

Contents lists available at [ScienceDirect](http://www.elsevier.com/locate/appet)

Appetite

journal homepage: www.elsevier.com/locate/appet

Attention! Can choices for low value food over high value food be trained?

Michael J. Zoltak^{a,*}, Harm Veling^a, Zhang Chen^a, Rob W. Holland^{a,b}

^a Behavioural Science Institute, Radboud University, Nijmegen, The Netherlands

^b Faculty of Social and Behavioural Sciences, University of Amsterdam, Amsterdam, The Netherlands

ARTICLE INFO

Article history:

Received 14 February 2017

Received in revised form

7 June 2017

Accepted 8 June 2017

Available online xxx

Keywords:

Cue-approach training

Behavioral change

Food choice

Value

Attention

ABSTRACT

People choose high value food items over low value food items, because food choices are guided by the comparison of values placed upon choice alternatives. This value comparison process is also influenced by the amount of attention people allocate to different items. Recent research shows that choices for food items can be increased by training attention toward these items, with a paradigm named cued-approach training (CAT). However, previous work till now has only examined the influence of CAT on choices between two equally valued items. It has remained unclear whether CAT can increase choices for low value items when people choose between a low and high value food item. To address this question in the current study participants were cued to make rapid responses in CAT to certain low and high value items. Next, they made binary choices between low and high value items, where we systematically varied whether the low and high value items were cued or uncued. In two experiments, we found that participants overall preferred high over low value food items for real consumption. More important, their choices for low value items increased when only the low value item had been cued in CAT compared to when both low and high value items had not been cued. Exploratory analyses revealed that this effect was more pronounced for participants with a relatively small value difference between low and high value items. The present research thus suggests that CAT may be used to boost the choice and consumption of low value items via enhanced attention toward these items, as long as the value difference is not too large. Implications for facilitating choices for healthy food are discussed.

© 2017 Elsevier Ltd. All rights reserved.

The growing rates of obesity and obesity related diseases (Ogden, Carroll, Fryar, & Flegal, 2015) have spurred a debate regarding the importance of systematically changing food preferences towards a healthier diet. Over the past decade governments and NGO's have launched numerous campaigns in order to promote and spread knowledge about what a balanced diet should look like (Parmenter, Waller, & Wardle, 2000). Despite these efforts obesity rates are still rising, and it would seem that merely educating the populous is not sufficient to produce the desired effects (Marteau, Hollands, & Fletcher, 2012). Gaining knowledge about healthy diets seems not enough to change food choice (Wood & Neal, 2016).

Indeed, more recently an important distinction made in psychological research is between impulsive and deliberative food choice (e.g., Fujita & Han, 2009; Strack & Deutsch, 2004). People

often choose food impulsively rather than deliberately, meaning that their choice is largely determined by immediate responses activated upon perception of the food (Hofmann, Friese, & Strack, 2009; Nederkoorn, Guerrieri, Havermans, Roefs, & Jansen, 2009; Veling et al., 2017). These immediate responses can be acquired via basic learning mechanisms. For example, the consumption of a food item linked with a reward signal (e.g., high sugar content) reinforces subsequent consumption (Epstein, Carr, Lin, & Fletcher, 2011; Rangel, 2013). After such conditioning, mere perception of the food can draw attention towards the food item (Nijs, Muris, Euser, & Franken, 2010) and elicit motor activation aimed at obtaining that item (Brooks, Cedernaes, & Schioth, 2013). Indeed, these strong impulsive responses for high caloric palatable food could influence consumption (Friese, Hofmann, & Wanke, 2008). Hence, recent research has focused on influencing food choice without the reliance on deliberate considerations of available food options, but instead by manipulating immediate responses to food items (for a review see Stice, Lawrence, Kemps, & Veling, 2016).

Acknowledging the role of impulsive processes in food choice,

* Corresponding author. Montessorilaan 3, Radboud University, 6500 HE Nijmegen, The Netherlands.

E-mail address: m.zoltak@psych.ru.nl (M.J. Zoltak).

during the past decade, a number of different approaches have been put forward in order to change immediate responses to food items. For example, research has shown that consumption of palatable, high caloric food can be reduced by, for example, linking images of appealing food with aversive images (Hollands, Prestwich, & Marteau, 2011), or by repeatedly presenting these images with no-go cues in a go/no-go task (e.g., Adams, Lawrence, Verbruggen, & Chambers, 2017; Houben & Jansen, 2011). Furthermore, scholars have aimed to alter responses to unhealthy food items by linking high-energy food items to avoidance responses (Becker, Jostmann, Wiers, & Holland, 2015; Fishbach & Shah, 2006).

In the current research, we focus on a different type of training that aims at increasing attention for specific food items. Attention to food items has been related to choices for these foods (Kemps & Tiggemann, 2009; Krajbich, Armel, & Rangel, 2010), and directing attention toward a particular item can result in choice shifts, especially for appetitive items (Armel, Beaumel, & Rangel, 2008; Krajbich & Rangel, 2011; Shimojo, Simion, Shimojo, & Scheier, 2003). Kemp, Tiggemann, Orr, and Grear (2014) further demonstrated that training-induced attentional biases toward certain food items can translate into changes in consumption. Hence, attention training can potentially be a promising way of influencing choices and perhaps, in turn, subsequent consumption.

One paradigm recently developed to train attention toward certain food items is the cue-approach training (CAT; Bakkour, & Leuker et al., 2016; Bakkour, Lewis-Peacock, Poldrack, & Schonberg, 2016; Schonberg et al., 2014). During the CAT, participants are presented with images of food items one at a time and around 25% of the food items are paired with a tone (the cued items). Participants are instructed to press a button *when* they hear a tone, and *before* the image disappears from the screen (1s after it appears). The task is kept constantly challenging by using a tracking procedure on the presentation of the tone: the delay between tone onset and food item disappearance is reduced after every successful response, making the response window narrower, and is increased after participants fail to respond in time. Overall participants respond in time around 75% of the time.

After CAT, participants receive a binary food choice task in which they are instructed to choose one of two food items for real consumption within 1500 ms. On experimental trials one of the items is cued and the other uncued, and both items are matched on value assessed with a willingness to pay measurement before the CAT. Across a series of studies, Schonberg et al. (2014) have shown a consistent effect of the CAT, namely that cued items were preferred to uncued items (particularly when both food items were of high value) on around 60–65% of the trials and this effect has been replicated in subsequent studies (Bakkour, & Lewis-Peacock et al., 2016, Bakkour, & Leuker et al., 2016). The effect of CAT was visible up to two months after the initial training (Schonberg et al., 2014).

