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Theo Besson[a], Fanny Lalot[b], Nicolas Bochard[c], Valentin Flaudias[d,e], Oulmann Zerhouni[a,*]

[a] University Paris Nanterre, Laboratoire Parisien de Psychologie Sociale, Département de Psychologie, 200 Avenue de la République, 92000, Nanterre, France
[b] University of Geneva, Département de Psychologie Sociale, Faculté de Psychologie et des Sciences de l'Education, 40 boulevard du Pont d'Arve, 1205, Geneva, Switzerland
[c] University Grenoble-Alpes, Laboratoire Inter-universitaire de Psychologie, Université Grenoble Alpes, CS 40700, 38 058, Grenoble Cedex 9, France
[d] CHU of Clermont Ferrand, Université Clermont Auvergne, EA NPsy-Sydo, 28 Place Henri-Dunant, F-63000, Clermont-Ferrand, France
[e] CHU Clermont-Ferrand, Pôle Psychiatrie B, 58 Rue Montalembert, F-63001, Clermont-Ferrand, France

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ABSTRACT

Specific attributes of a food product can cause it to be spontaneously but wrongly perceived as healthier than it really is (i.e., the health halo effect). Notably, there is preliminary evidence that individuals evaluate organic food as less caloric than regular, non-organic food. However, explanations regarding the cognitive mechanisms underlying the health halo effect remain scarce. Drawing from the implicit cognition literature, we hypothesize that this effect could be due to (a) the reactivation in memory of implicit positive evaluations and/or (b) the reactivation of a semantic association between the concepts "organic" and "non-caloric". We first conducted a 2 (Product label: organic versus non-organic) × continuous (Valence-IAT score) × continuous (Calorie-IAT score) study (N = 151) to test these hypotheses, and conducted a conceptual replication in a second study (N = 269). We computed Bayesian analyses alongside frequentist analyses in order to test for potential null hypotheses, as well as frequencies and Bayesian meta-regression including both datasets. Both methods provided consistent results. First, Bayesian analyses yielded extremely strong evidence in favor of the hypothesis that the organic label leads to an underestimation of caloric value. Second, they provided strong evidence that this effect is *not* moderated by implicit evaluations. Hence, we replicated the organic halo effect but showed that, surprisingly, it does not arise from implicit associations. We discuss these findings and propose directions for future research regarding the mechanisms underlying calories (under)estimation.

1. Introduction

Obesity is and remains a major public health problem. Worldwide obesity, which has more than doubled since 1980, is indeed a high risk factor for multiple diseases such as cardiovascular diseases and cancer (Flegal, Kit, Orpana, & Graubard, 2013). In 2008, 1.5 billion adults (20 years of age and older) were overweight and among them, over 200 million men and nearly 300 million women had passed the threshold for obesity. Sixty-five percent of the world's population live in countries where overweight and obesity kill more people than underweight. Additionally, nearly 43 million children under the age of five were considered overweight in 2010 (World Health Organization, 2011).

Simultaneously, organic food consumption has been steadily increasing. For example in 2015, 65% of French people reported eating organic products regularly, against 37% in 2003 (Agence Bio[1] and the CSA[2] Barometer, 2015, see also Willer, Sorensen, & Yussefi-Menzler, 2008). Moreover, consumption of organic products seems to result from a deliberate, conscious effort: 63% of organic products' consumers reported doing so in order to preserve their health and 46% considered the organic label as a proof that the product is healthy. However, this increased consumption of organic products could have unexpected negative consequences, should one want to keep a balanced diet. Indeed, labeling products as "organic" could lure people into underestimating their calories intake, which could in turn hinder weight loss and health. This cognitive bias, known as the health halo effect, has received initial attention from researchers in marketing, but also in health science and psychology. In the present paper, we propose to explore implicit associations as a potential mechanism underlying the

* Corresponding author.
E-mail address: ozerhouni@parisnanterre.fr (O. Zerhouni).

[1] The French agency for the development and promotion of organic farming is a public interest group created on 15 October 2001 by the minister in charge of agriculture and ecology.

[2] The CSA Consumer Institute, Science & Analytics is a French company specialized in market research and opinion polls.

health halo effect.

1.1. Complexity and bias in calories estimation

Calories estimation is the action by which one generates a judgment about the number of calories contained in a food product. Calories estimation often results in inaccurate estimations (Lansky & Brownell, 1982; Lichtman et al., 1992). Even trained professionals and dieticians (Lansky & Brownell, 1982; Tooze et al., 2004) generally tend to *underestimate* the caloric value of a food product (see Livingstone & Black, 2003; for a review). Indeed, individuals have a dichotomous view of diet, in which a product is either healthy or unhealthy (Chernev, 2011; Oakes & Slotterback, 2005; Raghunathan, Naylor, & Hoyer, 2006; Rozin, Ashmore, & Markwith, 1996; Wertenbroch, 1998). Thus, when evaluating the number of calories in a food product, they tend to rely on a binary evaluation to formulate an opinion (e.g., fruits and vegetables are classified as “good for health”, whereas candies, bacon and popcorn fell in the “bad for health” category). Brands and labels are similarly subject to this healthy/unhealthy binary assessment (Chernev & Chandon, 2010).

How do we estimate calories then? Research shows that when information is not directly available, it is inferred from contextual cues (e.g., Mussweiler, 2003). Hence, calories estimation could be biased by the presence of unrelated positive or negative cues, such as brands or labels, which lead consumers to infer that the food product has other (un)healthy but unclaimed attributes (e.g., a high/low caloric value). This cognitive bias is known as the health halo effect (see Thorndike, 1920, for an early account of the halo effect). It implies that individuals subjectively consider the caloric value of a given product as high or low in function of other cues such as brand or marketing positioning, or simply by comparing it with similar products (e.g., Kardes, Posavac, & Cronley, 2004), which in turn leads to estimation errors. Several studies have illustrated this bias, notably in the case of products labeled as “low-fat", whose caloric value is greatly underestimated (e.g., Fernan, Schuldt, Niedereppe, 2018). A low-fat label being a relevant cue when judging a product's caloric value, it is likely to be used by consumers. Likewise, this effect can be found on products labeled “gluten free” (e.g., Prada, Godinho, Rodrigues, Lopes, & Garrido, in press) or “low carb” (Labiner-Wolfe, Lin, & Verrill, 2010). It is, however, more surprising to see that the same effect arises with less relevant labels such as “fair-trade” (e.g., Schuldt, Muller, & Schwarz, 2012) or “organic” (e.g., Prada, Garrido, & Rodrigues, 2017; Schouteten, Gellynck, & Slabbinck, 2019). Recently, Schuldt and Schwarz (2010) showed that participant evaluated organic cookies as less caloric than non-organic cookies and considered that the former could be eaten more often (see also Chandon & Wansink, 2007; Wansink & Chandon, 2006). The organic versus non-organic label has a similar impact on other related outcomes, such as taste (Lee, Shimizu, Kniffin, & Wansink, 2013), perception of serving size and consumption guilt (Wansink & Chandon, 2006), or willingness to pay (Sörqvist et al., 2015).

If the health halo effect begins to be well documented, studies exploring its underlying processes remain scarce. By definition, the health halo effect should depend on a disposition toward automatic positive evaluations of organic food product (for a similar reasoning, see Songa & Russo, 2018 or Songa, Slabbinck, Vermeir, & Russo, 2019). An alternative explanation, however, would be that of a mere association with semantic contents related to low caloric value. In other words, calorie misestimation could be due to an association of the organic concept with positive characteristics of organic food, which is then generalized to a wider range of unrelated attributes of the food product. However, it could also be attributable to a direct association with the semantic attribute “low-in-calories”, which becomes readily available to generate a judgment. We aim here to test these two competing possibilities.

1.2. Aims of the present research

The first aim of this paper is to replicate and quantify the evidence in favor of the “organic” health halo effect with a Bayesian approach (see below for details). Secondly and more importantly, the objective is to explore implicit and automatic cognitions as mechanisms underlying the halo effect.

