Report

Current Biology

Positive serial dependence in ratings of food images for appeal and calories

Highlights

- Ratings of food images for calories or appeal are not serially independent
- Both rating types show an “attraction” bias toward the previously seen food
- For appeal ratings, the bias declined with hunger and age and increased with BMI
- This perceptual bias in food appraisal could augment existing clinical interventions

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In brief

Alais et al. show that ratings of food images for appeal or calories are biased toward foods previously seen, with current ratings being higher after a highly rated food (and vice versa). Many visual stimuli show this bias, thought to arise at sensory levels. This bias could be used to nudge sensory food responses higher or lower to moderate food behaviors.

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Positive serial dependence in ratings of food images for appeal and calories

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SUMMARY

Food is fundamental to survival, and our brains are highly attuned to rapidly process food stimuli. Neural signals show that foods can be discriminated as edible or inedible as early as 85 ms after stimulus onset,[1] distinguished as processed or unprocessed beginning at 130 ms,[2] and as high or low density from 165 ms.[3] Recent evidence revealed specialized processing of food stimuli in the ventral visual pathway,[4–6] an area that underlies perception of faces and other important objects. For many visual objects, perception can be biased toward recent perceptual history (known as serial dependence[7,8]). We examined serial dependence for food in two large samples ($n > 300$) who rated sequences of food images for either "appeal" or "calories." Ratings for calories were highly correlated between participants and were similar for males and females. Appeal ratings varied considerably between participants, consistent with the idiosyncratic nature of food preferences, and tended to be higher for males than females. High-calorie ratings were associated with high appeal, especially in males. Importantly, response biases showed clear positive serial dependences: higher stimulus values in the previous trials led to positive biases, and vice versa. The effects were similar for males and females and for calories and appeal ratings and were remarkably consistent across participants. These findings square with recently found food selectively in the visual temporal cortex, reveal a new mechanism influencing food decision-making, and suggest a new sensory-level component that could complement cognitive strategies in diet intervention.

RESULTS

Underlying the brain's rapid analysis of food stimuli is a large, distributed network composed of numerous regions, including decision-related areas in the prefrontal cortex and visual areas in the occipital cortex. Among prefrontal areas, appetizing food stimuli activate several regions, including orbitofrontal cortex,[9–11] medial prefrontal cortex,[9,12] and anterior cingulate,[13] with food saliency being linked particularly to orbitofrontal cortex[14] and anticipation of pleasure from the food associated with lateral orbitofrontal cortex.[15] There is also sensory-driven food-related activity in the visual cortex, including the lateral occipital complex and fusiform gyrus,[3,16–18] two visual object processing areas.[10] The strongest findings come from very recent studies analyzing fMRI responses to large image sets, which found highly selective food specialization in the ventral visual pathway. Khosla et al.[5] found distributed activation from food images that was not due to low-level image properties (i.e., color, shape, and texture). Jain et al.[4] found food-specific activity adjacent to the fusiform face area. Another study found food images drove color-biased ventral visual areas and predicted voxel responses.[6]

The involvement of the prefrontal cortex highlights the role of choice and decision-making in food behaviors. What to eat, when, and how much are critical decisions, whether for survival (e.g., meeting caloric needs when resources are scarce) or in affluent western societies where a surfeit of food choices leads us to make around 200 food decisions daily.[19] Following recent findings of robust food activity in ventral visual areas,[4–6] visual perceptual factors likely also influence food choice. This is relevant as recent perceptual history can bias current perceptual decisions so that they are not independent but biased toward recent input (known as "serial dependence"[20,21]). Many visual stimuli elicit this serial bias, from basic attributes (orientation, motion, spatial frequency, numerosity[22–25]) to more complex visual objects such as faces,[26–28] visual scenes,[29] and even artworks.[30] In particular, faces—another image category with high ecological significance processed in the fusiform gyrus—show strong serial biases for decisions about attractiveness, sex, identity, and emotion.[26,27,31–34] Given that serial dependence involves high-level (decisional) and low-level (sensory) factors[35–38] and that food is processed in frontal decisional and visual sensory regions, food images should also evoke serial biases. Here, we examine how rating food for appeal or calorie content affects subsequent food ratings (Figure 1). We find clear evidence of positive serial dependences for both calories and appeal, with current ratings biased toward previous ratings.