The effects of CAT on choice are explained via attention mechanisms (Bakkour, & Lewis-Peacock et al., 2016, Bakkour, & Leuker et al., 2016; Schonberg et al., 2014). Note that in cue-approach training attention is manipulated between trials, unlike, for instance, dot-probe training in which attention is manipulated within trials (e.g., Kemp, Tiggemann, Orr, & Grear, 2014). Specifically, during cue-approach training participants learn to expect a cue that is presented after a variable delay during presentation of cued food items, which is assumed to evoke heightened sustained attention to cued food items during the training. As a result, people attend more to the cued item in the subsequent choice task (Schonberg et al., 2014), which may increase their choice for these items (e.g., Krajbich et al., 2010). Eye-tracking data gathered by Schonberg et al. demonstrated that participants looked at cued items more often than uncued items during the choice task, even when they did not choose these items, suggesting that CAT drives attention toward

cued items. Bakkour, & Leuker et al. (2016) conducted several studies to narrow down the possible mechanisms engaged during CAT. Their work suggests that merely responding to cued items is not sufficient to induce a preference for cued items, but that this choice effect only occurs when the cue is presented relatively late in a trial during the training, so that the cued response requires sustained attention to the food item before cue presentation.

Recently, Veling et al. (2017) extended the findings by Schonberg and colleagues in two ways. First, they replicated the finding that participants preferred cued over uncued items when they made their choices within 1500 ms., but found that this preference disappeared when participants were asked to think about their choices or were simply given more time to make their decisions. This effect suggests that CAT creates impulsive choices for cued food items rather than deliberative choices. Second, their studies demonstrated that the effect of CAT was not constrained to high value food items (see also Bakkour, & Leuker et al., 2016), but could also increase choices for cued items when both items were of low value. This effect was found across two different stimuli sets, including snacks of high energy density, but also fruits and vegetables.

In sum, these studies provide promising evidence that choices for specific food items can be increased by cueing these items during CAT. However, one important and interesting question is to what degree this training can increase choices for low value food items over high value food items by training the low value items in the CAT. In previous experiments (Bakkour, & Leuker et al., 2016; Schonberg et al., 2014; Veling et al., 2017) participants chose between two food items of equal value (either both low value or high value). However, in everyday life we are rarely presented with (or choose between) two options of equal value. In fact, many of our food decisions in daily life concern decisions between alternatives of different values. For example, foods that are generally considered healthy (e.g. apple) and foods that are generally considered unhealthy (e.g. slice of cake) may differ greatly in the value assigned to them by the decision maker. For instance, energy-dense food items may be valued higher compared to low energy food items. Therefore, it is important to examine whether it is possible to increase choices for low value items in the context of high value alternatives.

Furthermore, it is of theoretical interest to examine whether attentional training, in the form of CAT, can overcome the effect of food value in changing food choice. Of course, high value items are generally preferred to low value items. In Schonberg et al. (2014) these decisions were also included as filler trials in which low value items were pitted against high value items (both of which were cued or uncued) and generally participants preferred high value to low value food items (around 80% of the time; see also Veling et al., 2017). Thus, one could argue that this preference for high value items is so strong that the CAT may be too weak to overcome this strong value effect. On the other hand, if CAT enhances attention in decision tasks, and enhanced attention influences food choice, as has been shown before (Armel et al., 2008), it might be possible that the general preference for high value items may be at least slightly reduced if the low value item is trained in the CAT and the high value item is not trained. The latter idea is further bolstered by the recent findings showing that CAT effects are not restricted to high value items, but also to relatively low value items (although in that case the choice was between two low value items; Veling et al., 2017).

1. Present research

We ran two identical experiments to test whether it is possible to influence choices made between low value and high value food items using the CAT. The sample sizes, exclusion criteria, methods, materials and hypotheses for both studies have been preregistered

on the Open Science Framework (for Experiment 1 see <https://osf.io/emvfg/>; for Experiment 2 see <https://osf.io/s8cgm/>).

2. Experiment 1

To investigate whether the CAT can increase choices for low value items when high value items constitute the alternative, participants in the current experiment consistently chose between a low value snack and a high value snack after the CAT for real consumption. On half of the choice trials, both items were either cued (the *both cued* trials, in which a cued low value item was paired with a cued high value item) or uncued (the *both uncued* trials, in which an uncued low value item was paired with an uncued high value item). On the other half of the choice trials, only one of the two items was cued (the *low cued* trials, in which a cued low value item was paired with an uncued high value item, and the *high cued* trials, in which an uncued low value item was paired with a cued high value item). First, in line with previous findings (e.g., [Schonberg et al., 2014](#); [Veling et al., 2017](#)), we expected that in the both cued and both uncued trials, participants should choose high value items more often than low value items, as both items received the same training and any influence of the CAT should be canceled out. These two types of trials therefore served as baselines for later comparison. We expected that compared to these baselines, participants would choose low value items more often on the low cued trials, as in the low cued trials only the low value items were cued during the CAT. Similarly, we predicted that on the high cued trials, the choices for high value items would be further increased in comparison to the baselines.

2.1. Methods

2.1.1. Participants

Participants were recruited via Radboud University on-line recruitment system (SONA). We based our sample size in both experiments on previous CAT studies, which range from 20 to 29 participants ([Bakkour, & Lewis-Peacock et al., 2016](#), [Bakkour, & Leuker et al., 2016](#); [Schonberg et al., 2014](#); [Veling et al., 2017](#)), and preregistered 28 participants as our planned sample size. Following [Schonberg et al. \(2014\)](#), a-priori we decided to exclude participants who bid less than 25 cents (0.25 euro) on more than 40 trials of the auction. One participant was excluded based on this criterion, and another participant was excluded due to error in data recording. The final sample consisted of 26 participants (14 females and 12 males; $M_{\text{age}} = 23.42$, $SD_{\text{age}} = 3.64$).

2.2. Procedure

2.2.1. Auction

Participants bid on 60 high energy snacks using the Becker-DeGroot-Marschak (BDM) willingness to pay (WTP) measure ([Plassmann, O'Doherty, & Rangel, 2007](#)). They were endowed with two euro's and told that they would have the opportunity to purchase one of the food items they have bid on for real consumption at the end of the experiment. During this phase, participants were presented with 60 food items that have been successfully employed before ([Veling et al., 2017](#)), one at a time, on a computer screen. They indicated their bids by using a 0 to 2 euro slider at the bottom of the screen with the mouse. The whole auction was self-paced and the next item would only appear after a successful bid. At the end of the experiment, the computer program would choose one auction trial out of a limited set of available items in the lab and generate a random bid. If the computer's bid was lower than the original bid of the participant, he or she could purchase the snack for the computer's bid.

2.2.2. Creating sets of low and high value food items

The program then sorted the food items based on WTP. The top and bottom 7 items were omitted to prevent ceiling and/or floor effects, resulting in items ranked 8 to 23 being used as high value items and items ranked 38 to 53 being used as low value items (see [Supplementary Fig. 1](#)). The high value items were divided into four sets, in such a way that the mean value in each set would be approximately equal. The same division was applied on the low value items. By using this selection procedure, we ensured that the value differences between high and low value items were matched on different types of choice trials. Any differences in food choices would therefore not be caused by value differences, but rather the treatment (i.e., cued vs. uncued) the items received in the CAT. Two sets of high value items and two sets of low value items were then selected as cued items in the following CAT. All the remaining items were used as uncued items in the training.

