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Investigation of eye tracking, electrodermal activity and facial expressions as biometric signatures of food reward and intake in normal weight adults

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ABSTRACT

Pervasive exposure to a vast and varied food repertoire has contributed to the obesity epidemic. Within this issue, there is a need for a better understanding of the psychophysiological responses to food cues that precede food choice and food intake to establish how these responses contribute to the link between food availability and increasing obesity levels. Biometric measures such as eye tracking, electrodermal activity and facial expressions may separately or collectively provide deeper insight into psychophysiological processes underlying food reward and food intake. We examined how biometric responses differed in foods varying in fat and taste and explored how these biometric signatures to food cues were related to food preference behaviours, food choice, and food intake. We developed and tested a biometric food preference task designed to concurrently assess biometric responses (eye tracking, electrodermal activity and facial expressions) and food reward to visual food stimuli from different food categories in 100 normal weight adults. Food intake and selection was examined using a simultaneous choice ad libitum buffet. The results from this cross-sectional study showed significant differences in visual attention towards foods varying in fat content and taste prior to making rapid food choice decisions. Furthermore, the study found positive associations between maintained attention during a forced choice paradigm and subsequent food reward and food intake measures. Attention, arousal and facial expression during passive viewing were not associated with food reward or intake measures, except for an association between negative valence and explicit liking such that less liked foods elicited stronger negative facial expressions. The findings indicate that implicit, biometric responses to food cues predict both food reward and actual food intake.

1. Introduction

Food intake is an important regulator of energy balance that has evolved under pressures from a leptogenic environment (Berthoud et al., 2020). However, we are now living in an environment with an abundant food supply consisting of processed, energy dense and palatable foods that promote passive overeating (Berthoud et al., 2020; Hall et al., 2019; Prentice, 2001). This has led to an increased prevalence of obesity and made it difficult for individuals to reverse weight gain while remaining exposed to obesogenic cues in the environment (Berthoud et al., 2020). Assessing the psychophysiological responses to food cues that may influence food intake and food choices is therefore important to understand and prevent obesity and its related comorbidities. Food intake and food choices are determined by a complex interplay of homeostatic and

Abbreviations: AOI, area of interest; BMI, body mass index; SBFPT, Steno Biometric Food Preference Task; SCR, skin conductance response; VAS, visual analogue scale.

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hedonic processes (Berthoud et al., 2020). These processes consist of various cognitive, sensory, and metabolic factors such as sensory pleasure, metabolic hunger state, and knowledge about food (De Wijk et al., 2014). In an obesogenic environment with an abundant food supply, cognitive, sensory, hedonic, and emotional processes often take precedence over food choice decisions, making these non-homeostatic aspects an important field of research (Lee & Dixon, 2017).

Measuring hedonic aspects of appetite often involves methods that rely on self-report. These methods require cognitive information processing and reasoning (De Wijk et al., 2014) and are affected by factors such as social desirability. However, with an extensive number of food decisions each day, our choices and behaviour related to foods and food cues may largely be dependent on motivational processes that we are unaware of, unable or unwilling to articulate (De Wijk et al., 2014; Münzberg et al., 2016). These implicit aspects of motivation are more challenging to measure, and existing methodological approaches have relied on measuring reaction times, grip force, or the reinforcing value of food (Gibbons et al., 2019). However, technological advances in automated biometric systems that measure psychophysiological parameters, provide possibilities to look closer into some of the subtle implicit processes that may contribute to food reward and food intake.

An existing method to measure both explicit and implicit hedonic and motivational aspects of food reward is the Leeds Food Preference Questionnaire developed to examine the reward components, 'liking' and 'wanting' (Oustric et al., 2020). This computer task collects ratings, choices, and reaction times in response to visual food stimuli from different food categories (Dalton & Finlayson, 2014). However, results from the task still leave open questions as to why people respond as they do, and what psychophysiological processes are enabled before and during behavioural responses to food cues. This introduces a potential for biometric science within the study of appetite regulation and sensory science to give a deeper insight into the first and subconscious responses to different food cues. Biometrics are non-invasive behavioural and physiological measurements that may reflect motivational and affective responses towards foods. The basic premise for biometric techniques is that they can identify individuals' traits based on biological and physiological characteristics (Jain et al., 2011). Within food science and especially consumer science the application of biometrics has included heart rate, electroencephalography, electromyography, and the devices applied in this study, eye tracking, electrodermal activity, and automated facial expression analyses (Bell et al., 2018).

Eye tracking is used as a direct behavioural measure to examine the visual attention to one or several objects. In the assessment of food cue responsiveness in normal weight individuals, there is evidence for differences in both maintained and initial attention towards high and low calorie food images with higher attention towards high calorie foods (Castellanos et al., 2009; Doolan et al., 2014; Graham et al., 2011). Furthermore, studies have found a positive relationship with food liking (Wang et al., 2018) or craving (Werthmann et al., 2011), but not with food intake (Nijs et al., 2010; Werthmann et al., 2011). Electrodermal activity is used as a measure of psychophysiological arousal through autonomic nervous system activity. Only a limited number of studies have examined electrodermal activity in relation to food cues or food intake and these are inconsistent with regards to differences between food categories (Danner et al., 2014; De Wijk et al., 2014; Pallavicini et al., 2016; Samant & Seo, 2020; Verastegui-Tena et al., 2017) and associations with food reward (Danner et al., 2014; Samant & Seo, 2019). However, electrodermal activity has been shown to differ between high and low calorie foods and food cue stimuli (Pallavicini et al., 2016) and from negative to positive or neutral food images (Verastegui-Tena et al., 2017). Facial expression analyses are based on video analyses of individuals' faces that are related to emotions using machine learning algorithms (McDuff et al., 2016). A limited number of studies have examined the differences in facial responses to viewing, tasting or smelling foods (Danner et al., 2014; Gunaratne et al., 2019; He et al., 2017; Lee et al., 2018) or how they relate to food reward (Danner et al., 2014; De Wijk et al., 2014), and results are inconsistent. No studies were found to examine how electrodermal activity or facial expressions relate to food intake. As this implies, the available studies are limited, inconsistent, and difficult to compare. Nevertheless, to promote a healthier diet we must investigate the individual motives and responses behind food choice and food intake. This implies the need to combine implicit measures from biometrics with already established, validated methods to measure hedonic aspects of appetite. Biometric responses may help to explain subsequent behavioural responses to different categories of foods. In line with other research, we examined responses to visual food cues, which have been shown to be similar to real foods in predicting eating behaviour and weight gain (Boswell & Kober, 2016).

The overall aim of this cross-sectional study in normal weight adults was to develop and test a biometric food preference task to simultaneously assess several biometric responses and food reward to visual food stimuli from different food categories and to explore how these biometric responses relate to food preference behaviours and food intake. Specifically, our objectives were i) to assess differences in biometric responses (eye tracking, electrodermal activity, and facial expressions) to visual food stimuli from four food categories varying in fat content and sweet/savoury taste using a biometric food preference task; ii) to assess differences in food reward (implicit wanting and explicit liking) in response to visual food stimuli from these four food categories using the biometric food preference task; iii) to assess differences in intake of foods from these four food categories during an ad libitum buffet; and iv) to examine associations of biometric responses with food preferences and with actual food intake.

2. Methods

The study involved three parts: 1) we developed and validated a Danish food image database representing foods and food categories commonly encountered in the Danish culture (described in Supplementary material [SM]); 2) we developed the Steno Biometric Food Preference Task (SBFPT) based on a validated behavioural methodology including implicit and explicit responses to foods (Oustric et al., 2020); and 3) we conducted an experimental study in 100 normal weight adults to explore the biometric responses, food preference behaviours, and food intake, and the relationship between these variables.

2.1. Steno Biometric Food Preference Task

The biometric food preference task was designed in the software platform, iMotions 7.1. (iMotions A/S, Frederiksberg, Denmark), to concurrently collect biometric responses of eye tracking, electrodermal activity, and facial expressions to standardized food image stimuli (Fig. 1). The food stimuli shown in the images varied along two dimensions: fat content (low or high) and taste (sweet or savoury), creating a total of four food categories: high-fat sweet, high-fat savoury, low-fat sweet, and low-fat savoury. The validation and selection of food image stimuli is described in SM Methods, SM Table 1, and SM Table 2. Moreover, the food reward responses, explicit liking and implicit wanting, were assessed by integrating the procedures of the Leeds Food Preference Questionnaire (Oustric et al., 2020) into the platform.

