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Training choices toward low value options

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Abstract

Food decisions are driven by differences in value of choice alternatives such that high value items are preferred over low value items. However, recent research has demonstrated that by implementing the Cue-Approach Training (CAT) the odds of choosing low value items over high value items can be increased. This effect was explained by increased attention to the low value items induced by CAT. Our goal was to replicate the original findings and to address the question of the underlying mechanism by employing eye-tracking during participants' choice making. During CAT participants were presented with images of food items and were instructed to quickly respond to some of them when an auditory cue was presented (cued items), and not without this cue (uncued items). Next, participants made choices between two food items that differed on whether they were cued during CAT (cued versus uncued) and in pre-training value (high versus low). As predicted, results showed participants were more likely to select a low value food item over a high value food item for consumption when the low value food item had been cued compared to when the low value item had not been cued. Important, and against our hypothesis, there was no significant increase in gaze time for low value cued items compared to low value uncued items. Participants did spend more time fixating on the chosen item compared to the unchosen alternative, thus replicating previous work in this domain. The present research thus establishes the robustness of CAT as means of facilitating choices for low value over high value food but could not demonstrate that this increased preference was due to increased attention for cued low value items. The present research thus raises the question how CAT may increase choices for low value options.

Keywords: cue-approach training, behaviour change, food choice, value, attention

1 Introduction

In recent years the importance of developing new ways of modifying food choice has become increasingly clear, as the rates of obesity and obesity related diseases have skyrocketed across the world (Malik, Willett & Hu, 2012). There appears a need for developing new methods to change dietary choices, as merely educating the populous seems to not produce behaviour change (Marteau, Hollands & Fletcher, 2012; Wood & Neal, 2007). Research over the past decade has provided us with insight into the underlying processes of food consumption, demonstrating that food consumption is often strongly influenced by reward signals, and that the strength of this signal can depend on, for example, the amount of sugar or fat within a given product (Kenny, 2011; Krajbich, Armel & Rangel, 2010; Stice, Spoor, Ng & Zald, 2009; Volkow, Wang & Baler, 2011). Therefore, the simple act of consuming a product linked with such a relatively strong reward signal can reinforce subsequent consumption (Epstein, Carr, Lin & Fletcher, 2011; Rangel, 2013). This basic process of conditioning can result in enhanced attention towards these food items (Nijs, Muris, Euser, & Franken, 2010), and produce motor impulses aimed at obtaining these items (Brooks, Cedernaes & Schiöth, 2013), which may facilitate consumption. Hence, recent psychological research has focused on modifying immediate food-related responses (for a review see Stice, Lawrence, Kemps, & Veling, 2016), which have been acquired via basic learning mechanisms (Rangel, 2009). This approach can be considered a boosting approach to behaviour change, as it aims to create training procedures or learning tasks that people may use to change their pavlovian biases toward rewarding food when they want this (in contrast to the popular nudging approach where behaviour change is changed via subtle environmental interventions; Hertwig & Grüne-Yanoff, 2017).

A number of approaches to modify immediate responses to food have been developed over the past decade, for example linking appetitive food to aversive images (Hollands, Prestwich & Marteau, 2011); repeatedly presenting appetitive food images with no-go cues in a go/no-go task (Veling, Chen et al., 2017; Veling, Lawrence et al., 2017), or linking appetitive food images to avoidance responses (Becker, Jostmann, Wiers & Holland, 2015). Another way of influencing food choice involves directly or indirectly manipulating at-

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tention toward or away from food items. Choices for food have been demonstrated to be linked to increased attention for the chosen food items prior to the choice (Kemps & Tiggemann, 2009; Krajbich, et al., 2010), and manipulating attention for specific items has been shown to result in choice shifts toward the attended-to items (Armel, Beaumel & Rangel, 2008; Krajbich & Rangel, 2011; Shimojo, Simion, Shimojo & Scheier, 2003).

One paradigm developed to train attention toward specific food items is the cue-approach training (CAT; Schonberg et al., 2014). During the CAT, participants are presented with food images on a computer screen one by one and are instructed to press a keyboard button as quickly as possible when they hear a tone, and before the image disappears from the screen (after 1 s). The tone is presented only on 25% percent of the trials and is consistently presented with some food items (cued items), but not others (uncued items). To keep the task challenging the onset of the tone is adjusted such that the tone is presented later during a trial when a response was successful and earlier when the response was not successful.