We propose a theoretical account of the health halo effect based on spontaneous evaluations and beliefs about the “organic” label. More specifically, we suggest that spontaneous associations and evaluations about this label would have been integrated and encoded in depth, over time. The strength of these associations and evaluations would then predict the magnitude of a health halo effect, across individuals. Hence, we aim to test whether implicit associations with the positive values of “organic” food, or implicit associations between “organic” and “non-caloric”, or both, drive the underestimation of organic food's caloric value.

We conducted two studies in which we measured participants’ implicit associations with organic food through two Implicit Association Tests (IATs). The first test assessed the strength of the association between “organic” and “non-caloric”, and the second, more broadly, the association between “organic” and “positive”. Participants were presented with a food product labeled either as organic or conventional (between-participant). We expected, first, a main effect of this label manipulation, representing a classic health halo effect. Second, we tested whether one or the other implicit association measures moderated this effect. We provide meta-analytic evidence for our conclusions.

2. Study 1 - methods

2.1. Participants and design

One hundred and fifty-one Psychology undergraduate students (73% female, 90% between 18 and 24 years of age[3]) completed an online study in exchange for course credits. They first completed a task evaluating implicit associations between the concepts of “organic” and valence and calories, respectively (i.e., Valence and Calorie-IATs). They were then randomly assigned to the organic versus non-organic label condition and were, accordingly, provided nutritional information about the food product: a cookie. They evaluated the cookie's calories content in comparison to other brands of cookies and indicated consumption recommendations. They finally indicated demographics.

2.2. Measures

2.2.1. Valence association with “organic” food: the Valence-IAT

The Valence-IAT included five blocks, three of them considered as training blocks (Blocks 1, 2 and 4) and two as test blocks (Blocks 3 and 5; see Table 1). Block 1 consisted of a simple categorization of target words into the categories “Organic” (e.g. “natural”) and “Artificial” (e.g. “processed”). Participants answered by pressing one of two predetermined keys, on the left versus right half of the keyboard. Block 2 consisted of a similar task for the categories “Good” (e.g. “pleasant”) and “Bad” (e.g. “unpleasant”; see Appendix I). Block 3 was the first test block, combining the categories of the previous blocks, with two concepts sharing a common response key. It was a “congruent” block, in the sense that the categories Organic and Good, on the one hand, and Artificial and Bad, on the other hand, shared the same response key. Block 4 was similar to Block 2 except that the response key for Organic and Artificial were reversed. Finally, Block 5 constituted the second, “incongruent”, test block in which Artificial was paired with Good, and

[3] A total of 160 participants started the study online but nine dropped out: six during the pre-test IAT measures and three during the product evaluation phase.

Table 1
Design for the valence IAT.

Block	Stimuli assigned to the « E » key (left of keyboard)	Stimuli assigned to the « T » (right of keyboard)	Number of Trials	Block Type
1	Organic	Artificial	20	Training
2	Good	Bad	20	Training
3	Organic + Good	Artificial + Bad	20 Practice + 40 Test	Test
4	Artificial	Organic	20	Training
5	Artificial + Good	Organic + Bad	20 Practice + 40 Test	Test

Organic with Bad. The order of Blocks 1 & 3 and 4 & 5 was counterbalanced between-subject. Each critical Block (i.e., Block 3 and 5) included 60 trials. Comparing latency responses in Blocks 3 and 5 allows to assess the direction and the intensity of the associations: an implicit preference for Organic would result in a faster classification of the Organic words when they share the response key with the Good category (i.e., congruent block) than when they are paired with the Bad category (i.e., incongruent block). An IAT *D* score was computed for each participant following the procedure suggested by Greenwald, Nosek, and Banaji (2003). We excluded response times exceeding 10,000 ms, as well as the data of participants who answered in less than 300 ms for more than 10% of the trials. The average response time for the congruent block was then subtracted to the average response time for the incongruent one, and this score was divided by the standard deviation of the participant's average response time. As such, the IAT score represents the level of implicit positive evaluation toward organic products, with higher scores representing a more positive evaluation of the Organic concept ($M_{Valence\text{-}IAT} = 0.4$; $SD = 1.24$).

2.2.2. Calorie-IAT

The Calorie-IAT (see Table 2) adopted a design similar to the Valence-IAT, at the only difference that participants categorized eight *pictures* related to the concept of Caloric (e.g., cake, hamburger) versus Non-caloric (e.g., salad, apple), in addition to the twelve words related to Organic versus Artificial (from the FoodPics Database, Blechert, Meule, Busch, & Ohla, 2014, see Appendix I). Calorific food can be considered tastier overall, hence more positive, than non-calorific food. To avoid a potential confound, we selected pictures in order to minimize the difference of valence score between the two categories (calorific stimuli: $M = 63.3$, non-calorific stimuli: $M = 55.9$; 0 = very negative, 100 = very positive). The IAT score was computed so that a higher score represented a stronger association between the concepts Organic and Non-caloric ($M_{Calorie\text{-}IAT} = -0.05$; $SD = 1.03$).

2.2.3. Organic and non-organic label manipulation

Depending on the experimental condition, participants were presented with nutritional information about either classic cookies or cookies "made from organic flour and sugar". Importantly, both texts included the same caloric information (i.e., "160 calories per portion of 34 g"). Instructions encouraged participants to pay attention to the provided information: "You will find below nutritional information from a package of Oreos [made from organic flour and sugar]. Please review this information before answering the next questions".

2.2.4. Calories evaluation

Participants made the calories evaluation following a procedure similar to Schuldt and Schwarz's (2010). They indicated whether the presented (organic versus non-organic) cookie contained fewer or more calories than other brands of cookies (7-point scale, 1 = fewer calories, 7 = more calories).

2.2.5. Consumption recommendations

Participants also indicated consumption recommendations following a procedure similar to Schuldt and Schwarz's (2010). They indicated whether cookies (organic versus normal) could be consumed more or less often than other brands of cookies (7- point scale, 1 = less often; 7 = more often).

2.3. Statistical analyses

Threshold for statistical significance for the frequentist analyses was set to $\alpha = 0.05$. We conducted a forward hierarchical multiple linear regression model including the main effect of the organic label (model 1) and all main effects and interaction terms (model 2). In both studies, all missing values were deleted listwise. Following recent recommendations by Quintana and Eriksen (2017), we additionally conducted analyses following a Bayesian approach. Bayesian analyses allow to test for the likelihood of either the alternative or the null hypothesis, hence distinguishing data showing no clear evidence whatsoever from data supporting the null hypothesis (Wagenmakers et al., 2017; 2018). The Bayes factor (BF) compares the probability of the data under one model to that under another and provides evidence in favor of either the null hypothesis (BF_{01}) or the alternative hypothesis (BF_{10}; Dienes, 2014; van de Schoot & Depaoli, 2014). We followed a model comparison approach, which evaluates the added value of each new predictor, in our case the potential moderators, i.e., Valence-IAT and/or Calorie-IAT scores. Inclusion Bayes factors for the moderating effect of each IAT scores are reported across matched models. The Inclusion Bayes factor reflects the evidence for all models with a particular term, compared to all models without this particular term. The Bayesian linear regression was conducted with all terms and interactions as covariates. For these analyses, Cauchy's prior was first set to 0.35, which means that 50% of the values from the prior distribution are comprised between $r = 0.35$ and -0.35. All analyses were conducted on JASP 0.8.5.0 (JASP Team, 2017).

Table 2
Design for the calorie IAT.

Block	Stimuli assigned to the « E » key (left of keyboard)	Stimuli assigned to the « T » (right of keyboard)	Number of Trials	Block Type
1	Organic	Artificial	20	Training
2	Caloric	Non Caloric	20	Training
3	Organic + Caloric	Artificial + Non Caloric	20 Practice + 40 Test	Test
4	Artificial	Organic	20	Training
5	Artificial + Caloric	Organic + Non Caloric	20 Practice + 40 Test	Test

3. Results

3.1. Preliminary analyses

We first tested for any bias in the implicit associations between the experimental conditions. No significant difference arose between the organic label and the control condition at baseline on either the Valence- ($M_{nonorganic}$ = 0.70, SD = 0.34, $M_{organic}$ = 0.75, SD = 0.38), t (149) = −0.09, p = .36, BF_{10} = 0.25, or the Calorie-IAT ($M_{nonorganic}$ = −0.47, SD = 0.37, $M_{organic}$ = −0.58, SD = 0.40), t (149) = 1.74, p = .08, BF_{10} = 0.70. Mean score for calories evaluation was slightly above the middle point of the scale (M = 3.37, SD = 1.09).