The task consists of three parts (Fig. 1) with continuous measurements of eye tracking reflecting participants' attention, electrodermal activity reflecting event related changes in the participants arousal levels, and facial recordings reflecting the valence of participants' facial expressions. During the first part, participants were presented with a food image for 7000 ms, which allowed enough time to capture electrodermal responses (passive viewing; Fig. 1A) (Boucsein et al., 2012). After each image, participants were asked to explicitly rate their expected liking ("How pleasant would it be to taste this food now?") or wanting ("How much do you want some of this food now?") on a 100-point visual analogue scale (VAS) (Fig. 1B). Altogether, 32 passive viewings and ratings were completed – 16 ratings related to explicit

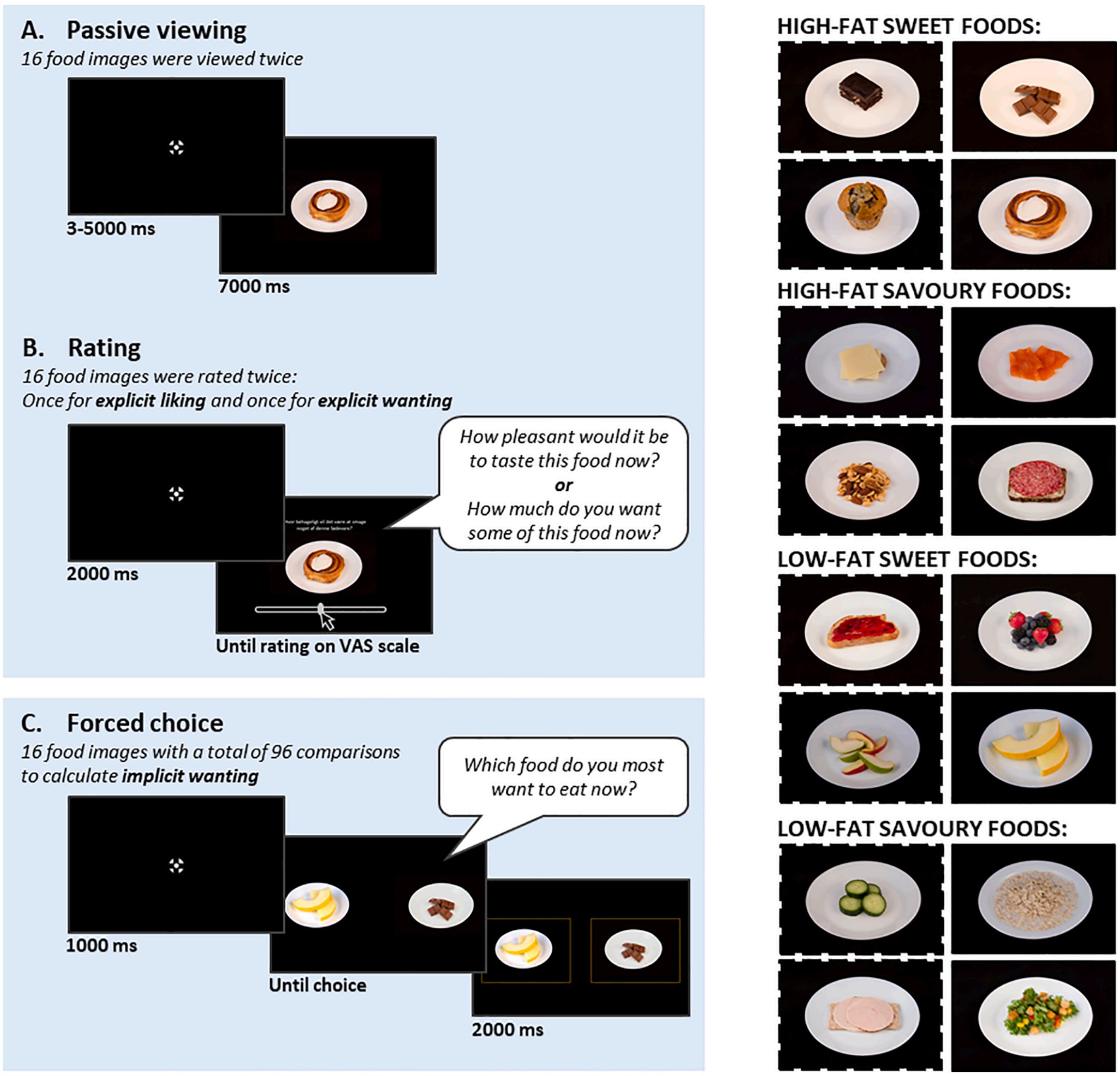

Fig. 1. Schematic presentation of the Steno Biometric Food Preference Task including the 16 food images selected for the task. The task consist of three parts: A) passive viewing of 16 food images viewed twice; B) rating of 16 food images according to explicit wanting and liking; and C) choosing between paired foods from different food categories with a total of 96 comparisons to calculate implicit wanting based on choices and reactions times. The food image shown in A) is subsequently rated in B) and thereafter a new image is viewed in A) and so forth in a random order. All 16 food images are first (viewed and) rated according to one food preference component (liking or wanting) and thereafter the other food preference component in a random order. The 16 food items are distributed into four combined food categories: high-fat sweet, high-fat savoury, low-fat sweet, and low-fat savoury. Food items with a dashed picture border were served in the ad libitum buffet. VAS, Visual analogue scale.

liking and 16 ratings related to explicit wanting. Before each passive viewing, participants were presented with a fixation target (Thaler et al., 2013) that varied randomly in exposure time (3000, 4000 or 5000 ms) to ensure that gaze was directed towards the centre of the screen and to make sure participants could not predict the exact onset of the next stimulus. Before rating, the participants were presented with a fixation target for 2000 ms to direct gaze to the centre of the screen. In the third part, using a forced choice methodology, participants had to choose between two food items ("Which food do you most want to eat now?") from different food categories (Fig. 1C). After each choice, the food images remained on screen for another 2000 ms for recording visual exploration of the food items using eye tracking. Choice and reaction times were measured for a total of 96 forced choices to calculate an implicit wanting score for each food category. Before each pair of food items, a fixation target was shown for 1000 ms.

2.2. Participants

Participants were 30- to 70-year-old men and women from the Greater Copenhagen area in Denmark with body mass index (BMI) in the normal weight range (18.5–24.9 kg/m^2). Exclusion criteria were allergies to any of the food items included in the ad libitum meal, self-reported history of eating disorders in the past three years, or self-reported weight change (>5 kg) within three months prior to inclusion. The study was conducted from October 2018 to August 2019 at Steno Diabetes Center Copenhagen, Gentofte, Denmark. One hundred ten people were screened for the study from whom 10 people were excluded due to screen failures. Out of the 100 participants included in the study, three were excluded from the analyses due to fainting or extreme nausea on the test day, or drinking coffee in the morning of the test day, leaving 97 participants for analysis. One participant did not complete the SBFPT due to technical issues but was kept in the analyses with the data that was available.

2.3. Study procedures

The study procedures are illustrated in SM Fig. 1. Participants arrived at the research facility at Steno Diabetes Center Copenhagen, Gentofte, Denmark in the morning between 7:30 and 9:00 after an 8-h overnight fast allowing only water. Inclusion and exclusion criteria presented above were assessed in combination with measures of anthropometry, haemoglobin A1c (HbA1c), blood pressure, heart rate, and questions concerning use of medication and family history of diabetes or cardiovascular disease. Before the SBFPT, participants were familiarized with the food items presented in the task. After the SBFPT, a dual-energy x-ray absorptiometry (DXA) scan (Discovery DXA System; Hologic, MA, USA) was performed to measure body composition. Lastly, participants were served an ad libitum buffet to measure food intake. Food was ingested over 25 min starting between 9:23 and 11:19 AM. Before and after the SBFPT and the ad libitum buffet, participants answered questions related to their subjective appetite sensations using a tablet with a 100-point VAS. All procedures conformed to the Declaration of Helsinki and were approved by the Ethics Committee of the Capital Region (H-18026293). All participants signed a written informed consent before taking part in the study. The study was exploratory in nature and registered with ClinicalTrials.gov (NCT03986619) with gaze duration bias as the primary outcome and other biometric measures as well as food reward and food intake as secondary outcomes.

2.4. Data collection and analyses

2.4.1. Anthropometry

Body weight was measured using an electronic scale (Tanita BWB-620A, Amsterdam, The Netherlands) to the nearest 0.1 kg and height was measured using a wall-mounted stadiometer (SECA, Vogel&Halke, Hamburg, Germany) to the nearest 1 mm. Body weight and height were used to calculate BMI (kg/m^2).

2.4.2. Biometric measures

The different hardware used to collect biometric data were all controlled and synchronized by iMotions software (iMotions 7.1, iMotions A/S, Frederiksberg, Denmark). The software was used to collect, postprocess, and analyse the raw time series of data. For every participant, each of the attentional, arousing, and emotional responses to 32 food images during the passive viewing of the SBFPT were grouped and averaged according to the four food categories: high-fat sweet, high-fat savoury, low-fat sweet, and low-fat savoury. A similar procedure was performed for the attentional responses to 96 choices during the forced choice of the SBFPT.

2.4.2.1. Attention. Eye movements were recorded with a Tobii Pro X2-60 screen-based eye tracker (Tobii, Stockholm, Sweden) with a sampling rate of 60 Hz. The food images were presented on a 24″ monitor with a screen resolution of 1920 × 1200 pixels. Before the task, participants completed a nine-point calibration procedure to ensure optimal eye tracking accuracy. The eye tracker uses near-infrared technologies to track and calculate gaze points, i.e. where participants are looking. Gaze points refer to raw samples captured by the eye tracker and are used to classify fixations using the I-VT Filter based on the speed of eye movements being lower than a velocity threshold of 30°/s (Komogortsev et al., 2010). To analyse eye tracking, the same sized and shaped area of interest (AOI) was defined to cover each food image in the software. Fixations within the AOIs were used to determine the time before looking and the time spent looking at each food. Eye tracking data

Table 1
Description of the biometric variables included in the analyses.

