Title: Tempting tastes in focus: A picture set of high-fat/high-carbohydrate foods for the population of Finland (FinnFoodPics)

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ABSTRACT

Background: Modern food items often contain high proportions of saturated fats and refined carbohydrates. Such dietary compositions contribute to the prevalence of obesity and metabolic disease. Food images are a valuable tool to study these diet effects on eating behavior and obesity development. ***Aims***: Creating and validating a novel food picture set to facilitate studies on food choice and eating behavior for the Finnish population called "*FinnFoodPics*". ***Material & Methods***: We photographed 72 commonly consumed Finnish food items and classified them into one of three macronutrient categories: high in carbohydrates, high in fat, or high in carbohydrates and fat (combo). Sixty-two participants rated these items for liking, familiarity, frequency of consumption, expected satiety, perceived healthiness, energy content, and energy density. We used Bayesian ANOVAs to provide information on food characteristics, visual properties, and participant ratings across categories. ***Results***: We found strong evidence of differences across macronutrient categories for all assessed parameters except for familiarity, which showed moderate uniformity across categories. Notably, foods in the carbohydrate category had higher fiber, and those in the fat category had higher protein content. ***Conclusion***: "*FinnFoodPics"* provides a robust tool for local researchers to study food-related behavior and facilitates the replicability and comparability of studies using visual snack food stimuli in Finland.

Keywords

Food image database, macronutrients, carbohydrates, fat, eating behavior

1. INTRODUCTION

The food environment people are exposed to has changed drastically throughout evolution (Cordain et al., 2005). This change was in part due to the domestication of animals and plants (Pontzer & Wood, 2021) and thereafter, the transition from manual to mechanized labor (Hall, 2023). A change that allowed entire populations to move from food scarcity to abundance (Hall, 2023; Pontzer & Wood, 2021). However, the same progress that created these food-rich environments also led to the current surplus of carefully engineered snacks with excessive amounts of fat and sugar (Hall, 2018; Speakman, 2022). Snacks that seem to significantly contribute to maladaptive eating behaviors, increased food intake, and the rise of non-communicable diseases (NCDs)(WHO, 2021).

1.1 The burden of obesity: Urgent need for modern research tools

Obesity contributes to the increased prevalence of NCDs, such as type 2 diabetes and cancers, and is also one of the leading causes of premature deaths worldwide (Lobstein et al., 2023). Moreover, current alarming developments suggest that meeting the 2025 global targets of limiting the increase in obesity is unlikely (Lobstein & Brinsden, 2020). In Finland, 28% of the adult population already suffers from obesity (Lehtoranta et al., 2023), and according to the data from 2017, obesity is a major public health issue only second to binge drinking (European Commission, 2019). In addition, in the same year, about 11,000 deaths were related to dietary risk factors (including high sugar consumption)(European Commission, 2019). Risk factors that not only contribute to the obesity epidemic (WHO, 2021) but also independently impair health (Clemente-Suárez et al., 2023). Further, on a societal level, obesity has been shown to have detrimental consequences for the local population in healthcare costs, and physical and psychological quality of life (Vesikansa, Mehtälä, Jokelainen, et al., 2022 a; Vesikansa, Mehtälä, Mutanen, et al., 2022 b). The aforementioned data emphasize the need to develop relevant research tools investigating the modern food environment. These tools are necessary to examine maladaptive eating behaviors that promote obesity and unhealthy food choices, which can increase the risk of mortality.

1.2 Food image databases

Nowadays, in developed countries not only our access to food is effortless but our constant exposure to palatable food cues affects our behavior (Finlay et al., 2022). This exposure has been associated with unhealthy food choices (Martinho, 2020), cognitive, physiological, and emotional responses (van der Laan et al., 2011) hunger, cravings, weight gain (Boswell & Kober, 2016; Boyland et al., 2024) and obesity prevalence (Goris et al., 2010). Hence, the evidence suggests that visual stimuli alone significantly influence food selection and intake (Linné et al., 2002), where repeated exposure to food cues creates conditioned responses (Boswell & Kober, 2016). Responses that are based on the capacity to pair post-ingestive information (e.g., caloric content) generated by nutrients to the foods we consume (F. Lucas & Sclafani, 1989; Sclafani & Nissenbaum, 1988). Therefore, visual cues of food can elicit behavioral and neural responses similar to real food (Blechert et al., 2014). This has led numerous behavioral and neuroimaging studies to use food images in order to examine disordered eating and unhealthy weight gain (Chae & Lee, 2023). Consequently, to address the need for cost-effective and ecologically valid studies on the field, several researchers developed image databases (Blechert et al., 2014; Charbonnier et al., 2016; DiFeliceantonio et al., 2018; Foroni et al., 2013; Fromm et al., 2021; King et al., 2018). However, when comparing available image databases, there is little to no standardization (Blechert et al., 2014; Charbonnier et al., 2016; DiFeliceantonio et al., 2018; Foroni et al., 2013; Fromm et al., 2021; King et al., 2018). From methods of creation (i.e., portion sizes and food groups) to image quality and target populations, the databases are often specific to studies and countries with similar dietary preferences. Even though Charbonnier et al. (2016) made a photographing protocol for creating standardized images and tested participants in 7 different countries (Netherlands, England, Scotland, Greece, Germany, Sweden, and Hungary). First, their protocol and database are not suitable for investigating modern macronutrient combinations. Second, the generalizability to very different populations risks decreasing familiarity among the citizens of Finland. A subjective variable inferring that familiar foods, which have been consumed, become conditioned stimuli. This enables individuals to predict the nutrient value of these foods based on their images. Thus, despite market globalization in the food industry and the promotion of Western diets (Drewnowski & Popkin, 1997), local food preferences are an important modulator of food choice (Rozin et al., 1999).

Subsequently, we aimed to develop a set of pictures of familiar Finnish foods that offer the possibility of investigating modern macronutrient combinations. While considering many aspects that affect experiments investigating eating behavior. For methods, image quality, and relevance, we modeled our design on two previous studies that examined macronutrient combinations in Germany and the United States of America (DiFeliceantonio et al., 2018; Fromm et al., 2021). Furthermore, we included food characteristics like nutrient composition and processing level, grouping snack foods by macronutrient combination (% of calories from carbohydrate and fat). Lastly, we covered visual properties of the image (e.g., colors), also known to bias study subjects, and individual differences (e.g., familiarity)(Blechert et al., 2014). As a result, we present *FinnFoodPics*, a database of 720 snack food stimuli in three macronutrient categories.

2. MATERIALS AND METHODS

2.1 Food pictures

We first independently selected a large sample of snack foods and classified them into three categories of interest (carbohydrate, fat, or carbohydrate + fat = combo). We based the classification on the nutrition information provided on the food packaging, detailing information on energy, fat, saturated fat, carbohydrate, sugars, protein, salt, fiber, and lactose (The European Banking Union, 2015). An independent nutritionist approved the following classification process: Items in the carbohydrate category had less than 20% of calories from fat and at least triple the amount of its calories from carbohydrates. The same logic in the opposite direction was used for the fat category. Items in the combo category had more than 20% calories from fat content, or the difference in % of calories between carbohydrate and fat content was less than triple the amount. With this preliminary list of snack food items, we consulted three expert nutritionists familiar with the dietary habits of Finns and requested feedback on each item's suitability (ex., Does this item fit average local food preferences?) and recommendations (ex., Is there any obvious item missing from the list). Following their feedback, we ended with 72 snack items (22 carbohydrates, 21 Fat, and 29 Combo). A professional photographer took high-quality images of the food items. For each food item, the entire database contains pictures of ten different portions (40, 80, 120, 160, 200, 240, 280, 320, 360, and 400 kcal). For the evaluation study, we used pictures that contained a 120-kcal food portion arranged in the middle of a white plate, as shown in Fig. 1. To provide visual references for the portion size, a glass, and a napkin were placed next to the plate in each photo. All images were color photographs with dimensions of 4252 x 2829 pixels and a resolution of 300 dots per inch (dpi).

