Title: Food-level predictors of self-reported liking and hedonic overeating: Putting ultra-processed foods in context.

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Abbreviations:

BMI = Body Mass Index

CFR = Carbohydrate-to-fat ratio

FPP = Food Perceptions Platform

HED = High Energy Density

HFSS = High Fat Sugar and Salt

LED = Low Energy Density

LMM = Linear Mixed Models

SM24 = SatMap-24

SM300 = SatMap-300

UPF = Ultra Processed Food

VAS = Visual Analogue Scale

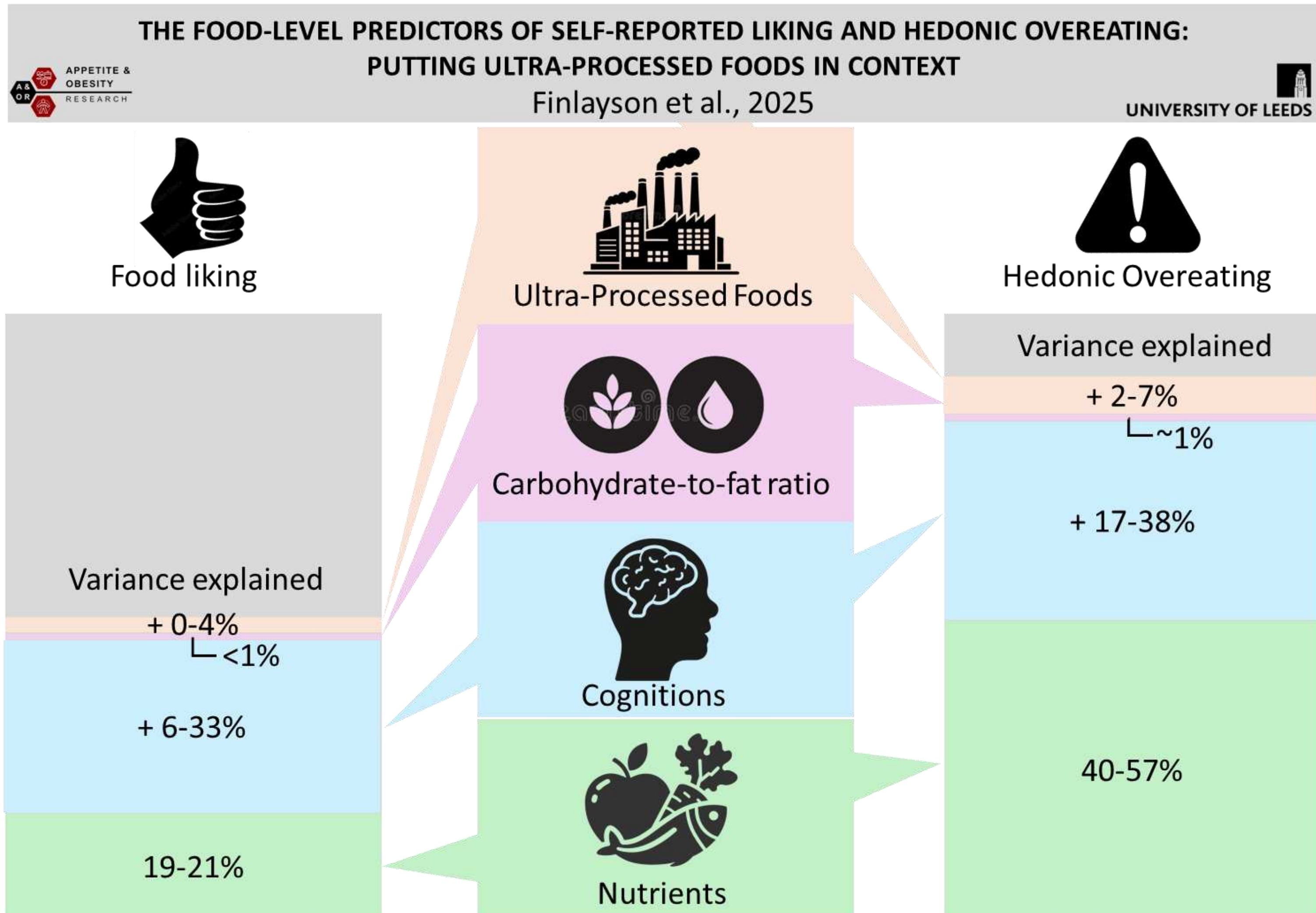
Keywords: Food liking; Hedonic eating; Nutritional composition; Food perceptions; Carbohydrate-to-Fat Ratio; Ultra-Processed Foods.

Word Count 9,350

Abstract

The reward value people assign to foods is determined by their intrinsic (food-level) properties and moderated by individual factors such as traits, states and beliefs. There is a need for more systematic, structured analyses of the food-level characteristics that explain cognitions about food reward such as palatability and their risk for reward-driven overeating. This research, consisting of three studies, aimed to explore the nutritional, sensory and cognitive characteristics and attributes of foods as determinants of food reward-related outcomes. Across three sequential online study designs, 1176 men and 2188 women from the general population rated sub-samples of 436 foods which were sampled from databases and photographed to represent ready-to-eat food and beverage products in the UK. The study outcomes were self-reported food liking and hedonic overeating, while the predictors were the nutritional composition of the foods including ultra-processed food status (UPFs) and carbohydrate-to-fat ratio (CFR); and participants' self-reported beliefs about the nutritional and sensory characteristics of the foods. Correlation and stepwise regression analyses were used to model significant nutritional components followed by hierarchical regression models to examine self-reported food-level attributes, or CFR and UPFs as potential additive models. Across all studies, the nutritional characteristics of foods explained ~20% variance in liking and 40-60% variance in hedonic overeating. Self-reported food-level attributes explained a further 6-33% variance in liking and 17-38% variance in hedonic overeating. UPFs explained 0-7% additional variance and CFR did not add to the nutritional models. This research demonstrates how nutritional characteristics of foods contribute to self-reported liking and hedonic overeating. Considering people's beliefs about nutrient and sensory attributes can explain more than nutrients alone, and there are negligible additive contributions from CFR or UPFs on food reward.

Graphical Abstract



1. Introduction

Due to the negative consequences of overeating leading to excess body fat and increased psychological and physical health risks (Allison et al., 2008), researchers have attempted to understand the determinants of food reward and the food-related factors that generate the pleasure of consuming food and its relationship to weight gain. Interest in this topic is reflected in both scientific and public discourse, where terms such as hyperpalatability, ultra-processing, food addiction and food-noise are gaining currency from experts in government and academia (O'Connor et al. 2023) and commentators in the media. However, a lack of agreed-upon operational definitions for these novel ways to conceptualise unhealthy foods may be causing confusion from incomplete, biased, or inaccurate concepts surrounding a complex scientific issue.

Eating our favourite foods is one of the most common sources of pleasure for most people, contributing to dietary satisfaction (Andersen & Hyldig, 2015) and overall quality of life (Vaudin et al., 2023). In a review of 119 studies, Bedard et al. (2020) highlighted that food enjoyment can promote healthy eating. Numerous authors have suggested food enjoyment should be emphasized more in the promotion of healthy eating (e.g., Jallinoja et al., 2010; Petit et al., 2016) and this concept has been made explicit in several national dietary guidelines including France (French High Council for Public Health, 2017), Canada (Government of Canada, 2020) and Brazil (Government of Brazil, 2014). Importantly, the loss of pleasure when consuming foods has a range of negative impacts. It is associated with the anorexia of ageing (Hanssen & Kuvan, 2016) and cancer-related cachexia (Otani et al., 2023), and in some extreme cases may be linked to depression and suicidal ideation (Bosquez-Berger et al., 2023).

Central to eating enjoyment is food liking, defined as the subjective experience of pleasure from the taste of food (Dalton & Finlayson, 2014). Food liking is determined not only by the sensory and nutritional characteristics of foods, but also their motivational relevance to an individual's homeostatic needs, emotional appraisal, and cognitive influences from attitudes and goals (Stussi & Pool, 2022). Food liking can influence food choice through the learned, expected hedonic impact of its taste based on memories of past eating experiences (Mela, 2006; Pool et al., 2016). In a recent scientific essay on this topic, food liking has been described as an immediate, but preliminary and editable, assessment of the affective value of a food, cemented in the long-term by a compound of nutritional, sensory, and motivational attributes through reinforcement learning (Dayan, 2022).

The role of food liking in the aetiology of obesity has been investigated, with results suggesting it is not reliably linked to satiety, loss of control over eating or weight gain (Mela, 2006). Recently, the construct of "hyperpalatability" has been coined to identify foods that may possess an enhanced palatability and pose a high risk for overeating (Avena et al. 2011; Fazzino, 2022). Research on the determinants of hyperpalatability has tended to focus on nutritional properties rather than the sensory evaluation or hedonic experience of eating. For example, Fazzino et al. (2019) conducted a data driven approach to develop a quantitative definition of hyperpalatable foods. Three ways of categorizing hyperpalatable foods by divergent nutrient pair combinations emerged; fat with sodium; fat with simple sugars; and carbohydrates with sodium. In a similar fashion, Monteiro and others use the NOVA classification system to categorise foods that have undergone extensive processing and often contain industrial additives that are rarely or never used in kitchens (Monteiro, 2019). Monteiro and colleagues propose that the processes and ingredients used to create ultra-processed foods (UPFs) are designed to create profitable (cheap to produce), convenient and hyperpalatable products, assuming that individuals will choose them over other NOVA food groups, particularly unprocessed and minimally processed foods. However, the NOVA system has been criticised for its simplistic focus which may classify some items as ultraprocessed which have important nutritional benefits for particular groups (McClements, 2024). Other researchers argue that a renewed focus is needed on sensory determinants of food palatability and overconsumption rather than the level of processing *per se*. For example, a review by Forde (2023) demonstrated that softer food textures are associated with faster eating rate and interact with energy density to determine energy intake within a meal. Hence, a food's sensory characteristics like texture and taste could also help to account for increased calories consumed with UPFs or hyperpalatable foods beyond their nutritional composition (Hall et al., 2019).

In a study published last year, Rogers and colleagues (Rogers et al., 2024a) investigated several nutritional and sensory determinants of food liking and desire to eat using ratings from 224 participants distributed across 52 different foods shown photographically in 50 gram portions. Combining both nutritional and sensory predictors, they found that subjective taste intensity, fibre content and carbohydrate-to-fat-ratio (CFR) were all independent predictors of food liking and the desire to eat, but there was no effect of energy density or ultra-processing (as defined by the NOVA classification). In a secondary analysis of the same study, Rogers and colleagues (Rogers et al., 2024b) investigated how these food categorisation metrics predicted food liking. The metrics used were nutrient clustering to identify hyperpalatable foods, the NOVA system for classifying UPFs, and profiling and fat, sugar and salt content to classify high fat, sugar and salt (HFSS) foods, respectively. The authors reported no significant difference in food liking between hyperpalatable foods and non- hyperpalatable foods, or between UPF and non-UPF, but HFSS foods were significantly more liked than non-HFSS food. Together, both studies demonstrated that certain taste qualities and basic nutritional components can influence food liking.

The present study aimed to comprehensively explore the nutritional, sensory and cognitive attributes of foods as predictors of food liking and hedonic overeating; with hedonic overeating defined as eating beyond energy requirements due to the expectation and/or experience of pleasure of consuming specific foods (Finlayson, 2017). The study is an analysis of data collected as part of the “SatMap project” (trial registrations NCT02012426; ISRCTN67732674). Three different survey designs were deployed over the course of the project, each involving large samples of UK men and women respondents and employing different approaches to achieve a structured sample of foods, presented as standardised photographic stimuli, to represent the breadth and variety of foods currently available in the UK diet. The primary analyses examined whether food liking and hedonic overeating could be predicted by the known nutritional composition of the foods in the surveys. We then tested whether respondents’ self-reported beliefs about the nutritional and sensory properties of the foods were able to explain additional variance in food liking and hedonic overeating, above the models that included only actual nutrients. Lastly, due to current public and scientific interest in CFR and UPFs as potentially important determinants of food reward, independent of their nutritional composition, we examined whether these novel nutritional constructs could explain any further unique variance in liking and hedonic overeating after controlling for basic nutritional characteristics.

2. Methods

2.1. Design overview

The present study used a cross-sectional online survey design. Three separate surveys containing photographic food stimuli using different food sampling strategies were used: Survey 1 - Food Perceptions Platform (FPP; data collection March-June 2014); Survey 2 - SatMap-24 (SM24; data collection July-September 2021); and Survey 3 - SatMap-300 (SM300; data collection June-October 2024). In the present paper, the study outcomes were food liking and hedonic overeating, while the predictors were the nutritional composition of the foods presented in the surveys and participants' self-reported beliefs about the nutritional and sensory characteristics of the foods. Other cognitive attributes of the foods were assessed including their perceived satiety value, self-reported frequency of consumption and associations with health and weight management. All survey participants were adult men and women recruited from the general population of the United Kingdom. Participants were excluded if they reported they were pregnant or breastfeeding in the prior 6 months; a history of or current eating disorder; weight loss surgery; medical condition or taking medication that affects appetite or body weight; age under 18 years old; self-reported body mass index (BMI) below 18.5kg/m^2. Ethical approvals were granted from the University of Leeds, School of Psychology Research Ethics Sub-committee (reference numbers: FPP, #14-0024, date approved: 09/02/2014; SM24, #PSC-280, date approved: 20/07/2021; SM300, #PSCETHS-707, date approved: 05/10/2023).