3.2. Frequentist analyses

3.2.1. Calories estimations

A first model considered only the cookie label variable (organic versus non-organic). It yielded a significant main effect, F(1,149) = 31.69, p < .001, η^2 = 0.17, revealing an estimation of the organic cookie as less caloric (M = 2.90, SD = 1.03) than the non-or-ganic cookie (M = 3.81, SD = 0.95). In the second model, which took into account both IATs and all interactions, the main effect of the label became non-significant, F(1,143) = 0.28, p = .59, η^2 = 0.001. Importantly, no other main effect or interaction was found to be sig-nificant (Fs < 1.33, ps > .29).

3.2.2. Recommendations

The initial model including only the label main effect yield no sig-nificant results, F(1,149) = 0.0003, p = .98, η^2 < 0.001. In the second model, which took into account both IATs and all interactions, the main effect of the label remained non-significant, and no other main effect or interaction was found to be significant (ps > .10).

3.3. Bayesian analyses

3.3.1. Calories estimations

Label, both IAT scores, and all their interactions were entered as predictors in a Bayesian linear regression. Results showed that the model including only the label yielded the strongest evidence for the alternative hypothesis compared to all other models, BF_{10} = 135′278 (see Appendix II for details). The next stronger model provided five times less evidence for the alternative hypothesis (BF_{10} = 27′218). When the Label term was included into the Null model (i.e., when its effect was removed from all alternative models), all BF_{10} dropped below 0.02. Inclusion BF showed overwhelming evidence in favor of an effect of the label, $BF_{Inclusion}$ = 50′933. Inclusion BF for all other terms and interactions were below 0.1 (see Appendix II for more details). In sum, while the frequentist analyses did not allow to conclude about the absence of a moderation of the halo effect by implicit processes, Bayesian analyses provided evidence that the implicit associations *did not* moderate the halo effect. On the other hand, Bayesian analyses consistently provided overwhelming evidence in favor of the existence of the health halo effect.

3.3.2. Recommendations

Label and IAT scores were entered as predictors of consumption recommendations in a Bayesian linear regression model. Results showed that no model provided strong evidence in favor of the alter-native hypothesis, with the exception of a model containing only the term Calorie-IAT, BF_{10} = 4.05. All other models showed virtually in-existent evidence in favor of the alternative hypothesis (All BF_{10} < 1.1). Instead, we found moderate evidence for the *null* hy-pothesis for the model containing only the label term, BF_{01} = 5.66, as well as for a moderating effect of the Valence-IAT and Calorie-IAT, as evidenced by a model containing all Label, IAT and interaction terms, BF_{01} = 5.61. Inclusion BF showed no substantial evidence for the al-ternative hypothesis for any of terms, $BF_{Inclusion}$ < 2.

4. Discussion

The present study aimed to replicate the health halo effect of the "organic" label and investigate its mechanisms in terms of implicit as-sociations between the concepts of "organic" and "positive" and "non-caloric", respectively. This study replicated previous findings from the literature (Schuldt & Schwarz, 2010), showing that organic foods are evaluated as comparatively less caloric than non-organic foods, despite providing participants with the same objective caloric information. However, a few limitations need to be highlighted. First, the study was conducted on a student population who may feel less concerned about the consumption of organic food than the general population. Indeed, this type of product remains relatively expensive and students are known to lack money to invest in a quality diet. While this may not have influenced the implicit associations with the "organic" label (the 'organic = non-caloric' belief being common knowledge), it may have hampered participants' involvement in the task. Let us note, however, that if participants were really indifferent about organic products, the health halo effect would have decreased drastically (as participants who are deeply involved toward "organic" foods tend to be more sensitive to the health halo effect; Schuldt & Schwarz, 2010, study 1; Sörqvist et al., 2013, study 1). Yet, we found reliable evidence for a health halo effect.

Second, IAT only measures relative associations (see De Houwer, 2002): the "organic" concept is only considered "non-caloric" as com-pared to "artificial", which implies that we could not test for a one-way association between "organic" and "non-caloric". Hence, it could be that calories evaluation was not moderated by the Calorie-IAT because the link between the "organic" and "artificial" categories was artifi-cially established. Such issues could be addressed by using other im-plicit tasks that do not rely on this comparative structure but rather measure the strength of a link between a target concept and an attri-bute, such as the Single Category IAT (see De Houwer & Gawronski, 2014; Nosek & Banaji, 2001).

We therefore replicated the first study by addressing both popula-tion bias (i.e., we sampled a more representative population) and methodological bias (i.e., we used the SC-IAT paradigm).

5. Study 2 - methods

5.1. Participants and design

Two hundred and sixty-nine participants from a general population (72% female, M_{age} = 30.6, SD = 12, 39% between 18 and 24 years of age) completed an online study. They indicated demographics before being randomly assigned to the organic versus non-organic cookie condition and provided nutritional information about the cookie. They evaluated the cookie's calories content in comparison to other brands of cookies, and indicated consumption recommendations as well as their willingness to pay for such a product. Finally, they completed two Single Category IATs (i.e., Calorie SC-IAT and Valence SC-IAT).

5.2. Measures

5.2.1. Organic and non-organic label manipulation, calorie evaluation, consumption recommendations, and willingness to pay

We used the same methodology as in Study 1 for the label manip-ulation, calories evaluation, and consumption recommendations. We added a willingness-to-pay measure, asking participants to estimate the amount they would be willing to pay for a batch of 4 × 2 biscuits, on a scale ranging from 0 to 2 euros.

Table 3
Design for the valence SC-IAT.

Block	Stimuli assigned to the « E » key (left of keyboard)	Stimuli assigned to the « T » (right of keyboard)	Number of trials	Block type
1	Positive	Negative	24	Training
2	Positive + Organic	Negative	24 Practice + 72 Test	Test
3	Positive	Negative + Organic	24 Practice + 72 Test	Test

Table 4
Design for the calorie SC-IAT.

Block	Stimuli assigned to the « E » key (left of keyboard)	Stimuli assigned to the « T » (right of keyboard)	Number of Trials	Block Type
1	Non-caloric	Caloric	24	Training
2	Non-caloric + Organic	Caloric	24 Practice + 72 Test	Test
3	Non-caloric	Caloric + Organic	24 Practice + 72 Test	Test

5.2.2. *Valence SC-IAT*

The Valence SC-IAT follows the same principle as the standard Valence IAT, except that there are only three categories of words to classify (i.e., Positive; Negative; Organic). It included three blocks, one of them considered as a training block (Blocks 1), and two as test blocks (Blocks 2 and 3; see Table 3). Block 1 consisted in a simple categorization of target words into the categories "Positive" (e.g. "pleasant") and "Negative" (e.g. "bad"), randomly assigned to the right and the left side of the screen (see Appendix III). Participants answered by pressing one of two predetermined keys, on the left versus right half of the keyboard. Block 2 was the first test block, adding the "Organic" category on the same response key as "Positive". Block 3 was similar to Block 2 except that "Organic" was moved so to share the same response key as "Negative". The order of Blocks 2 and 3 was counterbalanced between-subject.

5.2.3. *Calorie SC-IAT*

The Calorie SC-IAT included three categories of words to classify (i.e., Caloric; Non-caloric; Organic). It adopted a design similar to the Valence SC-IAT (see Table 4), at the only difference that participants categorized eight *pictures* from an food-pics database (Blechert et al., 2014) and the Amsterdam Beverage Picture Set (Pronk, van Deursen, Beraha, Larsen, & Wiers, 2015) related to the concept of Caloric (e.g., avocado, chips) versus Non-caloric (e.g., carrot, tea; Appendix III), in addition to the words related to Organic. Calorific food stimuli's valence was rated 54.8 on average, versus 49.4 for non-calorific stimuli. The calorific (vs. non-calorific) drink stimulus was rated 1.16 (vs. 2.30; −4 = very negative, +4 = very positive).