	Measured during	Description of variable
Eye tracking		
Fixation duration bias	Forced choice	Maintained attention calculated as the time spent fixating on a food as a proportion of the total time spent fixating at either food during an exposure*. Duration bias >0.5 reflects longer maintained attention to food within the category; 0.5 no bias; <0.5 reflects longer maintained attention to another food category.
Time to first fixation (ms)	Forced choice	The average time it took participants to direct their first fixation towards a food image*.
Total fixation duration (ms and %)	Forced choice (ms and %) Passive viewing (ms)	Maintained attention to a food image calculated as the absolute time (ms) or relative time (%) a participant spent looking at a food image*.
Fixation counts	Forced choice Passive viewing	Maintained attention calculated by counting the number of fixations within a food image AOI during a food image exposure*.
Duration of first visit (ms)	Passive viewing	Early maintenance of attention calculated as the duration of all fixations from the first visit on the food image until the eyes shifted away from the food to another place on the screen*.
Fixation counts of first visit (n)	Passive viewing	Early maintenance of attention reflected by the number of fixations during the first visit*.
Electrodermal activity		
Skin conductance response, SCR	Passive viewing	Binominal outcome reflecting whether a participant had a SCR during exposure to at least one food image in a food category (=1) or no SCR to a food category (=0). Threshold for SCR was 0.01 μS.
Sum of SCR amplitudes (μs)	Passive viewing	The magnitude of SCRs calculated as a sum of all SCR amplitudes to a food image*.
Average phasic response (μs)	Passive viewing	The average phasic response to a food image*.
Maximum phasic response (μs)	Passive viewing	The maximum phasic response to a food image*.
Facial expressions		
Negative valence (prob < −10%)	Passive viewing	The proportion of time below a likelihood threshold value of −10 out of the total food image exposure time*.
Positive valence (prob > 10%)	Passive viewing	The proportion of time above a likelihood threshold value of 10 out of the total food image exposure time*.
Minimum valence (prob)	Passive viewing	Calculated using a running mean throughout a food image exposure to find the continuous 10 samples (1/3 sec) where a participant expressed the highest likelihood for negative valence (=lowest value from −100 to 100)*.
Maximum valence (prob)	Passive viewing	Calculated using a running mean throughout a food image exposure to find the continuous 10 samples (1/3 sec) where a participant expressed the highest likelihood for positive valence (=highest value from −100 to 100)*.

AOI, area of interest; SCR, skin conductance response; prob, probability.
* averaged across all food images within a food category.

quality was calculated as valid data points collected in proportion to the maximum number of data points that could be collected. Stimuli with a quality below the 10th percentile were excluded from the study to correct for low trackability data from participants with glasses or droopy eye lids (Tobii, 2014). Low quality data equalled all stimuli with a quality <55% during passive viewing and <62% during forced choice. Four eye tracking variables during ratings and four during forced choice were used to assess each participant's objective visual attention to the four food categories (Table 1).

2.4.2.2. Arousal. Electrodermal activity was collected using a BIOPAC MP160 system (BioPac Systems, CA, USA) and disposable BIOPAC EL507 electrodes with isotonic gel attached to the plantar side of the participants' right foot. Signals were sampled at 500 Hz. Data were online band-pass filtered between 0.01 Hz and 1 Hz, and were subsequently analysed using the Continuous Decomposition Analysis (Benedek & Kaernbach, 2010) in the software Ledalab V3.4.9 (www.ledalab.de) to extract continuous phasic and tonic activity within a response window of 1–4 s. Two electrodermal activity variables describing the skin conductance responses (SCR) and two variables describing the general phasic response were chosen to assess each participant's arousal in response to food image stimuli (Table 1).

2.4.2.3. Facial expressions. The non-intrusive, automated facial action coding system, AFFDEX SDK 4.0 (Affectiva Inc., Waltham, USA) was implemented in the iMotions platform and used to analyse the facial expressions of participants. During exposure to food images, participants' faces were recorded using a webcam with a sampling rate of 30 frames per second. With the AFFDEX technology, a classifier algorithm (the Viola-Jones face detection algorithm (Viola & Jones, 2004)) was first used to detect the face via the webcam, followed by a detection of 34 landmarks within the face (e.g. eyebrows, eyes, nose, and mouth). Positions and movements of the landmarks were translated into facial actions (e.g. nose wrinkle or lip suck) using a classification algorithm (McDuff et al., 2016). Based on combinations of facial actions, scores of affective valence were derived (McDuff et al., 2016). The valence score is based on observed facial expressions that increase the likelihood of either a positive nature (smile and cheek raise) or negative nature (inner brow raise, brow furrow, nose wrinkle, upper lip raise, lip corner depressor, chin raise, lip press, and lip suck) of a participant's experience (Brand & Ulrich, 2019). Valence scores were expressed as a probability score from −100 to 100. A measure of 100 indicated a 100 percent likelihood of a positive experience, a measure of −100 indicated a 100 percent likelihood of a negative experience, and a measure of 0 indicated a neutral affect (Brand & Ulrich, 2019). From raw valence scores, four variables were derived describing the intensity and frequency of negative and positive valence during food image exposures (Table 1).

2.4.3. Food reward

Participants' subjective expectations of liking for the four food categories, subsequently described as explicit liking, were collected from ratings in the SBFPT. For each participant, explicit liking scores for the food items were grouped and averaged according to the four food categories ranging from 0 to 100. A low score indicated lower liking, whereas a high score indicated higher liking for a food category.

Implicit wanting for the four food categories was assessed during forced choice from choices and reaction times in the SBFPT. Implicit wanting was calculated as a composite score for one food category relative to the other categories. The score is based on frequency of choice, reaction time for chosen and non-chosen foods, and a mean reaction time using the following formula (Oustric et al., 2020):

$$\textit{Implicit wanting}: I_A = \sum_{i=1}^{Nchoice} \frac{\bar{t}}{t_i} - \sum_{j=1}^{Nnon-choice} \frac{\bar{t}}{t_j}$$

Formula legend: I_A = Implicit wanting for category A; N_{choice} = number of times category A was chosen; $N_{non\text{-}choice}$ = number of times category A was not chosen; $\bar{t}$ = mean of all reaction times.

A total score that was positive would indicate a more rapid preference for that food category compared to other food categories, whereas a negative score would indicate the opposite.

2.4.4. Food intake

In an ad libitum buffet, participants were served eight food items on separate plates. For practical reasons, only two of the four foods from each of the four food categories were presented in the buffet (Fig. 1). Certain criteria were set for selecting the two foods from each food category: they could represent the food category; they were available all seasons; and they were feasible to prepare uniformly in the Steno food laboratory kitchen. Participants were instructed to eat as much or as little as they wanted. Participants were eating alone in a room and instructed to stay in the room for 25 min until the researcher came to collect them. Throughout the ad libitum buffet, water was freely available. Each plate with foods was weighed before and after each meal to measure food intake (g) and calculate energy intake (kJ) of foods within each food category. For each participant, food intake (g) and energy intake (kJ) of each food was grouped and averaged according to the four food categories.

2.5. Statistical analyses

Statistical analyses were performed using R version 3.5.2 in Rstudio version 1.1.463 (Rstudio, Boston, MA, USA). All responses from biometrics, food reward and food/energy intake to food categories are reported as medians [interquartile range (IQR)]. We analysed between-group differences in food categories for all outcomes with linear mixed-effects models for the continuous outcomes and with generalised linear models for the binary responses (lmer and glmer functions from the lme4 Package version 1.1–21). Food categories were included as fixed effects and a participant-specific random intercept was included to account for the correlation of repeated measurements within participants.

Associations of biometric signatures as exposures with measures of food reward and food/energy intake as response were modelled using the same model as described above. The biometric variable as well as food category were included as fixed effects. Furthermore, an interaction term with food category and the biometric variable was first entered to assess the inter-dependency between a biometric response and a food category. However, no interactions were significant after testing for multiple comparisons, and the interaction term was therefore removed.

Visual inspection was used to assess normality of the model residuals and when necessary, the outcome variables were logarithmically transformed to obtain normally distributed model residuals. If it was not possible to obtain normality, the non-parametric Friedman test was used to compare food categories in analyses of between-group differences.

In case of significant results for both food category differences and association analyses, a post-hoc Benjamini-Hochberg procedure was used to control for multiple comparisons and the p-values with a false detection rate below 0.05 were marked (Benjamini & Hochberg, 1995). Statistical significance was determined by a two-sided $P < 0.05$.

3. Results

The food image stimuli used in the SBFPT were validated using online questionnaires, and results and characteristics of food images are summarised in SM Results and SM Table 3. Results from the experimental study is described below. Participant characteristics are summarized in Table 2 and the process for including and analysing participants is summarized in a flow diagram in SM Fig. 2.

Table 2
Participant characteristics (n = 97).

Women (n (%))	80 (82.5)
Age, years	63.3 [50.9, 66.0]
Weight, kg	63.3 (7.9)
BMI, kg/m^2	22.4 (1.5)
Education (%)	
Vocational/technical	4.1
Short	18.6
Medium	49.5
Long	25.8
Other	2.1
Occupation (%)	
Employed	52.6
Unemployed	6.2
Student	1.0
Retired	40.2

Data are presented as mean (SD) or median [Q1, Q3] unless otherwise stated. BMI, body mass index.