The effect of CAT on food choice is assessed with a subsequent binary food choice task in which participants are asked to choose between one of two food items (Schonberg et al., 2014). On experimental trials within this choice task, choices are made between cued and uncued items matched on value, as assessed beforehand by a willingness to pay measure. CAT produces a consistent effect, namely that cued items are preferred over uncued items for around 60–65% of the choices, particularly when both the cued and uncued snack items are of high value (Bakkour et al., 2016, 2017; Schonberg et al., 2014). The effect of CAT has also been found on choices for fruits and vegetables (Veling, Chen et al., 2017), and non-food stimuli (Salomon et al., 2018). Interestingly, effects of CAT on choice last for months (Salomon et al., 2018; Schonberg et al., 2014). The increased preference for cued items is explained by increased attention to these items during choice, which has been shown with eye-tracking (Schonberg et al., 2014).

In the initial experiments employing CAT cited above, choices between items within the CAT paradigm have been made between two items that are matched on value (e.g., high vs. high, or low vs. low). Thus, the experiments showed a shift in preference from one food item to another food item of approximately equal value. Thus, one question is whether this task can be used to shift a preference for a low value item over a high value item. That is, all else being equal, when people make a choice between a high and a low value product, one would expect them to select the high value product. Indeed, on so-called 'filler' trials of the CAT studies described above (Bakkour et al., 2016, 2017; Schonberg et al., 2014; Veling, Chen et al., 2017), high-value items were pitted against low value items (either both cued, or both uncued), and results from such trials have shown that participants generally select the higher valued option on approximately 80% of the trials. Would it be possible to boost choices for low value items when they are cued and pitted against uncued high value items?

We recently conducted two experiments that speak to this question (Zoltak, Veling, Chen & Holland, 2018). In two preregistered experiments, participants received choices between high and low value food items, and on the experimental trials the low value food item had been cued during CAT whereas the high value item had not been cued. We compared choices on these trials with a baseline in which both the low and high value item had not been cued. We found that participants on average preferred high to low items on both experimental and baseline trials. More important, cueing increased the odds of choosing the low value item over the high value item compared to baseline. These results appear surprising given the strong influence of value on decision making (for a review see Vlaev, Chater, Stewart & Brown, 2011) and the fact that participants made choices for real consumption (rather than vignettes or artificial choice). Apparently, training attention toward a food item can occasionally override the effect of food value.

In the present experiment, we aim to replicate these findings. Replication is important because the effect is surprising, as noted. Second, we examine an attention explanation in increasing the odds of choosing cued low value items over uncued high value items. In one of the experiments by Schonberg et al. (2014), eye-tracking during the choice task revealed that participants spend a larger proportion of the total gaze time on the chosen versus unchosen item (see also Krajbich & Rangel, 2011). More importantly, participants also looked more towards cued items versus uncued items even when they were not chosen. Note that these findings concerned choices between alternatives that were matched on value. It is unclear whether visual attention would also be affected by CAT in choices made between low value and high value items, because value has in itself a strong impact on visual attention, such that people's attention is drawn to high value items (Anderson, Laurent & Yantis, 2011). Therefore, we examined peoples' gaze patterns during the choice task in the present experiment.

2 Present research

Our current research thus has two main goals. First, a replication of our original findings in a larger sample (Zoltak et al., 2018). Second, we have employed the use of eye tracking during choice in order to see whether CAT shifts attention toward cued low value items. Following our preregistration (https://osf.io/39jnj/) we predict an increase in the probability of choosing low value items in the cued low compared to both uncued trials, as well as more total gaze time spent on looking at low value items during the cued low choice trials compared to both uncued choice trials.

2.1 Methods

2.1.1 Behavioural data

Participants. Participants were recruited via Radboud University on-line recruitment system (SONA). Our sample size was based on the effect obtained by Zoltak et al. (2018), basing our power calculations on the collapsed results from our two previous studies, and on a pair-wise t-test between the proportion of choosing low value option compared to the high value options within our main comparison, that is cued low compared to both uncued. To obtain our effect at a level of alpha = .05 with a power = 0.80, the projected sample size needed is 44 participants. We preregistered (https://osf.io/39jnj/) a total sample of 50 participants to leave some room for exclusion. Due to our exclusion criterion, described below, we excluded 3 participants before data analyses, resulting in a final sample of 47 participants (10 males and 37 females, M_{age} = 21.79, SD_{age} = 2.84)

Exclusion criterion. Based on Schonberg et al. (2014) and our previous work (Zoltak et al., 2018) we decided to a-priori exclude, from all analyses, participants who bid less than 25 cents (0.25 euro) on more than 40 items in the auction described below.