6. Statistical analyses

Threshold for statistical significance for the frequentist analysis was again set to $\alpha = 0.05$. We conducted two models, as well as Bayesian analyses like in study 1. The Frequentist and Bayesian linear regressions were conducted with all terms and interactions as covariates. Cauchy's prior was first set to 0.35.

7. Results

7.1. *Preliminary analysis*

We first tested for any bias in the implicit associations between the experimental conditions. No significant difference arose between the organic label and the control condition at the baseline on either the Valence ($M_{nonorganic} = 0.37$, $SD = 1.43$, $M_{organic} = 0.04$, $SD = 1.58$), $t(247) = 1.69$, $p = .09$, $BF_{10} = 0.54$, or the Calorie-IAT ($M_{nonorganic} = 0.29$, $SD = 1.22$, $M_{organic} = 0.17$, $SD = 1.15$), $t(249) = 0.77$, $p = .44$, $BF_{10} = 0.18$. Mean score for calories evaluation was slightly above the middle point of the scale ($M = 4.71$, $SD = 1.42$). Mean scores for recommendation and willingness to pay were respectively, $M = 2.62$, $SD = 1.49$, and $M = 1.04$ Euro, $SD = 0.44$.

7.2. *Frequentist analyses*

7.2.1. *Calories-estimation*

A first model considered only the cookie label variable (organic versus non-organic). It yielded a significant main effect, $F(1,267) = 8.25$, $p = .004$, $\eta^2 = 0.03$, revealing an estimation of the organic cookie as less caloric ($M = 4.47$, $SD = 1.37$) than the non-organic cookie ($M = 4.96$, $SD = 1.43$). In the second model, which took into account both IATs and all interactions, the main effect of the label stayed significant, $F(1,223) = 5.34$, $p = .02$, $\eta^2 = 0.02$. Importantly, no other main effect or interaction was found to be significant ($Fs < 0.001$, $ps > .97$).

7.2.2. *Recommendations*

The model considering only the cookie label variable (organic versus non-organic) on consumption recommendations yielded a significant main effect, $F(1,267) = 10.13$, $p = .001$, $\eta^2 = 0.04$, revealing recommendations to eat organic cookies more regularly ($M = 2.83$, $SD = 1.55$) than non-organic cookies ($M = 2.36$, $SD = 1.34$). In the second model taking into account both IATs and all interactions, the main effect of the label stayed significant, $F(1,223) = 8.27$, $p = .004$, $\eta^2 = 0.03$. No other main effect or interaction was found to be significant ($Fs < 2.03$, $ps > .15$).

7.2.3. *Willingness to pay*

The model considering only the cookie label variable (organic versus non-organic) on willingness to pay yielded no significant main effect, $F(1,267) = 1.09$, $p = .29$, $\eta^2 = 0.004$, with no difference between the organic ($M = 1.01$, $SD = 0.43$) and non-organic cookie ($M = 1.07$, $SD = 0.45$). In the second model taking into account both IATs and all interactions, the main effect of the label stayed non-significant, $F(1,223) = 0.22$, $p = .63$, $\eta^2 = 0.001$. No other main effect or interaction was significant ($Fs < 1.51$, $ps > .21$), except for a main effect of the Valence IAT, $F(1,223) = 4.53$, $p = .03$, $\eta^2 = 0.01$, showing that the higher the IAT scores, the higher the willingness to pay.

7.3. *Bayesian analyses*

7.3.1. *Calorie-estimation*

As in Study 1, Label, both IAT scores, and all their interactions were entered as predictors in a Bayesian linear regression. Results showed that the model including only the label yielded the strongest evidence for the alternative hypothesis, as compared to all other models, although the evidence was anecdotal, $BF_{10} = 1.31$ (see Appendix IVa for details). All other models had $BF_{10} < 0.67$. Inclusion BF showed small evidence in favor of an effect of the label, $BF_{\text{Inclusion}} = 0.81$. Inclusion

BF for all other terms and interactions were below 0.25 (see Appendix IVa for more details). Again, Bayesian analyses provided evidence that the implicit associations *did not* moderate the halo effect. On the other hand, Bayesian analyses reduced the evidence in favor of the existence of the health halo effect that we found in Study 1.

7.3.2. Recommendations

Results showed that the model including only the label yielded the strongest evidence for the alternative hypothesis compared to all other models, and this evidence was of moderate magnitude, $BF_{10} = 2.7$ (see Appendix IV for details). All other models had $BF_{10} < 1.3$. Inclusion BF showed small evidence in favor of an effect of the label, $BF_{\text{Inclusion}} = 1.67$. Inclusion BF for all other terms and interactions were below 0.28 (see Appendix IV for more details).

7.3.3. Willingness to pay

Results showed that the model including only the label yielded the strongest evidence for the alternative hypothesis compared to all other models, but this evidence was nonexistent, $BF_{10} = 0.17$ (see Appendix IVc for details). All other models had $BF_{10} < 1.2$. Inclusion BF showed no evidence in favor of an effect of the label, $BF_{\text{Inclusion}} = 0.11$. Inclusion BF for all other terms and interactions were below 0.58 (see Appendix IVc for more details). Hence, Bayesian analyses confirmed that we found no effect of the label on willingness to pay, and no moderation effects of the IATs scores.

8. Discussion

In this second study we replicated the health halo effect based on the organic label, not only on the evaluation of the number of calories in cookies but also on the recommended consumption frequency. Organic cookies were considered as more suitable for regular consumption than conventional cookies. In addition, we found again no effect of the caloric-organic associations, nor the positive-organic association, on any of the dependent variables. However, a marginal effect of attitude appeared on the willingness-to-pay measure, suggesting that people with more negative attitudes towards organic products are less willing to pay for this type of product. Regarding this last measure, our results suggest that the health halo effect does not affect the monetary value of food. Hence, it is quite possible that a different process is involved that would be more in line with, for example, the theory of planned behavior (Ajzen, 1991). The attitude would thus directly affect the behavioral intention to buy an organic product and therefore the amount attributed to it, without being moderated by other processes or with interaction with the context in which stimuli are presented.

9. Small-scale meta-regression

Given the variations of results between the two studies, we conducted a small-scale meta-regression in order to assess the reliability of our results with better confidence. First, we conducted a multilevel mixed-effects linear regression to estimate a global model for calories evaluation (Model 1a) and a second model for recommendations (Model 2a), aggregating the data from our two studies. Analyses were conducted with R (R Core Team, 2017) using the *lme4* and *LmerTest* packages and the *lmer* and *glmer* functions. We calculated the standardized β coefficients and used the same coding for independent variables as in the per-study analyses. All models used the same fixed effects as in the individual studies and included a random study effect (i.e., random intercept) in order to control for potential study heterogeneity. Model 1 yielded a significant effect of Label on calories estimation, $b = -0.28$, 95% CI [-0.41, -0.14], $F(1,373) = 16.44$, $p < .001$, but also a main effect of Valence IAT, $b = -0.15$, 95% CI [-0.27, -0.03], $F(1, 373) = 6.76$, $p = .009$, and of Calorie IAT, $b = 0.26$, 95% CI [-0.12, 0.40], $F(1, 373) = 14.38$, $p < .001$. Model 2 yielded a significant main effect of the label on recommendations, $b = 0.15$, 95% CI [0.02, 0.28], $F(1, 373) = 5.2$, $p = .02$, as well as a significant Label × Valence IAT interaction, $b = -0.11$, 95% CI [-0.23, -0.002], $F(1, 373) = 4.04$, $p = .04$. However, decomposition of the Label × Valence IAT interaction showed that the IAT scores did not predict recommendations either in the non-organic condition ($b_{nonorganic} = 0.12$, SE = 0.09), nor in the organic condition ($b_{organic} = -0.10$, SE = 0.07), respectively, $t(373) = 1.37$, $p = .17$ and $t(373) = -1.52$, $p = .12$. Random intercept variance was overall low, $\sigma^2 = 0.19$ for calorie evaluation, and for recommendations, $\sigma^2 = 0.03$.