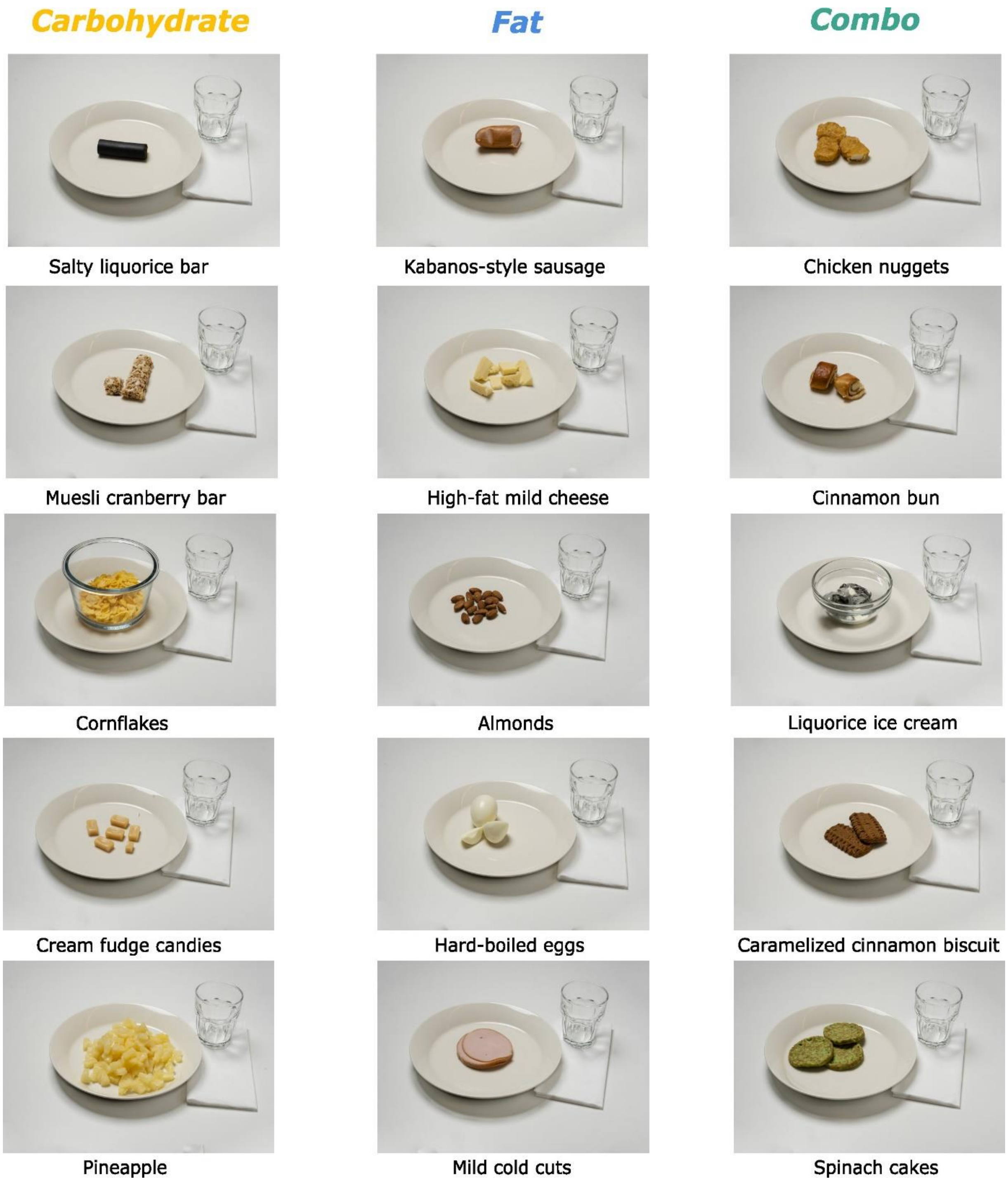

Fig. 1. Selection of *FinnFoodPics* images with corresponding food names selected into the final 72-item picture set. Items were grouped by macronutrient category: carbohydrate, fat, and the combination of carbohydrate and fat ("combo").

2.2 Food characteristics

We used information available in food packages to create a list of nutrients and categorize our food items into macronutrient categories. In food packages, according to the EU regulation on food information to consumers, the word *fat* means total lipids and phospholipids (saturates, monounsaturates, polyunsaturates), whereas *carbohydrates* refer to any carbohydrate that can be metabolized by humans (sugars, polyols/sugar alcohols, and starch)(The European Banking Union, 2015). Starch, polyols, fiber, lactose, monounsaturates, and polyunsaturates are indicated voluntarily (The European Banking Union, 2015). However, the amount of starch/polyols can be deducted based on the carbohydrate and sugar content (Starch or polyols = Carbohydrates - sugars). Here, *fiber* means edible carbohydrate polymers indigestible in the human small intestine (The European Banking Union, 2015). In contrast to the US packages, EU food items report salt instead of sodium, which is calculated using the formula: salt = sodium x 2.54 (The European Banking Union, 2015). All food composition information in grams (g) or milligrams (mg) per 100 grams was converted to g or mg per 120 kcal (equivalent to the amount shown in each image). The item price in Euros (€) per 120 kcal was determined from unit prices (Euros/package) at k-ruoka.fi, s-kaupat.fi, lidl.fi, and trips to the physical stores in the Helsinki area. Our final list included information on carbohydrate content, starch or polyols, fiber, sugars, fat, saturated fat, salt, protein, portion size, energy density, and price.

2.3 Visual properties

Since the visual image features of food stimuli are known to affect visual perception, we calculated the visual area taken up by food using ImageJ v1.51 and converted pixels to cm2 based on the measured dimensions of the plate (Schneider et al., 2012), similarly to Fromm et al., (2021). We also included image characteristics such as brightness, within-object contrast, spatial frequency, complexity, and color contents (red, green, blue) computed using MATLAB R2021b (The Mathworks Inc., Sherborn, MA, USA) based on scripts from Blechert et al., (2014).

2.4 Participants

Sixty-two healthy participants were recruited from the University of Helsinki and the greater Helsinki area via advertisements in public places and University facilities. The sample size was equivalent to a study that established a similar picture set for a North American population (i.e., United States)(Fromm et al., 2021). Inclusion criteria were age between 18 and 45 years, fluency in English, and having lived in Finland for the past 5 years with a maximum interruption of 9 months. The duration of their stay ensured that our participants were adequately familiar with the selected items. Exclusion criteria were serious or unstable medical illness (e.g., cancer), intake of medication that can affect alertness (e.g., benzodiazepines) or psychoactive drugs, anti-obesity agents, or implanted medical devices (e.g., pacemaker), and history of major psychiatric illnesses as defined by the DSM-V criteria (Diagnostic and Statistical Manual of Mental Disorders, 5th edition), pregnancy, color blindness, underweight (<18.5 kg/m^2), smell or taste dysfunction, food allergies/sensitivity, or dietary restriction for other reasons (Religious, choice, etc.). These criteria were checked via online screening questionnaires (Redcap) and follow-up email conversations prior to recruitment. Via behavioral questionnaires, we assessed the severity of depressive symptoms by means of the Beck Depression Inventory-II (BDI-II)(Beck et al., 1996) and the severity of anxiety symptoms through the Beck Anxiety Inventory (BAI)(Beck et al., 1988), because depression or anxiety and disordered eating, often co-occur and can influence one another (Frost et al., 1982; Mooreville et al., 2014; Rosenbaum & White, 2015; Zhang et al., 2021). Thus, we excluded individuals with scores indicating severe anxiety or depression. Participants gave written informed consent prior to participating in our study, and the study protocol qualified as ethically acceptable by the University of Helsinki Ethics Committee in the Humanities and Social and Behavioural Sciences.

2.5 Internal state ratings

Participants rated their current hunger, fullness, thirst, potential to eat, and desire to eat (Table 1) along a continuous horizontal 160-mm visual analog scale (VAS). VAS ratings were transformed into percentages of the scale.

Table 1. Questions and anchors for the internal state rating scales

Internal state	Question	Anchors
Hunger	How hungry do you feel?	Not at all hungry, Extremely hungry
Fullness	How full do you feel?	Not at all full, Extremely full
Thirst	How thirsty do you feel?	Not at all thirsty, Extremely thirsty
Potential to eat	How much do you think you could eat right now?	Not another bite, Extremely large amount
Desire to eat	How much do you want to eat right now?	Not at all, Extremely

2.6 Dietary intake questionnaires

We assessed eating behavior with the Dutch Eating Behavior Questionnaire (DEBQ)(van Strien et al., 1986) and habitual intake of saturated fat and added sugar with the Dietary Fat and Free

Sugar-Short Questionnaire (DFS)(Francis & Stevenson, 2013). The DEBQ comprises 33 questions with a five-point scoring system. Total scores are calculated to derive separate scores for restrained, emotional, and external eating. In our study, we used the English version (Wardle 1987). The DFS asks for the frequency of consumption over the past year ("less than once per month" up to "5 times per week or more") of 26 items or groups of items high in saturated fat and/or refined sugar. A higher total score indicates higher consumption of these items. The questionnaire also provides subscores for fat, sugar, and a combination of fat and sugar (fat-sugar), calculated by summing the responses for 11, 9, and 6 items within their respective categories.

