight, and n = 34 obese; right-handed) volunteered for this study. Participants were recruited via paper flyers, advertisements in local newspapers, posts on social media, and a recruitment company (Link2trials). Three participants (n = 1 healthy-weight, n = 2 obese) were excluded from analyses because they felt sick or claustrophobic in the scanner. Additionally, after fMRI motion correction, six participants (n = 3 healthy-weight, n = 3 obese) were discarded due to excessive head-movement, exceeding 3 mm in x, y or z direction (see Preprocessing of fMRI data). The final sample included 61 participants (n = 32 healthy-weight, n = 29 obese), and the two groups were matched on age and education level, see Table 1 for participant characteristics. Simulation studies of fMRI data (Desmond & Glover, 2002; Mumford & Nichols, 2008) indicate that a sample size of 60 participants (30 per BMI-group) should be sufficient.

The present study was pre-registered on ‘AsPredicted’ (https://aspr.edicted.org/XWV_C1H) and approved by the Ethics committee of the Faculty of Psychology and Neuroscience of Maastricht University (ERCPN, 159_15_12_2015_S8). All participants gave informed consent before participation and received a voucher of €25 as compensation at the end of the study.

3. Procedure

Approximately two weeks before the study, participants who signed up for the study were approached for the screening of pregnancy, psychiatric disorders, and history of neurological and/or gastric surgical interventions. Additionally, the compatibility of the participant with the MRI scanner was checked (e.g., pacemaker, prosthesis, permanent make-up, dental brace). At the same time, approximately two weeks before participation, the participant received two links via email asking to complete the online screening questionnaire and the Individual stimuli selection and rating questionnaires (Qualtrics).

On the day of testing, the participant first signed the informed consent, then completed the hunger assessment questionnaire. To control hunger level, each participant was instructed via email to eat something small (e.g., a sandwich and a piece of fruit) exactly 2 h before the start of the study, and to refrain from eating and drinking (except water) until the end of the session. Next, participants performed a brief practice session of the task (outside the scanner; 7 min), in which different food stimuli than in the actual session were presented. Before entering the scanner, to compute BMI, participant’s height and weight (with clothes, without shoes) were measured. The participant was instructed on the safety measures and possible risks of the MRI scanner.

At the end of the scanning session, outside the scanner, the participant performed the visual similarity rating task (approximately 10 min). Finally, each participant was awarded a €25 voucher for the participation. Notably, to avoid participants to spoil the content of the study to other potential participants, a detailed debriefing letter was sent, via email, only once testing phase was completed and the sample size reached. Taken together, each session took approximately 2 h to complete.

4. Materials and behavioral assessments

4.1. Online screening questionnaire

Dietary restraint was measured by the Restraint Scale (Herman & Polivy, 1980), and some filler items were interspersed with the actual questions to disguise the purpose of the study. Fillers contained general lifestyle-related items, such as ‘How much time, on average, do you spend with your family and/or friends?’ or ‘How many hours per week do you spend housekeeping?’. In addition, the online questionnaire contained items about participant’s education level and self-reported BMI.

4.2. Individual stimuli selection and rating

In a second online questionnaire, the participant was presented with a list of 43 high caloric foods and a list of 43 low caloric foods (see Table 2). The participant was asked to select her personal 3 most favorite and 3 least favorite foods from each of the lists. The participant was explicitly instructed not to select foods she was allergic to, or of which the taste was unknown to her. This resulted in four food categories for every individual: high caloric palatable [HC+], high caloric unpalatable (HC-), low caloric palatable (LC+), and low caloric unpalatable (LC-). The participant was asked to rate her selected foods on palatability and caloric content on 10-point Likert scales, ranging from 1 (not tasty/caloric at all), to 10 (very tasty/caloric).

Table 1

| Variable | Healthy-weight (n = 32) | Obese (n = 29) | t (59) | p |
|----------|------------------------|---------------|-------|---|
| M | SD | Range | M | SD | Range | |
| Age | 40.77 | 10.84 | 27-54 | 41.40 | 9.43 | 27-55 | 0.56 | .57 |
| BMI | 22.40 | 1.70 | 19-24.70 | 35.07 | 4.43 | 30-42.50 | 15.60 | <.0001 |
| RS | 10.40 | 4.71 | 2-19 | 17.71 | 4.70 | 10-30 | 7.24 | <.001 |
| Last eaten (min) | 137.66 | 24.29 | 100-200 | 135 | 21.09 | 100-180 | 0.30 | .76 |
| Hunger level (VAS) | 34.31 | 22.44 | 4.75 | 29.86 | 19.57 | 2-66 | 0.82 | .21 |

Abbreviations: BMI = Body Mass Index; RS = Restraint Scale (Herman & Polivy, 1980); VAS = Visual Analogue Scale (range: 0 = not hungry at all, 100 = very hungry).
Table 2
Overview of the food stimuli lists participants could choose from. Food stimuli are divided over high and low caloric content.

| High-caloric food items (N = 43) | Low-caloric food items (N = 43) |
|---------------------------------|---------------------------------|
| Bacon; BBQ worst; Bitterballs; Blue cheese; | Strawberries; Apricots; Pineapple; Apple; |
| Bonbon; Brie; Brownie; Butter; Butter biscuit; Cake; Crisps; Chocolate; Chocolate cookie; Chocolate bar; Chocolate soufflé; Chocolate cake; Croissant; Donut; Feta cheese; Fries; Frikandel; Herring; Hot dog; Cheese soufflé; Croquette; Cheesecake; Spring roll; Gouda cheese; Olives; Pate; Peanuts; Peanut butter; Pizza; Smoked sausage; Sausage rolls; Salami sausage; Schnitzel; Cream cake; Tiramisu; Tompouce; Grilled-cheese sandwich; Vanilla ice-cream; Walnuts | Artichoke; Asparagus; Aubergine (Egglplant); Cauliflower; Broccoli; Mushrooms; Cherry tomatoes; Grapes; Raspberries; Shrimps; Grapefruit; Honey melon; Codfish; Cherries; Kiwi; Cucumber; Lettuce; Corn; Mandarin; Mango; Muscles; Muesli; Pear; Peach; Pumpkin; Popcorn; Leek; Radish; Rice waffle; Red pepper; Orange; Beetroot; Celery; Green beans; Brussels sprouts; Watermelon; Chicory; Carrot; Sauerkraut |

4.3. Hunger level assessment

Participants’ hunger level was assessed by a three-item questionnaire. The first item assessed the time that elapsed since the last eating moment (in minutes), the second item asked what the participant ate last (brief description), and the third item assessed subjective hunger on a 100 mm VAS ranging from 0 (not hungry at all) to 100 (very hungry).

4.4. Stimuli

For each of the 86 foods, two pictures were selected, to avoid too much repetition during the fMRI-measurements, and potential picture-specific biases. During the experiment, each participant, viewed an individually tailored subset of 24 different food pictures (12 foods, 2 different pictures per food). Stimuli were retrieved from the Internet (e.g., iStockphoto), and from a database maintained by the University of Salzburg (Blechert et al., 2014, 2019). Pictures were formatted with Adobe Photoshop CS5.1 (image size: 454*454 pixels | 12*12 cm, resolution: 96 pixels/inch, canvas size: 12*12 cm). Visual food stimuli were divided centrally on the screen, on a light grey background (RGB: 191, 191). During rest periods, a black fixation cross appeared on screen. For each of the 86 foods, two pictures were selected, to avoid too much repetition during the fMRI-measurements, and potential picture-specific biases. During the experiment, each participant, viewed an individually tailored subset of 24 different food pictures (12 foods, 2 different pictures per food). Stimuli were retrieved from the Internet (e.g., iStockphoto), and from a database maintained by the University of Salzburg (Blechert et al., 2014, 2019). Pictures were formatted with Adobe Photoshop CS5.1 (image size: 454*454 pixels | 12*12 cm, resolution: 96 pixels/inch, canvas size: 12*12 cm). Visual food stimuli were divided centrally on the screen, on a light grey background (RGB: 191, 191). During rest periods, a black fixation cross appeared on screen.