3.1. Biometric measures

3.1.1. Attentional responses

In the SBFPT there were significant between-group differences in the participants' attentional responses to the four food categories during both forced choice and passive viewing (Table 3 and Fig. 2). During forced choice, we found significant differences for maintained attention to the food categories after correcting for multiple comparisons. This was observed for all variables related to maintained attention: fixation duration bias, total fixation duration (ms and %), and fixation counts. During passive viewing there was a significant difference in participants' initial attention to the food categories when measuring fixation counts of first visit. During both parts of the test, participants directed most attention towards low-fat sweet and low-fat savoury foods and least attention towards high-fat sweet foods.

3.1.2. Arousal

Results for electrodermal responses (reflecting participants' arousal) to each food category during passive viewing in the SBFPT are summarized in Table 3 and Fig. 2 and display no differences between food categories. Between 66 and 71% of participants had at least one skin conductance response towards any of the food images within a category. There was a large interindividual variability in how many food image stimuli elicited a skin conductance response with a median [range] of 7 [0–28] skin conductance responses during the 32 passive viewing stimuli.

3.1.3. Facial expressions

Results on facial expressions are displayed in Table 3 and Fig. 2 with no significant differences between food categories. The level of positive valence was close to zero when averaging across all food images within a food category. Conversely, there was a higher level of negative valence considering both the intensity and frequency parameter.

3.2. Food reward and food intake

Results describing food reward and food intake are summarized in Table 4 and Fig. 2 and display significant differences between food categories. Food reward outcomes, explicit liking and implicit wanting, as well as food intake (g) showed the same pattern across food categories as the eye tracking and facial expressions: participants had numerically higher preferences for and intake of low-fat compared to high-fat foods. Energy intake was higher for high-fat compared to low-fat foods. Numerically, all food reward and food intake variables showed higher preferences for high-fat savoury foods compared to high-fat sweet foods and higher preferences for low-fat sweet foods compared to low-fat savoury foods. Participants had an average (SD) total food intake of 348 (136) g and energy intake of 2944 (1072) kJ.

Table 3
Biometric characteristics of food categories (n = 96).

	HFSA	HFSW	LFSA	LFSW	p value
Attention (forced choice)					
Fixation duration bias	0.50 [0.46, 0.54]	0.43 [0.38, 0.48]	0.51 [0.47, 0.56]	0.56 [0.52, 0.59]	<0.001[a]
Time to first fixation (ms) [#]	513 [447, 629]	505 [440, 611]	503 [456, 604]	509 [453, 593]	0.290
Total fixation duration (ms)	440 [294, 570]	379 [228, 522]	444 [315, 580]	454 [329, 604]	<0.001[a]
Total fixation duration (%)	25.1 [16.8, 31.1]	21.5 [14.7, 25.9]	26.5 [16.7, 32.6]	27.3 [18.7, 33.4]	<0.001[a]
Fixation counts (n)	2.0 [1.6, 2.5]	1.8 [1.4, 2.3]	2.1 [1.6, 2.5]	2.1 [1.6, 2.5]	<0.001[a]
Attention (passive viewing)					
Total fixation duration (ms)	4509 [3058, 5422]	4447 [2980, 5470]	4513 [2935, 5497]	4547 [2991, 5590]	0.404
Fixation counts	14.8 [11.6, 17.0]	14.8 [10.8, 17.0]	15.2 [11.1, 17.5]	14.8 [12.0, 17.5]	0.005
Duration of first visit (ms)	3985 [2414, 4999]	3717 [2273, 4916]	3617 [2383, 5076]	4080 [2358, 5029]	0.354
Fixation counts of first visit (n)	13.0 [9.9, 16.0]	11.9 [9.3, 15.6]	13.8 [10.3, 15.9]	13.3 [10.7, 16.7]	<0.001[a]
Arousal					
SCR (%)	63 (66)	68 (71)	66 (69)	65 (68)	0.701
Sum of SCR-amplitudes (μS) [#]	0.077 [0.000, 0.383]	0.077 [0.000, 0.428]	0.078 [0.000, 0.374]	0.037 [0.000, 0.353]	0.454
Average phasic response (μS) [ł]	0.020 [0.008, 0.059]	0.016 [0.008, 0.067]	0.015 [0.008, 0.059]	0.014 [0.008, 0.053]	0.244
Max phasic activity (μS) [ł]	0.090 [0.041, 0.211]	0.085 [0.042, 0.207]	0.096 [0.046, 0.249]	0.091 [0.039, 0.219]	0.711
Facial expressions					
Negative valence (prob < −10%) [#]	5.5 [0.0, 29.1]	4.1 [0.0, 25.0]	6.0 [0.0, 29.5]	6.8 [0.2, 26.0]	0.115
Positive valence (prob > 10%) [#]	0.0 [0.0, 0.0]	0.0 [0.0, 0.0]	0.0 [0.0, 0.0]	0.0 [0.0, 0.0]	0.164
Minimum valence [#]	−8.75 [−19.55, −0.30]	−6.70 [−21.52, −0.44]	−9.25 [−21.10, −1.01]	−10.51 [−19.93, −1.47]	0.335
Maximum valence [#]	0.00 [−0.06, 0.00]	0.00 [0.00, 0.00]	0.00 [−0.04, 0.00]	0.00 [−0.09, 0.00]	0.860

Biometric characteristics for each food category are expressed as median [Q1, Q3]. P values for between-group differences in food categories were modelled by linear mixed-effects models unless otherwise stated. HFSW, high-fat sweet; LFSW, low-fat sweet; HFSA, high-fat savoury; LFSA, low-fat savoury; SCR, skin conductance response; prob, probability.

[a] = p value with a false detection rate below 0.05 (Benjamini-Hochberg Procedure),

[ł] = log-transformed outcome,

[#] = Friedman test.

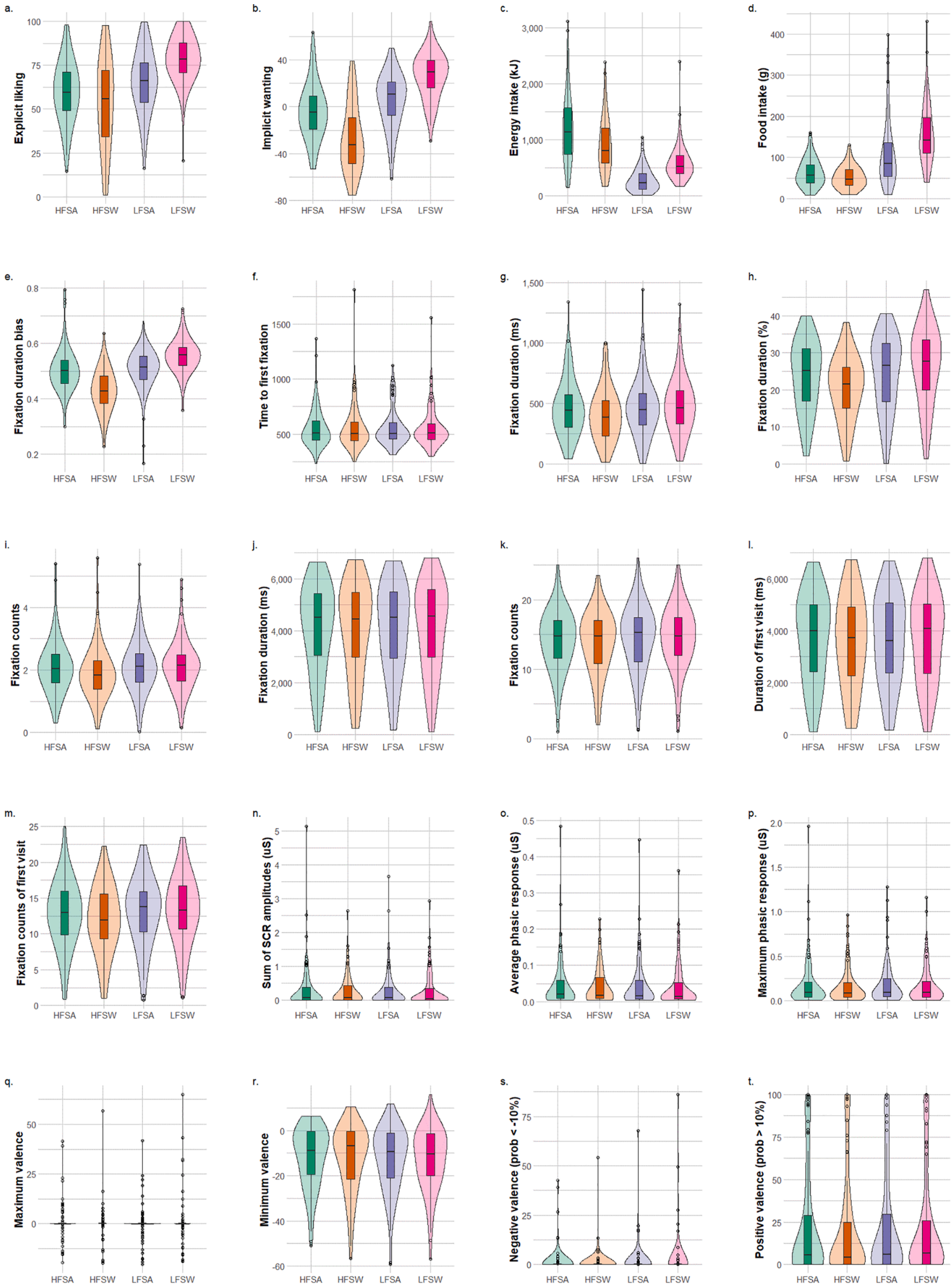

Fig. 2. Violin plots visualizing the distributions of responses to four food categories. a - b, food reward responses. c - d, food and energy intake responses. e - i, attentional responses during forced choice. j - m, attentional responses during passive viewing. n - p, Arousal responses during passive viewing. q - t, facial expressions during passive viewing. HFSW, high-fat sweet; LFSW, low-fat sweet; HFSA, high-fat savoury; LFSA, low-fat savoury.