Second, we conducted two Bayesian linear regressions on the aggregated dataset while entering the study term into the null model to account for study heterogeneity. As with the frequentist approach, we ran a model for calories evaluation (Model 1b) and a second model for recommendations (Model 2b). Model 1b yielded extremely strong evidence for the effect of the label on evaluations, $BF_{\text{Inclusion}} = 195.13$, as well as strong evidence for a main effect of the Calorie IAT, $BF_{\text{Inclusion}} = 87.91$ (all other $BF_{\text{Inclusion}} < 2.3$). However, Model 2b did not provide any evidence for an effect of the label on recommendations, or for any other effect (all $BF_{\text{Inclusion}} < 1$). When study was entered as a model term, we found extremely strong evidence for an effect of the study on calories evaluation, $BF_{\text{Inclusion}} = 903.33$, and anecdotal evidence on recommendations, $BF_{\text{Inclusion}} = 1.79$.

10. General discussion

Taken individually, as well as meta-analytically, our results highlight the potential boomerang effect the organic label could have in terms of calories estimation and, in turn, on actual consumption and eventually public health. Critically, our results did not provide any evidence for – and even showed evidence against – any implicit association mechanisms underlying calories estimation. This suggests that implicit processes (i) may not play any role in the health halo effect, but also that (ii) they could be a necessary, but not sufficient condition to produce a halo effect. In this last perspective, it could be that the implicit components would be incorporated in a second phase into a broader, higher-level reflective mechanism that would eventually lead to judgment. This is plausible in the sense that some associations in memory may only be relevant to certain products or contexts. For example, the associations between “organic” and “good”, and “organic” and “less caloric” may make sense, and consequently lead to a halo effect, but only concerning products for which low calorie content is considered a positive feature. Hence, it is possible that a sub-component (implicit or not) of the product's semantic network would be reactivated, depending on the utility or nature of the product, which would itself depend upon deliberative processes. For example, a product which purpose is to be caloric, such as dietary supplement, could be considered as more caloric when labeled organic, to the extent that individuals associate “organic” with “good".

A few limitations of the present research must be highlighted. Most notably, it lacks demographic information that could have been useful to take into account, such as body mass index, eating habits, health issues, or interest in health. These variables would have allowed us to conduct more detailed analyses on certain sub-populations who may have had different experiences with organic food, and therefore hold different implicit associations. In particular, it has been shown that individuals on a diet are more accurate in their estimates of products' energy value than non-dieters, and especially so in the case of healthy food products (Carels, Konrad, & Harper, 2007). Body mass index, for its part, does not appear to impact calorie estimation (Chandon & Wansink, 2007; Wansink & Chandon, 2006). Yet, it is possible that it impacts implicit associations linked to the organic construct. Hence, future research should be cautious to include such demographic variables and investigate their impact on the health halo effect.

We believe studying the processes underlying the health halo effect is of great importance, as it could indeed facilitate the development of public health interventions - or inform public policies - to raise awareness of and help avoiding this bias. If the health halo effect is based on automatic components, it should be possible to reduce it through interventions aiming at changing long-term attitudes (e.g., "Faking the IAT", Lai et al., 2016), or by ensuring one is not repeatedly exposed to associations between the "organic" label and positive elements.

In conclusion, we would advise caution when advocating the consumption of organic products, as the present research highlighted the importance for public health policies tackling obesity of taking into account a potential health halo effect. In particular, this research speaks in favor of the proposition by the European Council to promote the use of a nutritional score label (see Hawkes et al., 2015), which would provide specific information about nutritional value and could help people make calories evaluations more efficiently, relying less on external and heuristic sources of information such as the organic label. This research also showed that further explorations are needed in order to better understand the cognitive processes underlying the halo effect, and more particularly the relationship between automatic/implicit process and higher-level cognitive functions driving behavior.

Appendix J. Supplementary data

Appendix I

Words and images used for the valence-IAT and the calorie-IAT in Study 1.

- Words belonging to the Organic category: organic, ecological, biological, natural, environmental, sustainable
- Words belonging to the Artificial category: synthetic, industrialist, chemical, automatic, manufactured, mechanics
- Words belonging to the Positive category: pleasant, brilliant, wonderful, marvelous, positive, good
- Words belonging to the Negative category: negative, bad, boring, sad, hatred, failure
- Images belonging to the Caloric category:

- Images belonging to the Non-caloric category:

Appendix II

Model Comparison in favor of the alternative hypothesis - Calorie estimation with Valence-IAT and Calorie IAT and Label included in the null model with Cauchy's Prior set to 0.35.

Models	P(M)	P(M|data)	BF_M	BF_{10}	error %
Null model (incl. Label)	0.0714	0.6248	21.6544	1.0000	
IATVal	0.0714	0.1257	1.8694	0.2012	0.0114
IATKal	0.0714	0.1141	1.6757	0.1827	0.0116
IATVal + IATKal	0.0714	0.0295	0.3965	0.0473	0.0109
IATVal + IATKal + IATVal * IATKal	0.0714	0.0104	0.1368	0.0166	0.0095
IATVal + IATVal * Label	0.0714	0.0361	0.4875	0.0578	0.0105
IATVal + IATKal + IATVal * Label	0.0714	0.0099	0.1300	0.0158	0.0095
IATVal + IATKal + IATVal * IATKal + IATVal * Label	0.0714	0.0033	0.0437	0.0053	0.0112
IATKal + IATKal * Label	0.0714	0.0279	0.3742	0.0447	0.0110
IATVal + IATKal + IATKal * Label	0.0714	0.0084	0.1109	0.0135	0.0095
IATVal + IATKal + IATVal * IATKal + IATKal * Label	0.0714	0.0038	0.0507	0.0062	0.0113
IATVal + IATKal + IATVal * Label + IATKal * Label	0.0714	0.0033	0.0434	0.0053	0.0112
IATVal + IATKal + IATVal * IATKal + IATVal * Label + IATKal * Label	0.0714	0.0013	0.0179	0.0022	0.0153
IATVal + IATKal + IATVal * IATKal + IATVal * Label + IATKal * Label + IATVal * IATKal * Label	0.0714	0.0007	0.0099	0.0012	0.0096

Analysis of Effects – Calorie estimation with Valence-IAT and Calorie IAT and Label included in the null model with Cauchy's Prior set to 0.35.

Effects	P(incl)	P(incl|data)	$BF_{Inclusion}$
IATVal	0.7857	0.2326	0.0828
IATKal	0.7857	0.2132	0.0739
Label * IATVal	0.4285	0.0548	0.0774
Label * IATKal	0.4285	0.0458	0.0640
IATVal * IATKal	0.3571	0.0198	0.0363
Label * IATVal * IATKal	0.0717	0.0007	0.0099

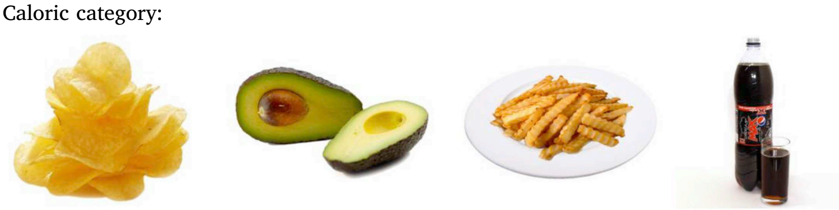
Model Comparison in favor of the Null hypothesis– Calorie estimation with Valence-IAT and Calorie IAT and Label included in the null model with Cauchy's Prior set to 0.35.