5. fMRI stimulation protocol

Each run (four in total, ~13 min each) included 24 blocks (~16 s each), with each condition (12 in total) presented twice per run. So, each condition was presented 8 times in total. Within each run, the order of the blocks was randomized and mirrored within each run (e.g., 1-3-6-2-4-9-11-10-5-12-7-8-7-12-5-10-11-9-4-2-6-3-1). Moreover, within each block, the order of the visual food stimuli was pseudo-randomized so that the same food stimulus could not appear twice in a row. Presentation Neurobehavioral systems (www.neurobs.com) was used for displaying the stimuli. Total time in the scanner was 1 h, including 52 min for the four functional runs and about 5 min for the anatomical scan (MPRAGE: Feinberg et al., 2010; Moeller et al., 2010; Setsompop et al., 2012), which was performed before the first functional run. Between runs, a short break was provided, during which the researcher reminded the participant not to move while in the scanner.

**Fig. 1.** Graphical schema of the one-back task used to manipulate attentional focus. In this figure, an example of high caloric palatable food (HC+) block with hedonic (taste) manipulation is presented. Top-right panel: in each block, one category of food stimuli was presented (either HC+, HC-, LC+, or LC-). Abbreviations: HC+: high caloric palatable foods; HC-: high caloric unpalatable foods; LC+: low caloric palatable foods; LC-: low caloric unpalatable foods.
5.1. fMRI data acquisition

Brain imaging was performed at Scannexus (Ultra-High-Field MRI center, Maastricht, The Netherlands), using a 3T MRI scanner (3T MAGNETOM Prisma Fit, Siemens Medical Systems, Erlangen, Germany) with a 64 channels head-neck coil. The participant was lying comfortably in the scanner, with the head stabilized using two foam pads on each side. During scanning, participants viewed the stimuli by means of a mirror attached to the head coil. An optimized magnetization-prepared rapid gradient-echo imaging sequence was used to extract high-resolution three-dimensional T1-weighted anatomical scan (MPRAGE pulse sequence, TR = 2250 ms, TE = 2.11 ms, flip angle = 9°, FOV = 256 × 192 mm², voxel size 1 × 1 × 1 mm) (Feinberg et al., 2010; Moeller et al., 2010; Setsompop et al., 2012). T2*-weighted functional images were gathered in an axial interleaved fashion using multiband gradient-echo planar imaging (EPI) volumes were optimized to minimize distortion artifacts and susceptibility in the OFC (Deichmann et al., 2003; Weiskopf et al., 2007). These measures included: (a) TE of 25 ms, (b) tilted slice orientation of approximately –15° to the transverse – coronal plane, (c) reduced voxel size to 2 × 2 × 2.5 mm. In each run, 386 brain volumes were obtained.

5.2. Visual similarity rating task

To rule out that differences in neutral activity can be explained by differences in visual characteristics between categories of stimuli, participants performed a visual similarity rating task. Right after the scanning session, the participant was instructed to compare the stimuli on shape and color, and rate similarity on 5-point scales, ranging from 1 (not at all similar) to 5 (highly similar). All possible unique pairs of the 12 selected foods were presented (66 pairs), with food stimuli of a pair presented simultaneously and side-by-side. The color and shape ratings were presented in two separate blocks, with the order counterbalanced across participants.

6. Data analysis

6.1. Stimulus ratings

To test if the individually tailored food items were perceived as intended, caloric content and palatability ratings were analyzed in 2 (BMI: healthy-weight vs. obese) × 2 (palatability: palatable vs. unpalatable) × 2 (caloric content: high caloric vs. low) mixed ANOVAs.

6.2. Manual response latencies

Manual response latencies in the one-back task were analyzed as a measure of cognitive demand. Trials without a response (5.36%) and trials with a response latency deviating more than 3 SD in each direction from the participants’ mean (too slow responses: 1.34%; too quick responses: 0%) were excluded from analyses. Response latencies were analyzed in a 2 (BMI: healthy-weight vs. obese) × 2 (palatability: palatable vs. unpalatable) × 2 (caloric content: high vs. low) × 3 (attentional focus: hedonic vs. health vs. neutral) mixed ANOVA.

6.3. Visual similarity ratings

Visual similarity ratings (color and shape) were analyzed to examine whether within-category perceptual similarity was greater than between-category perceptual similarity. To achieve this, pairs of food stimuli were divided according to caloric content (collapsed over palatability) or palatability (collapsed over caloric content). Then, the perceived similarity ratings for pairs of the same category (e.g., both high caloric or both palatable) and pairs of different categories (e.g., a pair including one high caloric and one low caloric food stimulus, or a pair including one palatable and one unpalatable food stimulus) were computed. Paired-samples t-tests were used to compare the perceived similarity scores between same and different category pairs. These analyses were performed for shape and color ratings.

7. fMRI data analyses

7.1. Preprocessing

Six preprocessing steps were implemented to clean the functional MRI data prior to performing the statistical analyses: slice-timing correction, motion correction, co-registration, spatial normalization, temporal filtering, and spatial smoothing. First, all functional images were slice-timing corrected by realigning the acquired voxel time series to the middle slice (reference slice). Second, to correct head motion inside the scanner, 3D motion correction was conducted using a 2nd degree B-spline interpolation. That is, both translation (in x, y, and z planes) and rotation (roll, pitch, and yaw) parameters were estimated by comparing each volume to the mean of the entire functional run. If motion exceeded 3 mm (in translation) and/or 3° (in rotation) in any of the directions within each run, the run was discarded from the analyses. As a result of this motion check, the third run of two participants needed to be discarded from the analyses. Subsequently, for each participant, the anatomical and functional data were co-registered, by warping the anatomical scan to the mean functional data space. Next, the data were spatially normalized and temporally filtered using a high-pass filter with a cut-off period of 128 s. Deformation fields derived from segmentation were used to transform all the functional images to MNI space (Montréal Neurological Institute, Montreal, Canada). Finally, data were spatially smoothed with a Gaussian Kernel of 6 mm full width half-maximum (FWHM). Importantly, the spatial smoothing procedure described above was applied for the univariate analyses only.

8. Univariate analyses

8.1. First level

A general linear model (GLM) was estimated for each participant. In the GLM, a predictor was defined for each condition, resulting in 12 predictors of interest per run. To obtain the time-courses of the predictors of interest, a box-car shaped function was convolved with a canonical two-gamma hemodynamic response function (HRF). Next, the six motion parameters estimated during the preprocessing were added as nuisance regressors. This procedure was repeated for each of run separately. Moreover, for each run, a mean intensity regressor was added to the GLM as a predictor of no interest. T-contrasts for the main effect of palatability and the main effect of caloric content were computed in both directions. To test the main effect of attentional focus, the caloric content × attentional focus interaction, and the palatability × attentional focus interaction, two t-contrasts were defined: hedonic > health and health > neutral.

8.2. Second level

A whole brain random effects analysis was performed, with the contrast images from the first-level analysis used as input, including BMI-group (healthy-weight, obese) as a between-subjects factor. T-tests against zero were used to test the main effect of caloric content and the main effect of palatability. F-tests using two 1st level t-contrasts as an input (hedonic > health and health > neutral) were used to test the main effect of attentional focus, the caloric content × BMI interaction and the palatability × BMI interaction. All statistical map were thresholded (α = 0.05) using voxel-level Family-Wise Error correction (FWE) to correct for multiple testing (Eklund et al., 2016; Han & Glenn, 2018). To
examine if dietary restraint affected any of the within-subjects main or interaction effects, a separate ANCOVA was performed, including dietary restraint as a covariate. As BMI and dietary restraint are related considerably in the present sample (r = 0.69, p < 0.001), these two factors could not be entered in one analysis simultaneously, to avoid problems with multicollinearity.