Food image ratings

Figure 2 shows ratings data for calories (Figure 2A) and appeal (Figure 2B). Data points show means and standard deviations

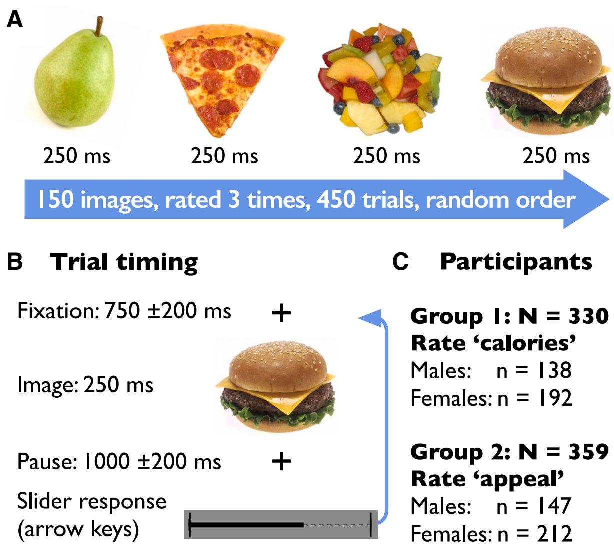

Figure 1. Stimuli and methods

(A) 150 food images were selected from the "transformed" and "natural food" categories of the FRIDa image set (https://foodcast.sissa.it/neuroscience). The set of 150 images was presented in a random order and then presented again two more times in new random orders (3 ratings per image).

(B) Each trial began with a blank screen averaging 750 ms (±200 ms random jitter), then a food image (250 ms), then a blank screen (1,000 ms ± 200), and then a response slider that participants controlled with keyboard arrow keys to indicate their rating of the food (recorded with a mouse click).

(C) Two groups were recruited from prolific so that two dependent variables could be measured. Group 1 (n = 330) rated the calorie value of the food, and group 2 (n = 359) rated the appeal of the food.

of ratings from male (blue) and female (red) participants for all 150 images, ordered by their average ranking. Calorie ratings show relatively close agreement between participants (average SD = 7.3), and the ratings span nearly the full range of the scale. Average male ratings correlated highly with average female ratings (r = 0.99), and there was no significant difference in average ranking (males, mean = 46.6; females, mean = 46.7; $t_{298} = 0.036$, $p = 0.97$). Appeal ratings showed a different pattern. Male ratings were on average significantly higher (males, mean = 54.6; females, mean = 50.7; $t_{298} = 2.52$, $p = 0.012$), and the variability in ratings was higher (average SD = 11.6). The range of average appeal ratings was less than for calories, presumably reflecting the weaker agreement between participants (see below). Again, there was reasonably good agreement between male and female average ratings (r = 0.90). Figures 2C and 2D plot the mean calorie and appeal ratings given for each of the 150 images by male (Figure 2C) and female (Figure 2D) participants. There was a significant correlation (higher calorie ratings associated with higher appeal) in both groups, with males (r = 0.56, $p < 0.0001$) showing a stronger association than females (r = 0.32, $p = 0.0001$). We further examined rating consistency between participants by correlating item ratings between all participant pairs. For calorie ratings (Figure 2E), the inter-participant consistency was high (mean r = 0.77, SD = 0.12), while appeal ratings (Figure 2F) were far less consistent between participants (mean r = 0.25, SD = 0.20), with 11% of correlations negative. The difference in participant consistency presumably reflects the fact that there exists a ground truth for the physical quantity calories, whereas appeal is more idiosyncratic because it is a more subjective attribute.