Models	P(M)	P(M|data)	BF_M	BF_{01}	error %
Null model (incl. Label)	0.0714	0.6248	21.6544	1.0000	
IATVal	0.0714	0.1257	1.8694	4.9701	0.0114
IATKal	0.0714	0.1149	1.6757	5.4724	0.0116
IATVal + IATKal	0.0714	0.0295	0.3965	21.1115	0.0109
IATVal + IATKal + IATVal * IATKal	0.0714	0.0104	0.1368	60.0046	0.0095
IATVal + IATVal * Label	0.0717	0.0361	0.4875	17.2874	0.0105
IATVal + IATKal + IATVal * Label	0.0714	0.0099	0.1300	63.1012	0.0095
IATVal + IATKal + IATVal * IATKal + IATVal * Label	0.0714	0.0033	0.0437	186.3398	0.01123195
IATKal + IATKal * Label	0.0714	0.0279	0.3742	22.3318	0.0110
IATVal + IATKal + IATKal * Label	0.0714	0.0084	0.1109	73.8244	0.0095
IATVal + IATKal + IATVal * IATKal + IATKal * Label	0.0714	0.0038	0.0507	160.6676	0.0113
IATVal + IATKal + IATVal * Label + IATKal * Label	0.0714	0.0033	0.0434	187.6649	0.0112
IATVal + IATKal + IATVal * IATKal + IATVal * Label + IATKal * Label	0.0714	0.0013	0.0179	452.7938	0.0153
IATVal + IATKal + IATVal * IATKal + IATVal * Label + IATKal * Label + IATVal * IATKal * Label	0.0714	0.0007	0.0099	815.5317	0.0096

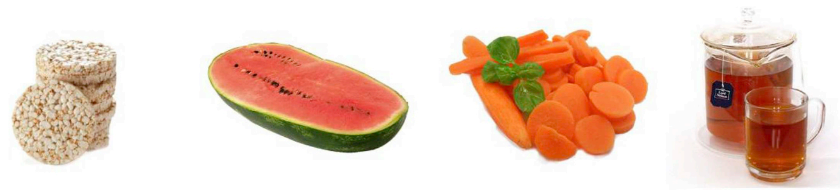
Appendix III

Words and images used for the valence-IAT and the calorie-IAT in Study 2.

- Words belonging to the Organic category: organic, ecological, biological, natural, environmental, sustainable
- Words belonging to the Positive category: pleasant, brilliant, wonderful, marvelous, positive, good
- Words belonging to the Negative category: negative, bad, boring, sad, hatred, failure
- Images belonging to the Caloric category:



- Images belonging to the Non-caloric category:F



Note

One will note that the avocado picture was used as a non-caloric stimulus in Study 1, and then a caloric stimulus in Study 2. In fact, we realized that the stimuli used in the first study were actually different not solely in terms of caloric versus non-caloric, but also in terms of non-processed versus processed food. We hence adapted the stimuli for the second study, taking care that both caloric and non-caloric categories included as many processed and non-processed food stimuli. Avocado being a natural, non-processed food product, but also a caloric one, it was a great stimulus to include in the caloric category. Hence the change of category.

Appendix IVa

Model Comparison.

Models	P(M)	P (M|data)	BF_M	BF_{10}	R^2
Null model	0.05263	0.17811	3.90068	1.00000	0.00000
cond	0.05263	0.23480	5.52326	1.31830	0.01919
cond + Calorie IAT	0.05263	0.11994	2.45326	0.67344	0.02645
cond + Valence IAT + cond ∗ Valence IAT	0.05263	0.07894	1.54262	0.44319	0.03443
Calorie IAT	0.05263	0.07151	1.38630	0.40149	0.00820
cond + Valence IAT	0.05263	0.06188	1.18721	0.34740	0.02022
cond + Calorie IAT + Valence IAT + cond ∗ Valence IAT	0.05263	0.04885	0.92441	0.27426	0.04079
cond + Calorie IAT + Valence IAT	0.05263	0.04014	0.75264	0.22534	0.02795
cond + Calorie IAT + cond ∗ Calorie IAT	0.05263	0.03454	0.64398	0.19393	0.02651
Valence IAT	0.05263	0.03090	0.57401	0.17351	0.00033
Calorie IAT + Valence IAT	0.05263	0.01881	0.34512	0.10563	0.00885
cond + Calorie IAT + Valence IAT + cond ∗ Calorie IAT + cond ∗ Valence IAT	0.05263	0.01717	0.31437	0.09638	0.04080
cond + Calorie IAT + Valence IAT + cond ∗ Valence IAT + Calorie IAT ∗ Valence IAT	0.05263	0.01715	0.31407	0.09629	0.04079
cond + Calorie IAT + Valence IAT + Calorie IAT ∗ Valence IAT	0.05263	0.01361	0.24842	0.07643	0.02829
cond + Calorie IAT + Valence IAT + cond ∗ Calorie IAT	0.05263	0.01331	0.24285	0.07474	0.02807
cond + Calorie IAT + Valence IAT + cond ∗ Calorie IAT + cond ∗ Valence IAT + Calorie IAT ∗ Valence IAT	0.05263	0.00653	0.11834	0.03667	0.04080
Calorie IAT + Valence IAT + Calorie IAT ∗ Valence IAT	0.05263	0.00611	0.11074	0.03433	0.00956
cond + Calorie IAT + Valence IAT + cond ∗ Calorie IAT + Calorie IAT ∗ Valence IAT	0.05263	0.00499	0.09019	0.02799	0.02839
cond + Calorie IAT + Valence IAT + cond ∗ Calorie IAT + cond ∗ Valence IAT + Calorie IAT ∗ Valence IAT + cond ∗ Calorie IAT ∗ Valence IAT	0.05263	0.00272	0.04900	0.01524	0.04105

Posterior Summaries of Coefficients.

						95% Credible Interval	
Coefficient	Mean	SD	P(incl)	P(incl|data)	$BF_{inclusion}$	Lower	Upper
Intercept	4.75325	0.09182	1.00000	1.00000	1.00000	4.57268	4.91078
cond	−0.17920	0.08619	0.73684	0.69455	0.81210	−0.31800	0.00000
Calorie IAT	0.07849	0.07133	0.73684	0.41538	0.25375	−0.01500	0.20038
Valence IAT	−0.03807	0.05801	0.73684	0.36110	0.20185	−0.11638	0.03506
cond ∗ Calorie IAT	0.00202	0.07133	0.31579	0.07925	0.18649	−0.04933	0.01584
cond ∗ Valence IAT	0.08098	0.05801	0.31579	0.17134	0.44801	0.00000	0.12674
Calorie IAT ∗ Valence IAT	−0.00342	0.03715	0.31579	0.05111	0.11670	0.00000	0.00000
cond ∗ Calorie IAT ∗ Valence IAT	0.00799	0.03715	0.05263	0.00272	0.04900	0.00000	0.00000

Appendix IVb

Model Comparison.

Models	P(M)	P (M|data)	BF $_M$	BF $_{10}$	R^2
Null model	0.05263	0.11322	2.29823	1.00000	0.00000
cond	0.05263	0.31271	8.18971	2.76186	0.02595
cond + Calorie IAT	0.05263	0.15513	3.30513	1.37015	0.03307
cond + Valence IAT	0.05263	0.07261	1.40936	0.64132	0.02599
cond + Calorie IAT + cond ∗ Calorie IAT	0.05263	0.05871	1.12275	0.51856	0.03592
cond + Calorie IAT + Valence IAT	0.05263	0.04352	0.81897	0.38436	0.03307
cond + Valence IAT + cond ∗ Valence IAT	0.05263	0.04170	0.78324	0.36829	0.03266
Calorie IAT	0.05263	0.03629	0.67773	0.32048	0.00609
cond + Calorie IAT + Valence IAT + cond ∗ Valence IAT	0.05263	0.03105	0.57678	0.27422	0.04079
cond + Calorie IAT + Valence IAT + Calorie IAT ∗ Valence IAT	0.05263	0.02245	0.41346	0.19832	0.03764
cond + Calorie IAT + Valence IAT + cond ∗ Valence IAT + Calorie IAT ∗ Valence IAT	0.05263	0.02153	0.39612	0.19018	0.04751
Valence IAT	0.05263	0.01914	0.35124	0.16904	0.00008
cond + Calorie IAT + Valence IAT + cond ∗ Calorie IAT	0.05263	0.01887	0.34612	0.16663	0.03595
cond + Calorie IAT + Valence IAT + cond ∗ Calorie IAT + cond ∗ Valence IAT	0.05263	0.01374	0.25082	0.12138	0.04308
cond + Calorie IAT + Valence IAT + cond ∗ Calorie IAT + Calorie IAT ∗ Valence IAT	0.05263	0.01086	0.19758	0.09589	0.04075
cond + Calorie IAT + Valence IAT + cond ∗ Calorie IAT + cond ∗ Valence IAT + Calorie IAT ∗ Valence IAT	0.05263	0.01031	0.18760	0.09110	0.04998
Calorie IAT + Valence IAT	0.05263	0.00921	0.16737	0.08137	0.00633
cond + Calorie IAT + Valence IAT + cond ∗ Calorie IAT + cond ∗ Valence IAT + Calorie IAT ∗ Valence IAT + cond ∗ Calorie IAT ∗ Valence IAT	0.05263	0.00502	0.09084	0.04435	0.05204
Calorie IAT + Valence IAT + Calorie IAT ∗ Valence IAT	0.05263	0.00392	0.07081	0.03461	0.00964