2.2.3. Cue-approach training

The training phase was similar to that of [Schonberg et al. \(2014\)](#) and lasted approximately 30 min. Participants viewed food items that appeared sequentially on a black background on a computer screen. They were instructed to press the B button on the keyboard with their dominant hand when (and only when) they heard a tone (1000 Hz for 0.2s). They were further instructed to press the button before the image disappeared from the screen. To keep the task challenging, the tone occurred after a variable delay after stimulus onset based on a staircase procedure. That is, the delay between stimulus onset and the tone (i.e., the go-signal delay, GSD), was initiated at 650 ms and increased by 17 ms if the participant managed to press the button before the image disappeared and decreased by 50 ms if he or she did not respond in time. Images appeared on screen one at a time and around 25% of the food items was paired with the tone. The entire set of items was presented 8 times, which means that participants were exposed to all items 8 times and needed to respond to each of the cued items 8 times.

2.2.4. Choice task

During the choice task, participants saw two food items simultaneously presented to the left and right of a central fixation cross, and they were asked to choose one of the items (by pressing either the U (left) or I (right) keyboard button) within 1500 ms. At the beginning participants were informed that one of the trials would be selected and they would receive the snack they chose on the selected trial for actual consumption. If a participant failed to respond in time a red text appeared prompting them to choose faster and the trial would be repeated later. The inter-trial interval was random and ranged from 1 to 2 s. After the participant made a choice a yellow frame appeared around the item of choosing as choice confirmation for 500 ms.

On all choice trials, participants chose between a high and low value item. In total, there were four trial types that differed in whether the high and low value item was cued or uncued. The experimental trials consisted of low cued trials (i.e., cued low value item vs. uncued high value item) and high cued trials (i.e., uncued low value item vs. cued high value item). The baseline trials consisted of both uncued trials (i.e., uncued low value item vs. uncued high value item) and both cued trials (i.e., cued low value item vs. cued high value item). Participants performed 64 trials in one block, and the trials were then repeated in a second block to counterbalance the left/right position of the images. For a visual representation of the aforementioned selection and an example of experimental pair see [Supplementary Fig. 1](#).

2.2.5. Memory task

After the choice task, participants performed a memory task.

They were presented with all 60 items and were asked whether a particular item was paired with a 'beep' or 'no beep' (forced choice). Items appeared on a black background in random order, one by one. The response was self-paced.

2.3. Procedure

Participants were asked to fast for at least 3 h before visiting the laboratory. Upon arrival, they completed the informed consent form, and were shown a large selection of snacks that were available for them to win for later consumption. They were also informed that after the task they would have to wait for 30 min in the laboratory and the only food that they would be able to consume would be the snacks obtained in the experiment. The aim of this was to make sure that participants bid on items they would actually like to consume later (see also [Schonberg et al., 2014](#); [Veling et al., 2017](#)).

Next, participants were given the instructions for the first auction (lasting around 10 min) serving as a measure for their WTP for each of the 60 snack foods. Then, participants underwent the CAT that lasted approximately 30 min. Immediately after the CAT participants completed the choice task and later the memory task. Finally, the auction was repeated. After completing the second auction participants viewed the snacks they had won/could buy and were given the opportunity to consume them during the 30-minute waiting period. For a visual representation of the procedure, see [Fig. 1](#).

2.4. Data analysis

With regard to our main analysis, it is important to point out that participants always chose between low and high value food items. Hence, choices for low value items or choices for high value items can be used as the dependent variable, and we use choices for low value item (yes vs. no) as our dependent variable. Therefore, our statistical design only includes trial type (low cued versus both uncued versus high cued versus both cued) as predictor, and we test for a main effect of this predictor on choices for low value items using a repeated measures logistic regression analysis.

2.5. Results

Overall, participants performed well in the CAT. For their performance in the CAT and the memory recall task, see [Table 1](#).

To check whether our selection procedure succeeded in creating stimulus sets that were matched on average WTP before the training, we conducted a 2 (value level, high vs. low) by 4 (trial type, low cued vs. high cued, vs. both uncued vs. both cued) repeated-measures ANOVA on the average WTP of all the sets. As would be expected, the main effect of value level is significant, $F(1, 25) = 93.11, p < 0.001, \eta_p^2 = 0.788$, suggesting that participants were indeed willing to pay more for the high value items ($M = 1.20$ euro, $SE = 0.052$) than for the low value items ($M = 0.61$ euro, $SE = 0.060$). More important, the main effect of trial type was not significant, $F(1.47, 36.63) = 0.283, p = 0.686, \eta_p^2 = 0.011$ and the interaction effect was also not significant, $F(1.73, 43.31) = 1.24, p = 0.295, \eta_p^2 = 0.047$, suggesting that the value differences between high and low value items were consistent across all four trial types in the choice task (for the descriptive statistics of WTP for high and low value items separated by trial type, see [Table 2](#)). Any difference in choice behaviors can thus not be explained by value differences as assessed in the auction, but is likely the result of CAT.

In line with the difference in WTP for high and low value items, participants also tended to choose high value items more often than low value items on all four types of trials in the choice task

(see [Fig. 2](#), in which the percentages of choosing low value items were all below 50%). Regarding our preregistered hypothesis, we have found an increase in choices for low value items when low value items were cued and high value items were not cued (cued low pairs; 29.8% choices for low value) compared to when both items were not cued (both uncued pairs; 19.7% choices for low value), with a significant 10.1 percentage point increase in choosing low value items in the first pair (OR = 1.73, 95% CI = [1.09, 2.74], Wald Chi-square = 5.43, $p = 0.020$, two sided repeated measures logistic regression). A similar significant contrast was obtained for low cued pairs (29.8% choices for low value) compared to when both items were cued (both cued; 19.5% choices for low value), with a 10.3 percentage point increase in choosing low value items in the first pair (OR = 1.76, 95% CI = [1.10, 2.79], Wald Chi-square = 5.66, $p = 0.017$, two-sided repeated measure logistic regression). Importantly, these results thus indicate that the probability of choosing low value items can be increased by the CAT, even in choice pairs where a low value item is pitted against a high value item.