Serial dependence in food ratings

We next analyzed the ratings data for serial effects to test whether successive responses were independent or influenced by the previous image. Given the idiosyncratic nature of appeal ratings (brought out clearly by the weaker correlation in Figure 2F), we defined the strength of each stimulus as the average rating for that image, separately for each participant. Figures 3A and 3B plot bias (average deviation from individual mean rating, averaged over all participants) of the current trial against the relative difference in stimulus strength (previous minus current trial), separately for calorie ratings (Figure 3A) and appeal ratings (Figure 3B). The curves show the classic serial dependence effect: rating for the current trial were biased toward higher values when the previous stimulus was high (upper right quadrant) and toward lower values when the previous trial stimulus was low (bottom left quadrant). For large relative differences, the effect dissipates and returns to baseline (typical of serial dependence effects[24,35,39,40]), well described by a difference-of-Gaussian (DoG) model. For our data, the amplitudes of the best-fitting DoGs were 1.04 and 1.05 (respectively for calories and appeal), and the bandwidths were 25.9 and 28.4. The indices of determination (R^2) were 0.96 and 0.98. There was no significant difference in parameters between male and female participants. A strong test that serial dependence is not driven by artifactual correlations in the data is to repeat the analysis against future rather than past stimuli (which cannot directly influence the current response). This led to negligible serial effects that were several times smaller for both calories and appeal (amplitude estimates of 0.13 and 0.19, respectively) and had poorer fits (R^2 = 0.55 and 0.70). The serial dependence based on the previous stimulus was highly significantly greater than with the future stimulus (both $p < 0.0001$).

This experiment was designed to run online with a large sample size but fewer trials (450 per observer) than is typical for serial dependence studies. For this reason, we planned an analysis based on aggregated data; however, reliable serial effects were also evident at the individual level. 84% of participants in the calorie rating group exhibited reliable DoG fits, and Figure 3C shows the group mean amplitude and bandwidth of those participants. The small differences between male and female participants were not significant for either amplitude ($t_{269} = 0.463$; $p = 0.643$) or bandwidth ($t_{269} = 0.416$; $p = 0.678$). Figure 3D shows the same analysis for the 83% of the calorie rating group who yielded reliable DoG fits. Again, there were no male/female differences for amplitude ($t_{288} = 1.027$; $p = 0.305$) or bandwidth ($t_{288} = 0.77$; $p = 0.442$). Overall, the analysis of the individual data agrees well with the aggregated data and was remarkably consistent between observers.

Ideal observer models predict that the magnitude of an observer's serial dependence should vary with their reliability on the task being measured,[23] where reliability is defined as the inverse of variance. We calculated the variance of each participant's ratings, after subtracting their mean rating for each image, for all of the 150 images. Figure 3E plots the root variance of each participant's calorie ratings against the amplitude of their serial