Posterior Summaries of Coefficients.

						95% Credible Interval	
Coefficient	Mean	SD	P(incl)	P(incl|data)	BF $_{inclusion}$	Lower	Upper
Intercept	2.60606	0.09565	1.00000	1.00000	1.00000	2.43331	2.79729
cond	0.23454	0.09024	0.73684	0.81822	1.60756	0.00000	0.36432
Calorie IAT	0.09618	0.07468	0.73684	0.44062	0.28132	−0.03817	0.18858
Valence IAT	0.01910	0.06074	0.73684	0.32394	0.17113	−0.08590	0.06042
cond ∗ Calorie IAT	−0.04798	0.07468	0.31579	0.11752	0.28852	−0.10236	0.00327
cond ∗ Valence IAT	−0.06600	0.06074	0.31579	0.12336	0.30489	−0.09152	0.00000
Calorie IAT ∗ Valence IAT	−0.03242	0.03890	0.31579	0.07410	0.17340	−0.03223	0.00000
cond ∗ Calorie IAT ∗ Valence IAT	−0.02450	0.03890	0.05263	0.00502	0.09084	0.00000	0.00000

Appendix IVc

Model Comparison.

Models	P(M)	P (M|data)	BF $_M$	BF $_{10}$	R^2
Null model	0.05263	0.26276	6.41554	1.00000	0.00000
Calorie IAT	0.05263	0.31731	8.36643	1.20760	0.01839
Calorie IAT + Valence IAT	0.05263	0.09441	1.87662	0.35931	0.02054
cond + Calorie IAT	0.05263	0.07818	1.52655	0.29752	0.01875
Valence IAT	0.05263	0.05021	0.95162	0.19110	0.00124
cond	0.05263	0.04688	0.88536	0.17841	0.00059
cond + Calorie IAT + Valence IAT	0.05263	0.02916	0.54055	0.11096	0.02110
cond + Calorie IAT + cond ∗ Calorie IAT	0.05263	0.02790	0.51653	0.10616	0.02067
Calorie IAT + Valence IAT + Calorie IAT ∗ Valence IAT	0.05263	0.02758	0.51055	0.10497	0.02056
cond + Valence IAT	0.05263	0.01371	0.25027	0.05219	0.00202
cond + Calorie IAT + Valence IAT + cond ∗ Calorie IAT	0.05263	0.01225	0.22324	0.04662	0.02338
cond + Calorie IAT + Valence IAT + Calorie IAT ∗ Valence IAT	0.05263	0.00978	0.17775	0.03721	0.02113
cond + Calorie IAT + Valence IAT + cond ∗ Valence IAT	0.05263	0.00975	0.17718	0.03710	0.02110
cond + Calorie IAT + Valence IAT + cond ∗ Calorie IAT + Calorie IAT ∗ Valence IAT	0.05263	0.00452	0.08175	0.01721	0.02343
cond + Calorie IAT + Valence IAT + cond ∗ Calorie IAT + cond ∗ Valence IAT	0.05263	0.00450	0.08144	0.01714	0.02339
cond + Valence IAT + cond ∗ Valence IAT	0.05263	0.00428	0.07734	0.01628	0.00211
cond + Calorie IAT + Valence IAT + cond ∗ Valence IAT + Calorie IAT ∗ Valence IAT	0.05263	0.00361	0.06525	0.01375	0.02113
cond + Calorie IAT + Valence IAT + cond ∗ Calorie IAT + cond ∗ Valence IAT + Calorie IAT ∗ Valence IAT	0.05263	0.00179	0.03235	0.00683	0.02344
cond + Calorie IAT + Valence IAT + cond ∗ Calorie IAT + cond ∗ Valence IAT + Calorie IAT ∗ Valence IAT + cond ∗ Calorie IAT ∗ Valence IAT	0.05263	0.00140	0.02532	0.00535	0.03004

Posterior Summaries of Coefficients.

						95% Credible Interval	
Coefficient	Mean	SD	P(incl)	P(incl|data)	BF $_{inclusion}$	Lower	Upper
Intercept	1.03117	0.02959	1.00000	1.00000	1.00000	0.97447	1.08907
cond	0.01168	0.02762	0.73684	0.24771	0.11760	−0.03082	0.04285
Calorie IAT	−0.04352	0.02286	0.73684	0.62215	0.58805	−0.08433	0.00000
Valence IAT	0.00754	0.01859	0.73684	0.26697	0.13007	−0.02276	0.02758
cond ∗ Calorie IAT	−0.01307	0.02286	0.31579	0.05237	0.11974	−0.01274	0.00000
cond ∗ Valence IAT	0.00663	0.01859	0.31579	0.02534	0.05633	0.00000	0.00000
Calorie IAT ∗ Valence IAT	0.00388	0.01191	0.31579	0.04869	0.11090	−0.00091	0.00013
cond ∗ Calorie IAT ∗ Valence IAT	−0.01312	0.01191	0.05263	0.00140	0.02532	0.00000	0.00000

References

Agence Bio, CSA (2015). *Baromètre de consommation et de perception des produits biologiques en France*.

Ajzen, I. (1991). The theory of planned behaviour. *Organizational Behaviour and Human Decision Process, 50*(2), 179–211.

Blechert, J., Meule, A., Busch, N. A., & Ohla, K. (2014). Food-pics: An image database for experimental research on eating and appetite. *Frontiers in Psychology, 5*, 617. https://doi.org/10.3389/fpsyg.2014.00617.

Carels, R. A., Konrad, K., & Harper, J. (2007). Individual differences in food perceptions and calorie estimation: An examination of dieting status, weight, and gender. *Appetite, 49*(2), 450–458.

Chandon, P., & Wansink, B. (2007). The biasing health halos of fast-food restaurant health claims: Lower calorie estimates and higher side-dish consumption intentions. *Journal of Consumer Research, 34*(3), 301–314.

Chernev, A. (2011). The dieter's paradox. *Journal of Consumer Psychology, 21*, 178–183.

Chernev, A., & Chandon, P. (2010). *Calorie estimation biases in consumer choice BT - leveraging consumer Psychology for effective health communications: The obesity challenge.* Leveraging Consumer Psychology for Effective Health Communications: The Obesity Challenge.

De Houwer, J. (2002). The implicit association test as a tool for studying dysfunctional associations in psychopathology: Strength and limitations. *Journal of Behavior Therapy and Experimental Psychiatry, 33*, 115–133.

De Houwer, J. (2014). *A propositional model of implicit evaluation.* Social Psychology and Personality Compass.

Dienes, Z. (2014). Using Bayes to get the most out of nonsignificant results. *Frontiers in Psychology, 5*, 781. https://doi.org/10.3389/fpsyg.2014.00781.