2.7 Food ratings

Participants rated the set of food pictures on a continuous scale for liking, familiarity, frequency of consumption, perceived healthiness, expected satiety, estimated energy content (calories), and estimated energy density (Table 2), similar to prior studies (DiFeliceantonio et al., 2018; Fromm et al., 2021). We defined satiety as the reduced urge to eat after a meal, so-called inter-meal satiety (Blundell et al., 2010). The term "expected" is added to satiety to describe the absence of hunger between meals the food is expected to deliver (Forde et al., 2015). Liking was rated on a vertical, labeled hedonic scale (Lim et al., 2009) and all the other values were assessed on a 160 mm horizontal scale adapted from Fromm and colleagues. Except for frequency of consumption (days/month) and estimated energy content (kcal), perceptual ratings were scored as a percentage of the scale at which the participant's marker was placed. Participants were given a short training after receiving the instructions to ensure that they performed the task correctly. All the food items were presented randomly during the task.

Table 2. Questions and labels for the food ratings

Subjective Variable	Question	Labels
Liking	How much do you like this food?	Most disliked sensation imaginable, Most liked sensation imaginable (end-to-end labels)
Familiarity	How familiar is this food?	Extremely unfamiliar, Extremely familiar
Frequency of consumption	How often do you eat this food?	<1x per month, 2-3x per month, 1-2x month, 3-4x per month, 5+x per month

Perceived healthiness	How healthy is this food?	Extremely unhealthy, Extremely healthy
Expected satiety	How filling do you expect this food portion to be?	Not filling at all, Extremely filling
Estimated energy content	How many calories are in this portion?	0, 60, 120, 180, 240 kcal
Estimated energy density	How energy dense is this food?	Extremely low, Extremely high

2.8 Procedure

Participants consented and completed an online screening survey where they provided demographic (e.g., age in years, sex assigned at birth: male or female) and anthropometric data (e.g., height in cm, weight in kg). BMI was calculated as weight divided by the square of height (in kg/m^2). They were instructed to fast 1 hour before the rating session. Upon arrival, we first obtained consent, checked for fasting compliance, and explained the task details to make sure each participant fully understood how to interpret and answer the internal state (Table 1) and perceptual ratings (Table 2). To ensure participants responded accurately they were also provided with definitions for key terms, such as a "calorie" defined as "a unit of energy derived from consumed foods or beverages," and "energy density" as "the concentration of calories within a given volume of food". Food images and response scales were presented using Psychopy 3 v2022.2.4 (Peirce et al., 2019). Screening data and the digital versions of DFS, DEBQ, BDI, and BAI were all self-reported at the end of the session and hosted at REDCap (Research Electronic Data Capture)(Harris et al., 2009). The sample size was pre-determined based on a prior study conducted with a U.S. population (Fromm et al., 2021). Each session lasted 1–1.5 hours, and participants were compensated with 15-euro vouchers.

2.9 Statistical analyses

We performed Bayesian and frequentist ANOVAs between the macronutrient categories (Carbohydrate, Fat, Combo) to compare food characteristics, visual properties, and food ratings. Classical statistical methods were applied to facilitate comparison and interpretation of results to readers unfamiliar with Bayesian methods. The category differences were computed as one average value for all participants per food item (only for food ratings). Because fat items had, on average, higher protein content and carbohydrate items had, on average, higher fiber content, we conducted explorative ANCOVAs for all food ratings with protein and fiber as covariates to control for their effects. We did not perform correction for multiple comparisons for the tests that were done under Bayesian inferences as they are more conservative than classical approaches based on Type I error (Berry & Hochberg, 1999; Gelman et al., 2009; Gelman & Tuerlinckx, 2000). To interpret the strength of evidence for the Bayes factors, we used Lee and Wagenmakers' adaptation of Jeffrey's scale (Lee & Wagenmakers, 2014). To improve the readability of the tables, we color-coded the grades of evidence. Strong, very strong, and extreme are green (10-30,30-100, >100), moderate is orange (3-10), and anecdotal is red (1-3). Bayes factor in favor of H1 (alternative hypothesis) is referred to as $\mathbf{BF_{10}}$, and Bayes factor in favor of H0 (null hypothesis) as $\mathbf{BF_{01}}$. As we did not have data to build informative priors, we followed a recommendation and used default (i.e., non-informative/uniform) priors to ensure the objectivity of the analysis and allow comparability with future experiments (Keysers et al., 2020). All frequentist p-values are corrected using the Bonferroni method. Additionally, to quantify the degree to which our measurement scales provided similar results among participants for the same snack food. We aimed to measure the unidimensional reliability of all items' food ratings. This measure provided us with an overall frequentist scale reliability (e.g., familiarity ratings' Cronbach alpha) and individual food item reliability statistics. Hence, despite the simplicity of our questions for the ratings (Table 2), first, it ensures that the scale measures the same construct. Second, it shows a correlation (item-rest correlation) between each item and the total score of the scale (excluding the item in question), where higher values indicate the item's consistency with the overall score (Zijlmans et al., 2018). Third, it calculates Crobach's alpha if the item is dropped. This means that if the Cronbach value increases without the item, for the scale's consistency, it should be considered for removal. The reliability measures were mainly performed for familiarity ratings as they highlighted the usefulness of our database, specifically for Finland. The remaining food ratings reliability scores were done exploratively.

Lastly, we conducted a secondary analysis to evaluate if any participant characteristics affected their ratings. First, we analyzed correlations of mean food ratings from each participant with emotional eating, external eating, restraint subscores of the DEBQ, DFS total score, hunger, age, and BMI. These correlations were deemed significant at $p < .007$, after applying Bonferroni correction for the 7 ratings analyzed within each participant characteristic with an alpha level of .05. There were no missing data points and no excluded participants. Except for the reliability measures, the data analysis plan was developed before data collection. All statistical analyses were performed using R in RStudio v4.3.0 (Posit team, 2023) and JASP v0.17.3.0 (JASP Team, 2023).

3. RESULTS

3.1 Sample descriptives

The mean ratings for hunger and fullness were 44.15±21.03 % and 41.80±22.75 %, respectively (N = 62). Hence, as instructed before our session, participants, on average, arrived neither full nor hungry. Due to their invalid answer, one participant was excluded from the calculation for years of education.

Table 3. Summary of participant characteristics

Participant descriptives and internal state ratings (Units)	Mean ± Standard deviation	Median	Range
Age (Years)	25.96±6.70	23.50	18-44
Sex	36 Female, 26 Male		
Years of education	15.11±2.62	15	12-22 (one participant excluded)
BMI (kg/m^2)	23.78 ±3.54	23.45	19.03-38.71
Hunger (% of scale)	44.15±21.03	48.55	1.5-79
Thirst (% of scale)	55.9±18.29	59.75	9.8-90.3
Fullness (% of scale)	41.80±22.75	38.05	4.4-84.3
Desire to eat (% of scale)	41.20±23.51	41.25	0-85
Potential to eat (% of scale)	45.48±22.57	41.25	5.9-100
BDI Score	5.53±4.63	4	0-19
BAI Score	7.59±6.62	6	0-30
DFS Total score	55.35±6.29	56.50	39-74
DFS Fat subscale score	28.90±4.65	29.50	18-38
DFS Sugar subscale score	10.75±2.44	11	6-17
DFS Fat Sugar subscale score	15.69±3.44	15.50	9-27

External eating	21±7.33	21	10-35
Restrained	31±4.23	31	24-40
Emotional eating	29.35±9.22	29	13-63

Associations between participant food ratings and participant characteristics

To test if participants' characteristics affected their food ratings, we performed correlations with several parameters (Age, BMI, DFS Score, DEBQ scores, and Hunger). We found no or weak associations of age, BMI, DFS score, external eating, restraint, or emotional eating with any of the rating variables (Fig. 2, Table S7). One notable positive association, despite its weakness, was between BMI and estimated energy content ($p = 0.01, r = 0.27$)(Fig. 2, Table S7). At the same strength, we also found a negative association between emotional eating and perceived healthiness ($p = 0.01$, $r = -0.27$)(Fig. 2, Table S7). Hunger and liking ratings showed a moderate positive association ($p = 0.001, r = 0.34$)(Fig. 2, Table S7).