2.1.2 Procedure

The procedure was almost identical to the one described in Zoltak et al. (2018). Participants were asked to fast for 3 hours before coming to the lab, to ensure that the snacks presented to them in the experiment were appealing. Upon their arrival, they were asked to complete the informed consent form, and were demonstrated large variety of snack items they could obtain at the end of the task. 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, Chen et al., 2017, Zoltak et al., 2018).

Because of common pitfalls with eye tracker calibration, such as the machine being unable to correctly determine the pupil size due to eye lash length or eye lid height, we made sure we could calibrate the eye tracker as soon as the participant entered the room and before any experimental tasks had been performed. In order to do so, participants' dominant eyes were determined, and the eye tracker was initially calibrated upon them entering the experimental room. After completing the initial calibration, participants performed the auction task and then underwent the CAT. After the CAT and before completing the choice task in the eye tracker, the machine was calibrated once again, in order to ensure correctness of data recording. After the choice task, participants performed a memory task and finally a second auction. After completing the final auction participants viewed the snack items they had obtained or could buy and were given the opportunity to consume them during the 30-minute waiting period. For an overview of the tasks see Figure 1.

Auction. Participants were asked to bid on 60 palatable food items using the Becker-DeGroot-Marschak (BDM) willingness to pay (WTP) measure (Becker, DeGroot & Marschak, 1964). At the beginning of the task they were given physical coins amounting to two euros and were informed they will be able to purchase one of the food items they have bid on for real consumption at the end of the experiment. All of the 60 food items have been successfully employed before (Veling, Chen et al., 2017, Zoltak et al., 2018). Participants indicated their bids by using a 0 to 2 euro slider at the bottom of the screen. The entirety of the 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 randomly pick one auction trial out of set of available items in the lab and generate a fully random bid. If the computer's bid was less than the bid of the participant, then the participant would purchase the snack for the computer's bid.

Creating sets of high value and low value items. Following Zoltak et al. (2018) the program then sorted the food items based on participants individual WTP. The top and bottom 7 items were not included, 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. Then, both the high value items as the low value items were divided into four sets of four items, in such a way that the mean value in each set would be approximately equal. This ensured that the value differences between high and low value items were matched for all types of choice trials and that any differences for type of choices between choice conditions would not be caused by value differences, but rather the CAT. Two sets of high value items and two sets of low values items were then selected as cued items in the following training and the other sets of high and low value items were selected as uncued items. This setup enabled us to create 4 sets of choice pairs later used in the choice task (i.e., cued low, both uncued, cued high, both cued), see below. For a visual demonstration of the selection procedure and choice pairs see supplementary Figure 1.

Cue approach training. The training phase was identical to that of Zoltak et al. (2018) and lasted around 30 min.