2.2. Online survey designs and participants

2.2.1. Survey 1 – Food Perceptions Platform

The research team sourced 359 foods from a major UK supermarket to generate a pool of products and meals aligned with the 5 food groups identified by the UK Department of Health dietary guidance tool, the Eatwell Plate (UK Department of Health, n.d.). A final sample of 100 foods were then selected for the survey based on the criteria that they were well-recognized (familiarity rated by the research team) and had no visible branding. Each food was photographed in the laboratory as a single portion, according to the manufacturers' recommendation or the median portion size listed in the food composition database (Finglas et al. 2015). Therefore, the amount shown on the plate varied by weight and energy per food. The foods in the survey ranged from 5 to 1,214 kcal. The foods' nutritional information was taken from the products' label and the UK Composition of Foods Database (Finglas et al., 2015).

Participants were recruited using volunteer sampling by responding to a notice which was sent to University of Leeds staff and student mailing lists via email, posts on social networking sites and online forums. The sample included 1,127 participants. See **Table 1** for descriptives of participant characteristics from the three surveys. Participants provided ratings on a subset of 25 foods from the total sample which were randomly distributed over 4 iterations of the survey (survey 1, n = 347; survey 2, n = 327; survey 3, n = 213 and survey 4, n = 240). The survey took approximately 10 minutes to complete. Upon completion, participants had the opportunity to enter a prize draw for £100 shopping vouchers. Methodology and data from the FPP have previously been published elsewhere (Buckland et al. 2015a; Buckland et al. 2015b).

2.2.2. Survey 2 – SatMap-24

The foods included in the SM24 survey were obtained by permission from the Intake24 online dietary recall platform developed by Newcastle University and Food Standards Scotland (Rowland et al., 2018; www.intake24.co.uk). The database comprises over 2,500 portion size adjusted food images aligned and coded to the National Diet and Nutrition Survey Nutrient Databank (Public Health England, 2020). To achieve a structured sample of foods to include in the final survey, the foods in the Intake24 database were divided into high or low energy density categories by median split then sub-categorized according to macronutrient composition by percentage energy to produce 6 categories (high or low energy density with high fat, high carbohydrate or high protein). The foods in each category were then screened by the research team to eliminate all but 10 images per category according to nutrient levels. Of these 120 candidate foods, 22 were removed due to presence of other foods/distractors in the image. The subsequent long list of foods was then screened by a panel of 4 researchers from the team based on the following exclusion criteria: Not available in a 240 kcal portion (±40kcal), mixed meals with hard to identify components, non-ready to eat foods, visible wrapping/branding, uncommon or unfamiliar products. The lists were compared and discussed by the panel including any missing common foods not in the long list but available in the bigger database. Of the 48 eligible foods remaining, the 4 per category closest to ~240kcal were selected with a final sample of 24 foods.

Participants were recruited using volunteer sampling, by responding to a recruitment email that contained the survey link which was sent to email lists managed by the University of Leeds, a recruitment database managed within the School of Psychology and posted on social media platforms. The final sample included 259 participants from the general population and student population at the University of Leeds. In the survey, participants were presented with 12 of the 24 foods with 11 randomly allocated and one fixed control food (white bread) shown to all participants. This allowed the food-level means to be adjusted for participant-level bread ratings. The survey took approximately 30 minutes to complete. After survey completion, participants had the opportunity to enter a prize draw to win either a £100 or one of five £50 shopping vouchers.

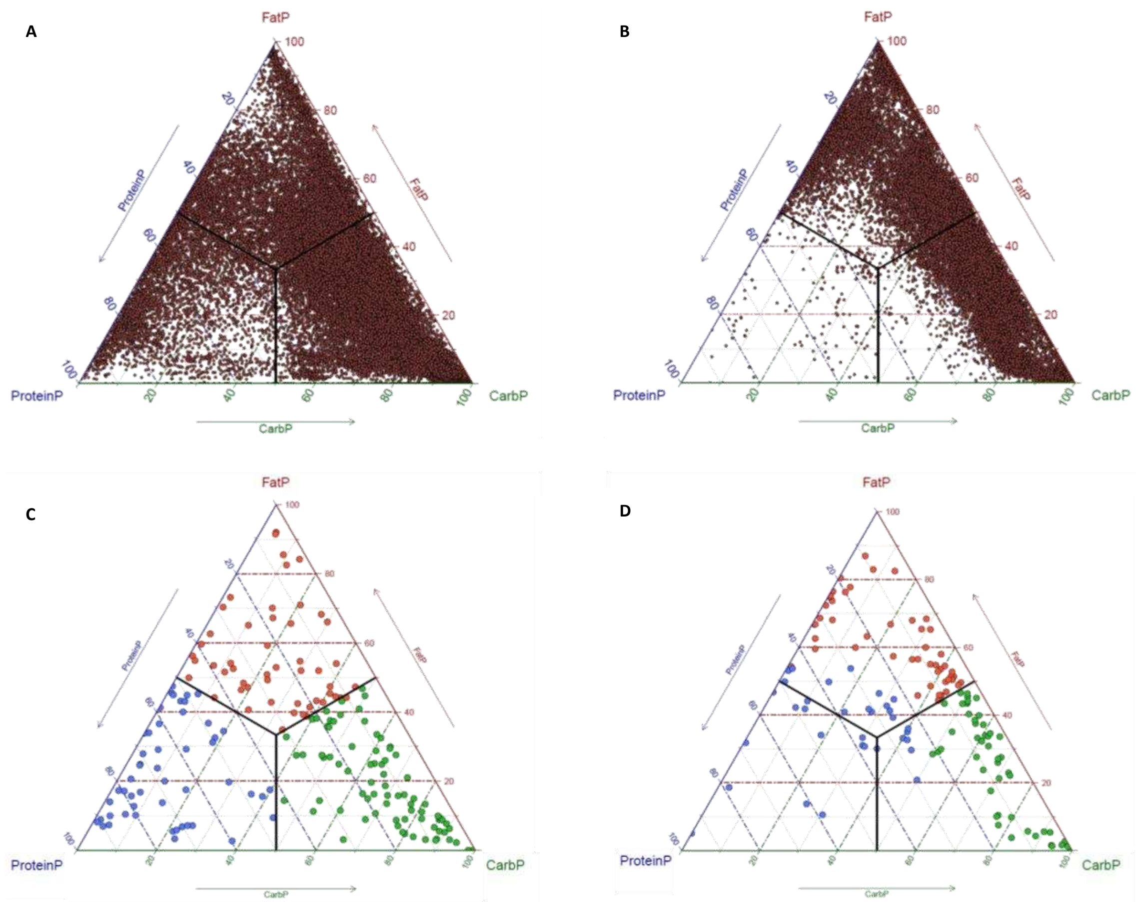
2.2.3. Survey 3 – SatMap-300

In the SM300 survey design, 312 foods were selected from a proprietary database (Slimming World, UK) of over 66,000 foods and beverages reported by >400,000 consumers. The company collects nutritional information on foods programme participants purchase; by having them scan the products (barcode) they buy in the supermarkets, which are then uploaded to a database. Therefore, the database reflects the real-life daily groceries and day-to-day eating habits of UK households, providing a representative sample of foods which are commercially available and common to the diet. Since the database lacked fruits and vegetables due to their typically unbarcoded packaging, purchasing data from Nectar UK (www.nectar360.co.uk) was used to include a range of commonly purchased fruits and vegetables. Following exclusion of duplicate and non-ready to eat foods and beverages (dressings, condiments, fats and oils, spreads and basic kitchen ingredients), 57,254 foods were divided by median split into high or low energy density categories then coded to one of three sub-categories according to their predominant macronutrient composition (Fat n=21,772; Protein n=4,756; Carbohydrate n=30,726). Next, 100 foods were selected at random from each sub-category (total N=600). To further narrow the selection of foods to approximately 300, foods were selected to achieve representation across major food groups, for foods to be currently available or feasible to prepare, to have a mix of single component and mixed-ingredient foods, to minimise duplication of specific food types, and for the high protein, high energy density category to include some meat-free foods. To support the selection process, ternary plots were used to ensure an even distribution of foods within macronutrient and energy density categories **(see Figure 1).** Due to the low number of eligible foods in the high protein high energy density sub-category, foods from the original database were re-considered and the inclusion criteria were widened to allow foods that were >25% protein but <50% carbohydrate and <50% fat by energy. Even with these looser criteria, 33 foods were suitable for the survey, falling short of the target 50 per sub-category. Finally, due to the low number of fruit and vegetable options, the 24 most commonly purchased fruits (n=12) and vegetables (n=12) were included to ensure representation of all food groups. Each food in the final survey (N=312) was then prepared as a 240 kcal portion and photographed by the research team using a standardised operating procedure.

Participants were recruited via the Prolific data collection service (www.prolific.com) to achieve a representative sample of UK adults, based on age, gender and ethnicity. The final sample consisted of 2,010 participants. In the survey, each participant was randomly allocated 10 of the 312 foods. The survey took approximately 30 minutes to complete. An incentive of £4.50 was offered to take part.

Figure 1.

Ternary Plots of Food and Beverage Database Used for SatMap-300 Survey.



Note. **A** Lower energy density foods determined by median split of 57,254 foods. **B** Higher energy density foods determined by median split of 57,254 foods. **C** Final 156 lower energy density foods selected for SatMap-300 survey. **D** Final 156 higher energy density foods selected for SatMap-300 survey. Food coordinates are composition of fat, protein and carbohydrate by percentage energy.

Coordinates denote the macronutrient content of each food by percentage energy of each macronutrient. Colours in panels C and D indicate foods identified as predominantly higher in protein (blue), carbohydrate (green) and fat (red).

Table 1

Sample Descriptives for the Three Surveys

	Food Perceptions Platform	SatMap-24	SatMap-300
Age (years)	32 ± 12	36 ± 18	46 ± 16
Gender			
Women	972 (86.25)	200 (77.22)	1016 (50.55)
Men	144 (12.77)	57 (22.01)	975 (48.51)
Non-binary	-	1 (0.39)	10 (0.50)
Prefer not to say	-	1 (0.39)	8 (0.40)
Other	-	-	1 (0.05)
Not reported	11 (0.98)	-	-
Self-reported ethnicity			
White	-	222 (85.71)	1752 (87.16)
Asian	-	20 (7.72)	149 (7.41)
Black African & Black other	-	4 (1.54)	61 (3.03)
Mixed Race	-	9 (3.47)	29 (1.44)
Other Ethnic groups	-	4 (1.54)	18 (0.90)
Education			
University	-	153 (59.07)	1156 (57.51)
High vocational	-	16 (6.18)	205 (10.20)
Secondary School	-	15 (5.79)	312 (15.72)
Sixth Form	-	69 (26.64)	307 (15.27)
Primary School	-	-	3 (0.15)
No Formal Education	-	-	3 (0.15)
Other	-	6 (2.32)	20 (1.00)
Occupation			
Student	349 (30.97)	93 (35.91)	169 (8.41)
Employed	439 (38.95)	124 (47.88)	1149 (57.16)
Unemployed	23 (2.04)	40 (15.44)	494 (24.58)
Other	316 (28.04)	2 (0.77)	198 (9.85)
BMI (kg/m^2)	24.62 ± 4.42	24.24 ± 4.05	26.98 ± 6.08

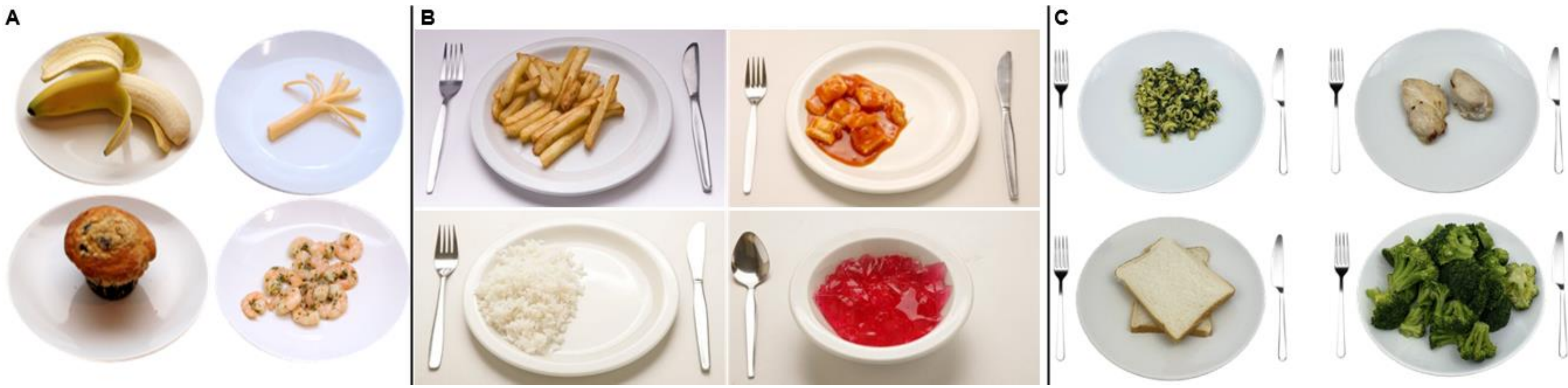
Data are mean $\pm$ SD and N (%).