Incongruent with our hypotheses, cueing a high value item did not further increase choices for such items (see [Fig. 2](#)). That is, in the high cued pairs, the percentage of low value choices was not significantly lower than that of the two baselines (compared to the both uncued condition, OR = 0.87, 95% CI = [0.53, 1.40], Wald Chi-square = 0.34, $p = 0.562$; compared to the both cued condition, OR = 0.88, 95% CI = [0.58, 1.34], Wald Chi-square = 0.35, $p = 0.552$, respectively). We speculate that this might be due to a possible floor effect. That is, although the percentage of choosing low value items in cued high trials is not 0%, empirical observation of people's choices suggests people will usually select a substantial number of low value items (see e.g., [Schonberg et al., 2014](#); [Veling et al., 2017](#), in which people chose low value items around 20% of the time). This may occur because the decision process is inherently noisy ([Krajbich et al., 2010](#)). Hence, the percentage of choices for low value items in high cued trials may be near the floor and it may not be possible to further decrease this number by cueing high value items.

3. Experiment 2

The results of Experiment 1 suggest that CAT boosts the probability of choosing low value food items even when low value items are pitted against high value items (cf. [Schonberg et al., 2014](#)). In order to test the robustness of this new finding, Experiment 2 was conducted as a direct preregistered (<https://osf.io/s8cgm/>) replication. We hypothesized an around 10% increase in choosing low value items in the low cued pairs compared to both uncued pairs (baseline 1) and both cued pairs (baseline 2).¹ Furthermore, based on Experiment 1, we expected a floor effect for choices for low value food items in high cued pairs. Thus, choices for low value items are expected not to be lower in high cued pairs than in both uncued pairs (baseline 1) and both cued pairs (baseline 2).

3.1. Methods

3.1.1. Participants

Twenty-seven participants were recruited via Radboud University on-line recruitment system (SONA). Two of them were excluded for bidding less than 25 cents on more than 40 items. The final sample included 25 participants (20 females and 5 males;

¹ We would like to point out a problem with our preregistered hypothesis. First, the word 'around' is ambiguous. Second, preregistering a specific number (in this case 10%) is not something that we usually do in our lab group.

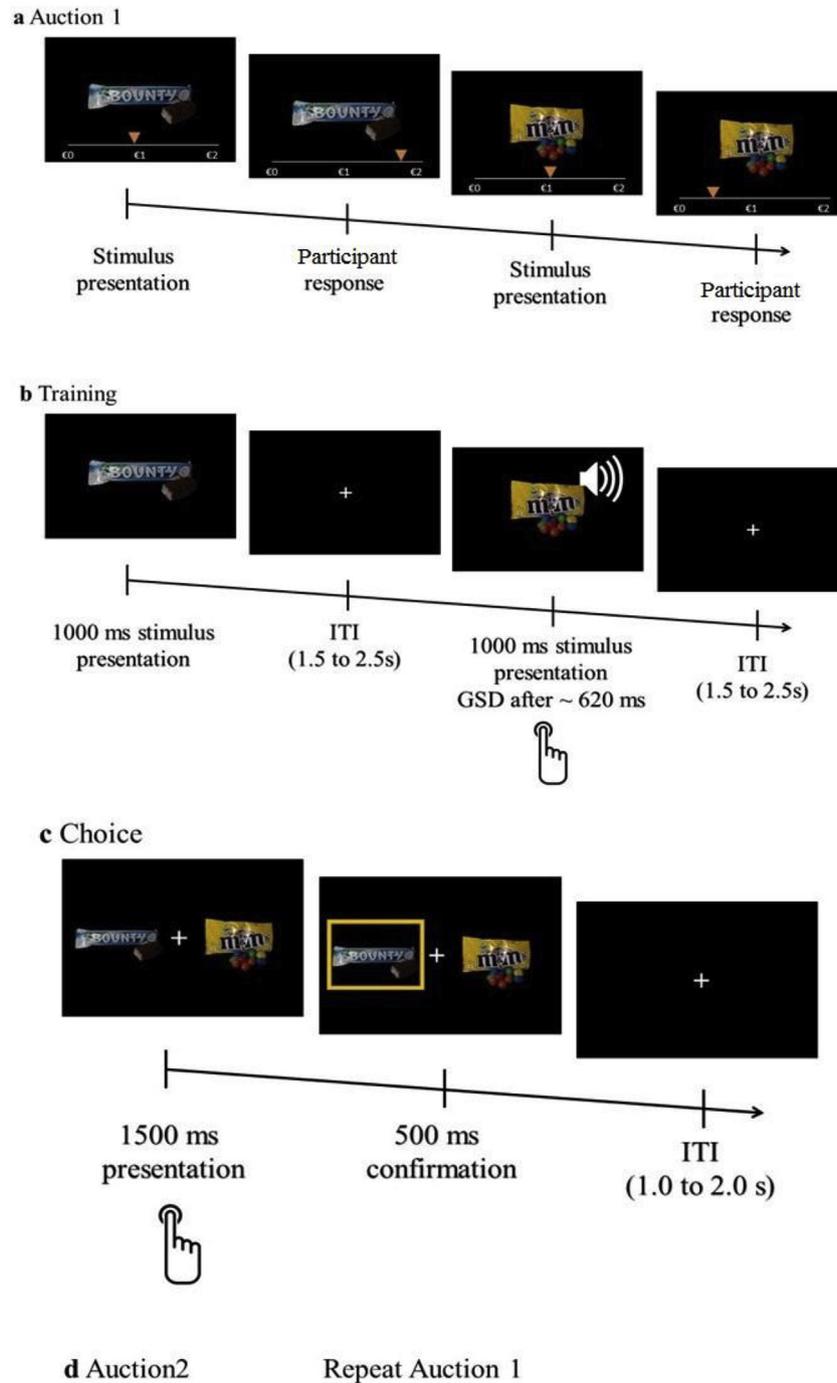


Fig. 1. Overview of the main procedure for all experiments. ITI = inter trial interval. GSD = go signal delay.

Table 1
Performance in the cue approach training and the memory recall task.

Experiment	Cued Acc	Uncued Acc	Cued RT (ms)	GSD (ms)	Memory Acc
1	73.2% (3.5%)	99.0% (1.3%)	328.4 (46.8)	596.3 (58.3)	71.9% (18.8%)
2	71.4% (7.9%)	99.2% (1.0%)	328.3 (79.3)	553.0 (133.5)	76.9% (18.8%)

Note: *Cued Acc* = accuracy on cued trials; *Uncued Acc* = accuracy on uncued trials; *Cued RT* = the average reaction time on cued trials when response was in time; *GSD* = go signal delay, the average go signal delay on all cued trials; *Memory Acc* = accuracy in the memory recall task. Standard deviations are reported in brackets.

Table 2
Mean willingness to pay during the pre and post auction across all conditions and experiments.