Table 4
Food reward (n = 96) and food intake (n = 97).

	HFSA	HFSW	LFSA	LFSW	p value
Food reward					
Explicit liking	60 [49, 71]	56 [34, 72]	66 [54, 76]	79 [71, 88]	<0.001[a]
Implicit wanting	−4.8 [−19.0, 9.0]	−32.5 [−48.3, −9.1]	10.7 [−7.1, 21.0]	29.4 [16.3, 39.3]	<0.001[a]
Food intake					
Energy intake (kJ) [ƚ]	1135 [741, 1572]	798 [587, 1210]	225 [118, 398]	523 [398, 714]	<0.001[a]
Food intake (g) [ƚ]	56 [38, 82]	46 [33, 71]	84 [54, 136]	141 [111, 197]	<0.001[a]

Food reward and food intake characteristics for each food category are expressed as median [Q1, Q3]. P values for between-group differences in food categories were modelled by linear mixed-effects models. HFSW, high-fat sweet; LFSW, low-fat sweet; HFSA, high-fat savoury; LFSA, low-fat savoury.
[a] = p value with a false detection rate below 0.05 (Benjamini-Hochberg Procedure),
[ƚ] = log-transformed outcome.

3.3. Associations of biometric responses with food preferences and food intake

3.3.1. Association of attention with food reward and food intake

Results showed associations between attentional responses to each food category measured during the forced choice methodology and food reward after correcting for multiple comparisons (Table 5). For food reward, participants' fixation duration bias and total fixation duration (%) during the forced choice methodology were positively associated with both explicit liking and implicit wanting for foods. Furthermore, total fixation duration (ms) and fixation duration counts were also positively associated with explicit liking for foods (Table 5). With regards to food intake, the participants' maintained attention, expressed as fixation duration (%), was positively associated with both the amount of food eaten (g) and the energy intake (kJ) within a food category (Table 6). After correcting for multiple comparisons, no attentional responses during passive viewing were associated with food reward or food intake. Association plots are displayed in SM Fig. 3 and SM Fig. 4.

3.3.2. Association of arousal with food reward and food intake

Participants' electrodermal responses were not significantly associated with food reward or food intake when correcting for multiple comparisons (Tables 5 and 6).

3.3.3. Association of facial expressions with food reward and food intake

The intensity of facial expressions related to negative valence was positively associated with participants' explicit liking for foods meaning that less liked foods elicited stronger negative facial expressions (Table 5 and SM Fig. 3). No other facial expressions were associated with food reward or food intake when correcting for multiple comparisons (Tables 5 and 6).

4. Discussion

In order to explore how biometric responses are associated with food reward and food intake, this study developed a novel methodological approach that combined several biometric measures and examined them in response to food cues. These biometric signatures were subsequently explored in relation to explicit and implicit reward measures and subsequent objective measures of ad libitum food intake. Overall, our study population displayed significant differences in attentional responses to the four food categories, i.e. maintained attention during forced choice and initial attention during passive viewing. No differences were found for arousal and facial expression for the food categories. There were

Table 5
Associations between biometric responses and food reward. (n = 96).

	Explicit liking		Implicit wanting	
	Estimate (95% CI)	p value	Estimate (95% CI)	p value
Eye tracking (forced choice)				
Fixation duration bias	79 (59; 99)	<0.001 [a]	193 (166; 220)	<0.001 [a]
Time to first fixation (ms)	−0.009 (−0.023; 0.004)	0.166	0.001 (−0.012; 0.015)	0.834
Total fixation duration (ms)	0.023 (0.012; 0.033)	<0.001 [a]	0.013 (0.002; 0.023)	0.015
Total fixation duration (%)	0.71 (0.45; 0.97)	<0.001 [a]	0.5 (0.26; 0.74)	<0.001 [a]
Fixation counts (n)	5.5 (2.5; 8.4)	<0.001 [a]	2.7 (−0.1; 5.5)	0.061
Eye tracking (passive viewing)				
Total fixation duration (ms)	−0.0001 (−0.0017; 0.0014)	0.861	−0.0003 (−0.0017; 0.0012)	0.700
Fixation counts	0.1 (−0.5; 0.7)	0.691	−0.1 (−0.6; 0.4)	0.717
Duration of first visit (ms)	−0.0002 (−0.0017; 0.0013)	0.802	−0.0004 (−0.0018; 0.0011)	0.618
Fixation counts of first visit (n)	0.0 (−0.5; 0.6)	0.868	−0.1 (−0.6; 0.4)	0.641
Electrodermal activity				
SCR (yes)	−1.8 (−6.4; 2.7)	0.422	0.0 (−5.1; 5.0)	0.993
Sum of SCR-amplitudes (μS) [b]	−0.1 (−0.3; 0.1)	0.394	0.0 (−0.2; 0.2)	0.983
Average phasic response (μS) [b]	−0.5 (−1.9; 1.0)	0.529	0.1 (−1.4; 1.5)	0.909
Max phasic response (μS) [b]	−0.2 (−1.8; 1.3)	0.799	0.0 (−1.5; 1.5)	0.993
Facial expressions				
Negative valence (prob < −10)	−0.07 (−0.15; 0.01)	0.076	0.00 (−0.08; 0.08)	0.972
Positive valence (prob > 10)	−0.06 (−0.34; 0.22)	0.681	−0.01 (−0.31; 0.28)	0.938
Minimum valence	0.25 (0.08; 0.42)	0.004 [a]	−0.01 (−0.18; 0.17)	0.944
Maximum valence	0.10 (−0.15; 0.34)	0.454	0.06 (−0.20; 0.32)	0.641

Linear mixed-effects models showing biometric associations with food reward. SCR, skin conductance response; prob, probability.
[a] = p value with a false detection rate below 0.05 (Benjamini-Hochberg Procedure),
[b] = log2-transformed.

strong associations of how long participants maintained their attention towards foods during forced choice with their liking and wanting (food reward) and with intake of foods within each food category. Attention, arousal, and facial expression responses during passive viewing were not associated with food reward or food intake measures, except for an association between negative valence and explicit liking such that less liked foods also elicited stronger negative facial expressions.

Visual processing of food cues initiates a set of early pre-prandial and cephalic phase responses that help to prepare the body for the intake of food (van der Laan et al., 2011). Together with our learned knowledge about a food, a food cue can create expectations of ingestive and post-ingestive effects and elicit a variety of anticipatory responses in the body (Boutelle et al., 2020; van der Laan et al., 2011; Verastegui-Tena et al., 2017). These responses include both physiological and cognitive processes (Boutelle et al., 2020; van der Laan et al., 2011), and measuring different aspects of these provide insight into what drives our eating behaviours. In this study, we assessed responses towards sweet or savoury and low- or high-fat foods. We know that taste of food is important for food choice (Puputti et al., 2019), and high-fat/sugar diets can promote higher food reward and overeating in animals and humans

Table 6
Associations between biometric outcomes and food and energy intake (n = 96).

	Energy intake (%)[ƚ]		Food intake (%)[ƚ]	
	Estimate (95%CI)	p value	Estimate (95%CI)	p value
Eye tracking (forced choice)				
Fixation duration bias	138 (0; 464)	0.050	135 (6; 417)	0.035
Time to first fixation (ms)	−0.013 (−0.054; 0.029)	0.552	−0.003 (−0.043; 0.037)	0.883
Total fixation duration (ms)	0.036 (0.004; 0.067)	0.028	0.035 (0.004; 0.065)	0.027
Total fixation duration (%)	1.23 (0.45; 2.02)	0.002 [a]	1.29 (0.53; 2.04)	0.001 [a]
Fixation counts (n)	3.7 (−5.3; 13.4)	0.434	2.4 (−6.1; 11.7)	0.583
Eye tracking (passive viewing)				
Total fixation duration (ms)	0.0049 (0.0004; 0.0093)	0.032	0.0035 (−0.0008; 0.0079)	0.110
Fixation counts	0.3 (−1.4; 2.0)	0.759	0.1 (−1.6; 1.7)	0.927
Duration of first visit (ms)	0.0053 (0.0009; 0.0097)	0.018	0.004 (−0.0003; 0.0082)	0.066
Fixation counts of first visit (n)	0.8 (−0.8; 2.4)	0.339	0.5 (−1; 2)	0.525
Electrodermal activity				
SCR (yes)	17.3 (0.9; 36.3)	0.038	12.5 (−2.4; 29.8)	0.105
Sum of SCR-amplitudes (μS) [b]	0.7 (0.1; 1.3)	0.033	0.5 (−0.1; 1.1)	0.075
Average phasic response (μS) [b]	3.8 (−0.8; 8.7)	0.104	4.1 (−0.3; 8.7)	0.069
Max phasic response (μS) [b]	2.3 (−2.3; 7.2)	0.333	2.8 (−1.7; 7.5)	0.226
Facial expressions				
Negative valence (prob < −10)	−0.20 (−0.44; 0.05)	0.114	−0.19 (−0.42; 0.05)	0.120
Positive valence (prob > 10)	0.23 (−0.68; 1.16)	0.619	0.22 (−0.65; 1.1)	0.619
Minimum valence	0.57 (0.03; 1.11)	0.037	0.36 (−0.17; 0.88)	0.180
Maximum valence	0.45 (−0.35; 1.26)	0.270	0.51 (−0.26; 1.28)	0.192

Linear mixed-effects models showing associations between biometric associations and food and energy intake. SCR, skin conductance response; prob, probability.
[a] = p value with a false detection rate below 0.05 (Benjamini-Hochberg Procedure),
[b] = log2-transformed,
[ƚ] = log-transformed and back-transformed, and the estimates therefore indicate the percentage change in energy and food intake per change in the biometric variable.