2.3. Food Stimuli

In the FPP, food stimuli were displayed on the centre of a white plate or a transparent bowl (see **Figure 2a** for an example). In SM24 and SM300, food stimuli were displayed on a white plate or white bowl (see **Figure 2b and 2c**) placed between a knife and fork to aid size estimation. Liquids were presented in a 200ml clear glass in all 3 surveys. The foods were unlabelled in the FPP with participants prompted to identify them from the image (i.e. "what is this food?") using free-text entry. If a respondent either left this blank or reported an incorrect answer their ratings for that specific food were not included in calculation of the means for that food. In the other surveys, foods were labelled with headings above each image. Details of the nutritional composition of the foods in the 3 surveys can be found in **Table 2**.

Figure 2

Example Food Stimuli Used in the Three Surveys



Note. **A** Food Perceptions Platform Example Food Stimuli. **B** SatMap-24 Example Food Stimuli. **C** SatMap-300 Example Food Stimuli.

Table 2

Nutritional Information of the Food Stimuli Used in the Three Surveys

	Food Perceptions Platform	SatMap-24	SatMap-300
Foods N (%)	100	24	312
Energy per portion (kcal)	263.79 ± 232.58	237.24 ± 15.00	240.00 ± 0.00
Kcal/100g	256.73 ± 178.21	223.31 ± 74.66	231.56 ± 145.93
Protein kcal/100g	6.79 ± 6.37	8.25 ± 7.66	13.20 ± 17.85
Carbohydrate kcal/100g	17.34 ± 20.51	18.91 ± 18.73	29.25 ± 40.64
Fat kcal/100g	8.29 ± 11.57	13.20 ± 17.21	15.30 ± 24.42
Saturated fat kcal/100g	4.20 ± 5.45	3.41 ± 3.07	-
Fibre kcal/100g	2.56 ± 2.81	1.83 ± 1.71	2.93 ± 5.60
Sugar kcal/100g	12.27 ± 16.88	6.15 ± 7.66	12.03 ± 24.38
Sodium (g) kcal/100g	0.47 ±0.61	0.21 ± 0.19	1.02 ± 1.96
% Protein	13.53 ± 16.08	16.14 ±14.72	20.08 ± 18.93
% Carbohydrate	47.83 ± 25.14	43.75 ± 29.97	33.94 ± 34.49
% Fat	32.38 ± 24.07	39.82 ± 26.44	38.77 ± 39.73
CFR	0.39 ±0.31	0.36 ± 0.30	0.39 ± 0.31
NOVA-4/UPF Status	53 (53)	15 (62.50)	211 (67.62)

CFR = Carbohydrate-to-fat ratio, UPF = Ultra-processed food. Data are mean ± SD and N (%).

2.4. Self-reported food characteristics, attributes and outcome measures

Table 3 details the variables assessed, the items used to assess them and the response scales.

Table 3. *Items and Response Scales Used to Assess the Study Variables*

Variable	Items	Response Scale
Nutritional Characteristics	"Now think about the nutritional qualities of this portion of food and rate the extent this portion of food is high in […]: calories; fat; protein; carbohydrate; fibre; sugar; salt; highly processed"	100-point Visual Analogue Scale (VAS) scale; 1 = 'not at all' to 100 = 'extremely'
Sensory Characteristics*	"Now think about the sensory qualities of this portion of food and rate the extent this portion of food is […]: Sweet; Savoury; Sour; Bitter; Salty"	100-point VAS; 1 = 'not at all' to 100 = 'extremely'
Cognitive Attributes		
Perceived Satiety Value	"Generally, how filling do you consider this food to be?"	100-point VAS; 1 = 'not at all' to 100 = 'extremely'
Self-Reported Frequency of Consumption	"How often do you consume this food?"	1 = 'never', 6 = 'almost every day'.
Association With Weight Management	"To what extent do you associate this food with successful weight management (e.g. weight loss, weight maintenance, or prevention of weight regain)?";	100-point VAS; 1 = 'not at all' to 100 = 'extremely'
Association With Health	"To what extent do you think this food is healthy?"	100-point VAS; 1 = 'not at all' to 100 = 'extremely'
Outcome variables		
Liking	"How pleasant does this food typically taste?"	100-point VAS; 1 = 'not at all' to 100 = 'extremely'
Hedonic Overeating	"To what extent do you associate this food with eating too much because of how desirable or pleasurable the food is"	100-point VAS; 1 = 'not at all' to 100 = 'extremely'

Note. All variables measured with the same items and response scales across 3 surveys unless noted with *

* For the Food Perceptions Platform Survey, the question was “Is this food sweet, savoury or bland tasting?" rated on a response scale of 1 = 'sweet', 4 = 'bland', 7 = 'savoury'.

2.5. Data Processing and Statistical Analyses

Estimated mean scores of valid ratings for each food were computed and transferred to a new dataset for food-level analyses. For SM24, the food-level means were computed after adjusting responses for participant-level bread ratings using the standardized residuals method. For SM300, to adjust for differences between participants, Linear Mixed Models (LMM) were constructed incorporating a random participant effect, resulting in estimated means which accounted for participant effects in all food-level variables. Two additional nutritional variables with hypothesized "supra-additive" effects (Gearhardt et al. 2023) on food reward were generated. Firstly, a continuous, part-to-whole measure of CFR (Rogers et al. 2024a) calculated as (kcal/100g) carbohydrate / (carbohydrate + fat). See **Figure 6** for frequency distribution of CFR for the FPP and SM300 surveys. Secondly, the foods were categorised based on the NOVA classification (Monteiro et al., 2018) into 4 groups (NOVA-1: unprocessed or minimally processed, NOVA-2: processed culinary ingredients, NOVA-3: processed food and NOVA-4: UPFs). To aim for consistency in classification, the guidelines provided by Monteiro et al. (2018) were followed with the formulas available on World Open Food Facts (Open Food Facts, n.d.). When there was uncertainty about which category a food should be placed in, it was discussed with the research team until consensus was reached. The foods were subsequently dichotomised by UPF status by separating NOVA-4 (UPF) and combining NOVA-1 and 3 groups (Fardet & Rock, 2019; Gibney et al., 2017). See **Figure 6** for frequency plot of UPF status foods in the FPP and SM300 surveys. Power calculations (see Supplemental Materials for R Code) were conducted to determine the minimum effect size (Cohen's f) required to achieve at least 80% power in multiple regression models with the parameters (sample size and max. number of predictors) from each survey inputted. The analysis used a bootstrap resampling method with 1,000 iterations to estimate the proportion of significant predictors ($p < 0.05$) for a range of effect sizes from small to large (Cohen's f = 0.02 to 0.35). Specifically, synthetic datasets were simulated with varying effect sizes and evaluated the power for each predictor. For each effect size, the maximum power across all predictors was calculated and the minimum effect size that achieved at least 80% power for at least one predictor was identified. The results indicated that for SM24 (259 participants, 24 foods, 2 IVs), $f \geq 0.07$ was the smallest effect size required for a significance criterion of alpha = 0.05 and power = 0.8. For FPP (1127 participants, 100 foods, 6 IVs), $f \geq 0.15$ for $\alpha = 0.05$ and

$\beta = 0.8$. For SM300 (2010 participants, 312 foods, 11 IVs) $f \geq 0.15$ for $\alpha = 0.05$ and $\beta = 0.8$. Power calculations and LMMs for the SM300 variables were conducted in R-Studio, version 1.4.1106 (Boston, US). All other analyses were completed using IBM SPSS Statistics, version 28 (IBM SPSS). Data will be made available on reasonable request.

2.5.1. Preliminary Analyses

Bivariate correlations and waterfall plots were performed to describe the association between the co-primary outcomes of food liking and hedonic overeating. Next, the internal validity of the survey outcomes and comparability between the surveys was explored by testing a series of intuitive associations between liking and hedonic overeating with self-reported frequency of consumption, perceived satiety value and healthiness. For these bivariate analyses, alpha was set at $p < .01$. Full bivariate correlation matrices for the primary outcomes with all nutritional variables are included in supplementary **Table S1**.

2.5.2. Multiple Regression Analyses

Multiple regression analyses were performed on the FPP and SM300 datasets as there was insufficient power in SM24 to explore beyond bivariate effects. Stepwise linear regressions were firstly conducted to investigate whether the nutritional composition of the survey foods were predictive of liking or hedonic overeating. After retaining the significant predictors for each outcome and verifying their theoretical coherence, hierarchical regression was used to investigate whether participants' self-reported beliefs about the nutritional or sensory characteristics of the foods could explain additional variance than the actual nutritional component models. Liking or hedonic overeating were entered as the dependent variable and the nutritional components that significantly predicted each outcome were entered as predictors in step 1. In step 2, the self-reported attributes of foods were introduced to the regression model using a forward stepwise selection approach to include variables in the model only if they made an additional contribution toward explaining the outcome variables with a probability of F-to-enter of <0.05 and a probability of F-to-remove of >0.10. Additional exploratory hierarchical regressions were performed to investigate if CFR or UPF status could explain unique variance in liking or hedonic overeating beyond the nutritional component models.

Finally, to address the possibility that the category a rated food belonged to (i.e. main meal, snack, dessert or beverage) was a confounder of the associations between the predictor variables and outcome variables, the foods were independently categorised by two of the study authors (GF and RA). Any discrepancies between the categorisation of foods were discussed and arbitrated by a third author (RJS). Differences between the four food categories on liking and hedonic overeating were examined by one-way ANOVA. Next, each hierarchical regression model was re-run, controlling for food category (Enter method) in the first step of each model. Dummy coding was used with dessert as the reference group. The results of these analyses did not change the nature or interpretation of any of the models in the main results (see supplemental Tables S3-S5).

Comprehensive diagnostic checks were conducted alongside the regression models in order to establish how well the models fitted the data. Residual statistics were examined to check for statistical outliers. Outliers were classified as scores which had residuals > 3 standard deviations. Influential cases were identified through Cook's Distance; Cook's distance scores > 1 were taken to indicate observations which had an undue influence over the parameters of the model. No outliers were identified for any analyses. Multicollinearity between predictors was assessed using variance inflation factors (VIF) and tolerance statistics, VIF scores greater than 10 and tolerance statistics below 0.2 were taken to indicate multicollinearity (Bowerman & O'Connell, 1990). The alpha was set at $p < .05$ for multivariate analyses. To control type 1 error rate, P-values were adjusted using the Benjamini-Hochberg procedure.

3. Results

3.1. Participant Characteristics of the Survey Samples

As shown in **Table 1**, the mean age and BMI of participants in the FPP and SM24 surveys were similar. These surveys had a higher proportion of women than men and ratio of students to non-students. As the SM300 sample was recruited by Prolific to be representative of the UK general population, the participants were evenly balanced between the sexes, older, possessing a higher BMI, and comprising a small proportion of students compared to those reporting as employed or unemployed.

3.2. The Association Between Food Liking and Hedonic Overeating

Across all 3 surveys there was a significant positive association between food liking and hedonic overeating: FPP; r (100) = .59, p < .001, R^2 = .34. SM24; r (24) = .83, p < .001, R^2 = .69. SM300; r (312) = .81, p < .001, R^2 = .66; see **Table 4**. As shown in **Figure 3** panels A, C and E, foods such as chocolate and ice-cream were rated high on both liking and hedonic overeating, while celery, cabbage and pea soup rated low on both outcomes. To further explore the relationship between the study outcomes, the ratings for each food were plotted in descending order of hedonic overeating. These waterfall plots (**Figure 4,** panels B, D and F) demonstrate that for some foods, liking and hedonic overeating scores diverged; with foods such as apple and porridge/oatmeal rated as well-liked but scoring low on hedonic overeating.

3.3. Intuitive Hypotheses in Relation to Liking and Hedonic Overeating

To explore the internal validity and comparability between surveys, associations between liking and hedonic overeating with a number of cognitive attributes were conducted. Food liking was associated with greater frequency of consumption (FPP: p < .001; SM24: p = .008;

SM300: $p < .001$), while hedonic overeating was associated with lower healthiness (FPP: $p < .001$; SM24: $p < .001$; SM300: $p < .001$). In FPP and SM300, hedonic overeating was also associated with lower perceived satiety (FPP: $p < .001$; SM300: $p < .001$) and (see **Table 4**).