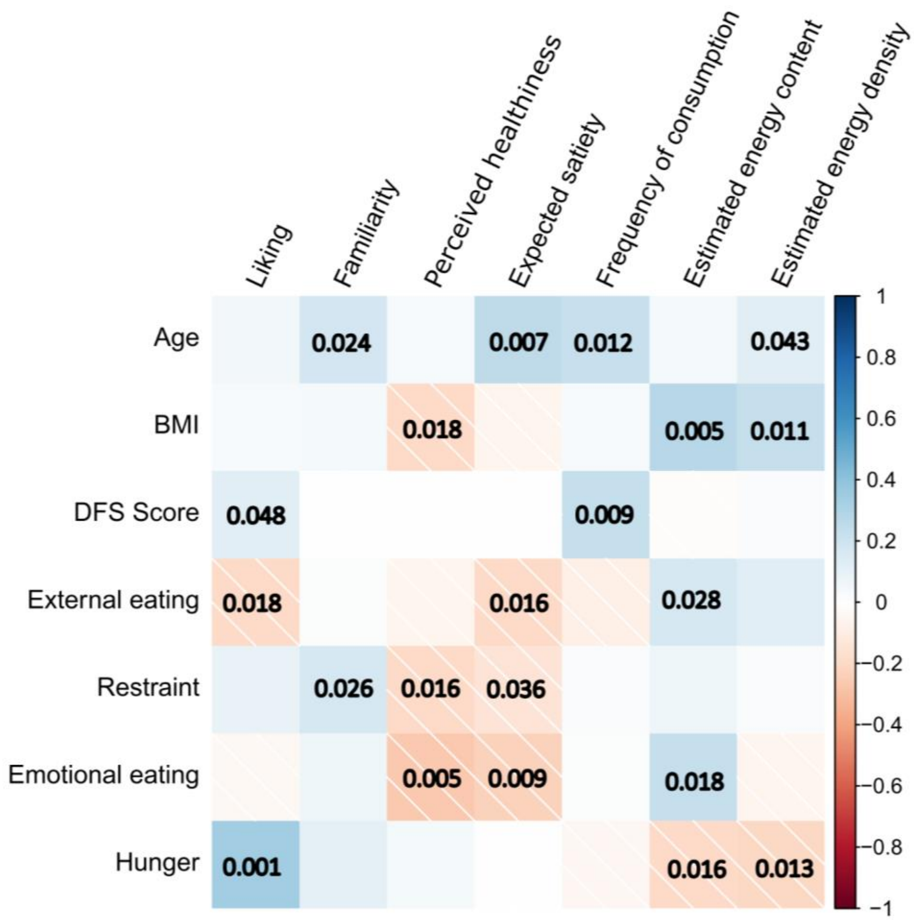

Fig. 2. Pearson's r correlations (color-coded) and p-values of all food ratings with participant characteristics. See also Table S7. *p < .007 (alpha = .05/7 food ratings tested per participant characteristic). The values shown represent only significant p-values. Food rating values were averaged per participant.

3.2 "FinnFoodPics"

3.2.1 Food nutrient information and visual properties

Descriptive statistics for the final set of pictures in our three macronutrient categories and Bayesian ANOVAs for the food characteristics are presented in Table 4a and Fig. 3a,b, and c; frequentist ANOVAs are reported in Table S2.

Our predefined macronutrient categorization showed the expected variations in carbohydrate and fat content. The carbohydrate category contains more carbohydrates (Mean = 24.49 g/120 kcal) than the fat (Mean = 1.27 g/120 kcal) and combo (Mean = 14.92 g/120 kcal) categories. Conversely, the fat category contained more fat (Mean = 9.56 g/120 kcal) than the carbohydrate (Mean = 0.89 g/120 kcal) and combo (Mean = 5.39 g/120 kcal) categories (Table 4a). Portion size and price showed anecdotal and moderate evidence of a difference between categories (Table 4a).

Starch/Polyols

Starch/polyols content showed anecdotal evidence in favor of a difference between categories (Table 4a, Fig. 3f), and post-hoc comparisons revealed the same trends as for carbohydrate and sugar content. The carbohydrate category exhibited extreme evidence for higher starch/polyols content compared to the fat category ($t(1,41) = 7.17$, $p_{bonf}<.001$, BF_{10} = 598507.85±0%) and moderate evidence for higher starch/polyols content compared to the combo category ($t(1,49) = 3.03$, $p_{bonf} = 0.01$, BF_{10} = 3.94±0%). Conversely, the combo category again displayed an extreme Bayes factor supporting that there was a higher starch/polyols content than in the fat category ($t(1,48) = 4.64$, $p_{bonf}<.001$, BF_{10} = 65146.05±0%).

Sugar

Additionally, the carbohydrate category showed extreme evidence in favor of a difference in sugar content in comparison to the fat ($t(1,41) = 5.17$, $p_{bonf}<.001$, BF_{10} = 557.21±0) category, and anecdotal for the combo ($t(1,49) = 2.34$, $p_{bonf} = 0.05$, BF_{10} = 1.53±0.01%) category. Evidence was also extreme when comparing sugar content of combo category items versus the fat category ($t(1,48) = 3.10$, $p_{bonf} = 0.008$, BF_{10} = 2002.22±0%)(Table 4a, Fig. 3d).

Saturated fat

For saturated fat content, categories differed extremely (Table 4a, Fig. 3e). Post-hoc there was evidence for an extreme difference between carbohydrate and combo ($t(1,49) = -3.99$, $p_{bonf}<.001$, BF_{10} = 6620.81±0%), and carbohydrate and fat categories ($t(1,41) = -8.31$, $p_{bonf}<.001$, BF_{10} = $1.41\text{x}10^{+7}$±0%) as well as between combo and fat ($t(1,48) = -4.91$, $p_{bonf}<.001$, BF_{10} = 164.54±0%).

Salt

In terms of salt content, categories were extremely different (Table 4a, Fig. 3g). Post-hoc there was evidence anecdotal evidence for a difference between carbohydrate and combo ($t(1,49) = -0.54$, $p_{bonf} = 1$, BF_{10} = 0.44±0.007%), very strong for carbohydrate and fat categories ($t(1,41) = -4.77$, $p_{bonf}<.001$, BF_{10} = 72.14±0%) and extreme between combo and fat ($t(1,48) = -4.55$, $p_{bonf}<.001$, BF_{10} = 106.50±0%).

Protein & Fiber

Items in the fat category also showed extreme evidence of higher protein content than carbohydrate ($t(1,41) = -5.39$, $p_{bonf}<.001$, BF_{10} = 349.89±0%) and combo categories ($t(1,48) = -5.92$, $p_{bonf}<.001$, BF_{10} = 2910.13±0%)(Fig. 3b). In a similar manner, carbohydrate items showed strong evidence that they had more fiber in comparison to combo ($t(1,49) = 3.42$, $p_{bonf}=.003$, BF_{10} = 11.43±0%) and moderate evidence versus fat category ($t(1,41) = 3.25$, $p_{bonf} = .005$, BF_{10} = 4.55±0%)(Fig. 3c). However, combo category showed anecdotal evidence versus fat category ($t(1,48) = 0.08$, $p_{bonf} = 1$, BF_{10} = 0.28±0.007%).

Visual properties

Macronutrient categories differed only in three visual properties: Extreme evidence for spatial frequency, moderate evidence for complexity, and anecdotal evidence for within-object contrast (WOC)(Table 4b). *Post-hoc* comparisons revealed strong differences in spatial frequency in the carbohydrate category versus fat category ($t(1,41) = 4.93$, $p_{bonf}<.001$, $BF_{10} = 116.85\pm0\%$), and combo versus fat category ($t(1,48) = 3.19$, $p_{bonf} = 0.006$, $BF_{10} = 73.21\pm0\%$) but not in carbohydrate versus combo category ($t(1,49) = 2.08$, $p_{bonf} = 0.12$, $BF_{10} = 1.92\pm0.008\%$).

Level of processing

Current Nordic Nutrition Recommendations (NNR2023) address only specific types of processed foods (e.g., sweet, confectioneries) but do not formulate any specific advice concerning ultra-processed foods (Blomhoff et al., 2023). As considering the level of food processing and not just nutrient content has become a subject of important debate in nutrition (Astrup & Monteiro, 2022; Monteiro & Astrup, 2022). Nonetheless, a scoping review for the NNR2023 revealed that some but not all ultra-processed foods are related to adverse health outcomes, and more studies are needed in order to reformulate Nordic dietary guidelines (Juul & Bere, 2024). Therefore, to enable researchers to explore questions about the level of processing and nutrient content, we also added the NOVA classification describing the level of processing to our database (Table S8). Based on the definitions by Monteiro and colleagues (Monteiro et al., 2019), in the carbohydrate category, two items were classified as minimally processed (NOVA Group 1), nine as processed (NOVA Group 3), and 11 as ultra-processed (NOVA Group 4)(Table S8). In the fat category, three items were classified as minimally processed, eight as processed, and ten as ultra-processed (Table S8). Finally, in the combo category, one item was processed, and 28 in the ultraprocessed NOVA group (Table S8).