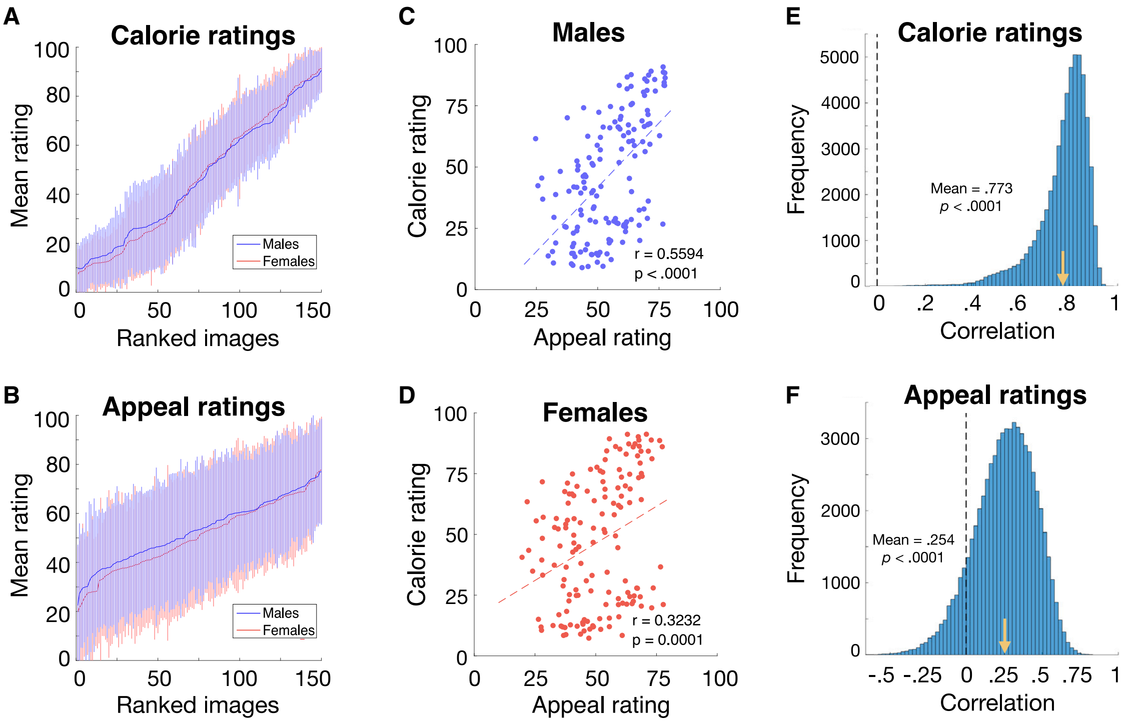

Figure 2. Mean food image ratings for males and females and between-participant correlations

(A) Mean ratings of the set of 150 food images rated for calories by group 1 (n = 330: M = 138, F = 192) and ordered by their average ranking. Calorie ratings did not differ between males and females and were well spread over the scale range, with relatively low standard errors (shaded area).

(B) Ordered mean ratings of the same 150 food images rated for appeal by group 2 (n = 359: M = 147, F = 212). Food appeal ratings did show a male/female difference, with mean male appeal ratings being significantly higher.

(C) Scatterplot showing the 150 images rated for calorie and appeal by male participants. Ratings are significantly positively correlated (higher calorie food rated as more appealing).

(D) Scatterplot of the 150 calorie and appeal ratings made by female participants. The ratings are again positively correlated, though less strongly than for males.

(E and F) Distributions of correlation coefficients calculated for all between-participant pairwise correlations for calorie ratings (E) and appeal ratings (F). Calorie ratings showed a strong internal consistency among participants (mean r = 0.77), while appeal ratings exhibited less consistency (mean r = 0.25).

effect, showing a highly significant positive correlation (r = 0.44, $p < 0.0001$). For calorie judgments (Figure 3F), there was a similar correlation between variability and serial effect size (r = 0.416, $p < 0.0001$). These positive correlations agree with central notion of the ideal observer model that the less reliable a judgment, the more efficient it is to integrate with past information to improve reliability.[7,23]

Finally, we analyzed seven demographic and self-report ratings provided prior to the experiment. Participants gave their age, height, and weight (from which BMI was calculated), as well as answering the following questions on a 0–100 scale: how hungry are you now? How thirsty are you now? How tired are you now? They also indicated in hours: How long since your last meal? How long since you last ate? To test if variation on any of these measures was associated with the changes in serial dependence, we correlated them with the amplitude of the serial effect. For calorie ratings, none of the correlations were significant (all $p > 0.166$). For appeal ratings, hours since last eating a meal were negatively correlated with serial amplitude (r = −0.126, p = 0.031), as was age (r = −0.170, p = 0.003), and BMI positively correlated with serial amplitude (r = 0.149, p = 0.011). The association between age and serial amplitude was further examined in a multiple regression analysis with age and reaction time as regressors to test if the age effect might be related to slower reaction times with increasing age. The standardized coefficient was significant for age ($\beta_1 = -0.170$, p = 0.004) but not for reaction time ($\beta_2 = 0.003$, p = 0.965).

DISCUSSION

This study was motivated by very recent findings showing that visual areas in human temporal cortex show a specialization for food images.[4–6] We examined whether participant ratings of food images would exhibit a bias known as serial dependence, just as occurs with ratings of faces, another prominent visual specialization in temporal cortex[41,42] and for many other visual attributes.[21] Ratings of food image sequences for calories and appeal both showed significant positive serial dependence (Figures 3A and 3B): rather than being sequentially independent, ratings tended to follow the rating strength of the preceding image. A high-calorie preceding food image led to a current food image being rated higher than its mean calorie rating (and vice versa: a preceding low-calorie image reduced a current image's calorie rating). Rating food images for appeal showed the same pattern of positive serial bias, and both kinds of rating exhibited serial effects with very similar amplitudes and bandwidths.