	Trial type	Low cued		High cued		Both cued		Both uncued	
		High	Low	High	Low	High	Low	High	Low
Exp1	Pre	1.19 (0.27)	0.61 (0.31)	1.20 (0.27)	0.61 (0.30)	1.20 (0.27)	0.61 (0.30)	1.19 (0.27)	0.61 (0.32)
	Post	1.08 (0.28)	0.76 (0.43)	1.11 (0.28)	0.71 (0.40)	1.17 (0.31)	0.71 (0.34)	1.11 (0.31)	0.68 (0.36)
Exp2	Pre	1.00 (0.35)	0.42 (0.31)	1.02 (0.34)	0.41 (0.31)	1.02 (0.34)	0.41 (0.31)	1.01 (0.34)	0.41 (0.31)
	Post	0.97 (0.36)	0.46 (0.31)	0.99 (0.35)	0.43 (0.29)	0.99 (0.36)	0.51 (0.31)	0.98 (0.39)	0.48 (0.30)

Note: Numbers reflect mean willingness to pay of items in all four trial types in euro. Standard deviations are reported in brackets. Exp = Experiment.

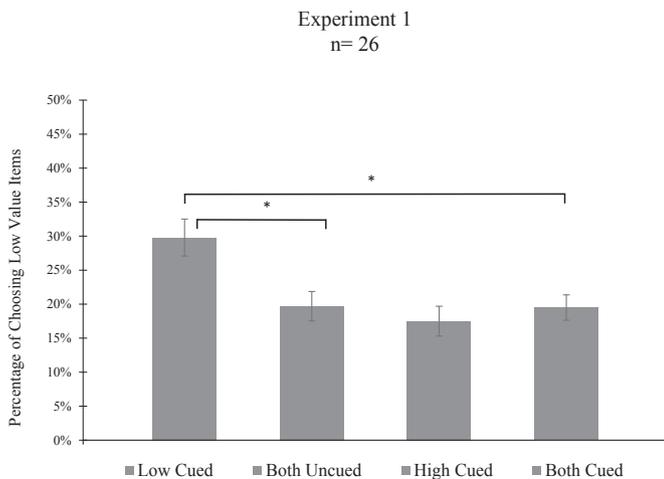


Fig. 2. Choices for low value items over high value ones across all trials. Significance levels reflect increase in choosing low value items between particular pairs using repeated logistic regression. * $p < 0.05$. Error bars, s.e.m.

$M_{age} = 23.7$, $SD_{age} = 4.04$).

3.1.2. Materials and procedure

The materials and procedure were identical to those from Experiment 1.

3.2. Results

As in Experiment 1, when using repeated measures ANOVA to check the WTP before the CAT, the main effect of value level was significant, $F(1, 24) = 106.72$, $p < 0.001$, $\eta_p^2 = 0.816$; the main effect of trial type is not significant, $F(1.82, 43.72) = 1.36$, $p = 0.266$, $\eta_p^2 = 0.054$. Contrary to our expectation, the interaction effect between value level and trial type was significant, $F(2.05, 49.09) = 5.01$, $p = 0.010$, $\eta_p^2 = 0.173$. To break down this interaction effect, we calculated the difference in average WTP between high and low value items for all four types of choice trials and submitted the differences in WTP to a one-way repeated-measures ANOVA. Pairwise comparisons showed that the difference between the low cued and high cued pairs was statistically significant ($p = 0.036$ with Bonferroni correction), while all the other comparisons failed to reach statistical significance ($ps > 0.136$). Since our analyses did not involve comparison between low cued and high cued trials, this significant difference between the two is therefore not a concern for testing our hypotheses.

Just as in Experiment 1, participants also tended to choose high value items more often than low value items on all four types of trials in the choice task (see Fig. 3, in which the percentages of choosing low value items were all below 50%). Also, in line with Experiment 1, participants chose low value items more often in the low cued pairs (22.7% choices for low value) compared to both

uncued baseline (15% choices for low value) with a 7.7 percentage point significant increase in choosing low value items in the first pair (OR = 1.67, 95% CI = [1.07, 2.61], Wald Chi-square = 5.03, $p = 0.025$, two sided repeated measures logistic regression). However, the difference in low value choices did not reach statistical significance between the low cued pairs (22.7% choices for low value) and the both cued pairs (18.5% choices for low value), although it was in the same direction as in Experiment 1 (OR = 1.30, 95% CI = [0.84, 2.00], Wald Chi-square = 1.38, $p = 0.241$, two sided repeated measures logistic regression). In line with Experiment 1 and our hypothesis, choices for low value items in the high cued pairs did not differ significantly from both cued pairs (OR = 0.62, 95% CI = [0.35, 1.11], Wald Chi-square = 2.61, $p = 0.106$) and both uncued pairs (OR = 0.80, 95% CI = [0.48, 1.34], Wald Chi-square = 0.71, $p = 0.400$, see Fig. 3).

4. Exploratory analyses on collapsed data

Since the two experiments were identical in procedure, we have decided to conduct exploratory analyses on the collapsed dataset from both experiments. To see whether the two datasets were sufficiently similar to justify their combination, we conducted four separate repeated-measures logistic regression analyses with trial type (low cued vs. both uncued, low cued vs. both cued, high cued vs. both uncued and high cued vs. both cued, for four analyses respectively), experiment and their interaction effect as predictors. In all four analyses, the main effects of experiment were not statistically significant, Wald Chi-squares < 0.797 , $ps > 0.372$, neither was any of the interaction effects, Wald Chi-squares < 0.911 , $ps > 0.340$. These results suggest that data from two experiments were

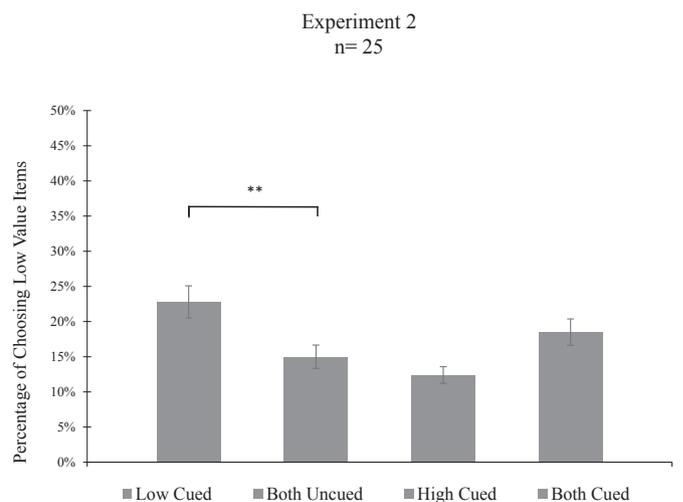


Fig. 3. Choices for low value items over high value ones across all trials. Significance levels reflect increase in choosing low value items between particular pairs using repeated logistic regression. * $p < 0.01$. Error bars, s.e.m.

similar and thus could be combined. We then proceeded with exploratory data analyses on the collapsed dataset.