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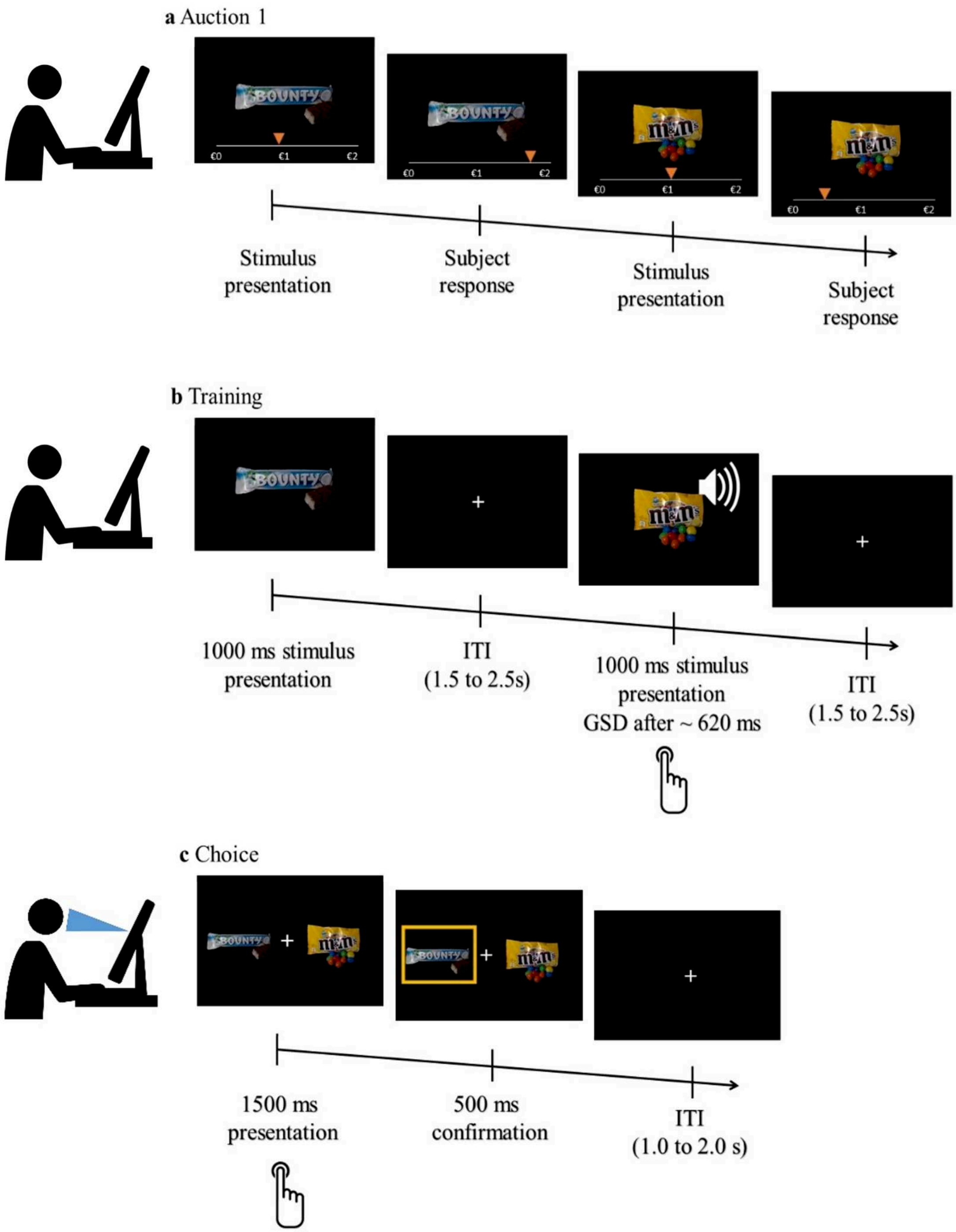

Figure 1: *Overview of main experimental procedure.* In the self-paced auction phase (a) participants bid a maximum of 2 euros on each of 60 palatable food items. During the training phase (b) participants performed the CAT, in which they responded via a button press to items which were paired with auditory cues. During the choice task (c) participants made choices between two items simultaneously presented on the screen, and their eye gaze was recorded during the whole choice task. ITI = inter trial interval, GSD = go-signal delay.

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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 60 items 8 times and needed to respond to each of the cued items 8 times.

Choice task. In the subsequent choice task, participants were simultaneously presented with two food items to the left and right of a central fixation cross. Each trial they were asked to choose one of the items (by pressing either the U (left) or I (right) keyboard button) within 1500 ms of stimulus onset. 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 participants did not respond within the time window a text would appear on the screen prompting them to choose faster. Those trials would be repeated later. The inter-trial interval was random and ranged from 1 to 2 s. After a choice was made a yellow frame would appear around the item of choosing for 500 ms., as confirmation. On all choice trials, participants made a choice between a high and a low value item. In total, there were four trial types that differed in whether the high and low value item was cued or uncued that were created from combinations between sets of high and low value item sets that were used in the training as cued or as uncued items (see Appendix). The experimental trials consisted of 16 low cued trials (i.e., cued low value item vs. uncued high value item) and 16 high cued trials (i.e., uncued low value item vs. cued high value item). The baseline trial consisted of 16 both uncued trials (i.e., uncued low value item vs. uncued high value item). We also added 16 both cued trials (i.e., cued low value item vs. cued high value item), however these did not serve as a main experimental baseline. 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. Eye tracking data was recorded during this phase of the experiment.

Eye tracking procedure. All eye tracking data was gathered using a SMI iView X machine (500Hz sample frequency). Dominant eye was determined for each participant before calibrating the eye tracker. In order to prepare the eye tracking data for analysis and determine the areas of fixation (left, middle, right) several steps were performed on the raw data.

Data preparation. Following Olsen (2012) we categorized eye-blinks and eye tracking coordinates that fell beyond the size of the monitor were marked as invalid data points. Subsequently, a linear interpolation was performed on the raw x- and y-coordinates. Linear interpolation was only performed if subsequent missing values (following one another) were shorter than 50 ms. Finally, data were smoothed with a moving median filter (time steps of 10 ms).