To follow-up the main effect of attentional focus, t-tests were performed. That is, significantly active clusters of brain activity were extracted using MarsBar (SPM toolbox, http://marsbar.sourceforge.net/), to create functional regions of interest (fROIs). From these fROIs, average beta values were extracted per attentional focus. The differences in beta values between attentional foci (i.e., hedonic vs. health, hedonic vs. neutral, health vs. neutral) were compared using paired samples t-tests (see Table 3).

9. Bayesian analyses

9.1. Main effect of palatability

Bayesian second level analysis was performed using BayesFactor, a MATLAB toolbox (Krekelberg, 2020). The analysis was based on the same GLM estimates, per participant, used in the frequentist first-level MATLAB toolbox (Krekelberg, 2020). The analysis was based on the functional regions of interest (fROIs). From these fROIs, average beta values were extracted per attentional focus. The differences in beta values between attentional foci (i.e., hedonic vs. health, health vs. neutral) were compared using paired samples t-tests (see Table 3).

9.2. Palatability × BMI interaction

To test the palatability × BMI interaction, a Bayesian ANOVA was performed. Due to high computational requirements, this analysis was performed only in four regions of interest (fROIs): left posterior fusiform gyrus, right posterior fusiform gyrus, left inferior frontal gyrus, and left middle insular cortex. These fROIs were based on the results of a meta-analysis on brain response to package food choices (van der Laan et al., 2011). Four spheres, which radius was equal to each ROI’s radius, were created around the center coordinates using SPM12 (see Table 8). For each fROI, a model containing only main effects of palatability and BMI was compared to a model containing those main effects, plus the palatability × BMI interaction. Finally, the distribution of Bayes factors was examined to assess the plausibility of the palatability × BMI interaction. Priors for the analyses were set in exactly the same way as for the main effect of palatability.

9.3. Multivoxel pattern analyses (MVPA)

To further investigate how visual food stimuli are represented in the brain, a whole-brain searchlight MVPA was performed (Ettel et al., 2013; Kriegeskorte et al., 2006; Mur et al., 2009; Norman et al., 2006; Yan et al., 2016). It was tested whether food caloric content and palatability could be decoded above chance from multi-voxel patterns of brain activity. Decoding analyses for caloric content and palatability were conducted both across attentional foci as well as for each attentional focus separately. Additionally, we tested whether decoding accuracy (%) for palatability and caloric content was moderated by BMI-group and/or by attentional focus. MVPA analyses were conducted using CoSMoMVPA (http://www.cosmomvpa.org/) (Oosterhof et al., 2016).

Table 3

Beta values of significant clusters from univariate analysis of main effect of attentional focus (p < 0.05, FWE corrected) across all participants (n = 61). Clusters detected when testing the main effect of attentional focus are grouped according to the observed pattern of beta weights. The first column indicates the cluster size, in voxels (all clusters ≥ 5 voxels).

| Cluster size | Beta values | p-values |
|--------------|-------------|----------|
|              | Hedonic     | health   | Neutral | hedonic vs. health | hedonic vs. neutral | health vs. neutral |
| beta value pattern: hedonic > health > neutral |
| 74           | 0.02        | 1.44     | 5.15    | 0.00001 | <0.00000 | 0.00035 |
| 37           | 2.56        | 2.54     | 2.41    | 0.0057  | <0.00000 | 0.00823 |
| 146          | -0.12       | 3.73     | -1.55   | 0.00005 | <0.00000 | 0.03715 |
| 23           | 3.53        | 2.36     | 0.53    | 0.00023 | <0.00000 | 0.00512 |
| 18           | 0.62        | -1.68    | -0.32   | 0.00164 | <0.00000 | 0.00135 |
| 78           | 2.42        | 1.26     | 0.38    | 0.00071 | <0.00000 | 0.02624 |
| 92           | 0.72        | 2.15     | -1.31   | 0.03623 | <0.00000 | 0.00145 |
| beta value pattern: hedonic > (health = neutral) |
| 32           | -2.74       | -3.42    | -5.83   | <0.00000 | <0.00002 | 0.12564 |
| 15           | 2.75        | 1.83     | 0.36    | <0.00000 | <0.00005 | 0.05762 |
| 52           | 0.17        | 2.72     | -1.80   | <0.00000 | <0.00000 | 0.82734 |
| 37           | -2.30       | 1.82     | 1.11    | 0.00005  | <0.00000 | 0.27482 |
| 18           | 1.24        | 1.46     | -2.90   | 0.00000  | <0.00000 | 0.14726 |
| 14           | -2.40       | 3.27     | -2.67   | 0.00001  | <0.00000 | 0.43826 |
| 46           | -0.24       | -2.82    | -3.74   | <0.00000 | 0.00005 | 0.13845 |
| 29           | 7.13        | 1.35     | 4.21    | <0.00000 | 0.00000 | 0.84284 |
| 14           | -0.34       | -2.17    | -3.50   | <0.00000 | 0.00000 | 0.92732 |
| 20           | 1.35        | -1.83    | -1.61   | <0.00008 | <0.00012 | 0.29434 |
| 12           | 0.68        | 2.82     | -2.46   | <0.00000 | <0.00000 | 0.32954 |
| 23           | -1.27       | 2.38     | -1.74   | <0.00000 | 0.00000 | 0.82912 |
| beta value pattern: neutral > (health = hedonic) |
| 36           | 3.23        | 7.13     | 2.83    | 0.32845 | <0.00000 | 0.00000 |
| 12           | 5.82        | 5.58     | 11.24   | 0.82542 | <0.00063 | <0.0001 |
| 27           | 2.28        | 3.11     | 7.28    | 0.79127 | <0.00081 | 0.00025 |
| 47           | 1.15        | 5.73     | 4.92    | 0.62945 | <0.00000 | 0.00000 |
| 22           | 3.65        | 5.73     | 8.62    | 0.52093 | <0.00002 | <0.00001 |
| beta value pattern: (neutral = health) > hedonic |
| 28           | 16.83       | 22.34    | 13.45   | <0.00001 | 0.00000 | 0.49245 |
in MATLAB.

Functional images, preprocessed as described above except for spatial smoothing (see MRJ data pre processing), were used as input for the analyses (Mur et al., 2009). The design matrix was extracted in the same way as for the univariate analysis, except that it contained one predictor per block, resulting in 24 predictors per run. An advantage of this procedure is that it yields more training examples as an input for the classification procedure. The whole-brain searchlight classification was performed using a 100-voxel spherical searchlight (radius 4 mm, 33 voxels) with a linear support-vector machine as classification algorithm. The accuracy level of the 100-voxel sphere was assigned to the center voxel of each sphere (Kriegeskorte et al., 2006; Wang et al., 2007).

10. Participant level analysis

To decode caloric content, data were divided into high vs. low caloric blocks, collapsing across palatability. To decode palatability, data were divided into high vs. low palatable blocks, collapsing across caloric content. This procedure was performed across attentional foci and for each attentional focus separately. Moreover, the difference in decoding accuracy between attentional foci was computed by specifying three contrasts (hedonic-health, hedonic-neutral, and health-neutral). Data of three functional runs were used to train the classifier, while data of the remaining run were used to test classification accuracy. This procedure was repeated four times, according to the leave-one-run-out cross-validation procedure (Mahmoudi et al., 2012).

11. Group level analysis

First, participant-level classification accuracy maps were spatially smoothed with a Gaussian kernel of 6 mm FWHM. Group analysis included only voxels that showed 90% overlap across participants (Kriegeskorte et al., 2006). To statistically test decoding accuracy within and across attentional foci, mean decoding-accuracies (%) for caloric content and palatability were non-parametrically tested against chance level, using Wilcoxon signed-rank tests. To test differences in decoding accuracy between attentional foci, the three contrasts (hedonic-health, hedonic-neutral, health-neutral) defined on first level were non-parametrically tested against zero using Wilcoxon signed-rank tests.