(Berthoud et al., 2020; Boutelle et al., 2020; Johnson & Wardle, 2014). With a rich set of information from the SBFPT in a large sample size, we were able to explore how food cues from different food categories affected physiological and cognitive processes, and how these processes were related to reward formation and actual food intake. Food cues, i.e. images, for the SBFPT were culturally adapted and validated to make sure they were appropriate for use in a Danish breakfast/brunch context (Oustric et al., 2020). Standardizing images according to culture minimizes the risk that parameters such as recognition, identification, and appropriateness will affect responses during the task.

In the following sections we discuss how the biometric responses differ according to food categories and how they are associated with food reward and food intake.

The visual system is one of the primary guides of food choice (van der Laan et al., 2011) and just the sight of food is known to activate reward centres in the brain (Nummenmaa et al., 2011). In this study, we examined different eye tracking variables related to initial and maintained visual attention and in response to looking at both single (passive viewing) and pairwise (forced choice) food images. Results showed that all maintained attentional response variables during pairwise image exposure differed between food categories in this population of normal weight adults. Contrary to existing literature (Castellanos et al., 2009; Doolan et al., 2014; Graham et al., 2011), our results indicated that participants directed more attention towards low-fat foods compared to high-fat foods. Initial attention is a measure of the immediate attention-grabbing effect of a food that may be related to the saliency of the food due to e.g. visual appearance, whereas maintained attention is a measure of the total attention-grabbing effect that may be related to higher cognitive functioning and in some participants to an avoidance response (Lee et al., 2018). The cognitive processing during maintained attention can be related to the hedonic evaluation of the foods and can also include inhibitory cognitive processes such as self-regulation (van der Laan et al., 2011). An explanation for the findings in our study could be that participants were able to resist temptations of palatable foods as a strategy to maintain their healthy body weight (van der Laan et al., 2011) by directing most attention towards foods that were not high-fat sweet. We found positive associations of maintained attentional responses with mainly explicit liking but also with implicit wanting as well as food- and energy intake, which could illustrate how the visual system is used for and related to hedonic evaluation. Also, it indicates that with a direct competition between two food images and a decision-goal, the relationship between viewing time and evaluation of the food is positive. Without this competition the relationship appears to be more complex: during passive viewing of a single food image, differences between food categories were found only for the initial fixation counts. This finding could indicate that differences between foods can be detected when measuring whether or how frequently fixations move within the AOI (exploration of food image) rather than measuring the total amount of time exploring a single food image. Less is known about absolute evaluations based on single image exposures compared to relative preference formation based on forced choice (Wolf et al., 2018). However, it has been found that single image exposures that are shown for a fixed amount of time as in this study (7000 ms) are not related to food evaluation compared to single images where participants can determine the viewing time (Wolf et al., 2018). This indicates that viewing a single image does not intrinsically influence and lead to an increased liking, which supports the lack of a relationship of single image exposures with food reward or intake in the present study. In support of our findings other studies have also found positive associations between viewing multiple foods and liking (Wang et al., 2018) or wanting (Werthmann et al., 2011) for foods. The association between attention and food intake found in this study compared to other studies, could indicate the importance of the specific eye tracking variables, as other studies examining the eye tracking variables, direction bias (Nijs et al., 2010; Werthmann et al., 2011) and duration bias (Nijs et al., 2010), instead of total fixation duration did not show significant associations with food intake.

Arousal responses did not differ significantly between food categories, which is in line with the few other studies examining skin conductance responses to different types of foods (De Wijk et al., 2014;

Samant & Seo, 2020). However, nutrient specific changes in emotional responsiveness to food has been proposed (Craeynest et al., 2008; Privitera et al., 2013), and some studies have shown differences (Danner et al., 2014; Pallavicini et al., 2016; Verastegui-Tena et al., 2017), i.e. higher responses in electrodermal activity to negative (worms) visual food cues compared to neutral (soy) and positive (chocolate) food cues. Negative cues can elicit aversive or defensive responses, whereas positive cues, as in our study, can elicit appetitive responses (Verastegui-Tena et al., 2017). This suggests that electrodermal activity may give more insight in certain contexts such as situations with contrasting exposures, compared to situations with similarly positive exposures. Furthermore, there was a relatively high percentage of participants having no skin conductance responses or very few skin conductance responses during exposure to a food category. This could indicate that images of liked foods are not arousing enough to elicit an actual skin conductance response. It has been argued that participants must find the sensory experience relevant to elicit strong responses of electrodermal activity (Verastegui-Tena et al., 2017). It is possible that actual intake of a food including the sensory attributes from odours, taste and texture would elicit a stronger physiological response compared to visual exposure to food cues. This view is supported by existing literature showing that autonomic nervous system responses, including electrodermal responses, differ depending on whether foods were viewed, smelled or tasted (de Wijk et al., 2012), the type of food presented during cooking and tasting (Brouwer et al., 2017), and the primary taste of drink solutions (Rousmans et al., 2000). After correcting for multiple comparisons, no associations between electrodermal activity and food reward and intake were observed. Comparable studies are limited, but one study observed that electrodermal activity did not contribute to the prediction of overall liking in different intensities of basic taste solutions (Samant & Seo, 2019), whereas another study observed that electrodermal activity increased with disliking (Danner et al., 2014) supporting the notion above on higher responses to aversive stimuli. This indicates that electrodermal activity may be an indicator of disliking but not liking. It is possible, though, that results would differ in other populations such as among people with overweight and obesity.

Some evidence suggests that facial expressions are sensitive enough to demonstrate differences in response to viewing low- and high-fat food images (Lee et al., 2018), taste of different juices (Danner et al., 2014), and smelling odours (He et al., 2014). One study has also found sad and angry facial expressions to be reflecting sensory specific satiety, i.e. facial expressions changed as to whether the same (increase in angry and decrease in sad expressions) or a different (decrease in angry and increase in sad expressions) food was served to a participant (He et al., 2017). However, the lack of differences in facial expressions between food categories in our study was also supported by a study examining chocolate samples with different tastes (Gunaratne et al., 2019). As this implies, results are inconsistent and differ with regards to the type of food exposure. More facial actions relate to negative compared to positive valence (*see description in Section 2.4.2.3*), which could explain why our results indicate higher frequency and intensity of negative facial expressions compared to positive expressions (Danner et al., 2014). This suggests that it is more difficult to measure positive expressions, which were expected to be the most prevailing expression in response to liked foods in this study. In support of this, a study reported that almost 15% of respondents had almost no facial expressions after tasting juices (Danner et al., 2014). Minimum valence was positively associated with explicit liking ratings, meaning that less liked foods also elicited stronger negative facial expressions. No other facial expressions were associated with food reward or intake.

There are different arguments as to why we propose a relationship between facial expressions and hedonic evaluation of food: First, from studies in infants and animals we know that different hedonic taste stimuli elicit different facial expressions (Morales & Berridge, 2020). Moreover, there is evidence for specific brain regions involved in producing facial expressions in response to stimuli, suggesting that facial expressions can be an objective measure of liking (Morales & Berridge, 2020). Lastly and despite small and heterogenous effects, facial expressions are found to elicit corresponding emotional experiences (Coles et al., 2019). Other studies within consumer science have found facial expression intensities to be inversely associated with liking (Danner et al., 2014; De Wijk et al., 2014) as also observed in our study. Altogether, facial expressions to a larger extent reflects disliking and not liking of foods. Facial expression responses can be detected using different algorithms and are numerous if all emotional expressions are included. In this study, we chose to summarize findings into two positive and negative valence variables. The intensity variable was developed as a running mean to capture the maximum expression of negative and positive valence. This variable was based on an assumption that the expression would not last throughout the whole exposure time (7000 ms) and that facial expressions occur with different latencies (Kessler et al., 2020). The low threshold for the frequency variable (10%) was chosen with the purpose of detecting very early signs of emerging facial actions (Brand & Ulrich, 2019).