Table 4

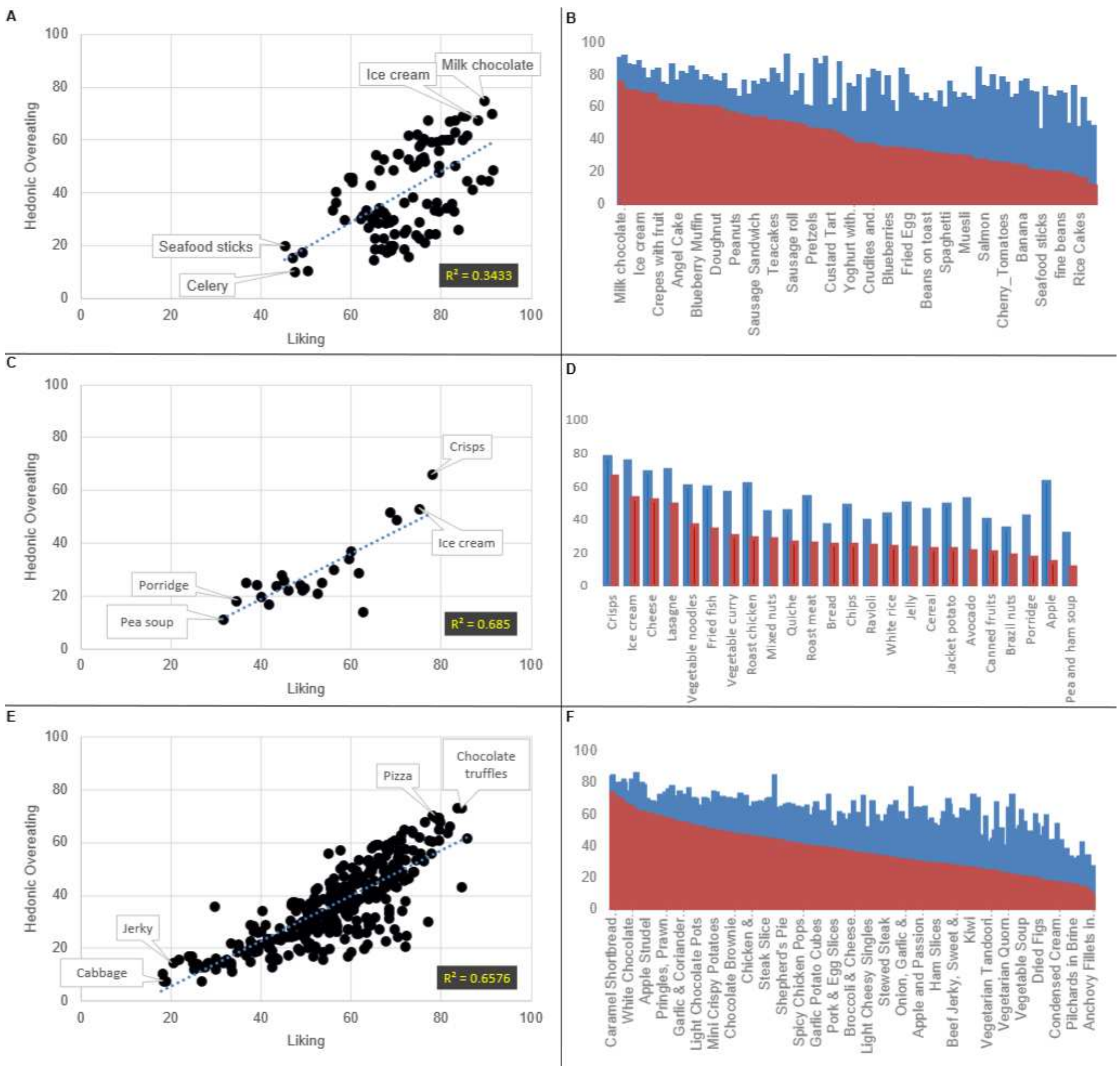
Correlation Results for Intuitive Correlations Between Hedonic Overeating, Liking and Other Variables Across the 3 Surveys.

				Food Perceptions Platform					
Variable	*n*	*M*	*SD*	1	2	3	4	5	6
1. Liking	100	5.07	0.71	-					
2. Hedonic Overeating	100	4.15	1.17	.586**	-				
3. Frequency Consumed	100	3.17	0.96	.404**	-.223*	-			
4. Perceived Satiety Value	100	4.00	0.96	-.148	-.530**	-.05	-		
5. Healthiness	100	3.90	1.91	-.143	-.836**	.556**	-.174	-	
				SatMap-24					
Variable	*n*	*M*	*SD*	1	2	3	4	5	6
1. Liking	24	51.84	12.82	-					
2. Hedonic Overeating	24	28.96	13.42	.828**	-				
3. Frequency Consumed	24	3.41	0.88	.527**	.357	-			
4. Perceived Satiety Value	24	21.338	6.75	-.168	-.303	.196	-		
5. Healthiness	24	45.38	19.43	-.283	-.643**	.19	.298	-	
				SatMap-300					
Variable	*n*	*M*	*SD*	1	2	3	4	5	6
1. Liking	312	56.37	14.10	-					
2. Hedonic Overeating	312	36.76	14.94	.811**	-				
3. Frequency Consumed	312	2.51	0.78	.545**	.204**	-			
4. Perceived Satiety Value	312	1.09	0.73	-.170**	-.484**	.375**	-		
5. Healthiness	312	38.76	21.37	-.344**	-.745**	.241**	.740**	-	

Note. ***p* < .01

Figure 3

The Association Between Liking and Hedonic Overeating and the Liking and Hedonic Overeating Ratings for Foods Across the 3 Surveys



Note. **A** and **B** Food Perceptions Platform**. C** and **D** SatMap-24**. E** and **F** SatMap-300**.** In panels A, C and E the food labels are for illustrative purposes. In panels B, D and F, the blue bars depict liking ratings for foods. The red bars depict hedonic overeating ratings for foods.

3.4. Do Nutritional Components of Food Predict Liking and Hedonic Overeating?

Stepwise multiple regression was used to test the extent to which the nutritional composition of the survey foods predicted liking and hedonic overeating. **Table 5** summarises the final models for each outcome in the FPP and SM300 surveys. **Figure 4** gives a visualisation of the standardized betas and variance explained in liking and hedonic overeating for the FPP and SM300.

3.4.1. Food Perceptions Platform:

In the FPP, the regression model for liking was significant (F (3, 95) = 9.29, p <.001) and indicated that saturated fat (p < .001) and carbohydrate (p = .004) content were positively associated, while protein (p = .010) was negatively associated. Collectively the model accounted for 23% of the variance in liking. A significant regression was also found for nutritional composition and hedonic overeating (F (4, 94) = 32.80, p <.001). The significant components in the model positively associated with hedonic overeating were energy density (p <.001) and saturated fat (p = .007), while protein (p = .006) and fibre (p < .001) were negatively associated. These predictors collectively accounted for 58% of the variance in hedonic overeating.

3.4.2. SatMap-300:

The regression model for food liking was also significant in the SM300 survey (F (4, 307) = 18.65, p <.001). The results showed that fat (p = .001) and carbohydrate (p = .001) content were positively associated, while protein (p = .001) and fibre (p = .001) were negatively associated. The final model accounted for 20% of the variance in liking. For hedonic overeating the regression was also significant (F (3, 308) = 68.08, p <.001) with energy density (p < .001) as the only positive predictor, and protein (p < .001) and fibre (p < .001) negatively associated. Together, these variables explained 39% of the variance in hedonic overeating.

Table 5

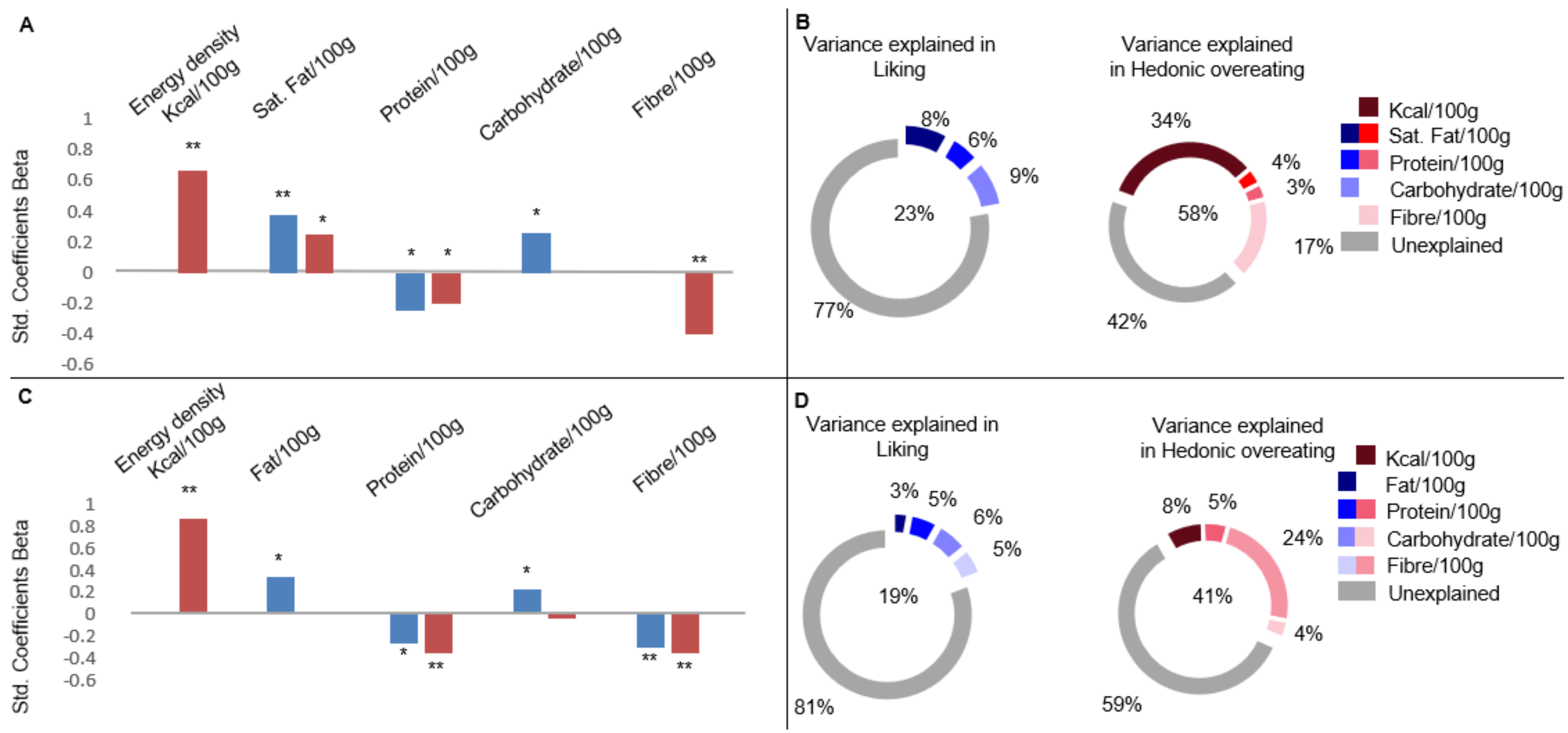
Final Model Summaries for the Variance Explained in Liking and Hedonic Overeating by Actual Nutrient Content in the Food Perceptions Platform and SatMap-300 Surveys

	Liking				Hedonic Overeating			
	Food Perceptions Platform		SatMap-300		Food Perceptions Platform		SatMap-300	
	Final Model		Final Model		Final Model		Final Model	
Variable	*B* [SE]	β	*B* [SE]	β	*B* [SE]	β	*B* [SE]	β
Nutritional Model - Stepwise Regression								
Constant	5.20 [0.11]		56.02 [1.03]		4.81 [0.14]		22.89 [1.45]	
Kcal per 100g	-	-	-	-	0.04 [0.01]	.67***	0.09 [0.01]	.87***
Carbohydrate per 100g	0.01 [0.00]	.27**	0.08 [0.02]	.23***	-	-	0.10 [0.03]	.28***
Fat per 100g	-	-	0.20 [0.04]	.35***	-	-	-	-
Saturated Fat per 100g	0.05 [0.01]	.38***	-	-	0.05 [0.02]	.25**	-	-
Protein per 100g	-0.03 [0.01]	-.25*	-.21 [0.05]	-.27***	-0.04 [0.01]	-.21**	-0.28 [0.04]	-.35***
Fibre per 100g	-	-	-0.77 [0.15]	-.31***	-0.17 [0.03]	-.40***	-0.94 [0.14]	-.35***
ΔF	6.84**		20.25***		7.73**		25.56***	
F	9.29***		18.65***		32.80***		50.92***	
R^2	.23		.20		.58		.40	

Note. *$p < .05$ **$p < .01$ ***$p < .001$ after FDR correction for multiple comparisons

Figure 4

The Variance Explained in Liking and Hedonic Overeating by Nutritional Component Models



Note. **A** and **B** Food Perceptions Platform. **C** and **D** SatMap-300. The blue bars demonstrate liking ratings for foods. The red bars demonstrate hedonic overeating ratings for foods.