4.1. Reaction times of low and high value choices

Participants overall chose high value items more often than low value items. However, their choices for low value items were not 0%. This raised the question why people would choose low value items when they valued the other item more. One explanation is that such choices for low value items can be thought of as mistakes. That is, participants might have accidentally pressed the key associated with low value items before they even compared the values of the two items, and such tendency might have been facilitated on the low cued trials since they had been consistently trained to respond quickly to the low value items. If this is the case, participants may choose more quickly when they choose low value items, compared to when they choose high value items. The attentional drift diffusion model as applied to binary choice (e.g., [Krajibich et al., 2010](#)), on the other hand, posits that decision-making process is inherently noisy, which is why people's choice and reaction time differ from trial to trial (and may choose low value items sometimes). More important, according to this model, it takes more time to choose low value items compared to high value items, because the speed with which the decision threshold is reached is influenced by the value of the item. That is, the threshold is reached more quickly for high compared to low value items. This means participants should choose more quickly when they choose high value items, compared to when they choose low value items.

We carried out an exploratory analysis on choice reaction times to see which one of the two opposing predictions was supported by data. For each type of choice trial (low cued, high cued, both cued vs. both uncued), we further divided them into two groups, depending on whether participants chose high or low value item on a particular trial. Twenty-two participants were excluded from this analysis since they chose low value items 0% on at least one type of the choice trials and hence no reaction time could be calculated. Twenty-nine participants remained in the analysis who had reaction time data for each trial type. The average choice reaction time was calculated and submitted to a 4 (trial type, low cued, high cued, both cued vs. both uncued) by 2 (chosen item value, high vs. low) repeated-measures ANOVA. In line with the prediction of attentional drift diffusion model, participants took more time when they chose low value items than when they chose high value items, $M_{diff} = 42$ ms, $SE = 15$ ms, $F(1, 28) = 7.77$, $p < 0.009$. The main effect of trial type and the interaction effect was not significant, $F_s < 0.297$, $p_s > 0.700$. Specifically testing the comparison between cued low vs. both uncued as trial type in the model revealed similar outcomes. Using the median reaction time instead of mean reaction time also gives the same results.

4.2. The role of value difference

Although we consistently pitted low value items against high value items in the choice task, the actual subjective value difference between high and low value items varied across participants. To explore whether this value difference would influence the effect of CAT, we selected the low cued and both uncued trials and for each participant calculated the following two scores: (1) the average value difference between the high value and low value items on these two types of choice trials (i.e., value difference score); (2) the difference between the percentage of choosing low value items on the low cued trials compared to that on the both uncued trials (i.e., choice difference score). Note that the second variable is an index of the effectiveness of the CAT. The larger the choice difference score, the more increase in low value choices on low cued trials compared

to both uncued trials, hence the more effective the CAT is in boosting choices for low value food for an individual. Thus, the more positive the choice difference score, the bigger the increase in choosing low value items as a function of CAT. We performed correlation analyses between the value difference scores and the choice difference scores with and without excluding univariate outliers (3 SD from sample mean) and bivariate outliers (Cook's distance $> 4/N$). The correlation analyses revealed a significant negative correlation between the two variables, $r(46) = -0.442$, $p = 0.002$ (excluding outliers), and $r(51) = -0.312$, $p = 0.026$ (including outliers), suggesting that for individuals with larger value difference between high and low value items, the CAT becomes less effective in increasing choices for low value items (see left panel of [Fig. 4](#)). Non-parametric correlations produced similar results, $r_\tau = -0.284$, $p = 0.007$ (excluding outliers), and $r_\tau = -0.226$, $p = 0.022$ (including outliers).

Using the second baseline, namely the both cued trials, gave similar results, although the correlation was only significant when outliers were excluded from the analyses: $r(49) = -0.395$, $p = 0.005$ (excluding outliers), $r(51) = -0.228$, $p = 0.107$ (including outliers; see right panel of [Fig. 4](#); for a repeated measures logistic regression approach, see Footnote ²). Non-parametric correlations using the aforementioned second baseline, again, produced similar results with the correlation only being significant when outliers were excluded from the analysis: $r_\tau = -0.227$, $p = 0.026$ (excluding outliers), and $r_\tau = -0.180$, $p = 0.067$ (including outliers).

In line with the analyses on choice reaction times, these results

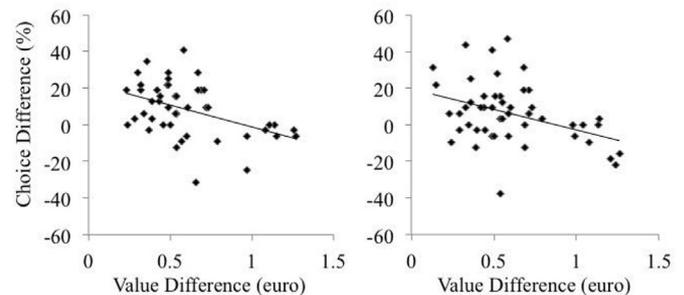


Fig. 4. Increase in Low Value Choices as a Function of Value Difference. Left panel: the both uncued trials as baseline; right panel, the both cued trials as baseline. Univariate and bivariate outliers are excluded in these plots.

² The exploratory analysis of value difference moderating the effect of CAT was also analyzed with a generalized linear mixed effect model approach using the `glmer` function of the `lme4`-package (version 1.1-10) in R Core Team. Distribution was set to binomial with a logit link function. The model included a fixed intercept, fixed effects for the factor IV1 (trial type) and for the (centered but not scaled) predictor IV2 (value difference), and their interaction. Contrasts were set to sum-to-zero. The repeated measures nature of the data was modeled by including a per-participant random adjustment to the fixed intercept ("random intercept"), as well as per-participant random adjustments to the slopes of IV1, IV2 and their interaction ("random slopes"). All possible random correlation terms among the random effects were included. Type 3 Likelihood Ratio Tests were used to determine p-values, as implemented in the mixed function of the package `afex`. The interaction of trial type and value difference was non-significant (Estimate = 0.18 (0.16), Chi-square(1) = 1.08, $p = 0.3$). We have run the same analysis using the both cued trials as baseline and the interaction was also non-significant (Estimate = 0.15 (0.13), Chi-square(1) = 1.22, $p = 0.27$). However, due to the selection procedure used in our paradigm, the value difference between high and low value items were matched on all the choice trials within participants. Therefore, the predictor value difference does not have much variation within participants. This means that the predictive power is limited, and hence these analyses may be less informative than the correlational analyses presented in the main text.

show that participants were sensitive to value differences between low and high value items, and suggest that choices for low value items were not caused by incidental motor responses, but products of a value comparison process.

4.3. Willingness to pay

To explore whether the CAT also influenced participants' willingness to pay toward the snack items, as measured after the choice, we conducted a repeated-measures ANOVA with measurement time (pre-vs. post-training), trial type (low cued vs. high cued vs. both uncued vs. both cued) and item value level (low vs. high) as the independent variables. The main effect of item value level was significant, $F(1,50) = 154.0$, $p < 0.001$. As would be expected, participants were willing to pay more for high value items than for low value items. The interaction effect between item value level and measurement time was also significant, $F(1, 50) = 31.8$, $p < 0.001$, which is likely due to regression to the mean (i.e., the willingness to pay for high value items decreased after training while willingness to pay increased for low value items). Crucially, all effects involving trial type were not statistically significant, $F_s < 1.72$, $p_s > 0.166$, suggesting that the CAT failed to systematically influence people's willingness to pay for the snack items as measured after the choice.