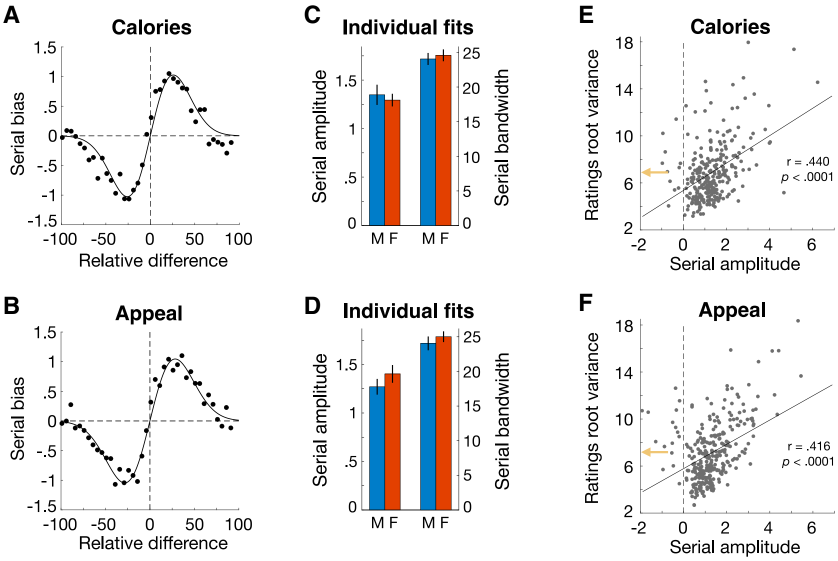

Figure 3. Positive serial dependence for food ratings and its dependence on rating variability

(A) Aggregated data from the 330 observers in group 1 who rated food images for calories. The serial bias is the deviation of the current trial rating from the mean of all ratings of that image and is plotted against the relative rating difference, defined by the previous trial's rating minus the current trial's rating. The bias deviates positively from the mean value when the previous stimulus was rated high for calories and negatively when the previous rating was low. This attraction to the previous value returns toward baseline for large differences between current and previous trial ratings and is well described by a difference-of-Gaussian (DoG) model.

(B) The same analysis conducted on appeal ratings (group 2, 359 observers) shows a very similar positive serial dependence.

(C and D) The serial effects were also evident at the individual level. Bars show group means with error bars indicating ±1 SEM.

(C) The mean amplitude and bandwidth of fits to individual participants rating calories. There was no significant difference between male and female participants for amplitude or bandwidth.

(D) The same analysis for appeal ratings, and again there were no male/female differences for amplitude or bandwidth.

(E) Scatterplot of the average root variance of each observer's calorie ratings distribution plotted against the amplitude of their serial effect. There is a highly significant positive correlation between the serial effect and root variance: observers with more variable ratings show larger serial effects.

(F) Same analysis for appeal rating variability and exhibits a similarly significant positive correlation between rating variability and serial effect size. Mean rating variability between rating types did not differ (yellow arrow).

Calorie and appeal ratings were positively correlated with each other (i.e., appealing foods tended to be high-calorie foods; Figures 2C and 2D), and participants showed an impressive consistency with each other in their calorie ratings (Figure 2E). Appeal ratings showed much less inter-participant consistency (Figure 2F), likely due to appeal being a more idiosyncratic factor. Overall, for both ratings, participants whose ratings were more variable exhibited larger serial dependence effects (Figures 3E and 3F).