** p<0.001, * p<0.01

3.5. Do Perceptions of Foods add Explanatory Power to Nutritional Models of Liking and Hedonic Overeating?

To understand if participants' own perceptions of nutritional and sensory attributes of foods could build on the significant nutritional component models and predict additional variance in food liking or hedonic overeating, hierarchical multiple regression was used. Firstly, the significant nutritional component variables were entered in step 1, followed stepwise by the self-reported nutritional and sensory attributes as rated by participants in the surveys. **Table 6** summarises the final models and **Figure 5** shows a visualisation of the findings from both surveys.

3.5.1. Food Perceptions Platform:

The regression showed that adding the psychological perceptions of foods explained an additional 6% variance in liking ($\Delta F(1, 94) = 7.36$, $p = .008$), increasing the total variance explained to 28%. Believed taste (higher score = savoury, lower score = sweet) was negatively associated with liking ($p = .008$) indicating that the more savoury / less sweet the food was rated, the more it was liked. Food perceptions also predicted additional variance in hedonic overeating ($\Delta F(2, 92) = 33.40$, $p < .001$). Similar to liking, believed taste was negatively associated with hedonic overeating ($p < .001$), but believed fat content was also positively associated ($p < .001$) in this model. Together these psychological variables added 18% variance to the nutritional model for hedonic overeating, with 76% total variance explained.

3.5.2. SatMap-300:

Adding the psychological variables of nutritional and sensory perceptions explained an additional 31% variance in liking ($\Delta F(1, 302) = 10.79$, $p < .001$) in the SM300. Similar to the FPP regression, the believed taste of the foods was positively associated with food liking (Believed sweetness: $p < .001$; Believed savouriness: $p < .001$). In addition, believed fat content was positively associated with liking ($p = .001$), while believed protein content ($p = .001$) and believed bitterness ($p < .001$) were negatively associated. The final model accounted for 51% of the total variance. Nutritional and sensory perceptions also added significantly to the nutritional component model for hedonic overeating ($\Delta R^2 = .376$; $\Delta F(7, 301) = 71.89$, $p < .001$). The regression coefficients indicated that believed fat content ($p < .001$), sweetness ($p < .001$) and savouriness ($p < .001$) were positively associated, while believed protein (p = .006), fibre (p < .001) and bitterness (p < .001) were negatively associated. The total variance explained in hedonic overeating was 78%.

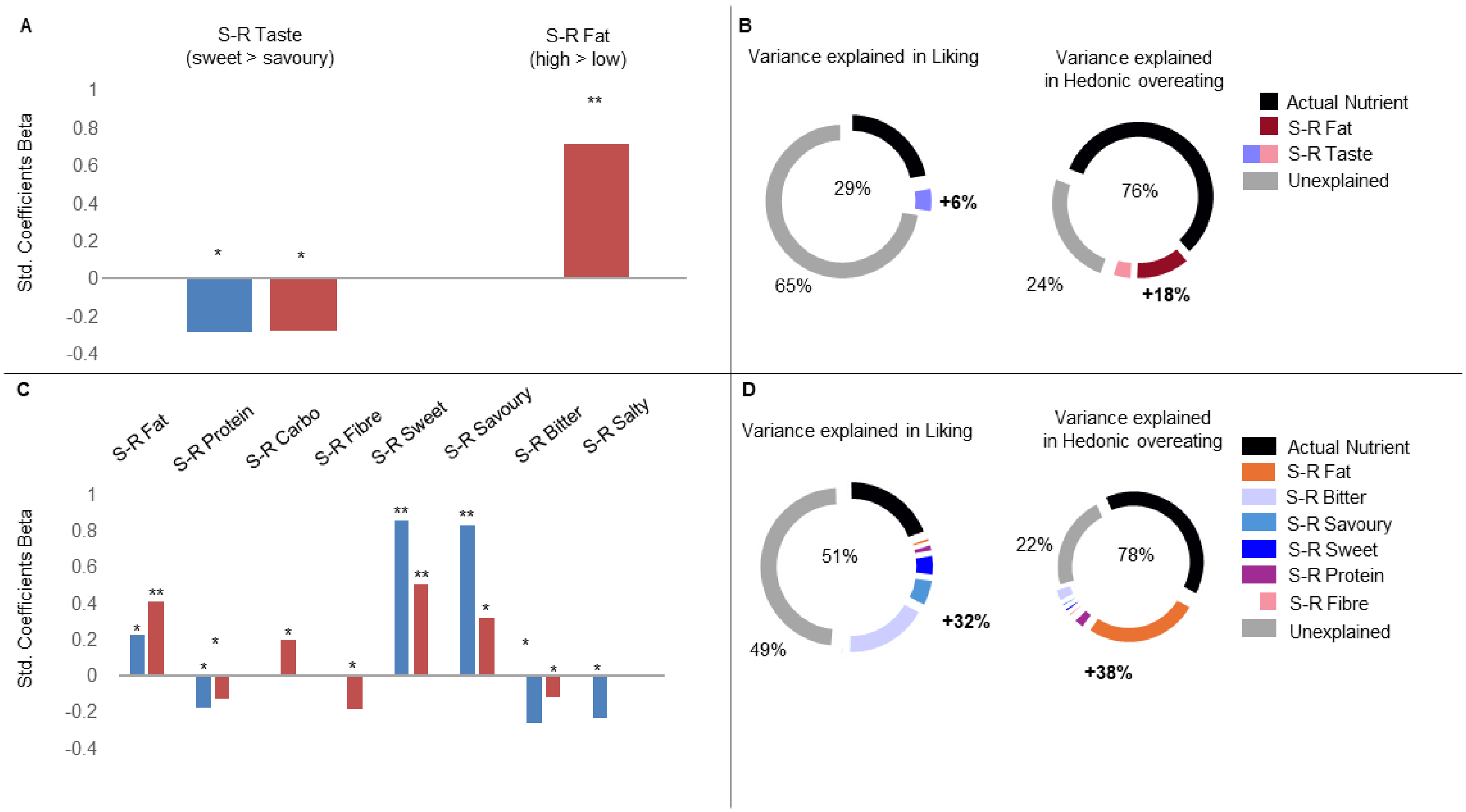
Table 6. *Final Model Summaries for the Variance Explained in Liking and Hedonic Overeating by Self-reported Beliefs About the Composition of Foods After Controlling for Actual Nutrient Content*

	Liking				Hedonic Overeating			
	Food Perceptions Platform		SatMap-300		Food Perceptions Platform		SatMap-300	
	Final Model		Final Model		Final Model		Final Model	
Variable	*B* [SE]	β	*B* [SE]	β	*B* [SE]	β	*B* [SE]	β
Nutritional Model With Self-reported Composition - Hierarchical Regression								
Constant	5.20 [0.11]		35.06 [6.29]		4.81 [0.14]		23.06 [1.27]	
Believed Sweetness/ Savouriness[1]	-0.11 [0.04]	-.28*	-	-	-0.18 [0.04]	-.28***	-	-
Believed Sweetness	-	-	0.38 [0.07]	.81***	-	-	0.25 [0.05]	.51***
Believed Savouriness	-	-	0.32 [0.08]	.61***	-	-	0.18 [0.06]	.33***
Believed Bitterness	-	-	-0.62 [0.10]	-.29***	-	-	-0.26 [0.08]	-.12**
Believed Saltiness	-	-	-	-	-	-	-	-
Believed Carbohydrate Content	-	-	-	-	-	-	0.17 [0.04]	.20***
Believed Fat Content	-	-	0.13 [0.04]	.19**	.44 [-0.06]	.74***	0.31 [0.04]	.42***
Believed Protein Content	-	-	-.13 [0.04]	-.19**	-	-	-0.09 [0.03]	-.12**
Believed Fibre Content	-	-	-	-	-	-	-.18 [0.04]	-.18***
ΔF	7.36**		10.79***		33.40***		71.89***	
ΔR^2	.06		.31		.18		.38	
F	9.27***		34.64***		48.07***		103.65***	
R^2	.28		.51		.76		.78	

Note. *$p < .05$ **$p < .01$ ***$p<.001$ after FDR correction for multiple comparisons. [1]The negative coefficients observed mean that lower believed savouriness or greater believed sweetness were related to greater liking and hedonic overeating.

Figure 5

The Variance Explained by Self-reported Beliefs About the Composition of Foods After Controlling for Actual Nutrient Content



Note. **A** and **B** Food Perceptions Platform. **C** and **D** SatMap-300. The blue bars demonstrate liking ratings for foods. The red bars demonstrate hedonic overeating ratings for foods

** p<0.001, * p<0.01

3.6. Do Carbohydrate-to-Fat Ratio or Ultra-Processed Foods Explain More Than the Basic Nutritional Component Models of Liking and Hedonic Overeating?

To explore the utility of two other more complex nutritional variables in accounting for food liking and hedonic overeating, i) CFR and ii) UPFs were examined due to their hypothesised "supra-additive" effects on food reward. Separate hierarchical regressions were performed for each variable, with the relevant predictor force-entered following entry of the significant nutritional component models previously established. **Table 7** summarises the final models and **Figure 6** shows a visualisation of the findings from both surveys.

3.6.1. Food Perceptions Platform:

The regression revealed that CFR explained no (<0.1%) additional variance in food liking ($\Delta F(1, 94) = .01$, $p = .927$). A similar non-significant result was found for hedonic overeating with CFR explaining 1% variance ($\Delta F(1, 93) = .16$, $p = .688$). In the models with UPF/NOVA-4 status, there was a non-significant effect of UPFs on food liking ($\Delta R^2 = .000$; $\Delta F(1, 94) = .01$, $p = .891$), and a small significant effect on hedonic overeating ($\Delta F(1, 93) = 4.36$, $p = .039$). In this model, UPFs explained an additional 2% variance in hedonic overeating.

3.6.2. SatMap-300:

In the SM300 survey, CFR explained <1% additional variance in liking which was non-significant ($\Delta F(1, 306) = 3.24$, $p = .073$). For hedonic overeating, a similar non-significant effect was found with CFR explaining <1% additional variance in hedonic overeating ($\Delta F(1, 307) = 3.35$, $p = .068$). When UPF status was examined, it was a significant predictor of food liking, explaining 4% additional variance and improving the overall model fit ($\Delta F(1, 306) = 16.35$, $p < .001$). A slightly larger effect was found for UPFs on hedonic overeating. This variable accounted for 7% additional variance and the overall model was significant ($\Delta F(1, 307) = 41.73$, $p < .001$).

Table 7

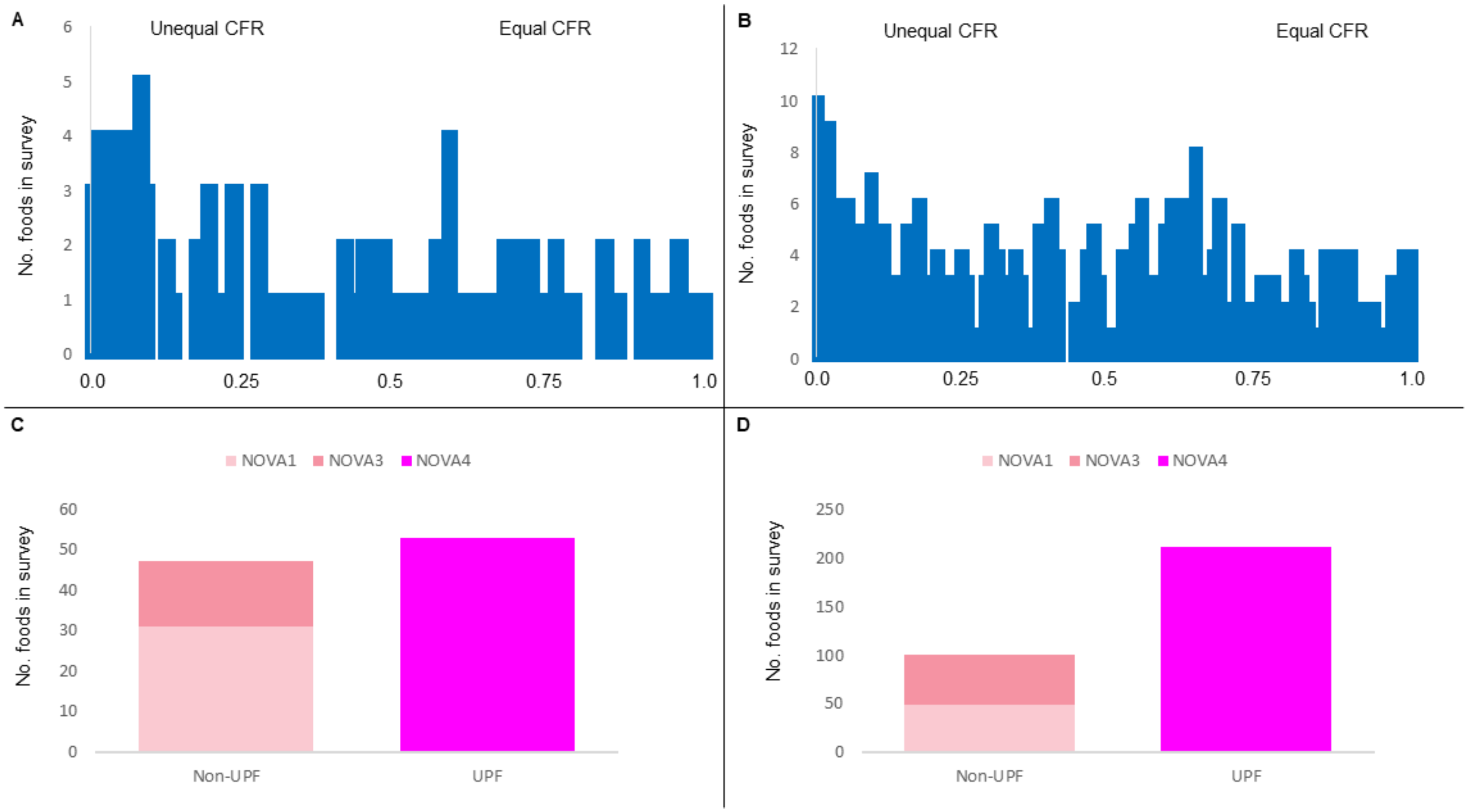
Final Model Summaries for the Variance Explained in Liking and Hedonic Overeating by Carbohydrate-to-Fat Ratio and Ultra-Processed Foods After Controlling for Actual Nutrient Content