5. General discussion

In two experiments, we examined whether choices for low value food items can be increased when high value food items constitute the alternative option. In all conditions participants showed a preference for high value food items over low value food items. This is in line with previous research, and suggests that the choices participants made are valid and reflect their preferences (Krajbich et al., 2010; Schonberg et al., 2014; Veling et al., 2017). More important, the results show an increase in the proportion of choices for low value items when only the low value item is cued, compared to when both items are uncued (Experiments 1 and 2), and to a lesser extent compared to when both items are cued (Experiment 1). These results suggest that by training attention to low value items, the CAT can reduce the effect of value on choice and increase the probability of choices for low value items over high value items.

It is important to note that Experiment 2 did not fully replicate the predicted increase in choices for low value items between low cued trials and both cued trials observed in Experiment 1. Post-hoc, we think the both cued trials may not have been the optimal baseline, because the low value items in these trials were cued and might still have received increased attention because of CAT. In fact, if we compare low cued trials with both cued trials, the difference is that the high value item is cued on both cued trials but not cued on low cued trials. This comparison therefore seems to test the effect of cueing high value items rather than the effect of cueing low value items. Important, in an additional recent experiment (not reported here) in which we employed the current procedure, we again found a significant difference in proportions of low value choices between low cued and both uncued trials, but not between low cued and both cued trials. The effect of increasing choices for low value food items by the training can hence be best observed (and understood) by using the both uncued trials as the baseline.

How is it possible that the probability of choosing low value items can be increased even when the alternatives constitute high value items? Based on the present experiments we cannot answer this question directly. Theoretically, CAT is assumed to enhance attention for cued food items and this increased attention can subsequently increase choices for these items. Consistent with this

account, previous work examining choices between cued and uncued food items of equal value found that cued items received more visual attention during the choice task as measured with an eye-tracker (Schonberg et al., 2014). According to attentional drift diffusion models (Krajbich et al., 2010), attention toward a food item will move the probability of choosing that item toward a decision threshold, and away from the decision threshold of the alternative item. The more valuable an item is relatively to the alternative item, the more quickly this item will reach the decision threshold. According to these models it is possible to choose a low value item over a high value item, but this will take more time than choosing a high value item over a low value item (i.e., because it takes longer to reach the decision threshold for low value items). Interestingly, the reaction time data of the current study are consistent with this account by showing that participants took more time to choose for the low value items across all trial types. This finding needs to be treated with caution, however, because participants choose high value items on the majority of trials (some participants chose high value items 100% of the item on certain types of trials), and thus we do not have a lot of data for reaction time analyses for low value choices. Thus, more work is needed to examine whether attentional mechanisms can explain the currently observed choice effect.

Although our results show that CAT can overcome value differences between low and high value items, our exploratory analyses suggest that the strength of this effect depends on the value difference between low and high value food items: The effect became weaker for those participants for whom the value difference was larger. It is important to note that even for those participants for whom the difference was relatively small there was still a value difference between the low value and high value items in the absolute sense (see Fig. 4). Thus, CAT can increase the probability of choosing low value items over high value items, but more work is needed to understand why this effect may be limited to relatively small value differences. For instance, is the effectiveness of the training constrained to people who do not differentiate strongly between food items, or do strong value differences between products negate the effect of the training? Manipulating the value difference between low and high value items systematically within participants could give more insight into this question.

Furthermore, previous research has shown that the effect of CAT on choice is washed out when participants receive unlimited time to make their choices. To explain this finding, Veling et al. (2017) argued that attention training (in the form of CAT) may provide little basis for a deliberative decision, but may especially influence choices when people do not think about their choices such as when they need to decide quickly. It would be interesting to further test under which choice conditions CAT can increase choices for low value food items.

In the present research, we used a relatively homogeneous stimulus set of energy-dense food items. Hence, an important and interesting question is whether similar effects can be obtained when food items of different categories are employed. For example, to what degree can the present findings be generalized to increase choices for certain categories of food that are generally considered healthy (e.g., vegetables) over other categories of foods that are generally considered unhealthy (e.g., snack foods high in sugar content). Our results suggest that this may, at least partly, depend on the value difference between items from the different categories.

From an applied perspective our findings raise the question whether it is possible to develop a training intervention, based on CAT, for people who wish to change their dietary choices. For instance, can CAT be used to increase choices for healthy food items (of relatively low value) over unhealthy food items (of relatively

high value)? Of course, and as our results show, even under conditions where the training is effective people will overall still prefer high value over low value items, and the training will thus not shift the balance from choosing primarily high value food toward choosing primarily low value food. Nonetheless, the training may facilitate occasional choices for low value food, which could be a helpful addition to people's tools to change their dietary behavior. It is important to mention that much research is still needed in order to fully understand the mechanisms of CAT, as well as means of adapting it to be effective in daily life. However, we feel that demonstrating, for the first time, that the probability of choosing low value over high value food can be increased with CAT is not only of theoretical importance, it is also an important step forward towards the application of this training procedure.

Concluding, we have demonstrated that it is possible to increase the probability of choices for low value items when people choose between low and high value items, with the use of CAT. Results from our studies provide new insight on the interplay between attention and food value in influencing food choices. Furthermore, the results raise new questions for applications within the health domain, where a natural step forward would be testing whether one can train choices towards healthy but low value stimuli (e.g. an apple) pitted against unhealthy, but high value ones (e.g. chocolate). Such research is required before we can evaluate whether such training can eventually be applied as a training that may help people to make healthier food choices.

Appendix A. Supplementary data

Supplementary data related to this article can be found at <http://dx.doi.org/10.1016/j.appet.2017.06.010>.