Due to the fact that eye tracking data was gathered during the choice task and sometimes participants failed to make a choice in the correct time, trials in which participants chose too late were excluded from analyses (1.6%). Next, trials in which more than 25% of the eye-tracking values were missing (raw data; 15.7%; e.g., due to blinking) were excluded from analyses. Finally, trials in which no fixations were detected within the regions of interest (ROI) were excluded from analyses (17.37%). The trials included in the analyses contained on average 1.2% (SD = 3.2%) interpolated data and from which 4.4% of the data within these trials was excluded.

Fixation identification. Fixations were identified using a dispersion threshold identification (I-DT) algorithm (Blignaut, 2009). The dispersion threshold was set to 1° of the visual angle (43.48 pixels; distance from eye to screen = 690 mm; screen size: 1920 x 1080 pixels). Gaze data were counted as fixations when the x- and y-coordinates measured over at least 100 ms did not exceed the dispersion threshold. The average x- and y-coordinates of the fixation and the length of the fixation were recorded.

Classification of fixations. Fixations were classified in one of three categories defined by a ROI (aligned with the position of the pictures): left fixation (130 < x < 830 pixels; 290 < y < 790 pixels), right fixation (1090 < x < 1790; 290 < y < 790), and middle fixation (830 < x < 1090; 290 < y < 790). The average time looked at either of the ROIs was similar (M_{left} = 206 ms; M_{right} = 202 ms; M_{middle} = 205 ms).

Eye tracker dependent variable. For each trial, proportion of looking time towards the low-valued picture was calculated by dividing the looking time at the low valued picture by the total looking time at the left and right picture.

Memory task. In the memory task participants were yet again presented with all 60 items and asked whether a particular item was paired with a sound during the training. Items appeared on a black background in random order, one by one. The response was self-paced.

TABLE 1: Performance in the cue approach training and memory recall task. S.D.'s in parentheses.

Cued Acc	Uncued Acc	Cued RT (ms)	GSD (ms)	Memory Acc
72.84%	99.63%	339.78	586.13	71.13%
(4.45%)	(0.60%)	(102.84)	(100.29)	(4.53%)

Cued Acc = accuracy on cued trials; Uncued Acc = accuracy on uncued trials;
Cued RT = the mean reaction time on trials when a response was in time;
GSD = go signal delay, the mean go signal delay on all cued trials;
Memory Acc = accuracy in the memory recall task.

2.2 Results

2.2.1 Confirmatory analyses.

Following our preregistration (https://osf.io/39jnj/) we conducted confirmatory analyses on our behavioural data.

Behavioural data. Overall, participants performed well in the CAT. For their performance in the CAT and the memory recall task see Table 1.

Choice data. Following our preregistration, we conducted a pair-wise t-test between the proportion of choosing low value options within our main comparison, that is cued low compared to uncued low pairs. As predicted, we found a significant increase in the proportion of choices of low value items in cued low pairs (M = .234; SE = .037) compared to both uncued pairs (M = .172; SE = .027); t (46) = 2.415, p = .02. In addition, we also analysed our data with a two-sided repeated measures logistic regression, which included a fixed intercept and fixed effect for condition (cued low vs. both uncued), which was dummy coded with the level both uncued as a reference group. The repeated measures nature of the data was modelled by including a per-participants random adjustment to the fixed intercept ("random intercept"). This analysis also revealed a statistically significant increase in choices for cued low value items (OR = 1.48, 95% CI = [1.10, 1.97], Wald Chi-square = 6.819, p = .01, two-sided repeated measures logistic regression, see Figure 2). This result replicates the findings of Zoltak et al. (2018), showing that CAT can indeed increase the odds of choosing low value items if the low value is cued comparted to when it is uncued.

We also analysed whether participants chose more low value items when comparing their choices to trials in which both items were cued, namely cued low compared to both cued. In this comparison we did not find a significant difference in choosing low value items (OR = 1.19, 95% CI = [0.91, 1.55], Wald Chi-square = 1.628, p = .20, two-sided repeated measures logistic regression). This finding is consistent with previous work (Zoltak et al., 2018).