Serial dependence has been recently an active field in perceptual decision-making. It is an attractive bias makes that makes current perception assimilate toward previously seen stimuli for successive stimuli that are not too different, returning to baseline for larger differences exactly as shown in Figures 3A and 3B. It is adaptive in that it leads to more efficient perception,[7,23] the reason being that stimuli that are not too different can be considered as noisy representations of the same object. It is widely reported in perceptual judgments from simple ones (e.g., such as orientation and spatial frequency[23,24]) to complex judgments about face perception (e.g., gender, attractiveness, and identity[8]), scene perception,[37] and aesthetics.[30] Serial dependence also occurs at the level of global information where elements are combined into ensemble objects[29] and may occur separately for individual objects in a multi-object scene.[37,43] It is also a real-world effect[44]: when realistic movie clips are used, current perception of objects is biased by information presented up to 15 s earlier,[45] and current emotion is biased for up to 12 s.[46] These findings suggest that food serial dependence is likely to occur in real-world contexts containing multiple food options, and future work could test this. For example, the order of food options presented in a buffet or smorgasbord could affect an individual's choices, and more controlled experiments using real food could be designed to extend our findings here obtained with food images to decisions about physical food.

Interestingly, the "real-world" implications of our findings do not necessarily depend on the use of real food as many food choices these days are image based. A common example is the increasing use of food delivery apps.[47] This involves the user swiping through multiple food images in a way that is very similar to the serial dependence procedure we have used here. Even when dining in a restaurant, it is increasingly common to access the menu with a QR code and browse images of the food options on a handheld device.[48] Our results speak directly to food decisions in these image-based contexts, and there are empirical findings indicating that similar serial effects would be obtained when choosing among physical food options. There is a good deal of literature showing that images of food are effective in driving many of the brain centers that are activated by real food (e.g., gustatory cortex, reward areas, etc.), and a vast number of behavioral and neural studies of food are conducted using food images. For example, fMRI data show that the brain tracks the energetic value of foods shown as images,[3] and cortical responses to high- and low-calorie food images show very distinct patterns of activity.[49] Viewing pictures of appetizing foods activates gustatory cortex and reward centers,[11] and individual differences in reward traits correlate with neural responses to food images.[50] It is even possible to decode the dominant taste of foods shown in images from primary gustatory cortical activity.[51]

Serial dependence amplitudes were robust across calorie and appeal ratings, and while sex differences are often observed in various measures of food behavior and perception,[52–54] we found no evidence of sex differences in the way serial dependence manifests in food ratings. There are, however, many other factors known to influence food decision-making,[55–57] and we therefore collected data from participants on variables such as age, BMI, hunger, tiredness, etc., and tested for correlations between these variables and serial amplitude. There were several significant correlations, and while they were modest in size, all showed high statistical significance in their association with serial amplitude and may yet prove useful in shaping real-world food choices. Much clinical and public health work aimed at shaping food consumption has focused on achieving behavioral change through the cumulative influence of many small factors in an approach known as "nudging."[58–60] Serial dependence is a new sensory-level component influencing food decision-making, and these correlations hint at several ways to further nudge the influence of the serial effect to optimize it as a complement to behavioral and cognitive intervention strategies. With the steady rise in obesity rates globally and its negative impact on cardiovascular disease and type 2 diabetes, future research into serial dependence and food decisions could be beneficial.

Given the high number of food decisions we make in our daily lives, serial dependence analyses are perfectly suited to uncovering drivers of food decision-making. We are surrounded by food options in affluent western countries, many highly processed with unhealthy combinations of calories, fat, sugar, and salt. High ultra-processed food intake is linked with poor physical health (cardiovascular disease, cancer, and overall mortality rate[61–63]) and mental health outcomes, with a recent meta-analysis finding greater odds of depressive and anxiety symptoms and increased risk of subsequent depression.[64] There is also evidence that such foods can induce eating addiction.[65–67] Understanding all aspects of food decision-making is therefore critical, and our novel finding that ratings of food appeal exhibit serial dependence reveals a useful new component that could be used either to make food look more appealing (after seeing a previous appealing food) or less appealing (following a food rated low in appeal). Equivalently, the calorie rating given to a food could be boosted or attenuated by the preceding food. These findings could help guide clinical interventions, adding a sensory-based component to predominantly cognitive-based strategies designed to either reduce food intake (e.g., when treating obesity or compulsion to eat) or increase it (e.g., when treating bulimia or anorexia nervosa).

RESOURCE AVAILABILITY

Lead contact

Requests for further information and requests for resources should be directed to and will be fulfilled by the lead contact, David Alais (david.alais@sydney.edu.au).