Table 4. Descriptive statistics and Bayesian ANOVAs on (a) food characteristics, (b) visual properties, and (c) food ratings of images across macronutrient categories. Strong, very strong, and extreme evidence are green (10-30,30-100, >100), moderate is orange (3-10), and anecdotal is red (1-3)

Food characteristics	**Carbohydrate**	**Fat**	**Combo**	**Category**
	Mean±SEM, Range			**Bayes Factor±error %**
Carbohydrate (g/120 kcal)	24.49±0.65, 17.90-28.88	1.27±0.35, 0.00-4.91	14.92±0.68, 9.04-22.68	$BF_{10}= 9.42e^{+31}\pm0\%$

Fat (g/120 kcal)	0.89±0.17, 0.00-2.57	9.56±0.42, 3.60-13.19	5.39±0.28, 2.86-7.82	BF_{10}= $3.45e^{+24}$±0%
Protein (g/120 kcal)	2.42±0.27, 0.00-4.64	6.85±0.96, 0.49-21.72	2.28±0.29, 0.46-7.72	BF_{10} = 147417.9±0%
Fiber (g/120 kcal)	1.64±0.42, 0.00-6.14	0.39±0.18, 0.00-2.95	0.42±0.12, 0.00-2.37	BF_{10} = 25.85±0.01%
Starch/Polyols (g/120 kcal)	13.60±1.73, 0.00-24.03	0.90±0.32, 0.00-4.73	8.63±1.04, 0.00-18.83	BF_{10} = $2.53e^{+6}$±0%
Salt (g/120 kcal)	0.18±0.04, 0.00-0.62	0.71±0.13, 0.00-2.45	0.24±0.03, 0.00-0.61	BF_{10} = 2361.44±0%
Saturated Fat (g/120 kcal)	0.27±0.07, 0.00-1.32	3.85±0.44, 0.91-7.27	1.86±0.25, 0.23-4.58	BF_{10} = $1873e^{+8}$±0%
Sugars (g/120 kcal)	10.88±2.20, 0.21-28.88	0.36±0.11, 0.00-1.90	6.29±1.00, 0.08-18.92	BF_{10} = 1516.27±0.01%
Portion size (g/120 kcal)	44.09±8.54, 28.24-222.2	47.74±5.73, 18.60-120	33.21±2.58, 20.98-77.42	BF_{01} = 1.943±0.03%
Energy density (kcal/g)	3.29±0.15, 0.54-4.25	3.14±0.33, 1.00-6.45	4.08±0.22, 1.55-5.72	BF_{10} = 3.79±0.01%
Price (Euros/120 kcal)	0.33±0.08, 0.03-1.82	0.51±0.07, 0.10-1.35	0.43±0.08, 0.13-2.50	BF_{01} = 3.61±0.03%

Visual properties	**Carbohydrate**	**Fat**	**Combo**	**Category**
	Mean±SEM, Range			**Bayes Factor±error %**
Visual area of food (cm^2)	75.54±10.93, 16.68-196.7	56.20±6.33, 21.80-132.5	76.99±13.20, 5.54-315.6	BF_{01} = 4.015±0.03%
Red	0.34±0.00, 0.33-0.35	0.34±0.00, 0.33-0.34	0.34±0.00, 0.33-0.35	BF_{01} = 1.36±0.02%
Green	0.33±0.00, 0.33-0.33	0.33±0.00, 0.33-0.33	0.33±0.00, 0.33-0.34	BF_{01} = 1.88±0.02%

Blue	0.32±0.00, 0.31-0.32	0.32±0.00, 0.31-0.32	0.32±0.00, 0.30-0.32	BF_{01} = 1.10±0.02%
Brightness	61.52±1.31, 46.42-72.17	59.40±0.90, 53.27-68.70	59.38±0.64, 50.83-65.65	BF_{01} = 2.47±0.03%
Within-object contrast (WOC)	30.90±1.25, 23.87-45.11	27.21±1.06, 21.67-43.26	29.04±0.59, 22.86-34.53	BF_{10} = 1.47±0.01%
Spatial frequency	17.04±0.13, 15.88-18.39	16.33±0.11, 15.59-16.99	16.76±0.04, 16.21-17.18	BF_{10} = 54.74±0.01%
Complexity	0.03±0.00, 0.01-0.06	0.02±0.00, 0.02-0.03	0.02±0.00, 0.01-0.03	BF_{10} = 3.65±0.01%

Food ratings	**Carbohydrate**	**Fat**	**Combo**	**Category**
	Mean±SEM, Range			**Bayes Factor±error %**
Familiarity (% of scale)	71.29±1.75, 54.72-84.22	74.96±1.21, 65.17-84.44	71.61±2.07, 48.42-87.48	BF_{01} = 3.59±0.03%
Liking (% of scale)	57.01±0.86, 48.99-65.09	59.30±1.25, 47.96-72.18	61.82±0.99, 49.32-71.88	BF_{10} = 8.03±0.02%
Frequency (% of scale)	2.79±0.56, 0.22-10.83	4.34±0.56, 1.12-10.04	2.36±0.35, 0.22-7.11	BF_{10} = 3.35±0.01%
Perceived healthiness (% of scale)	42.27±5.17, 6.54-76.52	46.35±3.38, 23.55-74.96	26.30±3.32, 9.21-68.26	BF_{10} = 35.12±0.01%
Expected satiety (% of scale)	38.86±2.47, 17.46-57.69	45.45±1.77, 29.58-63.69	37.58±1.90, 22.51-62.30	BF_{10} = 2.30±0.01%
Estimated energy density (% of scale)	55.46±2.28, 29.48-72.71	64.54±1.72, 44.12-74.57	64.44±1.42, 41.88-72.99	BF_{10} = 43.55±0.01%
Estimated energy content (kcal)	118.6±3.22, 96.26-154.9	125.5±3.79, 98.13-168.8	130.7±3.37, 95.98-163.3	BF_{10} = 1.29±0.02%

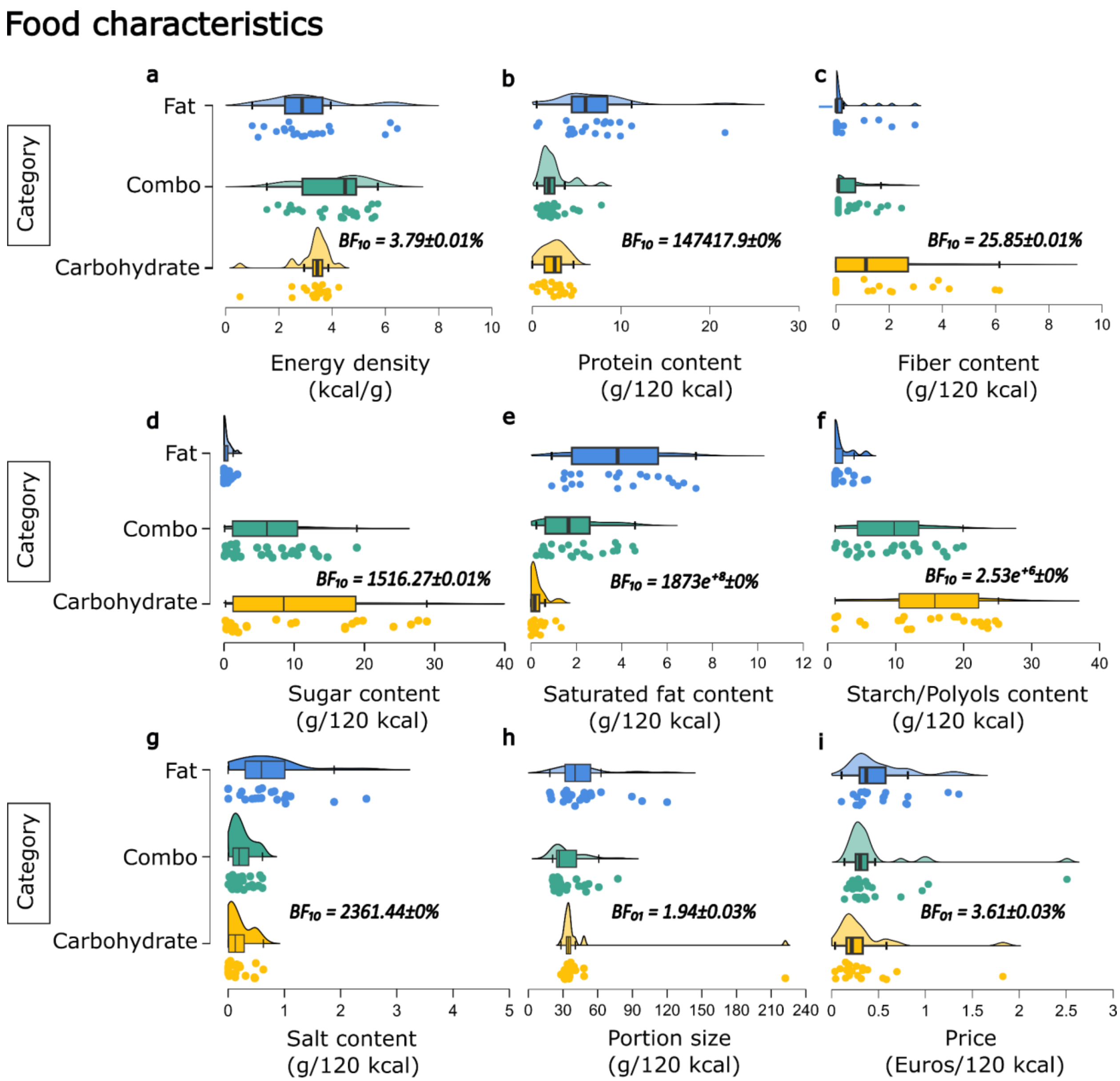

Fig. 3. Mean ± SEM and distribution of energy density (a), protein content (b), fiber content (c), sugar content (d), saturated fat content (e), starch/polyols content (f), salt content (g), portion size (h) and price (i) across macronutrient categories of the *FinnFoodPics* picture set.