	Liking				Hedonic Overeating			
	FPP		SM300		FPP		SM300	
Variable	*B* [SE]	β	*B* [SE]	β	*B* [SE]	β	*B* [SE]	β
Nutritional Model With CFR - Hierarchical Regression								
Constant	5.20 [0.11]		56.02 [1.03]		4.81 [0.14]		23.06 [1.27]	
Carbohydrate-to-Fat Ratio	0.03 [0.27]	.01	-5.84 [3.25]	-.12	.13 [0.33]	.04	-4.65 [2.54]	-.09
ΔF	.00		3.24		.16		3.35	
ΔR^2	.00		.01		.00		.01	
F	6.90***		15.67***		26.04***		52.29	
R^2	.23		.20		.58		.41	
Nutritional Model With UPFs - Hierarchical Regression								
Constant	5.20 [0.11]		56.02 [1.03]		4.81 [0.14]		23.06 [1.27]	
Ultraprocessed Foods	-0.01 [0.04]	-.02	1.64 [0.41]	.22***	.11 [0.05]	.19	2.28 [0.35]	.29***
ΔF	.02		16.35***		4.36*		41.73	
ΔR^2	.00		.04		.02		.07	
F	6.90***		18.93***		28.05***		68.24	
R^2	.23		.24		.60		.47	

Note. *$p < .05$ **$p < .01$ ***$p < .001$ after FDR correction for multiple comparisons

Figure 6

The Distribution of Carbohydrate-to-Fat Ratio and Ultra-Processed Foods



Note. **A** and **C** Food Perceptions Platform. **B** and **D** SatMap-300.

4. Discussion

The present study aimed to systematically quantify a large sample of foods according to their actual and self-reported characteristics to provide a more complete account of the determinants of palatability. However, liking alone is not sufficient to account for overconsumption leading to excess accumulation of body fat (Mela, 2006). In neurobiological models (Berridge, 2009), liking is only one sub-component of food reward that works in parallel with wanting (incentive salience) and learning. Liking and wanting interact with hunger and can distinguish between participants with and without obesity and those exhibiting disordered eating behaviour traits (Finlayson & Dalton, 2012). A more recent construct proposed to account for reward-driven overeating is “hyperpalatability” where unlike the localized brain subregions and mesocorticolimbic circuitry implicated in liking and wanting, the focus lies with the characteristics of the food and not the individual. Evidence for the nutritional determinants of overconsumption has tended to focus on energy density and macronutrient composition of foods, in part due to theoretical models of energy balance regulation based on homeostatic feedback from specific nutrients and energy stores (Stubbs et al. 2023). However single nutrient accounts (including sugars and sodium) fail to capture the complexity of most modern food products that make up the total diet. In the literature, the concept of hyperpalatable food is appealing because some authors propose it is the presence of combinations of certain nutrients in those foods (e.g. fat/sugar, fat/sodium, carbohydrate/sodium; Fazzino et al. 2019), the ratio of macronutrients (carbohydrate-to-fat ratio, DiFeliceantonio et al. 2019) and/or the industrial processes required to produce those foods (Monteiro et al. 2018) that can produce supra-additive effects on food reward that override the ability to control the amount eaten. The present study advances the current literature by incorporating a range of food characteristics and attributes from nutritional (including UPF and CFR), sensory and cognitive domains as potential correlates of food reward.

4.1. Liking and hedonic overeating

This study demonstrated across three different survey methodologies that food liking was positively associated with hedonic overeating, which we define as eating in excess of energy requirements from the anticipation (wanting) or experience (liking) of pleasure from consuming specific foods (Finlayson, 2017). This confirmed that the constructs overlap due to food liking being part of the conceptual definition of hedonic overeating. Nevertheless, the non-shared variance between these measures across the three surveys ranged from 32%-66% allowing for meaningful differences in the predictors of these outcomes to be revealed. Moreover, when both sets of rating were compared food by food, it was apparent that some foods were rated as well-liked but also had a low risk of hedonic overeating (for example fruits and some vegetables). This observation supports that for certain foods these constructs were separable and could be clearly discriminated by participants.

4.2. Non-nutritional and cognitive food-level correlates of liking and hedonic overeating

Further evidence for the separability and validity of liking and hedonic overeating was demonstrated by their differing associations with several subjective and objective foods metrics, which showed high consistency across the 3 separate survey designs. Firstly, liking was positively associated with the reported frequency of consumption. This relationship is often reported in studies, with people tending to like foods they eat more frequently (de Castro et al. 1997; Birch, 1999), and more likely to purchase foods that are well-liked (Liem et al., 2019). Conversely, hedonic overeating was not associated with eating frequency and even a weak negative coefficient was observed in the FPP survey. In the larger FPP and SM300 surveys, the perceived satiety value of foods was negatively associated with hedonic overeating but no relationship was revealed for food liking. This is supported by other studies that have assessed expected satiety, liking and food reward using a variety of methods (Brunstrom & Shakeshaft, 2009; Irvine et al., 2013). The healthiness of food was strongly negatively associated with hedonic overeating which may suggest an understanding among participants that overconsumption is detrimental for long-term health. For food liking there was only a weak negative association with healthiness in the SM300 survey, and no relationship in FPP or SM24. These results fit with the mix of findings in the literature illustrating how food pleasure can promote healthy eating (Bedard et al. 2020) as well as being a characteristic of individuals who are susceptible to overeating (Dalton & Finlayson, 2014). Overall these bivariate associations give support for the internal validity of the study outcomes in these online survey designs.

4.3. Nutritional components of food determine liking and hedonic overeating

To address its main aim, the study used multivariate analyses to examine the nutritional composition of foods as determinants of food liking and hedonic overeating in the FPP and SM300 surveys. Near identical models were revealed for the two different survey designs giving more confidence to the reliability of the findings. For liking, the three primary macronutrients were all retained as predictors with fat (or specifically saturated fat) and carbohydrate positively associated and protein negatively associated with food liking. The positive coefficients for carbohydrate and fat indicate that these macronutrients are independent predictors of food liking which is supported by neurobiological and animal experiments revealing that these nutrients affect reward via different pathways along the gut-brain axis (de Araujo et al. 2020). The negative association between protein and food liking could be more complex due the presence of protein more likely to displace carbohydrate and fat from foods. As found during the food selection process for the SM300 (see **Figure 1**), of nearly 60,000 foods reported in the UK consumer database, high protein/high energy dense products were relatively rare and therefore our results are consistent with the literature showing that liking tends to be lower for less frequently consumed foods (Birch, 1999; Liem et al., 2019). The nutritional component models across the two surveys also suggest that adding protein to a food product may reduce its pleasantness, while also reducing the risk of overeating due to its lower reward value. Indeed, the nutritional composition of foods was able to predict more than double the variance overall in hedonic overeating compared to liking. The most significant predictor of hedonic overeating in both surveys was energy density, which is the nutritional variable most frequently identified as part of the modern obesogenic environment (Meiselman et al. 1974; Prentice & Jebb, 2003), a powerful determinant of overconsumption (Buckland et al. 2018), and has been reliably shown to activate reward regions in the brain (Carnell et al., 2014; Fearnbach et al., 2016), independent of absolute energy content in the test food (Mengotti et al. 2019). Rogers et al. (2024a) hypothesized that due to its low energy-to-satiety ratio, energy density would be strongly positively associated with liking and desire to eat at lower levels of energy density, and more weakly associated at higher energy density. However, unlike the present study, they found no linear or curvilinear effects. It is possible that differences in the number and sampling method of foods may account for some of the discrepancies between these studies. After energy density, the other notable nutritional predictor of hedonic overeating was fibre. Here, the findings were consistent with Rogers et al. and in terms of the energy-to-satiety hypothesis, increasing fibre tends to add water which dilutes energy and increases dietary bulk thus lowering a foods palatability. Higher fibre foods are also often associated with increased oral/sensory satiety and slower eating rate (Forde & Bolhuis, 2022; Stribiţcaia et al., 2020) which may reduce the overall hedonic experience of eating (Slavin & Green, 2007). Interestingly, studies have shown the impact of fibre on food reward can be independent from its palatability (McCrickerd & Forde, 2016). The present study lends some support to this argument as fibre was independently negatively associated with hedonic overeating in both surveys, but had no effect on food liking in the FPP survey. Interestingly, the FPP model for hedonic overeating revealed that energy density and saturated fat were both significant predictors. Theoretically it is possible that these correlated nutritional components may explain different aspects of why people overeat: Energy density could predict overall liking while the distinct sensory-altering properties of saturated fat (e.g. texture, flavour intensity) may predict greater indulgence, even at the same calorie level. Further research manipulating different levels of these specific nutrients within foods to examine the impact on liking and hedonic overeating is warranted.

4.4. People's beliefs about the nutritional and sensory properties of food can improve the prediction of liking and hedonic overeating beyond their actual nutrient composition

Building on the nutritional predictors revealed in these initial models, the present study further aimed to investigate whether participant's perceptions and ratings of the nutritional and sensory properties of foods were able to explain more variance than the foods' nutritional composition alone. For the FPP, which measured relatively few perceptual attributes, self-reported taste (rated from extremely sweet to extremely savoury) was negatively associated with both liking and hedonic overeating, meaning sweeter foods were more liked and rated a greater risk for hedonic overeating. Several studies from our group have shown that liking and wanting for sweet taste (relative to savoury foods) are elevated in women with high trait disinhibition (Finlayson et al., 2012) and binge eating (Dalton & Finlayson, 2014), while others have found that high sweet preferers with binge eating disorder report more bingeing episodes than other sweet preferers (Goodman et al., 2018). Sweet taste was also a key predictor of liking and hedonic overeating in the SM300; however in this survey, sweet and savoury taste were assessed independently and both taste modalities were retained in the final models. This difference could be due to constraints in the bipolar scale for sweet/savoury in the FPP, and/or the equal number of men compared to women in the SM300. Broadly these findings on taste are consistent with Rogers et al. (2024a) who reported a positive association between 'taste intensity' and desire to eat in their sample of 52 foods, where taste intensity was averaged from ratings of sweetness, saltiness, and flavour intensity. Another important self-reported nutritional predictor in both surveys was fat content which predicted unique variance in hedonic overeating even after controlling for the significant objective nutrient components in the models. People are generally good at broadly identifying differences in a food's fat content from visual cues, which can influence energy intake (Viskaal-van Dongen et al., 2009). In the present study, strong associations were found between actual and self-reported fat content (Supplemental Table S2. FPP: R^2 = .51; SM300: R^2 = .31). In the SM300 survey a more comprehensive set of nutritional and sensory variables were assessed which contributed further unique variance in both outcomes. Specifically, self-reported protein, bitterness and saltiness predicted food liking, while self-reported protein, carbohydrate and fibre predicted additional variance in hedonic overeating. Taken together, the models for actual and self-reported nutritional and sensory food characteristics accounted for substantially more variance in food liking and hedonic overeating than nutritional models alone. Moreover, both actual and self-reported nutrient composition were stronger predictors of hedonic overeating than of liking. This could be because hedonic overeating reflects how useful a food is thought to be for weight management (Buckland et al. 2015a). Therefore, foods believed to have more calories, more carbohydrate, and/or more fat will be foods that carry the potential for overconsumption, and the sensory characteristics of sweetness and savouriness may add to this tendency.