All results were FDR corrected on a voxel-level (Benjamini & Hochberg, 1995; Genovese, Lazar, & Nichols, 2002). Finally, a random permutation test (Eklund et al., 2015) was used to compare decoding accuracies for palatability and caloric content between BMI-groups. The analysis, consisting of n = 1000 permutation tests, was repeated within and across attentional foci. In a separate analysis, to avoid problems with multicollinearity, correlations between dietary restraint and decoding accuracy were computed.

**Table 4** Overview of palatability rating of the individually tailored food stimuli per food category and per BMI-group.

| BMI-groups         | HC + M (SD)       | HC - M (SD)       | LC + M (SD)       | LC - M (SD)       |
|--------------------|-------------------|-------------------|-------------------|-------------------|
| Healthy-weight pp  | 9.15 (1.06)       | 2.24 (1.36)       | 8.79 (1.18)       | 2.83 (1.52)       |
| Obese pp (n = 29)  | 9.12 (0.98)       | 2.16 (1.41)       | 8.40 (1.23)       | 2.67 (1.38)       |

Abbreviations: M = mean; SD = standard deviations; BMI = Body Mass Index; pp = participants; HC+ = high caloric palatable foods; HC− = high caloric unpalatable foods; LC+ = low caloric palatable foods; LC− = low caloric unpalatable foods.

12. Results

12.1. Palatability ratings

As expected, palatable foods were rated as much more palatable than unpalatable foods ($F_{1,60} = 385.01, p < 0.0001, \eta^2_p = 0.88$). There was no significant effect of caloric content on the palatability ratings ($F_{1,60} = 0.005, p = 0.94, \eta^2_p = 0.0001$). The caloric content × palatability interaction was significant ($F_{1,60} = 9.70, p = 0.02, \eta^2_p = 0.09$), indicating that the difference between palatable and unpalatable foods was a bit larger for high caloric than for low caloric foods (see Table 4 for relevant means and SDs). Moreover, no main effect or interaction effects involving BMI-group (obese vs. healthy-weight) were observed, all $F$s < 0.42, all $p$s > 0.35.

12.2. Caloric content ratings

As expected, high caloric foods were rated as more caloric than low caloric foods ($F_{1,60} = 331.57, p < 0.0001, \eta^2_p = 0.92$). Furthermore, palatable foods were rated as more caloric than unpalatable foods ($F_{1,60} = 71.50, p < 0.0001, \eta^2_p = 0.58$). The caloric content × palatability interaction was also significant ($F_{1,60} = 17.36, p < 0.0001, \eta^2_p = 0.29$), suggesting that the perceived difference in caloric content between palatable and unpalatable foods was larger for high caloric than for low caloric foods (See Table 5 for relevant means and SDs). In conclusion, these results indicate that individual tailoring of food stimuli was successful, and the four stimulus categories were perceived as intended. Furthermore, no main effect or interaction effects involving BMI-group were observed, all $F$s < 0.64, all $p$s > 0.28.

12.3. Hunger level

On average and across the whole sample, the elapsed time since the last eating moment was approximately as instructed (120 min). Elapsed time since last eating moment and self-reported hunger were not significantly different between participants with obesity versus a healthy-weight (see Table 1).

12.4. Manual response latencies

Response latencies were analyzed in a 2 (BMI: healthy-weight vs. obese) x 2 (palatability: palatable vs. unpalatable) x 2 (caloric content: high vs. low) x 3 (attentional focus: hedonic vs. health vs. neutral) mixed ANOVA. We observed a significant main effect of attentional focus, $F(2,57) = 15.87, p < 0.0001, \eta^2_p = 0.22$). Follow-up t-tests showed that participants responded faster in the neutral attentional focus compared to the hedonic attentional focus, $t(60) = 2.96, p = 0.004, d = 0.20$ and compared to the health attentional focus, $t(60) = 3.84, p < 0.0001, d = 0.31$ (see Fig. 2 for means and SDs). The difference between the hedonic and health attentional focus was not significant, $t(60) = 1.05, p = 0.30, d = 0.12$. The remaining main and interaction effects were not significant either, all $F$s < 1.79, all $p$s > 0.17.

12.5. Visual similarity ratings

Food pairs of similar caloric content (color: $M = 1.20, SD = 0.55$; shape: $M = 1.87, SD = 0.46$) were perceived as more similar in color and
shape than food pairs of different caloric content (color: \( M = 1.03, SD = 0.53 \); shape: \( M = 1.58, SD = 0.43 \)) (color: \( t_{60} = 7.06, p < 0.0001, d = 0.72 \); shape: \( t_{60} = 6.16, p < 0.0001, d = 0.65 \)). Food pairs of similar palatability (color: \( M = 1.94, SD = 0.50 \); shape: \( M = 1.76, SD = 0.47 \)) were perceived as slightly more similar in color than food pairs of different palatability (color: \( M = 1.87, SD = 0.52 \); shape: \( M = 1.68, SD = 0.39 \)) (color: \( t_{60} = 2.45, p = 0.01, d = 0.14 \), and trend-significantly more similar in shape: \( t_{60} = 1.99, p = 0.05, d = 0.18 \). Importantly, across participants, the overall perceived similarity of the foods in each pair was low (range: 1.58–2.19 on a 5-point scale (1 = not similar at all to 5 = highly similar)). Moreover, the difference in perceived similarity between same-category pairs and different-category pairs was numerically small (range: 0.08–0.41).

13. Univariate analyses results

The main effects of palatability and of caloric content, as well as the palatability x attentional focus interaction and the caloric content x attentional focus interaction did not result in significant clusters of brain activity, nor were these effects significantly moderated by BMI-group or dietary restraint. The main effect of attentional focus yielded 26 significantly active clusters (see Table 6 & Fig. 3) and was not moderated by BMI-group or dietary restraint. A significantly higher level of brain activity was observed in the hedonic focus as compared to both the health and the neutral focus. Taken together, the level of brain activity depended on the induced attentional focus and was not significantly affected by food palatability or caloric content, nor moderated by BMI or dietary restraint.

Repeating the analysis using a more lenient uncorrected threshold (cluster defining threshold \( p < 0.001 \), cluster size threshold \( \geq 10 \) voxels) yielded clusters not located in areas typically associated with food decision-making (e.g., mesocorticolimbic system, prefrontal cortex) except for one rather small cluster of voxels located in the insula (10 voxels, see Tables 1 and 2 in the Supplementary material). Moreover, recent evidence showed how false positive rates up to 70% can be found using lenient thresholding procedure (Eklund et al., 2006).

14. Bayesian analyses results

14.1. Main effect palatability

Comparing the distribution of Bayes factors on the actual data (Fig. 4, blue distribution) with a distribution of Bayes Factors on simulated data (Fig. 4, red distribution) suggests that the actual data provide some support for the alternative hypothesis. That is, some voxels showed increased brain activity for palatable vs unpalatable foods. In Fig. 4, positive values on the x-axis represent evidence for the alternative hypothesis, whereas negative values represent evidence for the null hypothesis. Notably, the evidence for the alternative hypothesis was mostly weak and limited to 5.2% of the total number of voxels (i.e., 7984 out of 152200 voxels) (Rouder et al., 2012). More specifically, 4256 voxels (2.8%) were observed in the weak range (0–0.5), 2791 (1.8%) voxels in the substantial range (0.5–1), and only 937 (0.6%) voxels in the strong range (1–1.5). For reference values, see Kass and Raftery (1995) and Jeffreys (1961). In Table 7, the brain regions in support of the alternative hypothesis are reported. Overall, this Bayesian analysis revealed some weak evidence for an effect of palatability, but the extent of this across the brain was very limited.

14.2. Palatability × BMI interaction

A region-of-interest (ROI) analysis was performed for the
Moreover, in the left inferior frontal gyrus (Fig. 5, panel B) limited evidence provided only weak and very limited evidence for the alternative hypothesis for both the main effect of palatability and BMI. Furthermore, Bayesian analyses can be decoded above chance from patterns of brain activity located in several occipital and frontal brain regions. Notably, decoding accuracies of palatability and caloric content were not significantly affected by either BMI or attentional focus.