Food reward and food intake show the same pattern as for attentional responses and facial expressions: higher preferences for and intake of low-fat compared to high-fat foods and lowest preferences and food intake of high-fat sweet food items, which may indicate that this is a health-conscious population with strategies to maintain their normal body weight. This could be supported by the sex distribution with predominantly female participants in the study, who has been found to place more importance on healthy eating and body weight regulation (Wardle et al., 2004). Potentially, results on food reward and food intake also reflect the laboratory environment in which we assessed these responses. Social desirability and knowledge of participating in a health research study at a diabetes centre may affect participants' explicit responses and intake towards foods that are considered most healthy.

This study has certain limitations such as a technically challenging setup which make it useful primarily in a laboratory setting. Moreover, the length of the task (25 min) may have caused some degree of test fatigue among some participants. However, as all food images were randomised this was not expected to affect the overall results. Furthermore, we measured biometric and food reward responses to 16 visual food items in the SBFPT but for practical reasons we measured ad libitum intake of only 8 of these 16 food items. The two foods from each food category were selected to represent the food category, and criteria for this selection were that they should be available throughout the year so that an unvarying ad libitum meal could be served to all participants. An assumption for analyses was that the two foods represented the four foods in the food category, but we might have seen different strengths of associations had we measured intake of all 16 foods. Moreover, it is unknown whether the difference in participants' starting time for the ad libitum buffet and thereby duration of fasting could have affected participants' food selection and intake and thereby potentially increased the variability in this. However, the time span between the SBFPT and the ad libitum buffet did not differ between participants and starting time for the ad libitum buffet was therefore not expected to affect associations between biometric responses and subsequent food intake. Furthermore, we would probably have collected stronger electrodermal activity and facial expression responses in relation to eating compared to exposure to food cues. Eating would introduce sensory stimulation from odour, taste, and texture. However, in daily life we rely on anticipation and expectations about various sensory attributes of foods, which highlights the importance of also increasing our knowledge about responses to food cues specifically. Lastly, there are limitations to the generalizability of our findings to both sexes, as results were based on a predominantly female sample. The study and novel methodological approach also come with several strengths such as concurrent collection of data on biometric responses and food reward to the same images. Additionally, we were able to examine eye tracking in two different contexts (during passive viewing and forced choice) allowing for insight into different processes of attention. The results bring new insight into the combined usage of biometrics in the study of eating behaviours, and the implicit nature of these sensors help us understand the underlying psychophysiological processes in relation to food preferences and food intake. Implicit aspects of behaviour are difficult to capture and not possible with questionnaires that require higher cognitive functions. The SBPTF aids deeper assessment of behaviour with presentation of responses from both the early and subconscious phase and during the subsequent cognitive processing. Basing the SBFPT on an existing validated behavioural methodology adds further strength to this study.

This study shows the potential of combining different explicit and implicit behavioural and biometric measures in the study of food cue responsiveness. It provides deeper insight into several aspects of the psychophysiological responses to food cues and their relation to actual food intake. Methodological advances in this field can guide future health interventions as to which behavioural or physiological responses are modulated by the nutritional composition and taste of foods, and how interventions for the treatment of obesity and metabolic disorders affect food cue responsiveness.

In conclusion, this study provides a deeper insight into our responses to the food cues that we are continuously exposed to in the abundant food environment. We provide evidence for differences in how long participants maintain their attention (measured using eye tracking) to foods varying in fat content and taste prior to making rapid food choice decisions. Moreover, we report differences in food reward and food intake for these same foods. Lastly, we provide evidence that maintained attentional responses and negative facial expressions are related to measures of food reward and food intake in a sample of normal weight individuals.

Declaration of Competing Interest

HP is employed by iMotions A/S, Frederiksberg, Denmark.

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Author contributions

Author's contributions were as follows: HP, JSQ, MMJ, KKBC, KF and GF contributed to the design of the study; HP, MMJ and KKBC collected the data; KKBC and DV contributed to the data analyses; HP performed the analyses and drafted the manuscript. All authors contributed with critical revision of the manuscript and approved the manuscript.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.foodqual.2021.104248.

References

Bell, L., Vogt, J., Willemse, C., Routledge, T., Butler, L. T., & Sakaki, M. (2018). Beyond self-report: A review of physiological and neuroscientific methods to investigate consumer behavior. *Frontiers in Psychology, 9*(SEP), 1–16. https://doi.org/10.3389/fpsyg.2018.01655

Benedek, M., & Kaernbach, C. (2010). A continuous measure of phasic electrodermal activity. *Journal of Neuroscience Methods, 190*(1), 80–91. https://doi.org/10.1016/j.jneumeth.2010.04.028

Benjamini, Y., & Hochberg, Y. (1995). Controlling the false discovery rate: A practical and powerful approach to multiple testing. *Journal of the Royal Statistical Society: Series B (Methodological), 57*(1), 289–300. https://doi.org/10.1111/j.2517-6161.1995.tb02031.x

Berthoud, H. R., Morrison, C. D., & Münzberg, H. (2020). The obesity epidemic in the face of homeostatic body weight regulation: What went wrong and how can it be fixed? *Physiology and Behavior, 222*(April), 1–10. https://doi.org/10.1016/j.physbeh.2020.112959

Boswell, R. G., & Kober, H. (2016). Food cue reactivity and craving predict eating and weight gain: A meta-analytic review. *Obesity Reviews, 17*(2), 159–177. https://doi.org/10.1111/obr.12354

Boucsein, W., Fowles, D. C., Grimnes, S., Ben-Shakhar, G., Roth, W. T., Dawson, M. E., & Filion, D. L. (2012). Publication recommendations for electrodermal measurements. *Psychophysiology, 49*, 1017–1034. https://doi.org/10.1111/j.1469-8986.2012.01384.x

Boutelle, K. N., Manzano, M. A., & Eichen, D. M. (2020). Appetitive traits as targets for weight loss: The role of food cue responsiveness and satiety responsiveness. *Physiology and Behavior, 224*, 1–8. https://doi.org/10.1016/j.physbeh.2020.113018

Brand, R., & Ulrich, L. (2019). I can see it in your face. affective valuation of exercise in more or less physically active individuals. *Frontiers in Psychology, 10*(December), 1–11. https://doi.org/10.3389/fpsyg.2019.02901

Brouwer, A.-M., Hogervorst, M. A., Grootjen, M., van Erp, J. B. F., & Zandstra, E. H. (2017). Neurophysiological responses during cooking food associated with different emotions. *Food Quality and Preference, 62*, 307–316. https://doi.org/10.1016/j.foodqual.2017.03.005

Castellanos, E. H., Charboneau, E., Dietrich, M. S., Park, S., Bradley, B. P., Mogg, K., & Cowan, R. L. (2009). Obese adults have visual attention bias for food cue images: Evidence for altered reward system function. *International Journal of Obesity, 33*(9), 1063–1073. https://doi.org/10.1038/ijo.2009.138

Coles, N. A., Larsen, J. T., & Lench, H. C. (2019). A meta-analysis of the facial feedback literature: Effects of facial feedback on emotional experience are small and variable. *Psychological Bulletin, 145*(6), 610–651. https://doi.org/10.1037/bul0000194

Craeynest, M., Crombez, G., Koster, E. H. W., Haerens, L., & De Bourdeaudhuij, I. (2008). Cognitive-motivational determinants of fat food consumption in overweight and obese youngsters: The implicit association between fat food and arousal. *Journal of Behavior Therapy and Experimental Psychiatry, 39*(3), 354–368. https://doi.org/10.1016/j.jbtep.2007.09.002

Dalton, M., & Finlayson, G. (2014). Psychobiological examination of liking and wanting for fat and sweet taste in trait binge eating females. *Physiology and Behavior, 136*, 128–134. https://doi.org/10.1016/j.physbeh.2014.03.019

Danner, L., Haindl, S., Joechl, M., & Duerrschmid, K. (2014). Facial expressions and autonomous nervous system responses elicited by tasting different juices. *Food Research International, 64*(June), 81–90. https://doi.org/10.1016/j.foodres.2014.06.003

De Wijk, R. A., He, W., Mensink, M. G. J., Verhoeven, R. H. G., & De Graaf, C. (2014). ANS responses and facial expressions differentiate between the taste of commercial breakfast drinks. *PLoS ONE, 9*(4), 1–9. https://doi.org/10.1371/journal.pone.0093823

de Wijk, R. A., Kooijman, V., Verhoeven, R. H. G., Holthuysen, N. T. E., & de Graaf, C. (2012). Autonomic nervous system responses on and facial expressions to the sight, smell, and taste of liked and disliked foods. *Food Quality and Preference, 26*(2), 196–203. https://doi.org/10.1016/j.foodqual.2012.04.015

Doolan, K. J., Breslin, G., Hanna, D., Murphy, K., & Gallagher, A. M. (2014). Visual attention to food cues in obesity: An eye-tracking study. *Obesity, 22*(12), 2501–2507. https://doi.org/10.1002/oby.20884

Gibbons, C., Hopkins, M., Beaulieu, K., Oustric, P., & Blundell, J. E. (2019). Issues in measuring and interpreting human appetite (satiety/satiation) and its contribution to obesity. *Current Obesity Reports, 8*(2), 77–87. https://doi.org/10.1007/s13679-019-00340-6