4.5. Little evidence for additive effects of Carbohydrate-to-Fat Ratio and Ultra-Processed Foods on food reward

Lastly, there has been a recent increase in scientific interest in the role of UPFs (Calcaterra et al., 2023; Rolls et al., 2020; Rogers et al., 2024a; Rogers et al., 2024b; Sutton et al., 2024) and CFR (DiFeliceantonio et al., 2018; Perszyk et al., 2021; Rogers et al., 2024a; Rogers et al., 2024b) on food reward. These novel nutritional variables have been hypothesized to generate a 'supra-additive' effect on neural and behavioural reward outcomes (DiFeliceantonio et al., 2018), to mean greater than would be expected from the sum of their nutritional components. Recently, a number of influential scientists, public health and food policy experts have argued that associations between UPF consumption and disease outcomes persist independently of the nutritional composition of UPF (e.g. Monteiro et al. 2022). The implications of these arguments are that the risks caused by UPF cannot be mitigated by choosing healthier UPF with less fat, sugar, salt, carbohydrate, or different nutrient profiles. Instead, UPF are proposed to drive overeating due to industrial processing techniques per se. However, other scientists have warned that the current mechanistic uncertainty on UPF and health outcomes pose a major challenge to providing consumer guidance that is apolitical and evidence-based (Robinson & Johnstone, 2024). Therefore the present study applied the food-level databases from the FPP and SM300 surveys to explore whether CFR or UPF were able to explain unique variance beyond the basic nutritional component models predicting liking and hedonic overeating. The results showed there was no additional variance explained by CFR and only partial evidence for a small effect of UPF relative to non-UPF foods (explaining between 0-7% variance). The Rogers et al. study was most similar to the present one with both conducting food-level analyses using structured samples of foods that varied in nutritional characteristics. Despite the similarities, Rogers et al. (2024a) found no difference in liking or desire to eat between UPFs and non-UPFs, but minimally processed foods had significantly lower scores than unprocessed or processed foods. Furthermore, the authors found CFR was positively associated with liking and desire to eat. A possible explanation for the different findings between the present study and others in the literature are the large number of foods it was possible to include in the FPP and SM300 surveys. In particular the latter survey, using the ternary plot approach, was able to ensure the overall sample was well-balanced across macronutrient composition and levels of energy density which is harder to achieve with smaller food databases. Consequentially, the analyses were powered to consider multiple nutritional predictors simultaneously in the models, while reducing multicollinearity between variables. In the surveys there was a good representation of foods ranging from zero carbohydrate or fat containing foods to nearly equal ratios of carb-to-fat by % energy. There were also sufficient numbers of UPF compared to non-UPF as defined by the NOVA classification criteria. Overall, the findings suggest that more research is warranted to understand the specific mechanisms by which UPF may impact palatability and hedonic overeating beyond the nutritional components assessed in the present study. One putative candidate being food texture (Forde et al., 2020; Teo et al., 2022).

4.6. Strengths and limitations of the present study

A strength of the present study was its size in terms of the amount of data collected over a period of several years in 3 separate online surveys. This provided the ability to replicate and clarify many of the main results across different samples of participants and foods. Moreover, these datasets permit tests of more complex hypotheses and models relating, for example, protein, sugar, energy density or UPFs to food reward and other appetitive outcomes, within and between samples at the food- and participant-level. There are also a number of limitations to acknowledge in the current study. Firstly, the nature of online survey research means that researchers have little control over environmental distractors or the participants' mental state that might affect the reliability of their responses. Furthermore it was not feasible to test the reliability of survey responses due to only assessing each item once per food, per participant. Another issue with online surveys is that the foods were being assessed 'virtually' via images and rely on participant's episodic memory for past experiences of tasting and eating the foods depicted. It is unknown the extent to which liking or hedonic overeating ratings predict these same outcomes when measured with real foods or real eating situations. Finally although the designs differed in the number of foods randomised to each participant and produced largely consistent results, time constraints limited both the number of foods allocated and the number of items assessed for each food. Moreover, while SM300 was representative of UK adults, the surveys under-represented groups often underserved in research, who are most affected by overweight and obesity. The samples in SM24 and FPP were also proportionally more highly educated than the general population. Therefore, more data with larger, representative sample sizes are needed to increase confidence in the generalizability of the findings to other foods and populations within and outside the UK.

4.7. Implications and future directions

This research has implications for stakeholders who wish to understand more about the food-level determinants of palatability and hedonic overeating. This includes consumers who wish to buy healthy products without sacrificing diet satisfaction; food manufacturers who can alter the nutritional and sensory components of foods and influence consumer perceptions through design and marketing; health professionals who wish to support patients and the public in complying with nutritional guidance and treatment plans; and researchers/clinicians seeking mechanistic insight to how medications or interventions may affect appetite. Other ongoing and future work should now focus on bridging the gap between modelling of food-level characteristics and prediction of actual food behaviours measured in controlled laboratory studies using structured samples of food and beverage products. Future work should also begin to investigate person-level determinants of food liking and hedonic overeating in conjunction with food-level determinants. For example, moderators such as sex, age, BMI status and eating behaviour traits would help to understand the stability of food-level models across these variables or whether the models can be improved for different population sub-groups. Our team are currently investigating whether food-level determinants of food reward in individuals engaged in weight loss differ from the general population. Finally, NOVA is one way of categorising food, but other methods include food type (i.e. beverage, snack, main meal, dessert, breakfast item, and so on), nutrient profiling (Scarborough et al. 2007), as well as a quantitative definition for ‘hyper-palatable’ foods (Fazzino et al. 2019). It would be valuable in future work to investigate sub-categories of UPF, rather than treating UPF-status as a single binary category by examining food type within UPF vs non-UPF as predictors of food reward.

4.8. Conclusion

The present study has demonstrated across three different survey methodologies, that food liking is strongly related to hedonic overeating, but participants discriminated between these outcomes at the food level as not all highly liked foods were perceived as a risk for overeating. Frequently consumed foods tended to be those that were well-liked whereas foods that were perceived as a risk for overeating, tended to be perceived as low in satiety (per kcal), less healthy and low cost (per kcal). The actual nutritional composition of foods was able to explain about 20% of the variance in liking and 40-60% of the variance in hedonic overeating. Adding individuals' perceptions of the nutritional and sensory attributes of foods to the models was able to explain a further 6-33% of the variance in liking and 17-38% of the variance in hedonic overeating. CFR did not explain additional variance above the simple nutritional models and UPFs explained only zero to 7% additional variance. These findings need to be challenged and extended with new surveys using other large and more diverse samples of foods and participants. Moreover, there is a need to adapt and validate these food-level models in the laboratory and beyond in free-living individuals attempting to lose weight or maintain weight loss.

CREDIT Author Statement

GF: Conceptualization, Methodology, Formal analysis; Investigation, Data Curation; Writing - Original Draft; Visualization, Supervision. RA: Validation, Formal analysis, Writing - Original Draft, Visualization. AB: Methodology, Investigation, Data Curation. KB: Methodology, Writing - Review & Editing. NB: Conceptualization, Methodology, Investigation, Data Curation, Writing - Review & Editing. CDa: Methodology, Investigation, Data Curation, Writing - Review & Editing, Project administration. MD: Methodology, Data Curation, Writing - Review & Editing. RO: Methodology, Data Curation, Writing - Review & Editing. CDu: Methodology, Data Curation, Writing - Review & Editing. CG: Writing - Review & Editing, Supervision, Project administration. MH: Writing - Review & Editing. JS: Conceptualization, Methodology, Writing - Review & Editing, Supervision, Funding acquisition.

Data share statement

The data associated with this study are available by request from the corresponding author.

Ethical statement

The study received ethical approvals from the School of Psychology Research Ethics Sub-committee at the University of Leeds (FPP, #14-0024, date approved: 09/02/2014; SM24, #PSC-280, date approved: 20/07/2021; SM300, #PSCETHS-707, date approved: 05/10/2023) and complied with the principles for human experimentation described in the Declaration of Helsinki.

Declaration of competing interest

JS performs consultancy for Slimming World, UK.

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Supplementary materials

Table S1

Bivariate Correlations for Hedonic Overeating, Liking and Nutritional Variables Across the 3 Surveys.

								Food Perceptions Platform							
Variable	*n*	*M*	*SD*	1	2	3	4	5	6	7	8	9	10	11	12
1. Liking	100	5.07	0.71	-											
2. Hedonic Overeating	100	4.15	1.17	.586**	-										
3. Kcal/100g	100	256.73	178.21	.034	.584**	-									
4. Protein/100g	100	6.79	6.37	-.185	.077	.441**	-								
5. Carbohydrate /100g	100	17.34	20.51	-.258**	.191	.519**	.157	-							
6. Fat/100g	100	8.23	11.53	-.05	.279**	.615**	.355**	.304**	-						
7. Saturated fat /100g	100	4.16	5.44	.284**	.573**	.643**	.256*	.091	.284**	-					
8. Fibre/100g	100	2.56	2.81	-.228*	-.163	.376**	.191	.242*	.320**	.111	-				
9. Sugar/100g	100	12.27	16.88	.244*	.476**	.382**	-.191	-.111	.028	.272**	-.087	-			
10. Sodium (g) /100g	100	0.47	0.61	-.125	.234*	.245*	.339**	.376**	.054	.214*	-.043	-.207*	-		
11. CFR	100	0.39	0.31	0.151	.406**	.464**	.224*	.087	.299**	.618**	.059	-.029	.264**	-	
12. NOVA-4/ UPF Status	100	2.12	2.01	0.055	.622**	.556**	.091	.406**	.188	.496**	-.107	.354**	.308**	.462**	-

								Sat-Map 24							
Variable	*n*	*M*	*SD*	1	2	3	4	5	6	7	8	9	10	11	12
1. Liking	24	51.84	12.82	-											
2. Hedonic Overeating	24	28.96	13.42	.828**	-										
3. Kcal/100g	24	223.31	174.69	.009	.312	-									

Table S1 (continued)

								Sat-Map 24							
Variable	*n*	*M*	*SD*	1	2	3	4	5	6	7	8	9	10	11	12
4. Protein/100g	24	8.25	7.66	.119	.235	.522**	-								
5. Carbohydrate /100g	24	18.91	18.73	.008	.206	.231	-.299	-							
6. Fat/100g	24	13.20	17.21	-.012	.213	.920**	.526**	-.140	-						
7. Saturated fat /100g	-	-	-	-	-	-	-	-	-	-					
8. Fibre/100g	24	1.83	1.71	-.119	.093	.668**	-.009	.333	.604**	-	-				
9. Sugar/100g	24	6.05	7.51	.047	-.018	-.06	-.422*	.503*	-.210	-	.037	-			
10. Sodium (g) /100g	24	0.21	0.19	.32	.485*	.286	.459*	.322	.082	-	.105	-.293	-		
11. CFR	24	0.36	0.30	.395	.452*	.005	-.014	.139	-.051	-	-.065	-.101	.474*	-	
12. NOVA-4 /UPF Status	24	2.50	1.98	.109	.293	-.143	.021	.361	-.332	-	-.191	.048	.442*	.554**	-

									Sat-Map 300						
Variable	*n*	*M*	*SD*	1	2	3	4	5	6	7	8	9	10	11	12
1. Liking	312	56.37	14.10	-											
2. Hedonic Overeating	312	36.76	14.94	.811**	-										
3. Kcal/100g	312	231.56	145.93	.177**	.488**	-									
4. Protein/100g	312	13.20	17.85	-.173**	.023	.520**	-								
5. Carbohydrate /100g	312	29.25	40.64	.251**	.488**	.753**	.021	-							
6. Fat/100g	312	15.30	24.42	.170**	.342**	.825**	.463**	.430**	-						
7. Saturated fat /100g	312	-	-	-	-	-	-	-	-	-					
8. Fibre/100g	312	2.93	5.60	-.105	.025	.535**	.232**	.402**	-	.493**	-				
9. Sugar/100g	312	12.03	24.38	.247**	.422**	.581**	-.026	.762**	-	.398**	.189**	-			

Table S1 (continued)

				Sat-Map 300											
Variable	*n*	*M*	*SD*	1	2	3	4	5	6	7	8	9	10	11	12
10. Sodium (g) /100g	312	1.02	1.96	-.155**	.029	.315**	.600**	.016	-	.227**	.091	-.061	-		
11. CFR	312	0.44	0.29	.036	.177**	.127*	-.036	.059	-	.149**	.103	.044	-.027	-	
12. NOVA-4 /UPF Status	312	2.71	1.87	.279**	.450**	.214**	-.119*	.335**	-	.008	.067	.197**	-.070	.449**	-

Note. *$p < .05$ **$p < .01$

Table S2

Bivariate Correlations for Actual and Self-reported Nutritional Variables in the FPP and SM300 Surveys.