15. Discussion

The aim of the present study was to investigate the influence of food palatability and caloric content, attentional focus (hedonic vs. healthy) and BMI (healthy-weight vs. obese) on brain responses to visual food stimuli. The three main findings of our study are: (1) caloric content and palatability do not significantly affect the level of brain activity, nor is this effect moderated by BMI. So, the level of brain activity is not proportionate to the reward value of the presented visual food stimuli, either defined as caloric value or as palatability, and people with obesity do not show significantly higher brain activity in response to high caloric palatable foods. (2) Brain activity was higher in the hedonic attentional focus than in the health and neutral attentional focus in several regions of the mesocorticolimbic system, independent of food palatability and caloric content. (3) Palatability and caloric content can be decoded above chance from patterns of brain activity located in several occipital and frontal brain regions. Notably, decoding accuracies of palatability and caloric content were not significantly affected by either BMI or attentional focus.

The present study shows that while viewing visual food stimuli, the level of brain activity is not proportionate to the reward value of food, as the level of brain activity did not differ significantly between palatable versus unpalatable foods or between high versus low caloric foods, across both people with a healthy weight and people with obesity. Repeating the analysis using a more lenient uncorrected threshold (cluster defining threshold: \( p < 0.001 \), cluster size threshold: \( > 10 \) voxels) yielded the same results except for a small cluster of voxels located in the insula for the contrast palatable-unpalatable (10 voxels, see Tables 1 and 2 in the Supplementary material). Furthermore, Bayesian analyses provided only weak and very limited evidence for the alternative hypothesis for both the main effect of palatability and the palatability \times BMI interaction. Overall, considering the lack of significant effects in the mass-univariate frequentist analyses, which is corrected for multiple testing, and the only weak and limited evidence in the Bayesian analyses (no correction for multiple testing), it seems fair to conclude that the level of activity in the brain is not different for palatable versus unpalatable foods, not even, or specifically, for people with obesity.

These findings are in line with earlier work (Chikazoe et al., 2014a; Suzuki et al., 2017), which similarly observed that stimulus valence was not associated with a significant differential level of brain activity. Furthermore, the present findings are inconsistent with the theory claiming that food-related reward value is associated with increased activity in the mesocorticolimbic system, specifically for people with obesity (Berthoud, 2012; Haahr et al., 2012; LaBar et al., 2001; Leigh & Morris, 2018; Schulte et al., 2016; Volkow et al., 2011, 2013; Zhang et al., 2015).

The current findings add to a large set of diverse and inconsistent research findings pertaining to brain responses to visual food stimuli in people with overweight versus people with healthy-weight (Morss et al., 2020; Ziauddeen et al., 2012). Whereas some studies did find that obesity is associated with increased brain activity in response to visual high caloric food stimuli (e.g., Batterink et al., 2010; Makaronidis & Batterham, 2018; Rothemund et al., 2007; Stice et al., 2008; Stoeckel et al., 2008), other studies found no differences (e.g., Boswell & Kober, 2016; Doornweerd et al., 2018; García-García et al., 2013; Morss et al., 2006), both across attentional foci (see Fig. 6), and for each attention focus separately (see Supplementary material, Figs. 4–6).

We also tested if decoding accuracy for caloric content and palatability differed between attentional foci. The analyses show that palatability and caloric content could be significantly decoded above chance in several occipital and frontal brain regions across attentional foci (see Tables 9 and 10). We did not observe significant differences in decoding accuracies between attentional foci (hedonic, health, neutral) and BMI-group (healthy-weight vs. obese). No significant correlation between dietary restraint and decoding accuracy was observed.
or found the opposite (e.g., Davids et al., 2010; Gautier et al., 2001; Han & Glenn, 2018; J. E. Han et al., 2018; Heni et al., 2014; van der Laan et al., 2011). Moreover, research findings do not consistently show that brain responses are proportionate to the palatability or caloric content of foods either, with some studies supporting this idea (e.g., Kahnt et al., 2014; Pfabigan et al., 2014; Pujol et al., 2018; Siep et al., 2009; Suzuki et al., 2017), whereas others do not (e.g., Frank et al., 2010; Killgore et al., 2003; LaBar et al., 2001; Martin et al., 2010; Rothemund et al., 2007). So, the level of brain activity as elicited by visual food stimuli might not be so informative regarding the neural representation of reward value or for understanding differences between people with a healthy weight versus overweight.

Note that the sample size in many previous studies was rather low, ranging from 9 to 16 participants per group (e.g., Beaver et al., 2006; Benedict et al., 2012; Bohon & Stice, 2012; Martin et al., 2010; Oltmanns et al., 2012; Page et al., 2011; Porubská et al., 2006; Rolls & McCabe, 2018; Murdaugh et al., 2012), or found the opposite (e.g., Davids et al., 2010; Gautier et al., 2001; Han & Glenn, 2018; J. E. Han et al., 2018; Heni et al., 2014; van der Laan et al., 2011). Moreover, research findings do not consistently show that brain responses are proportionate to the palatability or caloric content of foods either, with some studies supporting this idea (e.g., Kahnt et al., 2014; Pfabigan et al., 2014; Pujol et al., 2018; Siep et al., 2009; Suzuki et al., 2017), whereas others do not (e.g., Frank et al., 2010; Killgore et al., 2003; LaBar et al., 2001; Martin et al., 2010; Rothemund et al., 2007). So, the level of brain activity as elicited by visual food stimuli might not be so informative regarding the neural representation of reward value or for understanding differences between people with a healthy weight versus overweight.

Note that the sample size in many previous studies was rather low, ranging from 9 to 16 participants per group (e.g., Beaver et al., 2006; Benedict et al., 2012; Bohon & Stice, 2012; Martin et al., 2010; Oltmanns et al., 2012; Page et al., 2011; Porubská et al., 2006; Rolls & McCabe, 2018; Murdaugh et al., 2012), or found the opposite (e.g., Davids et al., 2010; Gautier et al., 2001; Han & Glenn, 2018; J. E. Han et al., 2018; Heni et al., 2014; van der Laan et al., 2011). Moreover, research findings do not consistently show that brain responses are proportionate to the palatability or caloric content of foods either, with some studies supporting this idea (e.g., Kahnt et al., 2014; Pfabigan et al., 2014; Pujol et al., 2018; Siep et al., 2009; Suzuki et al., 2017), whereas others do not (e.g., Frank et al., 2010; Killgore et al., 2003; LaBar et al., 2001; Martin et al., 2010; Rothemund et al., 2007). So, the level of brain activity as elicited by visual food stimuli might not be so informative regarding the neural representation of reward value or for understanding differences between people with a healthy weight versus overweight.

Note that the sample size in many previous studies was rather low, ranging from 9 to 16 participants per group (e.g., Beaver et al., 2006; Benedict et al., 2012; Bohon & Stice, 2012; Martin et al., 2010; Oltmanns et al., 2012; Page et al., 2011; Porubská et al., 2006; Rolls & McCabe, 2018; Murdaugh et al., 2012), or found the opposite (e.g., Davids et al., 2010; Gautier et al., 2001; Han & Glenn, 2018; J. E. Han et al., 2018; Heni et al., 2014; van der Laan et al., 2011). Moreover, research findings do not consistently show that brain responses are proportionate to the palatability or caloric content of foods either, with some studies supporting this idea (e.g., Kahnt et al., 2014; Pfabigan et al., 2014; Pujol et al., 2018; Siep et al., 2009; Suzuki et al., 2017), whereas others do not (e.g., Frank et al., 2010; Killgore et al., 2003; LaBar et al., 2001; Martin et al., 2010; Rothemund et al., 2007). So, the level of brain activity as elicited by visual food stimuli might not be so informative regarding the neural representation of reward value or for understanding differences between people with a healthy weight versus overweight.