3.2.2 Food ratings

Macronutrient category effects on food ratings

Except for familiarity, all ratings produced evidence in favor of differences between the macronutrient categories. The evidence for differences was very strong for estimated energy density and perceived healthiness, moderate for frequency of consumption and liking, and anecdotal for expected satiety and estimated energy content (Table 4c, Fig. 4a-g).

Liking ratings showed strong evidence in favor of lower ratings in the carbohydrate category compared to the combo category ($t(1,49) = -3.32$, $p_{bonf} = 0.004$, $BF_{10} = 32.49\pm0\%$). There was no evidence for a difference in carbohydrate versus fat categories ($t(1,41) = -1.46$, $p_{bonf} = 0.44$, $BF_{10} = 0.74\pm0.006\%$) nor combo versus fat categories ($t(1,48) = 1.72$, $p_{bonf} = 0.26$, $BF_{10} = 0.80\pm0.007\%$)(Fig. 4b).

Expected satiety ratings showed no evidence in favor of a difference for carbohydrate category versus combo ($t(1,49) = 0.44$, $p_{bonf} = 1$, $BF_{10} = 0.30\pm0.007\%$), anecdotal evidence for carbohydrate versus fat ($t(1,41) = -2.12$, $p_{bonf} = 0.11$, $BF_{10} = 1.81\pm0.008\%$) but moderate for combo versus fat category ($t(1,48) = -2.70$, $p_{bonf} = 0.02$, $BF_{10} = 7.778\pm0\%$)(Fig. 4c).

Frequency of consumption ratings showed no evidence indicating a difference for carbohydrate category versus combo ($t(1,49) = 0.63$, $p_{bonf} = 1$, $BF_{10} = 0.33\pm0.007\%$), Anecdotal evidence suggested lower ratings for the carbohydrate versus fat categories ($t(1,41) = -2.16$, $p_{bonf} = 0.10$, $BF_{10} = 1.35\pm0.007\%$), while moderate evidence was observed for lower ratings in the combo versus fat category comparison ($t(1,48) = -2.93$, $p_{bonf} = 0.01$, $BF_{10} = 12.66\pm0\%$)(Fig. 4d).

Estimated energy content ratings exhibited moderate evidence for a difference between carbohydrate and combo categories ($t(1,49) = -2.50$, $p_{bonf} = 0.04$, $BF_{10} = 3.54\pm0.009\%$). Additionally, anecdotal evidence suggested a difference in energy content ratings between carbohydrate versus fat ($t(1,41) = -1.33$, $p_{bonf} = 0.56$, $BF_{10} = 0.65\pm0.006\%$) and for combo versus fat categories ($t(1,48) = 1.05$, $p_{bonf} = 0.89$, $BF_{10} = 0.43\pm0.007\%$)(Fig. 4e).

Post-hoc tests revealed strong evidence in favor of a difference where the carbohydrate category has lower estimated **energy density** ratings than combo ($t(1,49) = -3.61$, $p_{bonf} = 0.002$, $BF_{10} = 29.72\pm0\%$) and fat ($t(1,41) = -3.38$, $p_{bonf} = 0.004$, $BF_{10} = 12.49\pm0\%$) categories. There was no evidence of a difference between combo and fat categories ($t(1,48) = -0.03$, $p_{bonf} = 1$, $BF_{10} = 0.28\pm0.007\%$)(Fig. 4f).

Perceived healthiness ratings showed moderate evidence in favor of higher ratings in the carbohydrate category versus combo ($t(1,49) = 2.90$, $p_{bonf} = 0.01$, $BF_{10} = 5.12\pm0\%$), and no evidence for a difference in carbohydrate versus fat categories ($t(1,41) = -0.68$, $p_{bonf} = 1$, $BF_{10} = 0.35\pm0\%$) and extreme evidence for lower ratings in combo category versus fat category ($t(1,48) = -3.59$, $p_{bonf} = 0.002$, $BF_{10} = 161.06\pm0\%$)(Fig. 4g).

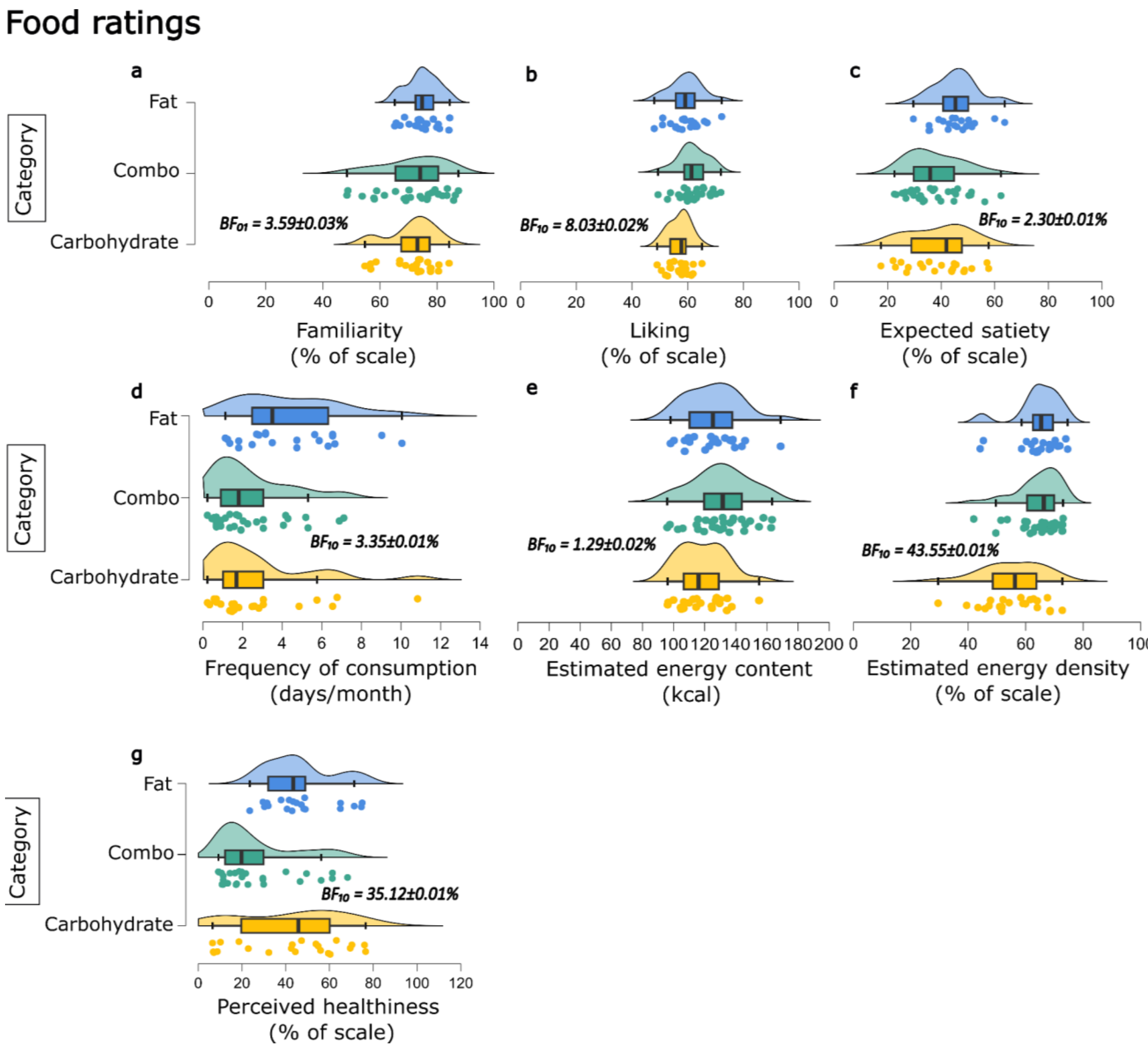

Fig. 4. Mean ± SEM and distribution of selected food ratings (a-g) across macronutrient categories of the *FinnFoodPics* picture set. Each point represents the average of a food item in that category.