	Food Perceptions Platform												
Variable	*n*	*M*	*SD*	1	2	3	4	5	6	7	8	9	10
1. Believed calories	100	4.34	1.82	-									
2. Believed fat content	100	3.91	1.96	.956**	-								
3. Believed Sweetness/ Savouriness	100	3.76	1.88	-.029	.120	-							
4. Kcal/100g	100	256.73	178.21	.727**	.708**	-.054	-						
5. Protein/100g	100	6.79	6.37	.341**	.414**	.484**	.441**	-					
6. Carbohydrate /100g	100	17.34	20.51	.328**	.288**	.159	.519**	.157	-				
7. Fat/100g	100	8.23	11.53	.426**	.433**	.020	.615**	.355**	.304**	-			
8. Saturated fat /100g	100	4.16	5.44	.635**	.685**	-.106	.643**	.256*	.091	.284**	-		
9. Fibre/100g	100	2.56	2.81	-.045	-.004	.090	.376**	.191	.242*	.320**	.111	-	
10. Sugar/100g	100	12.27	16.88	.359**	.175	-.647**	.382**	-.191	-.111	.028	.272**	-.087	-
11. Sodium (g) /100g	100	0.47	0.61	.374**	.445**	.455**	.245*	.339**	.376**	.054	.214*	-.043	-.207*

Table S2 (continued)

				SatMap 300																	
Variable	*n*	*M*	*SD*	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18
1. Believed calories	312	54.17	18.71	-																	
2. Believed fat conten	312	45.24	20.28	.892**	-																
3. Believed protein	312	42.19	21.31	-.126*	.106	-															
4. Believed carbohydr	312	41.91	17.57	.529**	.315**	-.408**	-														
5. Believed fibre	312	31.67	14.67	-.537**	-.609**	-.104	.139*	-													
6. Believed sugar	312	33.59	24.13	.521**	.240**	-.544	.259**	-.254**	-												
7. Believed salt	312	35.84	18.48	.365**	.548**	.422	.185**	-.301**	-.417**	-											
8. Believed sweetness	312	34.29	29.74	.301**	.041	-.544	.090	-.128*	.940**	-.607**	-										
9. Believed savoury	312	52.92	26.49	-.059	.170**	.542	.071	.011	-.822**	.778**	-.926**	-									
10. Believed sourness	312	11.51	8.23	-.301**	-.300**	-.087	-.286**	.056	-.046	-.136*	.005	-.124*	-								
11. Believed bitternes	312	10.58	6.70	-.41**5	-.310**	-.025	-.388**	.173**	-.208**	-.130*	-.144*	-.040	.697**	-							
12. Believed saltiness	312	35.04	20.71	.155**	.380**	.512**	.034	-.205**	-.588**	.955**	-.728**	.849**	-.081	-.015	-						
13. Kcal/100g	312	231.56	145.93	.560**	.511**	-.213**	.318**	-.228**	.376**	.182**	.251**	-.129*	-.244**	-.142*	.079						
14. Protein/100g	312	13.20	17.85	.156**	.260**	.329**	-.115*	-.132*	-.125*	.329**	-.150**	.176**	-.140*	.005	.332**	.520**	-				
15. Carb/100g	312	29.25	40.64	.439**	.235**	-.548**	.443**	-.156**	.614**	-.074	.498**	-.383**	-.133*	-.176**	-.188	.753**	.021	-			
16. Fat/100g	312	15.30	24.42	.367**	.416**	-.136*	.109	-.133*	.198**	.086	.146**	-.089	-.203**	-.010	.037	.825**	.463**	.430**	-		
17. Fibre/100g	312	2.93	5.60	.066	.031	-.132**	.193**	.250**	.123*	-.022	.113*	-.108	-.104	.044	-.027	.535**	.232**	.402**	.493**	-	
18. Sugar/100g	312	12.03	24.38	.402**	.217**	-.438**	.133*	-.242**	.715**	-.298**	.651**	-.574**	-.086	-.095	-.393**	.581**	-.026	.762**	.398**	.189**	-
19. Sodium/100g	312	1.02	1.96	.153**	.276**	.143*	-.081	-.191**	-.146*	.457**	-.200**	.241**	-.056	.011	.446**	.315**	.600**	.016	.227**	.091	-.061

Note. *$p < .05$ **$p < .01$

Table S3

Final Model Summaries for the Variance Explained in Liking and Hedonic Overeating by Actual Nutrient Content After Controlling for Food Type

	Liking				Hedonic Overeating			
	Food Perceptions Platform		SatMap-300		Food Perceptions Platform		SatMap-300	
	Final Model		Final Model		Final Model		Final Model	
Variable	*B* [SE]	β	*B* [SE]	β	*B* [SE]	β	*B* [SE]	β
Nutritional Model - Stepwise Regression								
Constant	5.47 [.21]		64.11 [2.90]		4.15 [0.29]		35.66 [2.90]	
Food Type: Dessert v Beverage	-	-	-10.70 [6.31]	-.10	-	-	-12.26 [5.66]	-.10*
Food Type: Dessert v Snack	-0.646 [0.21]	-.41***	-8.89 [2.93]	-.29**	0.76 [0.28]		-14.65 [2.69]	-.45***
Food Type: Dessert v Main Meal	-0.56 [0.23]	-.32**	-8.53 [2.91]	-.30**	0.54 [0.32]		-11.76 [2.58]	-.39***
Kcal per 100g	-	-	-	-	0.04 [0.01]	.52***	0.07 [0.01]	.72***
Carbohydrate per 100g	-0.01 [0.04]	.26**	0.06 [0.03]	.18**	-	-	0.02 [0.04]	.24**
Fat per 100g	-	-	0.18 [0.04]	.31***	-	-	-	-
Saturated Fat per 100g	0.05 [0.02]	.31**	-	-	-	-	-	-
Protein per 100g	-0.03 [0.01]	-.20*	-0.19 [0.05]	-.24***	-0.02 [0.02]	-.10	-0.20 [0.06]	-.24***
Fibre per 100g	-	-	-0.66 [0.16]	-.26***	-0.13 [0.04]	-.26**	-0.70 [0.14]	-.26***
ΔF	6.14**		12.39***		9.74**		34.50***	
F	6.03***		12.41***		9.91***		36.06***	
R^2	.24		.20		.39		.44	

Note. *p < .05 **p < .01 ***p<.001 after FDR correction for multiple comparisons

Table S4. *Final Model Summaries for the Variance Explained in Liking and Hedonic Overeating by Self-reported Beliefs About the Composition of Foods After Controlling for Actual Nutrient Content and Food Type*

	Liking				Hedonic Overeating			
	Food Perceptions Platform		SatMap-300		Food Perceptions Platform		SatMap-300	
	Final Model		Final Model		Final Model		Final Model	
Variable	*B* [SE]	β	*B* [SE]	β	*B* [SE]	β	*B* [SE]	β
Nutritional Model With Believed composition - Hierarchical Regression								
Constant	5.68 [0.22]		23.02 [7.16]		4.72 [0.37]		7.40 [5.33]	
Food Type: Dessert v Beverage	-	-	0.49 [5.05]		-	-	-3.95 [3.71]	-.03
Food Type: Dessert v Snack	-0.24 [0.22]		6.75 [2.71]		-0.53 [0.28]	-.23	1.58 [1.98]	.05
Food Type: Dessert v Main Meal	0.18 [0.28]		3.21 [3.42]		-0.54 [31]	-.21	1.13 [2.48]	.04
Believed Sweetness/ Savouriness[1]	-0.13 [0.05]	-.32*	-	-	-	-	-	-
Believed Sweetness	-	-	0.43 [0.07]	.91***	-	-	0.26 [0.08]	.51***
Believed Savouriness	-	-	0.50 [0.10]	.93***	-	-	0.18 [0.06]	.31**
Believed Bitterness	-	-	-0.55 [0.10]	-.26***	-	-	-0.26 [0.08]	-.12***
Believed Saltiness	-	-	-	-	-	-	-	-
Believed Carbohydrate Content	-	-	-	-	-	-	0.18 [0.04]	.21***
Believed Fat Content	-	-	0.21 [0.04]	.30***	.22 [-0.09]	.36*	0.31 [0.04]	.42***
Believed Protein Content	-	-	-.14 [0.04]	-.17**	-	-	-0.09 [0.03]	-.12**
Believed Fibre Content	-	-	-	-	-	-	-.19 [0.04]	-.19***

Table S4 (continued).

	Liking				Hedonic Overeating			
	Food Perceptions Platform		SatMap-300		Food Perceptions Platform		SatMap-300	
	Final Model		Final Model		Final Model		Final Model	
Variable	*B* [SE]	β	*B* [SE]	β	*B* [SE]	β	*B* [SE]	β
ΔF	6.07*		8.09**		6.00*		17.45***	
ΔR^2	.05		.31		.04		.32	
F	6.31***		34.64***		9.83***		73.93***	
R^2	.29		.51		.43		.78	

Note. *p < .05 **p < .01 ***p<.001 after FDR correction for multiple comparisons. [1]The negative coefficient observed mean that lower believed savouriness or greater believed sweetness was related to greater liking and hedonic overeating.

Table S5

Final Model Summaries for the Variance Explained in Liking and Hedonic Overeating by Carbohydrate-to-Fat Ratio and Ultra-Processed Foods After Controlling for Actual Nutrient Content and Food Type

	Liking				Hedonic Overeating			
	FPP		SM300		FPP		SM300	
Variable	*B* [SE]	β	*B* [SE]	β	*B* [SE]	β	*B* [SE]	β
Nutritional Model With CFR - Hierarchical Regression								
Constant	5.54 [0.22]		64.48 [3.06]		4.14 [0.31]		34.34 [2.98]	
Food Type: Dessert v Beverage	-	-	-10.91 [6.34]	-.10	-	-	-11.49 [5.65]	-.10
Food Type: Dessert v Snack	-0.46 [0.21]	-.29*	-9.04 [2.96]	-.29**	0.76 [0.28]	.32**	-14.08 [2.69]	-.43***
Food Type: Dessert v Main Meal	-0.23 [0.24]	-.14	-8.46 [2.92]	-.29**	0.54 [0.32]	.21	-12.04 [2.57]	-.40***
Carbohydrate-to-Fat Ratio	-0.25 [0.27]	<.01	--0.99 [2.60]	-.02	0.06 [0.41]	.02	4.22 [2.29]	-.08
ΔF	0.69		0.15		0.02		3.38	
ΔR^2	.01		<.01		<.01		.01	
F	5.12***		10.85***		8.41***		32.23***	
R^2	.25		.20		.39		.45	

Table S5 (continued)

	Liking				Hedonic Overeating			
	FPP		SM300		FPP		SM300	
Variable	*B* [SE]	β	*B* [SE]	β	*B* [SE]	β	*B* [SE]	β
Nutritional Model With UPFs - Hierarchical Regression								
Constant	5.62 [0.22]		59.79 [3.06]		4.28 [0.32]		29.86 [2.91]	
Food Type: Dessert v Beverage	-	-	-8.77 [6.20]	-.078	-	-	-9.80 [5.34]	-.08
Food Type: Dessert v Snack	-0.54 [0.21]	-.34*	-6.72 [2.93]	-.22*	0.66 [0.29]	.28*	-11.92 [2.58]	-.36***
Food Type: Dessert v Main Meal	-0.29 [0.24]	-.17	-8.02 [2.86]	-.28**	0.53 [0.32]	.21	-11.28 [2.44]	-.37***
Ultraprocessed Foods	-0.08 [0.05]	-.19	1.54 [0.42]	-.21***	-0.07 [0.07]	.12	2.28 [0.35]	.27***
ΔF	2.58		13.78***		1.02		36.59	
ΔR^2	.02		.03		<.01		.06	
F	5.54***		13.04***		8.64***		39.82	
R^2	.26		.24		.40		.50	

Note. *p < .05 **p < .01 ***p<.001 after FDR correction for multiple comparisons

R Code for Power Simulation

```
# Load necessary libraries
library(boot)

# Set seed for reproducibility
set.seed(123)

# Define sample size and number of predictors
n <- XX  # Number of observations
p <- XX    # Number of predictors
target_power <- 0.80  # Power threshold

# Function to run power simulation for a given effect size (f)
simulate_power <- function(f) {
  f2 <- f^2  # Convert to f^2
  R2 <- f2 / (1 + f2)  # Convert to R^2

  # Generate synthetic data
  X <- as.data.frame(matrix(rnorm(n * p), nrow = n, ncol = p))
  colnames(X) <- paste0("X", 1:p)

  # Assign effect sizes
  beta <- rep(sqrt(R2 / p), p)  # Spread effect size across predictors
  y <- as.matrix(X) %*% beta + rnorm(n, sd = sqrt(1 - R2))  # Add noise

  # Define function for bootstrapping
  boot_function <- function(data, indices) {
    d <- data[indices, ]  # Resample data
    model <- lm(y ~ ., data = d)
    summary(model)$coefficients[, 4]  # Return p-values of predictors
```

```
  }

  # Combine response and predictors
  data <- cbind(y, X)

  # Run bootstrap with 1,000 iterations
  boot_results <- boot(data, statistic = boot_function, R = 1000)

  # Compute power: proportion of times each predictor is significant (p < .05)
  predictor_powers <- colMeans(boot_results$t[, -1] < 0.05)  # Exclude intercept

  # Return the highest power among all predictors
  return(max(predictor_powers))  # Ensure at least one predictor hits 80% power
}

# Search for the minimum effect size needed for 80% power
effect_sizes <- seq(0.02, 0.35, by = 0.01)  # Range of Cohen's f values
power_results <- sapply(effect_sizes, simulate_power)

# Find the smallest effect size that achieves at least 80% power for at least one predictor
required_f <- min(effect_sizes[power_results >= target_power])

# Print the results
cat("Minimum Cohen's f needed for 80% power with n = 24:", required_f, "\n")

# Plot power curve
plot(effect_sizes, power_results, type = "b", pch = 19, col = "blue",
    xlab = "Cohen's f", ylab = "Power", main = "Effect Size vs. Power")
abline(h = 0.80, col = "red", lty = 2)  # Mark the 80% power threshold
```