Note that the sample size in many previous studies was rather low, ranging from 9 to 16 participants per group (e.g., Beaver et al., 2006; Benedict et al., 2012; Bohon & Stice, 2012; Martin et al., 2010; Oltmanns et al., 2012; Page et al., 2011; Porubská et al., 2006; Rolls & McCabe, 2018; Murdaugh et al., 2012), or found the opposite (e.g., Davids et al., 2010; Gautier et al., 2001; Han & Glenn, 2018; J. E. Han et al., 2018; Heni et al., 2014; van der Laan et al., 2011). Moreover, research findings do not consistently show that brain responses are proportionate to the palatability or caloric content of foods either, with some studies supporting this idea (e.g., Kahnt et al., 2014; Pfabigan et al., 2014; Pujol et al., 2018; Siep et al., 2009; Suzuki et al., 2017), whereas others do not (e.g., Frank et al., 2010; Killgore et al., 2003; LaBar et al., 2001; Martin et al., 2010; Rothemund et al., 2007). So, the level of brain activity as elicited by visual food stimuli might not be so informative regarding the neural representation of reward value or for understanding differences between people with a healthy weight versus overweight.

Note that the sample size in many previous studies was rather low, ranging from 9 to 16 participants per group (e.g., Beaver et al., 2006; Benedict et al., 2012; Bohon & Stice, 2012; Martin et al., 2010; Oltmanns et al., 2012; Page et al., 2011; Porubská et al., 2006; Rolls & McCabe, 2018; Murdaugh et al., 2012), or found the opposite (e.g., Davids et al., 2010; Gautier et al., 2001; Han & Glenn, 2018; J. E. Han et al., 2018; Heni et al., 2014; van der Laan et al., 2011). Moreover, research findings do not consistently show that brain responses are proportionate to the palatability or caloric content of foods either, with some studies supporting this idea (e.g., Kahnt et al., 2014; Pfabigan et al., 2014; Pujol et al., 2018; Siep et al., 2009; Suzuki et al., 2017), whereas others do not (e.g., Frank et al., 2010; Killgore et al., 2003; LaBar et al., 2001; Martin et al., 2010; Rothemund et al., 2007). So, the level of brain activity as elicited by visual food stimuli might not be so informative regarding the neural representation of reward value or for understanding differences between people with a healthy weight versus overweight.
used a rather lenient multiple comparison correction, cluster extent threshold $p < 0.001$ uncorrected, with a high risk of false positives (e.g., Dimitropoulos et al., 2012; Eklund et al., 2016; Franssen et al., 2020; Gautier et al., 2001; Heni et al., 2014; Martin et al., 2016; Nummenmaa et al., 2012; Otman et al., 2012; Scharmüller et al., 2012). Moreover, most previous studies did not distinguish between palatable and unpalatable food stimuli, and did not tailor to the participants’ taste preferences (Born et al., 2010; Dimitropoulos et al., 2012; Ely et al., 2014; Ho et al., 2012; Lawrence et al., 2012; Luo et al., 2013; Murdaugh et al., 2012; Passamonti et al., 2009; Scharmüller et al., 2012; Schur et al., 2009; Tryon et al., 2013). Instead, most previous studies used standard sets of high caloric food stimuli (e.g., chocolate, chips, hamburger), which were typically compared to neutral non-food stimuli (for a review, see Pursey et al., 2014). As both positive and negative valence can make stimuli salient (Cooper & Knutson, 2008; Kahnt et al., 2014; Litt et al., 2011; Ogawa & Suzuki, 2004; Plassmann et al., 2010), these previous studies therefore could not disentangle valence from salience. Thus, brain activity in response to high caloric food stimuli observed in the previous studies may be driven mostly by salience, not valence.

The current study found that the level of brain activity – spread across the mesocorticolimbic system – was significantly higher in the hedonic attentional focus as compared to both the health and the neutral attentional focus, independently of food palatability and caloric content. Notably, these findings closely replicate and extend the findings from two recent studies (Franssen et al., 2020; Kochs et al., 2022). That is, these studies similarly found no significant difference in the level of brain activity (mass-univariate analysis) between palatable and unpalatable food stimuli (Franssen et al., 2020), between high caloric and low caloric foods (Kochs et al., 2022), and also found specifically increased brain activity in the hedonic attentional focus compared to the neutral (Franssen et al., 2020) and health and neutral attentional foci (Kochs et al., 2022). The current study extends the findings of Franssen and colleagues (2020) by showing no significant difference in the level of brain response between high and low caloric foods and between people with obesity versus a healthy weight. Importantly, this main effect of attentional focus cannot be explained by differences in cognitive demand between the three attentional foci (hedonic, health, and neutral). Though response latencies in the neutral focus were significantly shorter than in the hedonic and health focus, this difference in response latencies was not observed between the hedonic and the health focus, whereas brain activity in the hedonic attentional focus was greater compared to both the neutral and the health focus.

Taken together, the results of the mass-univariate analyses of the current study are in line with theories stating that the level of brain activity in response to food stimuli reflects the motivational salience (either positive or negative) rather than the reward value of these food stimuli (Chikazoe et al., 2014b; Roefs et al., 2015, 2018; Suzuki et al., 2017). More specifically, brain activity in the dopaminergic mesocorticolimbic system is considered to reflect motivational salience (Salamone & Correa, 2012). This interpretation is supported in two ways: (1) lack of evidence for brain activity to be proportionate to reward value, either defined by palatability or by caloric content (see also: Chikazoe et al., 2014; Kahnt et al., 2014; Pfäbigan et al., 2014; Pujol et al., 2018; Suzuki et al., 2017), and (2) specifically increased brain activity in the hedonic focus condition. Arguably, shifting people’s attention to the taste, highlights the foods’ salience. So, it seems that when viewing food with a focus on taste, properties reflecting motivational salience are emphasized as compared to non-indulgent properties linked to caloric content and color.

Using multivariate analyses, this study clearly showed that both food caloric content and palatability could be decoded above chance from patterns of brain activity in several occipital and frontal brain regions, replicating previous findings (Chikazoe et al., 2014; Suzuki et al., 2017; Franssen et al., 2020; Kochs et al., 2022). So, food reward value, either defined by caloric content or palatability, seems not reflected in the level of brain activity, but is represented in multivoxel patterns of brain activity. Notably, these MVPA results are unlikely to be explained by differences in visual features between the categories of the presented food stimuli (HC+, HC-, LC+, LC-), as each participant viewed a different set of stimuli, tailored to her individual preferences, and food stimuli were

**Fig. 5.** Bayes Factors distribution assessing Palatability × BMI interaction in each ROIs (A–D). Values in the x axis were rescaled to log10 for visualization purposes.
rated as visually rather dissimilar, with the within-category similarity only slightly higher than the between-category similarity.

Unexpectedly, the decoding accuracy of palatability and caloric content was not affected by either attentional focus or BMI, which is not in line with an earlier study (Franssen et al., 2020). That is, Franssen and colleagues (2020) found seven brain regions (fusiform gyrus, superior frontal gyrus, Inferior frontal gyrus, inferior parietal lobule, insula/putamen, middle frontal gyrus, precuneus) in which palatability could be decoded significantly better, and above chance, in the hedonic attentional focus as compared to the neutral attentional focus. Note that the sample size in Franssen et al. (2020) was smaller (23 overweight participants), and a more lenient correction method was used for the between-attentional foci comparison ($p < 0.001$, uncorrected).