Reliability of Familiarity ratings

To increase confidence in our familiarity ratings, we measured the reliability of the scale and how closely related the food items were in terms of familiarity (unidimensional reliability statistics). Internal consistency was excellent (≥ 0.9)(Salkind, 2006) for all stimuli and for each category separately (Table 5). For the carbohydrate category, only two items (Multigrain hoops, Dried dates) seem increase internal consistency in familiarity ratings if they were to be dropped (Cronbach's alpha = 0.912 and 0.910 respectively), with all other values remaining excellent (Cronbach's alpha ≥ 0.903)(Table S5a). The same two items also showed the lowest item-rest correlation of all (0.374 and 0.446)(Table S5a). Concerning the fat category, only the removal of two items (Kabanos-style sausage and hard-boiled eggs) could increase consistency (Cronbach's alpha = 0.909 and 0.906 respectively) and had the lowest item-rest correlations (0.346 and 0.371)(Table S5b). The rest of the items, even when dropped, remained excellent (Cronbach's alpha ≥ 0.909)(Table S5b). The combo also had only extreme internal consistency values (Cronbach's alpha ≥ 0.922), with 5 items showing the potential to increase Cronbach's alpha if they were dropped (Caramelized sugar and cinnamon biscuit, liquorice ice cream, Chocolate covered crunchy corn puffs, apple pockets, vanilla cream donut)(Table S5c). Scale reliability statistics for the remaining ratings are summarized in Table S6.

Table 5. Summary of familiarity scale reliability statistics

	All stimuli	Carbohydrate	Fat	Combo
Estimate	Cronbach's alpha	Cronbach's alpha	Cronbach's alpha	Cronbach's alpha
Point estimate	0.969	0.914	0.906	0.927
95 % CI lower bound	0.957	0.878	0.866	0.897
95 % CI upper bound	0.979	0.942	0.936	0.950

Protein and Fiber content effects on food ratings

To examine the influence of fiber and protein content on food ratings, we performed a Bayesian ANCOVA on the food ratings, including the macronutrient category (carbohydrate, fat, combo) as a fixed factor and the food items' protein and fiber content as a covariate. In order to account for the shared variance between fiber and protein (r = -0.105) we defined a base model where the macronutrient category was added to the null and protein remained a covariate. Then, both category and protein were added to the null, and fiber was the covariate.

The effect of protein is anecdotal for liking ($F(2,68) = 4.65$ $p = 0.03$, BF_{10} = 1.52±1.67%) and perceived healthiness ($F(2,68) = 1.50$ $p = 0.22$, BF_{01} = 1.25±14.94%), extreme for expected satiety ($F(2,68) = 22.44$ $p<0.001$, BF_{10} = 3993.24±0.86%), strong for frequency of consumption ($F(2,68)$ = 7.17 $p = 0.009$,BF_{10} = 11.08±0.76%), moderate for energy content ($F(2,68) = 7.74$ $p = 0.007$, BF_{10} = 4.80±1.61%) and energy density estimations ($F(2,68) = 1.19\times10^{-4}$ $p = 0.99$, BF_{01} = 3.45±1.37%)(Table S2, Table S3a-f).

The effect of fiber is anecdotal for liking ($F(2,68) = 0.72$ $p = 0.39$, BF_{01} = 2.23±1.30%), estimated energy content ($F(2,68) = 0.76$ $p = 0.38$, BF_{01} = 2.18±1.84%) and frequency of consumption ($F(2,68) = 3.52$ $p = 0.06$, BF_{10} = 1.48±0.94%) strong for expected satiety ($F(2,68) = 9.16$ $p = 0.003$, BF_{10} = 47.09±1.65%) and estimated energy density ($F(2,68) = 8.02$ $p = 0.006$, BF_{10} = 14.70±1.57%), but extreme for perceived healthiness ($F(2,68) = 25.37$ $p<.001$, BF_{10} = 5802.57±14.94%)(Table S2, Table S4a-f).

4. DISCUSSION

We developed "*FinnFoodPics*", a 72-item image database to assess the influence of macronutrient content on eating behavior, specifically in citizens of Finland. We separated our snack items into three distinct macronutrient categories: (1) predominantly carbohydrate, (2) predominantly fat, and (3) high proportions of both carbohydrate and fat, referred to as combo. Sixty-two participants rated all our food images on liking, familiarity, perceived healthiness, frequency of consumption, expected satiety, estimated energy density, and energy content and we compared perceptual ratings between categories. Further, we compared the categories on nutrient information and visual properties of the images. Our main objective was to provide a database with three familiar but discernible macronutrient categories.

Our results demonstrated that the selected snack foods for carbohydrate, fat, and combo categories were familiar to a local sample. In addition, familiarity ratings showed high values of consistency for all food stimuli and macronutrient categories separately. For the other food ratings, there was moderate to very strong evidence of differences between macronutrient categories in liking, frequency of consumption, estimated energy density, and perceived healthiness. The observed differences in expected satiety and estimated energy content were anecdotal, as indicated by the Bayes factor. The stimuli in the three categories were similar in portion size, visual area, Red-Blue-Green image colors, as well as brightness, and within-object contrast.

Notably, all categories were well separated by macronutrient content. The analysis of ratings revealed that fat category items are perceived as satiating and consumed frequently, but combo items are not perceived as satiating and healthy despite being the most liked. Overall, the *FinnFoodPics* database offers a flexible tool to dissociate the effects of macronutrients and potentially address population differences in food choice and ingestive behavior.

4.1 Food ratings

Without any adjustments to our preselected pictures, we were able to create a set of familiar snack foods with no differences between macronutrient categories (Table 4c, Fig. 3a). Furthermore, the consistency of the familiarity ratings for all stimuli and each category were excellent as all Cronbach values were above .09 (Table 5). When looking at individual items' reliability and item-rest correlation, each category revealed a few items that could be removed in order to improve the scale's consistency. Consistent with prior work, beyond our main rating of interest, items in the fat category were rated as more energy dense (DiFeliceantonio et al., 2018; Fromm et al., 2021), and snacks in the carbohydrate category were rated as the least dense (Table 4c, Fig. 2a). However, combo items had a higher actual energy density on average, and fat had the lowest value (Table 4c, Fig. 2a). Fat items were also rated as the most frequently consumed with no differences between combo and carbohydrate category (Table 4c, Fig. 3d). Further, participants' estimation of caloric content was very close to the true values across macronutrient categories (Table 4c, Fig. 3e). But they rated the combo category as the most caloric, with 10 kcal higher than the 120 kcal in the image (Table 4c, Fig. 3e). Combo items were also seen as the least healthy, and most likable in comparison (Table 4c, Fig. 3b,g). More importantly, participants rated combo snacks as the least satiating (Table 4c, Fig. 3c). Energy-dense combo snacks are omnipresent in retail stores (Dicken & Batterham, 2022; Monteiro et al., 2013; Powell et al., 2017; Small & DiFeliceantonio, 2019) and contribute to increased energy intake (James Stubbs et al., 2023). Expected satiety ratings for the combo category align with research indicating that low satiety expectations of high-energy foods encourage the selection of bigger portions (Brunstrom et al., 2008), leading to greater overall intake (de Castro, 2004). Nevertheless, recent studies challenged the idea that energy-rich foods promote passive overconsumption showing that humans are sensitive to energy density and calories (Brunstrom et al., 2023; Flynn et al., 2022a, 2022b, 2023). It is, therefore, essential to develop robust tools that permit us to explore these questions further.

4.2 FinnFoodPics unpacked: A detailed look at nutrient information

A more detailed description of carbohydrates

FinnFoodPics was categorized based on the carbohydrate and fat content given on the food packages and online platforms. Carbohydrate quality is an important factor in diet and human health (Reynolds et al., 2019). For example, increased sugar consumption is associated with health issues like dental caries, obesity, type 2 diabetes (T2D), and cardiovascular diseases (Kohlmeier, 2015; Reynolds et al., 2019; SACN, 2015). Conversely, higher fiber intake is associated with a lower risk of NCDs like T2D, cardiovascular disease, and colorectal cancer and mortality (Anderson et al., 2009; Reynolds et al., 2019; SACN, 2015). Our findings are particularly intriguing because dietary fiber is underconsumed, and sugar is overconsumed, despite nutritional recommendations (Anderson et al., 2009; Powell et al., 2016). For example, people living in Finland receive 60 % of their sugar consumption from added sugar (Kaartinen et al., 2017) and intake of added sugar is associated with lower fiber intake (Kaartinen et al., 2017). However, carbohydrate describes a very general class of different molecules spanning from simple ones like glucose (i.e., monosaccharides) to more complex ones like amylopectin (i.e., polysaccharides)(Kohlmeier, 2015). A class that includes molecules with a variety of physical properties, compositions, and several forms associated with the risk of unfavorable health outcomes (Kohlmeier, 2015, Chapter 6; Stevenson & Francis, 2023). These carbohydrate forms are often present in the packaging and consist of sugars, starch, polyols (sugar alcohols), and fiber. Our analysis shows that in the carbohydrate category, the sugar, fiber, and starch/polyol content is higher in comparison to the combo and fat categories (Table 4a, Fig. 2c,d,f). However, in the case of fiber content, the difference between combo and fat category is negligible (Table 4a, Fig 2c). Thus, when we compare our categories, the higher the carbohydrate content, the more likely it is that sugar, starch/polyol, and fiber are also high. These results are very likely an indirect consequence of our categorization but provide necessary details of our food items. By including the mean values for total carbohydrates and their components, including fiber (Table 4a, Fig. 2c), our food image database could thus be a good complementary tool for investigating food-related behavior in our modern dietary environment.