References

- Adams, R. C., Lawrence, N. S., Verbruggen, F., & Chambers, C. D. (2017). Training response inhibition to reduce food consumption: Mechanisms, stimulus specificity and appropriate training protocols. *Appetite*, *109*, 11–23.
- Armell, C., Beaumel, A., & Rangel, A. (2008). Biasing simple choices by manipulating relative visual attention. *Judgment and Decision Making*, *3*, 396–403.
- Bakkour, A., Leuker, C., Hover, A. M., Giles, N., Poldrack, R. A., & Schonberg, T. (2016). Mechanisms of choice behavior shift using cue-approach training. *Frontiers in Psychology*, *7*, 421. <http://dx.doi.org/10.3389/fpsyg.2016.00421>.
- Bakkour, A., Lewis-Peacock, J. A., Poldrack, R. A., & Schonberg, T. (2016). Neural mechanisms of cue-approach training. *Neuroimage*. <http://dx.doi.org/10.1016/j.neuroimage.2016.09.059>.
- Becker, D., Jostmann, N. B., Wiers, R. W., & Holland, R. W. (2015). Approach avoidance training in the eating domain: Testing the effectiveness across three single session studies. *Appetite*, *85*, 58–65. <http://dx.doi.org/10.1016/j.appet.2014.11.017>.
- Brooks, S. J., Cedernaes, J., & Schioth, H. B. (2013). Increased prefrontal and parahippocampal activation with reduced dorsolateral prefrontal and insular cortex activation to food images in obesity: A meta-analysis of fMRI studies. *PLoS One*, *8*(4), e60393. <http://dx.doi.org/10.1371/journal.pone.0060393>.
- Epstein, L. H., Carr, K. A., Lin, H., & Fletcher, K. D. (2011). Food reinforcement, energy intake, and macronutrient choice. *American Journal of Clinical Nutrition*, *94*(1), 12–18. <http://dx.doi.org/10.3945/ajcn.110.010314>.
- Fishbach, A., & Shah, J. Y. (2006). Self-control in action: Implicit dispositions toward goals and away from temptations. *Journal of Personality and Social Psychology*, *90*(5), 820–832. <http://dx.doi.org/10.1037/0022-3514.90.5.820>.
- Friese, M., Hofmann, W., & Wanke, M. (2008). When impulses take over: Moderated predictive validity of explicit and implicit attitude measures in predicting food choice and consumption behaviour. *British Journal of Social Psychology*, *47*(Pt 3), 397–419. <http://dx.doi.org/10.1348/014466607X241540>.
- Fujita, K., & Han, H. A. (2009). Moving beyond deliberative control of impulses. *Psychological Science*, *20*(7), 799–804. <http://dx.doi.org/10.1111/j.1467-9280.2009.02372.x>.
- Hofmann, W., Friese, M., & Strack, F. (2009). Impulse and self-control from a dual-systems perspective. *Perspectives on Psychological Science*, *4*, 162–176. <http://dx.doi.org/10.1111/j.1745-6924.2009.01116.x>.
- Hollands, G. J., Prestwich, A., & Marteau, T. M. (2011). Using aversive images to enhance healthy food choices and implicit attitudes: An experimental test of evaluative conditioning. *Health Psychology*, *30*(2), 195–203. <http://dx.doi.org/10.1037/a0022261>.
- Houben, K., & Jansen, A. (2011). Training inhibitory control. A recipe for resisting sweet temptations. *Appetite*, *56*(2), 345–349. <http://dx.doi.org/10.1016/j.appet.2010.12.017>.
- Kemps, E., & Tiggemann, M. (2009). Attentional bias for craving-related (chocolate) food cues. *Experimental and Clinical Psychopharmacology*, *17*(6), 425–433. <http://dx.doi.org/10.1037/a0017796>.
- Kemps, E., Tiggemann, M., Orr, J., & Gear, J. (2014). Attentional retraining can reduce chocolate consumption. *Journal of Experimental Psychology: Applied*, *20*, 94–102. <http://dx.doi.org/10.1037/xap0000005>.
- Krajibich, I., Armell, C., & Rangel, A. (2010). Visual fixations and the computation and comparison of value in simple choice. *Nat Neurosci*, *13*(10), 1292–1298. <http://dx.doi.org/10.1038/nn.2635>.
- Krajibich, I., & Rangel, A. (2011). Multialternative drift-diffusion model predicts the relationship between visual fixations and choice in value-based decisions. *Proceedings of the National Academy of Sciences*, *108*(33), 13852–13857. <http://dx.doi.org/10.1073/pnas.1101328108>.
- Marteau, T. M., Hollands, G. J., & Fletcher, P. C. (2012). Changing human behavior to prevent disease: The importance of targeting automatic processes. *Science*, *337*(6101), 1492–1495. <http://dx.doi.org/10.1126/science.1226918>.
- Nederkoorn, C., Guerrieri, R., Havermans, R. C., Roefs, A., & Jansen, A. (2009). The interactive effect of hunger and impulsivity on food intake and purchase in a virtual supermarket. *International Journal of Obesity (London)*, *33*(8), 905–912. <http://dx.doi.org/10.1038/ijo.2009.98>.
- Nijs, I. M., Muris, P., Euser, A. S., & Franken, I. H. (2010). Differences in attention to food and food intake between overweight/obese and normal-weight females under conditions of hunger and satiety. *Appetite*, *54*(2), 243–254. <http://dx.doi.org/10.1016/j.appet.2009.11.004>.
- Ogden, C., Carroll, M., Fryar, C., & Flegal, K. (2015). *Prevalence of obesity among adults and youth: United States, 2011–2014*. NCHS data brief, no 219. Hyattsville, MD: National Center for Health Statistics.
- Parmenter, K., Waller, J., & Wardle, J. (2000). Demographic variation in nutrition knowledge in England. *Health Education Research*, *15*(2), 163–174. <http://dx.doi.org/10.1093/her/15.2.163>.
- Plassmann, H., O'Doherty, J., & Rangel, A. (2007). Orbitofrontal cortex encodes willingness to pay in everyday economic transactions. *Journal of Neuroscience*, *27*, 9984–9988. <http://dx.doi.org/10.1523/JNEUROSCI.2131-07.2007>.
- Rangel, A. (2013). Regulation of dietary choice by the decision-making circuitry. *Nature Neuroscience*, *16*(12), 1717–1724.
- Schonberg, T., Bakkour, A., Hover, A. M., Mumford, J. A., Nagar, L., Perez, J., et al. (2014). Changing value through cued approach: An automatic mechanism of behavior change. *Nature Neuroscience*, *17*(4), 625–630. <http://dx.doi.org/10.1038/nn.3673>.
- Shimojo, S., Simion, C., Shimojo, E., & Scheier, C. (2003). Gaze bias both reflects and influences preference. *Nature Neuroscience*, *6*(12), 1317–1322. <http://dx.doi.org/10.1038/nn1150>.
- Stice, E., Lawrence, N. S., Kemps, E., & Veling, H. (2016). Training motor responses to food: A novel treatment for obesity targeting implicit processes. *Clinical Psychology Review*, *49*, 16–27. <http://dx.doi.org/10.1016/j.cpr.2016.06.005>.
- Strack, F., & Deutsch, R. (2004). Reflective and impulsive determinants of social behavior. *Personality and Social Psychology Review*, *8*, 220–247. http://dx.doi.org/10.1207/s15327957pspr0803_1.
- Veling, H., Chen, Z., Tombrock, M., Verpaalen, I., Smits, L., & Dijksterhuis, A. (2017). Training impulsive choices for healthy sustainable food. *Journal of Experimental Psychology: Applied*, *23*(2), 204–215.
- Wood, W., & Neal, D. T. (2016). Healthy through habit: Interventions for initiating & maintaining health behavior change. *Behavioral Science & Policy*, *2*, 71–83.