Taken together, the current study showed that the level of brain activity is not proportionate to the palatability and caloric content of the presented food stimuli and is not affected by BMI. Instead, the level of brain activity depends strongly on attentional focus and is generally largest with a hedonic attentional focus. So, brain responses to the exact same food stimuli vary according to the induced attentional focus and are not significantly moderated by BMI. These findings suggest that the level of brain activity does not reflect food reward value (i.e., palatability and caloric content), but appears to reflect motivational salience. In addition, our study clearly showed the importance of performing both univariate and multivariate analyses (MVPA) on fMRI data. Whereas univariate analyses of fMRI data are only informative regarding the involvement of certain brain regions in certain tasks, multi-voxel pattern analysis (MVPA) of fMRI data decodes representational content in the brain (Haxby et al., 2001; Norman et al., 2006). Specifically for this study, the univariate analyses showed that the involvement of several brain regions crucially depended on attentional focus, and was not affected by either food palatability or caloric content. Multivariate analyses showed that value of stimuli – food palatability and caloric content – could be decoded above chance from multivoxel patterns of brain activity. Future research may extend these findings to male participants to increase the generalizability of our findings. As was done in our study, future studies are advised to implement tight control of participants’ mental processes, permitting clearer conclusions from neuroimaging results, and avoid falling into the trap of reverse inference.

Fig. 6. Multivariate analysis, clusters with decoding accuracy significantly above chance ($p < 0.05$, FDR corrected) across all participants ($n = 61$). Panel A: decoding caloric content (across attentional foci). Panel B: decoding palatability (across attentional foci). Visualization was made using FreeSurfer (https://surfer.nmr.mgh.harvard.edu/) and Surfice (https://www.nitrc.org/projects/surfice/).
Institute.

Kriegeskorte et al., 2008; Popal et al., 2019) could be implemented to

L. Pimpini et al.

Anterior Cingulate L 9

Inferior Frontal R 22 32 -66 -30 51.16

Medial Frontal L 11 -10 -72 -28 51.03

Gyrus/Superior Frontal Gyrus

5 Insula L 67

4 Inferior Frontal

2 Superior Frontal Gyrus

3 Middle Frontal

1 Inferior Frontal

Gyrus/Superior Frontal Gyrus

2 Anterior Cingulate L 9

1 Superior Frontal Gyrus

Table 9
Food decision making brain regions with decoding accuracy significantly greater than chance (p < 0.05, FDR corrected) for decoding caloric content; H = hemisphere, L = left, R = right, B = Bilateral, MNI = Montreal Neurological Institute.

| Cluster | Brain region | H | Cluster size | Peak coordinates (MNI) | Percentage of accuracy |
|---------|--------------|---|--------------|------------------------|-----------------------|
| 1       | Superior Frontal Gyrus | R | 16 | 40 -70 -36 | 51.29 |
| 2       | Middle Frontal Gyrus | L | 40 | -26 -62 -34 | 51.30 |
| 3       | Anterior Cingulate Inferior Frontal Gyrus | R | 22 | 32 -66 -30 | 51.16 |
| 4       | Inferior Frontal Gyrus | L | 22 | -22 -78 -26 | 51.29 |
| 5       | Insula | L | 11 | -10 -72 -28 | 51.03 |
| 6       | Medial Frontal Gyrus | L | 14 | -54 6 -22 | 51.26 |
| 7       | Anterior Cingulate Gyrus | R | 86 | 56 -22 -20 | 51.66 |
| 8       | Middle Frontal Gyrus | B | 18385 | -10 -96 0 | 59.38 |
| 9       | Inferior Frontal Gyrus | L | 5 | -54 4 -8 | 51.28 |
| 10      | Insula | R | 28 | 36 22 0 | 51.44 |
| 11      | Superior Frontal Gyrus | L | 86 | -36 42 8 | 51.31 |
| 12      | Medial Frontal Gyrus | L | 35 | -58 -32 6 | 5.14 |
| 13      | Middle Frontal Gyrus | L | 65 | -6 42 8 | 51.75 |
| 14      | Medial Frontal Gyrus | R | 30 | 52 34 6 | 51.45 |
| 15      | Inferior Frontal Gyrus | R | 39 | 42 44 10 | 51.07 |
| 16      | Superior Frontal Gyrus | R | 277 | 26 60 14 | 52.08 |
| 17      | Anterior Cingulate Gyrus | L | 9 | -32 60 12 | 51.06 |
| 18      | Medial Frontal Gyrus | R | 59 | 52 4 18 | 51.50 |
| 19      | Insula | L | 76 | -14 60 18 | 51.31 |
| 20      | Medial Frontal Gyrus | B | 364 | 0 48 28 | 51.92 |
| 21      | Insula | L | 18 | -20 56 20 | 51.31 |
| 22      | Medial Frontal Gyrus | R | 12 | -46 54 20 | 51.09 |
| 23      | Anterior Cingulate Gyrus | R | 28 | 50 8 34 | 51.35 |
| 24      | Middle Frontal Gyrus | R | 192 | 28 34 42 | 51.72 |
| 25      | Anterior Cingulate Gyrus | L | 24 | -56 -26 32 | 51.23 |
| 26      | Middle Frontal Gyrus | R | 27 | 10 28 38 | 51.77 |
| 27      | Cingulate Gyrus | R | 25 | 6 36 40 | 51.28 |
| 28      | Medial Frontal Gyrus | L | 34 | -38 14 40 | 51.35 |
| 29      | Superior Frontal Gyrus | L | 5 | -26 20 42 | 50.93 |
| 30      | Medial Frontal Gyrus | L | 12 | -22 26 42 | 51.23 |
| 31      | Anterior Cingulate Gyrus | L | 103 | 28 8 58 | 52.08 |
| 32      | Medial Frontal Gyrus | L | 34 | -10 30 54 | 51.54 |
| 33      | Medial Frontal Gyrus | L | 12 | -22 22 -56 | 51.42 |
| 34      | Superior Frontal Gyrus | L | 182 | 10 -50 2 | 52.13 |

Finally, event-related designs (D’Esposito et al., 1999; Dale, 1999), and Representational Similarity Analysis (RSA) (Carota et al., 2017; Kriegeskorte et al., 2008; Popal et al., 2019) could be implemented to investigate in a more detailed way how the brain represents various characteristics of food. Of note as well is that whereas people with overweight and/or obesity all share a high BMI (e.g., Hill, 2006; Roefs et al., 2015; 2018; Webber, 2003), they may have otherwise less in
common than is often assumed. Possibly, increased brain activity in response to (high-caloric) palatable foods contributes to a positive energy balance only in a subgroup of people with overweight and/or obesity. Therefore, obesity research may benefit from a more person-alized approach (e.g., El-Sayed Moustafa & Froguel, 2013).

Data and scripts availability

Unthresholded statistical maps of the univariate analysis and searchlight classification accuracy maps are available on NeuroVault: https://neurovault.org/collections/ZTUMGZWH/.

The scanning protocol, analyses scripts and additional figures are available on OSF: https://osf.io/5rjxs/?view_only.

Appendix A. Supplementary data

fmRI raw data are available, from the corresponding author, upon reasonable request.

Author contributions

Anne R. obtained the funding for the study; L.P., S.F., S.K., and Anne R. designed the study; Alard R. advised on the fMRI sequence, L.P. and S. K. collected the data. L.P., S.F.S.K., G.V. and J.H. analyzed the data. L.P. and Anne R. wrote the manuscript. All authors gave feedback on the manuscript and approved the final version.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Data will be made available on request.

Acknowledgements

We thank Giuseppe Marruzzo (PhD candidate at the Department of Cognitive Neuroscience, Faculty of Psychology and Neuroscience, Maastricht University) for his help with the analyses. This study was financed by a VIDI grant of the Dutch Research Council (NWO) (452.16.007) awarded to Prof. dr. Anne Roefs. AL. designed the study; ALard R. advised on the fMRI sequence, L.P. and S. F. and S. K. obtained the funding for the study; L.P., S.F., S.K., and Anne R. wrote the manuscript. All authors gave feedback on the manuscript and approved the final version.

References

Batterink, L., Yokum, S., & Stice, E. (2010). Body mass correlates inversely with obesity. Therefore, obesity research may benefit from a more person-alized approach (e.g., El-Sayed Moustafa & Froguel, 2013).