Starch has many forms (Champ et al., 2003; Englyst et al., 1992): One being *resistant starch (RS), which* is not naturally well-digested in the human intestine and releases glucose within hours (Kohlmeier, 2015). Processing can shift starches to digestible polysaccharides or refined forms of carbohydrates that release glucose in shorter timelines (Cummings et al., 1996; Englyst et al., 1992; Kohlmeier, 2015). Yet, starch form and content are unspecified in the nutrition labels (The European Banking Union, 2015). Thus, we calculated and added starch content information to our database to provide a better picture of carbohydrates in our items. To our knowledge, our food image database is the first to provide this information.

It is worth noting that the majority of our items were chosen to represent modern consumption behaviors, so very few snack foods were classified as minimally processed, according to NOVA (Monteiro et al., 2019). Nevertheless, *FinnFoodPics* can be a useful complement to food composition databases for evaluating the carbohydrate content and quality of the foods people consume.

The fat, the salt, and the pricey

Saturated fat content follows the same trend as fat content, and it is high in the fat category and consistently the lowest in the carbohydrate category (Table 4a, Fig. 2e). In all cases, the amount (g/120 kcal) of saturated fat for the combo category is between the carbohydrate and fat category (Table 4a, Fig. 2e). Salt content also shared similar trajectories with fat and saturated fat (Table 4a, Fig. 2g). The presence of salt in packaged food equals sodium x 2.54 (The European Banking Union, 2015); thus, it can be easily converted for any project with interest in sodium - a micronutrient with an already high mean intake in Finland (2 mg per day)(Lemming & Pitsi, 2022). Accordingly, the items selected for our picture set have average salt values (Table 4a, Fig. 2g) that could easily surpass recommendations of adequate intake at 3.75 grams of salt per day if consumed frequently (Blomhoff et al., 2023). Moreover, sodium has been shown to affect flavor and food valuation (Liem et al., 2011; L. Lucas et al., 2011) which opens avenues of research for taste preferences and more implicit behaviors. Further, portion size was the lowest for the combo category since those items have a higher energy density.

Finally, the carbohydrate category had the lowest prices, followed by the combo and the fat category. Interestingly, the same pattern emerged in the North American *MacroPics* but without a significant difference (Fromm et al., 2021). Although the average price in all categories of our database was lower than *MacroPics* (Table 4a, Fig 2i). These results open up more interesting avenues as a previous study using *MacroPics* suggested food cost is an important mediator for our motivation to eat (Perszyk et al., 2021). In other words, via image databases, socioeconomic factors like the cost of living could reveal important population differences in food choices (Perszyk et al., 2021).

Effects of Protein and Fiber

Similar to Fromm et al. (2021), the fat category contained more protein in comparison to the other categories, but our food items also contained more fiber in the carbohydrate category (Table 4a, Fig. 2b, 2c). The combo and carbohydrate categories did not differ in protein content (Table 4a, Fig. 2b). As previously mentioned, fiber is a type of carbohydrate that is not categorized with other carbohydrates on EU nutrition labels (The European Banking Union, 2015). Consequently, our method of categorization indirectly puts items with lower fiber content in the fat and combo categories. Additionally, fiber and protein content have been shown to affect parameters like estimated energy density and satiety (Fromm et al., 2021; Hervik & Svihus, 2019; MacLean & Graham, 1979; Slavin & Green, 2007; Westerterp-Plantenga et al., 2012). In addition, protein is the most satiating macronutrient, followed by carbohydrates and fat (Astrup, 2005; Westerterp-Plantenga et al., 1999). For that reason, we also explored whether protein and fiber content could have affected participant ratings (Table S2, S3, S4). Our analysis demonstrated that both protein and fiber content had a significant impact on satiety ratings (Table S2, S3b, S4b). Concerning estimated energy density and perceived healthiness, only fiber content seemed to have a strong impact (Table S2, S4c, S4e). However, estimated energy content and frequency of consumption were associated with protein content (Table S2, S3d, S3f). These results advocate for future studies that use *FinnFoodPic*s to consider these relevant confounders.

4.3 The influence of visual properties

In our pictures, we observed notable differences in spatial frequency and complexity of the images (Table 4b). Our results revealed that images representing the fat category had lower spatial frequencies, but this pattern was not seen for image complexity. Spatial frequency refers to how often intensity values (i.e., luminance) change in the image and indicates the level of fine detail it is possible to observe (Blechert et al., 2014), while complexity refers to the amount of detail and number of distinct elements and structures (i.e., variation) within an image (Blechert et al., 2014). Our procedure was the same for all items during the photography, and we tried to replicate the same conditions for each image. However, prior studies suggest image properties like frequency and complexity affect the processing of visual stimuli and should be controlled (Ball et al., 2014; Caharel et al., 2013; Rossion & Jacques, 2008; Thierry et al., 2007; Vuilleumier et al., 2003). Even though most of the research is done in the context of face recognition, spatial frequency has been shown to influence emotional responses (Delplanque et al., 2007). In addition, the manner and the color in which food is presented (i.e., packages) can influence people's reactions and build expectations of taste and flavor (Laan et al., 2012; Spence et al., 2010, 2016). Therefore, studies using *FinnFoodPics* should monitor and potentially control for the visual properties of the images to avoid undesired effects.

4.4 Study limitations and future directions

Participants were required to adhere to a minimum 1-hour fast before testing, but the testing times varied from morning to late afternoon. Thus, some participants had an overnight fast while others matched almost precisely our criteria, which led to a large variability in hunger ratings. As hunger has an impact on liking (Goldstone et al., 2009), the hunger variation in our sample confounded liking ratings (Fig. 1, Table S7). Our picture set was designed to be representative of food snacks that are often present and purchased by the average population in Finland. Another criterion for our study was omnivorousness of participants; therefore, our participant ratings cannot be extended to a sample with more restrained dietary choices. Despite an ongoing debate on the use of the term ultra-processed food (UPF)(Astrup & Monteiro, 2022; Monteiro & Astrup, 2022) and a relative lack of evidence on the impact of industrial food processing procedures on human health (Aas et al., 2023; Blomhoff et al., 2023; Sensoy, 2014), UPF represents most products in modern supermarkets (Monteiro et al., 2013). Therefore, it is reasonable to apply the classification and allow independent teams to scrutinize its role in eating behavior and health outcomes.

4.5 Conclusion/Use of FinnFoodPics

Our findings underscore the importance of accounting for various confounding factors in future studies utilizing *FinnFoodPics*, including not only nutritional aspects but also energy density, portions, and snack price. Our data (e.g., cost) hold promise for addressing broader inquiries regarding environmental influences on eating behaviors. Plus, the additionally available portion sizes (40, 80, 160, 200, 240, 280, 320, 360, and 400 kcal) and the NOVA classification make the database an even better candidate for wider use. The detailed nutritional information provided enables research teams to easily adjust and incorporate *FinnFoodPics* into their studies and specific research questions. Moreover, based on existing knowledge and our results, we recommend special attention be paid to protein, salt, and fiber content. Finally, it is crucial for studies using our images to monitor and potentially control visual image properties to prevent undesired influences. The development and use of robust research tools like *FinnFoodPics* remain essential in order to investigate the impact of combo foods on conscious and unconscious mechanisms like expected satiety, liking, or anticipated reward in food-related behavioral and neuroimaging studies. Overall, the *FinnFoodpics* database provides a versatile resource for disentangling the effects of carbohydrate and fat nutrients in food choice and eating behavior.

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ETHICAL STATEMENT

This study was conducted in compliance with the principles of the Declaration of Helsinki and was reviewed and deemed ethically acceptable by the Ethical Review Board in Humanities and Social and Behavioural Sciences of the Medical Faculty at the University of Helsinki (Statement 35/2022). All participants provided written informed consent before participation and were compensated for their time.

AUTHORSHIP CONTRIBUTION STATEMENT

AK, HH, DF, and AH: Conceptualization **AK, HH, DF, XSD, EP, NEK, PW and, AH**: Methodology **AK:** Writing Original draft, **AK, DF**: Software **AK**: Formal analysis **AK, WV, BP**: Investigation **AK, AN**: Data curation, **AK**: Visualization, **AK, NEK, TP, US, EP, XSD**: Resources **AK, HH, DF, WV, BP, XSD, EP, AN, NEK, TP, US, PW and, AH**: Writing-Review & editing **AH**: Supervision, Funding acquisition.

Conflict of interest

The authors declare no competing commercial or financial interests.

Data availability statement

The final 72-item list is publicly available at https://obrainlab.com/resources/

Declaration of Generative AI and AI assisted technologies in the writing process

During the preparation of this work, the author sparingly used ChatGPT to improve readability and language. After using this tool, the author reviewed and edited the content as needed and takes full responsibility for the publication's content.

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