Materials availability

This study did not generate new unique reagents.

Data and code availability

Data reported in this study and the custom code for analyses are deposited at Open Science Framework (https://osf.io/e3byv/).

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AUTHOR CONTRIBUTIONS

D.A. conceived the experiments, and T.A.C. collected the data. D.A. and D.B. carried out the analyses, and D.A. visualized and interpreted results and wrote the draft manuscript for submission. D.A., T.A.C., and D.B. edited later drafts and revisions.

DECLARATION OF INTERESTS

The authors declare no competing interests.

STAR★METHODS

Detailed methods are provided in the online version of this paper and include the following:

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- EXPERIMENT MODEL AND STUDY PARTICIPANT DETAILS
- METHOD DETAILS
  - General methods

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STAR★METHODS

KEY RESOURCES TABLE

REAGENT or RESOURCE	SOURCE	IDENTIFIER
Deposited data		
Psychophysical data	This paper	https://osf.io/e3byv/
Software and algorithms		
Online code & data	This paper	https://osf.io/e3byv/
MATLAB R2021a	This paper	RRID: SCR_001622
Psychtoolbox-3	This paper	RRID: SCR_002881
JASP version 0.18.3	This paper	RRID: SCR_015823

EXPERIMENT MODEL AND STUDY PARTICIPANT DETAILS

Experiment 1 measured calorie ratings and involved 330 participants; 138 males (42% of sample) and 192 females (58%). Experiment 2 measured appeal ratings and involved 359 participants; 147 males (41% of sample) and 212 females (59%). Participants gave informed consent and the research procedures were approved by the University of Sydney Human Research Ethics Committee (HREC 2021/048).

METHOD DETAILS

General methods

Stimuli

Food images were selected from the FRIDa image set (https://foodcast.sissa.it/neuroscience). We used 150 images drawn from the 'transformed' and 'natural food' categories (75 per category, available at https://osf.io/e3byv/) that were selected to approximately evenly span the calorie range. These are all color images, cropped and presented on a white background, and were standardized to a size of 375 x 375 pixels and a resolution of 72 dpi. Stimulus presentation duration 250 ms.

Procedure

The procedure was the same for Experiments 1 and 2. After instructions and practice trials to become familiar with the procedure participants were presented with 450 trials (a set of 150 food images presented three times with each set in a new random order). The trial sequence was: (i) a blank screen with a fixation cross for 750 ms (randomly varied in the range of ±200 ms), (ii) an image presentation for 250 ms, (iii) a blank fixation screen again for 1000 ms (randomly varied within ±200 ms), and (iv) a keyboard-driven ratings bar used to record the participant's response. The ratings bar ranged from 0 – 100 with the slider initially set to 50 and needing to be adjusted before a response was accepted. In Experiment 1 (n=330) the task was to rate the foods for calories. In Experiment 2 (a different sample of n=359) the task was to rate the foods for appeal.

Demographic data were collected for every participant (age, gender, height, weight) and responses to the following: rate your hunger; rate your thirst; rate your tiredness; are you currently dieting?; how long since you last ate (hours)?; how long since your last meal (hours)?

Design and data analysis

The aim of the study was to measure ratings for a large number of food images (n=150). Collecting data online meant that a large number of participants could be reached so that variability in demographic variables such as gender and BMI could be analyzed. The use of a large set of food images has the potential limitation of relatively few ratings per image (3 ratings each) yet having a large sample means this is easily overcome by analyzing data as single aggregate subject (a 'super subject' analysis) and using a bootstrapping procedure to obtain measures of variance and to calculate confidence intervals.

Given that food ratings can be idiosyncratic (e.g., Figure 2F), we defined stimulus strength individually for each participant as the average of their three ratings of a given image, rather than as an overall group average. Biases on a given trial were then defined as deviations from this mean and either analyzed as an aggregate data set over all participants (Figures 3A and 3B) or within single participants (Figures 3C and 3D). The variability of each participant's overall ratings data was calculated (after subtracting the mean rating for each item) so that rating reliability could be calculated to test how individual serial amplitude varied with serial amplitude (Figures 3E and 3F).