Fernan, C., Schuldt, J. P., & Niederdeppe, J. (2018). Health halo effects from product titles and nutrient content claims in the context of “protein” bars. *Health Communication, 33*(12), 1425–1433.

Flegal, K. M., Kit, B. K., Orpana, H., & Graubard, B. I. (2013). Association of all-cause mortality with overweight and obesity using standard body mass index categories. *Journal of the American Medical Association, 309*(1), 71–82.

Greenwald, A. G., Nosek, B. A., & Banaji, M. R. (2003). Understanding and using the implicit association test: I. An improved scoring algorithm. *Journal of Personality and Social Psychology, 85*(2), 197.

Hawkes, C., Smith, T. G., Jewell, J., Wardle, J., Hammond, R. A., Friel, S., et al. (2015). Smart food policies for obesity prevention. *The Lancet, 385*(9985), 2410–2421.

JASP Team (2017). *JASP (version 0.8.5)[computer software]*.

Kardes, F. R., Posavac, S. S., & Cronley, M. L. (2004). Consumer inference: A review of processes, bases, and judgment contexts. *Journal of Consumer Psychology, 14*(3), 230–256.

Labiner-Wolfe, J., Jordan Lin, C. T., & Verrill, L. (2010). Effect of low-carbohydrate claims on consumer perceptions about food products’ healthfulness and helpfulness for weight management. *Journal of Nutrition Education and Behavior, 42*(5), 315–320.

Lai, C. K., Cooley, E., Devos, T., Xiao, Y. J., Simon, S., Joy-Gaba, J. A., et al. (2016). Reducing implicit racial preferences: II. Intervention effectiveness across time. *Journal of Experimental Psychology: General, 145*(8), 1001–1016.

Lansky, D., & Brownell, K. D. (1982). Estimates of food quantity and calories: Errors in self-report among obese patients. *American Journal of Clinical Nutrition, 35*, 727–732.

Lee, W. C. J., Shimizu, M., Kniffin, K. M., & Wansink, B. (2013). You taste what you see: Do organic labels bias taste perceptions? *Food Quality and Preference, 29*(1), 33–39.

Lichtman, S. W., Pisarska, K., Berman, E. R., Pestone, M., Dowling, H., Offenbacher, E., et al. (1992). Discrepancy between self-reported and actual caloric intake and exercise in obese subjects. *New England Journal of Medicine, 327*(27), 1893–1898.

Livingstone, M. B. E., & Black, A. E. (2003). Markers of the validity of reported energy intake. *Journal of Nutrition, 133*(3), 895S–920S.

Mussweiler, T. (2003). Comparison processes in social judgment: Mechanisms and consequences. *Psychological Review, 110*(3), 472.

Nosek, B. A., & Banaji, M. R. (2001). The go/no go association task. *Social Cognition, 19*, 625–664.

Oakes, M. E., & Slotterback, C. S. (2005). Too good to be true: Dose insensitivity and stereotypical thinking of foods' capacity to promote weight gain. *Food Quality and Preference, 16*(8), 675–681.

Prada, M., Garrido, M. V., & Rodrigues, D. (2017). Lost in processing? Perceived healthfulness, taste and caloric content of whole and processed organic food. *Appetite, 1*(140), 175–186.

Prada, M., Godinho, C., Rodrigues, D., Lopes, C., & Garrido, M. V. (2019). The impact of gluten-free claim on the perceived healthfulness, calories, level of processing and expected taste of food products. *Food Quality and Preference* (in press).

Pronk, T., van Deursen, D. S., Beraha, E. M., Larsen, H., & Wiers, R. W. (2015). Validation of the Amsterdam beverage picture set: A controlled picture set for cognitive bias measurement and modification paradigms. *Alcoholism: Clinical and Experimental Research, 39*(10), 2047–2055.

Quintana, D., & Eriksen, D. R. (2017). *Bayesian alternatives for common null-hypothesis significance tests in psychiatry: A non-technical guide using JASP.* Open Science Framework.

Raghunathan, R., Naylor, R. W., & Hoyer, W. D. (2006). The unhealthy = tasty intuition and its effects on taste inferences, enjoyment, and choice of food products. *Journal of Marketing, 70*(4), 170–184.

R Core Team (2017). *R: A language and environment for statistical computing.* Vienna, Austria: R Foundation for Statistical Computing. http://www.R-project.org/.

Rozin, P., Ashmore, M., & Markwith, M. (1996). Lay American conceptions of nutrition: Dose insensitivity, categorical thinking, contagion, and the monotonic mind. *Health Psychology, 15*(6), 438.

van de Schoot, R., & Depaoli, S. (2014). Bayesian analyses: Where to start and what to report. *The European Health Psychologist, 16*(2), 75–84.

Schouteten, J. J., Gellynck, X., & Slabbinck, H. (2019). Influence of organic labels on consumer's flavor perception and emotional profiling: Comparison between a central location test and home-use-test. *Food Research International, 116*, 1000–1009.

Schuldt, J. P., & Schwarz, N. (2010). The" organic" path to obesity? Organic claims influence calorie judgments and exercise recommendations. *Judgment and Decision Making, 5*(3), 144.

Schuldt, J. P., Muller, D., & Schwarz, N. (2012). The "Fair Trade" effect: Health Halos from social ethicsclaims. *Social Psychological and Personality Science, 3*(5), 581–589.

Songa, G., & Russo, V. (2018). IAT, consumer behaviour and the moderating role of decision-making style: An empirical study on food products. *Food Quality and Preference, 64*(September 2017), 205–220.

Songa, G., Slabbinck, H., Vermeir, I., & Russo, V. (2019). How do implicit/explicit attitudes and emotional reactions to sustainable logo relate? A neurophysiological study. *Food Quality and Preference, 71*, 485–496.

Sörqvist, P., Haga, A., Langeborg, L., Holmgren, M., Wallinder, M., Nöstl, A., et al. (2015). The green halo: Mechanisms and limits of the eco-label effect. *Food Quality and Preference, 43*, 1–9.

Sörqvist, P., Hedblom, D., Holmgren, M., Haga, A., Langeborg, L., Nöstl, A., et al. (2013). Who needs cream and sugar when there is eco-labeling? Taste and willingness to pay for “Eco-Friendly” coffee. *PLoS One, 8*(12), e80719.

Thorndike, E. L. (1920). A constant error in psychological ratings. *Journal of Applied Psychology, 4*(1), 25–29.

Tooze, J. A., Subar, A. F., Thompson, F. E., Troiano, R., Schatzkin, A., & Kipnis, V. (2004). Psychosocial predictors of energy underreporting in a large doubly labeled water study. *American Journal of Clinical Nutrition, 79*, 795–804.

Wagenmakers, E. J., Love, J., Marsman, M., Jamil, T., Ly, A., Verhagen, J., ... Morey, R. D. (2018). Bayesian inference for psychology. Part II: Example applications with JASP. *Psychonomic Bulletin and Review, 25*(1), 58–76. http://doi.org/10.3758/s13423-017-1323-7.

Wagenmakers, E.-J., Marsman, M., Jamil, T., Ly, A., Verhagen, J., Love, J., et al. (2017). Bayesian inference for psychology. Part I: Theoretical advantages and practical ramifications. *Psychonomic Bulletin & Review*, 1–42.

Wansink, B., & Chandon, P. (2006). Can “low-fat” nutrition labels lead to obesity? *Journal of Marketing Research, 43*(4), 605–617.

Wertenbroch, K. (1998). Consumption self-control by rationing purchase quantities of virtue and vice. *Marketing Science, 17*(4), 317–337.

Willer, H., Sorensen, N., & Yussefi-Menzler, M. (2008). The world of organic agriculture 2008: Summary. The world of organic agriculture: Statistics and emerging trends 2008. https://doi.org/10.4324/9781849775991.

World Health Organization (WHO) (2011, March 1). *Obesity and overweight factsheet from the WHO.* Retrieved November 29, 2017, from http://www.thehealthwell.info/search-results/obesity-and-overweight-factsheet-who?&content=resource&member=572160&catalogue=none&collection=Obesity&tokens_complete=true.