Graham, R., Hoover, A., Ceballos, N. A., & Komogortsev, O. (2011). Body mass index moderates gaze orienting biases and pupil diameter to high and low calorie food images. *Appetite, 56*(3), 577–586. https://doi.org/10.1016/j.appet.2011.01.029

Gunaratne, T. M., Fuentes, S., Gunaratne, N. M., Torrico, D. D., Viejo, C. G., & Dunshea, F. R. (2019). Physiological responses to basic tastes for sensory evaluation of chocolate using biometric techniques. *Foods, 8*(7), 1–16. https://doi.org/10.3390/foods8070243

Hall, K. D., Ayuketah, A., Brychta, R., Cai, H., Cassimatis, T., Chen, K. Y., … Zhou, M. (2019). Ultra-processed diets cause excess calorie intake and weight gain: An inpatient randomized controlled trial of ad libitum food intake. *Cell Metabolism, 30*(1), 67–77.e3. https://doi.org/10.1016/j.cmet.2019.05.008

He, W., Boesveldt, S., De Graaf, C., & De Wijk, R. A. (2014). Dynamics of autonomic nervous system responses and facial expressions to odors. *Frontiers in Psychology, 5*(FEB), 1–8. https://doi.org/10.3389/fpsyg.2014.00110

He, W., Boesveldt, S., Delplanque, S., de Graaf, C., & de Wijk, R. A. (2017). Sensory-specific satiety: Added insights from autonomic nervous system responses and facial expressions. *Physiology and Behavior, 170*, 12–18. https://doi.org/10.1016/j.physbeh.2016.12.012

Jain, A. K., Ross, A. A., & Nandakumar, K. (2011). In *Introduction to Biometrics*. Boston, MA: Springer US. https://doi.org/10.1007/978-0-387-77326-1. p. Ch. 1.

Johnson, F., & Wardle, J. (2014). Variety, palatability, and obesity. *American Society for Nutrition, 94*(5), 851–859. https://doi.org/10.3945/ajcn.110.010264

Kessler, S. J., Jiang, F., & Andrew Hurley, R. (2020). The state of automated facial expression analysis (AFEA) in evaluating consumer packaged beverages Samuel. *Beverages, 6*(2), 1–24. https://doi.org/10.3390/beverages6020027

Komogortsev, O. V., Gobert, D. V., Jayarathna, S., Koh, D. H., & Gowda, S. M. (2010). Standardization of automated analyses of oculomotor fixation and saccadic behaviors. *IEEE Transactions on Biomedical Engineering, 57*(11), 2635–2645. https://doi.org/10.1109/TBME.2010.2057429

Lee, I. S., Preissl, H., Giel, K., Schag, K., & Enck, P. (2018). Attentional and physiological processing of food images in functional dyspepsia patients: A pilot study. *Scientific Reports, 8*(1), 1–9. https://doi.org/10.1038/s41598-017-19112-0

Lee, P. C., & Dixon, J. B. (2017). Food for thought: Reward mechanisms and hedonic overeating in obesity. *Current Obesity Reports, 6*(4), 353–361. https://doi.org/10.1007/s13679-017-0280-9

McDuff, D., Mahmoud, A., Mavadati, M., Amr, M., Turcot, J., & El Kaliouby, R. (2016). AFFDEX SDK: A cross-platform real-time multi-face expression recognition toolkit. In *Conference on Human Factors in Computing Systems - Proceedings*. https://doi.org/10.1145/2851581.2890247

Morales, I., & Berridge, K. C. (2020). 'Liking' and 'wanting' in eating and food reward: Brain mechanisms and clinical implications. *Physiology and Behavior, 227*(January), Article 113152. https://doi.org/10.1016/j.physbeh.2020.113152

Münzberg, H., Qualls-Creekmore, E., Yu, S., Morrison, C. D., & Berthoud, H. R. (2016). Hedonics act in unison with the homeostatic system to unconsciously control body weight. *Frontiers in Nutrition, 3*(February), 1–5. https://doi.org/10.3389/fnut.2016.00006

Nijs, I. M. T., Muris, P., Euser, A. S., & Franken, I. H. A. (2010). Differences in attention to food and food intake between overweight/obese and normal-weight females under conditions of hunger and satiety. *Appetite, 54*(2), 243–254. https://doi.org/10.1016/j.appet.2009.11.004

Nummenmaa, L., Hietanen, J. K., Calvo, M. G., Hyönä, J., & Greenlee, M. W. (2011). Food catches the eye but not for everyone: A BMI– contingent attentional bias in rapid detection of nutriments. *PLoS ONE, 6*(5), e19215. https://doi.org/10.1371/journal.pone.0019215

Oustric, P., Thivel, D., Dalton, M., Beaulieu, K., Gibbons, C., Hopkins, M., Blundell, J., & Finlayson, G. (2020). Measuring food preference and reward: Application and cross-cultural adaptation of the Leeds Food Preference Questionnaire in human experimental research. *Food Quality and Preference, 80*, 1–10. https://doi.org/10.1016/j.foodqual.2019.103824

Pallavicini, F., Serino, S., Cipresso, P., Pedroli, E., Chicchi Giglioli, I. A., Chirico, A., Manzoni, G. M., Castelnuovo, G., Molinari, E., & Riva, G. (2016). Testing augmented reality for cue exposure in obese patients: An exploratory study. *Cyberpsychology, Behavior, and Social Networking, 19*(2), 107–114. https://doi.org/10.1089/cyber.2015.0235

Prentice, A. M. (2001). Overeating: The health risks. *Obesity Research, 9 Suppl 4* (November), 234–238. https://doi.org/10.1038/oby.2001.124

Privitera, G. J., Antonelli, D. E., & Creary, H. E. (2013). The effect of food images on mood and arousal depends on dietary histories and the fat and sugar content of foods depicted. *Journal of Behavioral and Brain Science, 03*(01), 1–6. https://doi.org/10.4236/jbbs.2013.31001

Puputti, S., Hoppu, U., & Sandell, M. (2019). Taste sensitivity is associated with food consumption behavior but not with recalled pleasantness. *Foods, 8*(10), 1–21. https://doi.org/10.3390/foods8100444

Rousmans, S., Robin, O., Dittmar, A., & Vernet-Maury, E. (2000). Autonomic Nervous System Responses Associated with Primary Tastes.

Samant, S. S., & Seo, H.-S. (2019). Personality traits affect the influences of intensity perception and emotional responses on hedonic rating and preference rank toward basic taste solutions. *Journal of Neuroscience Research, 97*(3), 276–291. https://doi.org/10.1002/jnr.v97.310.1002/jnr.24321

Samant, S. S., & Seo, H. S. (2020). Influences of sensory attribute intensity, emotional responses, and non-sensory factors on purchase intent toward mixed-vegetable juice products under informed tasting condition. *Food Research International, 132*, 1–11. https://doi.org/10.1016/j.foodres.2020.109095

Thaler, L., Schütz, A. C., Goodale, M. A., & Gegenfurtner, K. R. (2013). What is the best fixation target? The effect of target shape on stability of fixational eye movements. *Vision Research, 76*, 31–42. https://doi.org/10.1016/j.visres.2012.10.012

Tobii. (2014). Tobii X2-30 Eye Tracker User's manual v.1.0.3. <www.tobii.com>.

van der Laan, L. N., de Ridder, D. T. D., Viergever, M. A., & Smeets, P. A. M. (2011). The first taste is always with the eyes: A meta-analysis on the neural correlates of processing visual food cues. *NeuroImage, 55*(1), 296–303. https://doi.org/10.1016/j.neuroimage.2010.11.055

Verastegui-Tena, L., Schulte-Holierhoek, A., van Trijp, H., & Piqueras-Fiszman, B. (2017). Beyond expectations: The responses of the autonomic nervous system to visual food cues. *Physiology and Behavior, 179*, 478–486. https://doi.org/10.1016/j.physbeh.2017.07.025

Viola, Paul, & Jones, Michael J. (2004). Robust real-time face detection. *International Journal of Computer Vision, 57*(2), 137–154.

Wang, E., Cakmak, Y. O., & Peng, M. (2018). Eating with eyes – Comparing eye movements and food choices between overweight and lean individuals in a real-life buffet setting. *Appetite, 125*, 152–159. https://doi.org/10.1016/j.appet.2018.02.003

Wardle, J., Haase, A. M., Steptoe, A., Nillapun, M., Jonwutiwes, K., & Bellisle, F. (2004). Gender differences in food choice: The contribution of health beliefs and dieting. *Annals of Behavioral Medicine, 27*(2), 107–116. https://doi.org/10.1207/s15324796abm2702_5

Werthmann, J., Roefs, A., Nederkoorn, C., Mogg, K., Bradley, B. P., & Jansen, A. (2011). Can(not) take my eyes off it: Attention bias for food in overweight participants. *Health Psychology, 30*(5), 561–569. https://doi.org/10.1037/a0024291

Wolf, A., Ounjai, K., Takahashi, M., Kobayashi, S., Matsuda, T., & Lauwereyns, J. (2018). Evaluative processing of food images: A conditional role for viewing in preference formation. *Frontiers in Psychology, 9*(JUN), 1–11. https://doi.org/10.3389/fpsyg.2018.00936