References

Batterink, L., Yokum, S., & Stice, E. (2010). Body mass correlates inversely with obesity. Therefore, obesity research may benefit from a more person-alized approach (e.g., El-Sayed Moustafa & Froguel, 2013).

References
Ely, A. V., Childress, A. R., Jagannathan, K., & Lowe, M. R. (2014). Differential reward response to palatable food cues in past and current dieters: A fMRI study. Obesity, 22 (10), 238-245. https://doi.org/10.1038/oby.2014.123

Etzel, J. A., Zacks, J. M., & Braver, T. S. (2013). Searchlight analysis: Promise, pitfalls, and potential. NeuroImage, 78, 261–269. https://doi.org/10.1016/j.neuroimage.2013.05.047

Feinberg, D. A., Moeller, S., Smith, S. M., Auerbach, E., Ramanna, S., Glasser, M. F., Miller, K. L., Ugurbil, K., & Yacoub, E. (2010). Multiscale echo planar imaging for sub-second whole brain fMRI and fast diffusion imaging. PLoS One, 5(12), https://doi.org/10.1371/journal.pone.0015710

Frank, T. C., Kim, G. L., Krzemien, A., & Tobler, P. N. (2014). Disentangling neural correlates of dietary self-control in healthy adults: A meta-analysis of functional connectivity data. Cerebral Cortex, 178(13), 2017–2028. https://doi.org/10.1093/cercor/bht227

Feinberg, D. A., Moeller, S., Smith, S. M., Auerbach, E., Ramanna, S., Glasser, M. F., Miller, K. L., Ugurbil, K., & Yacoub, E. (2010). Multiscale echo planar imaging for sub-second whole brain fMRI and fast diffusion imaging. PLoS One, 5(12), https://doi.org/10.1371/journal.pone.0015710

Frank, T. C., Kim, G. L., Krzemien, A., & Tobler, P. N. (2014). Disentangling neural correlates of dietary self-control in healthy adults: A meta-analysis of functional connectivity data. Cerebral Cortex, 178(13), 2017–2028. https://doi.org/10.1093/cercor/bht227

Feinberg, D. A., Moeller, S., Smith, S. M., Auerbach, E., Ramanna, S., Glasser, M. F., Miller, K. L., Ugurbil, K., & Yacoub, E. (2010). Multiscale echo planar imaging for sub-second whole brain fMRI and fast diffusion imaging. PLoS One, 5(12), https://doi.org/10.1371/journal.pone.0015710

Frank, T. C., Kim, G. L., Krzemien, A., & Tobler, P. N. (2014). Disentangling neural correlates of dietary self-control in healthy adults: A meta-analysis of functional connectivity data. Cerebral Cortex, 178(13), 2017–2028. https://doi.org/10.1093/cercor/bht227

Feinberg, D. A., Moeller, S., Smith, S. M., Auerbach, E., Ramanna, S., Glasser, M. F., Miller, K. L., Ugurbil, K., & Yacoub, E. (2010). Multiscale echo planar imaging for sub-second whole brain fMRI and fast diffusion imaging. PLoS One, 5(12), https://doi.org/10.1371/journal.pone.0015710

Frank, T. C., Kim, G. L., Krzemien, A., & Tobler, P. N. (2014). Disentangling neural correlates of dietary self-control in healthy adults: A meta-analysis of functional connectivity data. Cerebral Cortex, 178(13), 2017–2028. https://doi.org/10.1093/cercor/bht227

Feinberg, D. A., Moeller, S., Smith, S. M., Auerbach, E., Ramanna, S., Glasser, M. F., Miller, K. L., Ugurbil, K., & Yacoub, E. (2010). Multiscale echo planar imaging for sub-second whole brain fMRI and fast diffusion imaging. PLoS One, 5(12), https://doi.org/10.1371/journal.pone.0015710

Frank, T. C., Kim, G. L., Krzemien, A., & Tobler, P. N. (2014). Disentangling neural correlates of dietary self-control in healthy adults: A meta-analysis of functional connectivity data. Cerebral Cortex, 178(13), 2017–2028. https://doi.org/10.1093/cercor/bht227

Feinberg, D. A., Moeller, S., Smith, S. M., Auerbach, E., Ramanna, S., Glasser, M. F., Miller, K. L., Ugurbil, K., & Yacoub, E. (2010). Multiscale echo planar imaging for sub-second whole brain fMRI and fast diffusion imaging. PLoS One, 5(12), https://doi.org/10.1371/journal.pone.0015710

Feinberg, D. A., Moeller, S., Smith, S. M., Auerbach, E., Ramanna, S., Glasser, M. F., Miller, K. L., Ugurbil, K., & Yacoub, E. (2010). Multiscale echo planar imaging for sub-second whole brain fMRI and fast diffusion imaging. PLoS One, 5(12), https://doi.org/10.1371/journal.pone.0015710

Feinberg, D. A., Moeller, S., Smith, S. M., Auerbach, E., Ramanna, S., Glasser, M. F., Miller, K. L., Ugurbil, K., & Yacoub, E. (2010). Multiscale echo planar imaging for sub-second whole brain fMRI and fast diffusion imaging. PLoS One, 5(12), https://doi.org/10.1371/journal.pone.0015710

Feinberg, D. A., Moeller, S., Smith, S. M., Auerbach, E., Ramanna, S., Glasser, M. F., Miller, K. L., Ugurbil, K., & Yacoub, E. (2010). Multiscale echo planar imaging for sub-second whole brain fMRI and fast diffusion imaging. PLoS One, 5(12), https://doi.org/10.1371/journal.pone.0015710
Volkow, N. D., & Wise, R. A. (2005). How can drug addiction help us understand obesity? *Nature Neuroscience, 8*(5), 555–560. https://doi.org/10.1038/nn1452

Wadden, T. A., Brownell, K. D., & Foster, G. D. (2002). Obesity: Responding to the global epidemic. *Journal of Consulting and Clinical Psychology, 70*(3), 510–525. https://doi.org/10.1037/0022-006X.70.3.510

Wang, Z., Childress, A. R., Wang, J., & Detre, J. A. (2007). Support vector machine learning-based fMRI data group analysis. *NeuroImage, 36*(4), 1139–1151. https://doi.org/10.1016/j.neuroimage.2007.03.072

Weiskopf, N., Hutton, C., Josephs, O., Turner, R., & Deichmann, R. (2007). Optimized EPI for fMRI studies of the orbitofrontal cortex: Compensation of susceptibility-induced gradients in the readout direction. *Magnetic Resonance Materials in Physics, Biology and Medicine, 20*(1), 39–49. https://doi.org/10.1007/s10334-006-0067-6

Yan, C., Su, L., Wang, Y., Xu, T., Yin, D. Z., Fan, M. X., Deng, C. P., Hu, Y., Wang, Z. X., Cheung, E. F. C., Lim, K. O., & Chan, R. C. K. (2016). Multivariate neural representations of value during reward anticipation and consummation in the human orbitofrontal cortex. *Scientific Reports, 6*(June), 1–12. https://doi.org/10.1038/srep29079

Yokum, S., Ng, J., & Stice, E. (2011a). Attentional bias to food images associated with elevated weight and future weight gain: An fMRI study. *Obesity, 19*(9), 1775–1783. https://doi.org/10.1038/oby.2011.168

Zhang, B., Tian, D., Yu, C., Zhang, J., Tian, X., von Deneen, K. M., Zang, Y., Walter, M., & Liu, Y. (2015). Altered baseline brain activities before food intake in obese men: A resting state fMRI study. *Neuroscience Letters, 584*, 156–161. https://doi.org/10.1016/j.neulet.2014.10.020

Ziaudddeen, H., Farooqi, I. S., & Fletcher, P. C. (2012). Obesity and the brain: How convincing is the addiction model? *Nature Reviews Neuroscience, 13*(4), 279–286. https://doi.org/10.1038/nrn3212