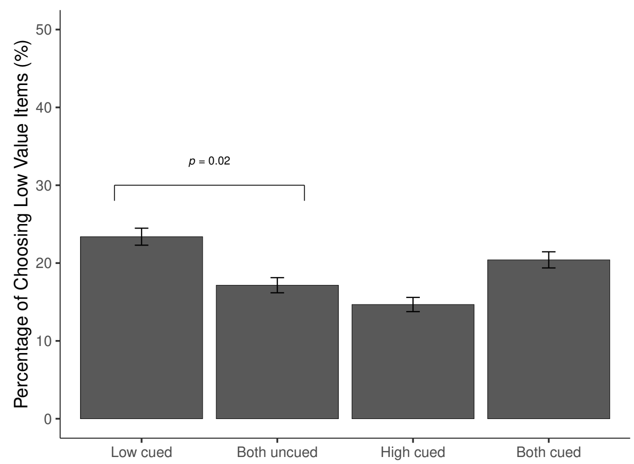

FIGURE 2: *Choices for low value items over high value ones across all trials.* Significance level reflects the increase in choosing low value items between the conditions using a pair wise t-test. Error bars, S.E.

2.2.2 Exploratory analysis on behavioural data.

Following the suggestions of two anonymous reviewers we added an additional analysis of our data using a multiple regression approach. Participants' choices (0 = high valued item, 1 = low valued item) during the cue approach training were analysed using a generalized linear mixed model approach using the "glmer" function of the lme4 package (Bates, Maechler, Bolker & Walker, 2013) in R (R Core Team, 2017). The model included a fixed intercept and fixed effects for condition (high cued vs. low cued vs. both cued and vs. both uncued) and value difference as a continuous variable (higher values indicating a higher value difference). Additionally, interaction terms between condition and value difference were included. Value difference was centered. The fixed effect condition was dummy coded with the level "both uncued" as reference group. The repeated measures nature of the data was modelled by including a per-participant random adjustment to the fixed intercept ("random intercept"). All p-values were computed using likelihood ratio tests as implemented by the function *mixed* in the package "afex" (Singmann, Bolker, Westfall & Aust, 2018).

Choice data. Firstly, we found a significant effect of condition, $\chi^2(3) = 39$, $p < .001$, indicating that the degree to which participants chose the low valued item was different between conditions. Specifically, we found that participants chose the low valued item more often in the low cued condition compared to the both uncued condition (estimate = 0.23, SE = 0.06)[1], thus replicating the results of our initial preregistered analysis by indicating that the CAT can influence people to choose the low valued cued item when pitted against uncued high valued item. Additionally, participants chose the low valued item less often in the high cued condition compared to the both uncued condition (estimate = −0.65, SE = 0.12)[2], indicating that the CAT was successful in influencing choice when a high valued cued item when pitted against uncued low valued item. Together, these results suggest that the CAT was successful in modifying choice behaviour.

We also analysed whether participants chose more low value items when comparing their choices to trials in which both items were cued, namely cued low compared to both cued. In this comparison we did not find a significant difference in choosing low value items (estimate = −0.13, SE = 0.11).[3] This finding is consistent with our preregistered analysis and further proves that the both uncued baseline is the more reliable baseline (Zoltak et al., 2018).

Choice data and value difference. We also explored whether the CAT effect is related to the value difference between choice alternatives and whether we can replicate the original findings of Zoltak et al. (2018) showing that on the participant level the strength of CAT on choice is negatively correlated with difference in value between the choice alternatives. In other words, we tested whether smaller differences in value between the choice alternatives are related to stronger CAT effects in the low cued condition compared to the both uncued baseline. Hence, 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. We then 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). These correlation analyses revealed a significant negative correlation between the two variables, r (40) = −.340, p = .03 (including outliers); r (38) = −.398, p = .01 (excluding outliers). In order to accommodate issues with non-uniform residuals, we also computed Spearman rank-order correlations, which produced similar results (r_τ (40) = −.216, p = .05 including outliers; r_τ (38) = −.242, p = .03 excluding outliers). These results show that the effect of CAT in increasing the odds of choosing low value items is stronger when the value difference between high and low value items is smaller when averaging between participants.

Secondly, following the suggestions of an anonymous reviewer, we investigated whether we can find the influence of value difference and CAT effect on an item level. In order to test this, we included value difference, in the form of a continuous measure, as a fixed intercept and fixed effect, as well as an interaction term with condition, in our binomial mixed effects model with condition (cued low versus uncued) described above. We found a significant effect of value difference (estimate = −2.83, SE = 0.32)[4], indicating that participants became less likely to choose the low valued item when the difference between items was high. However, we found no support for the hypothesis that the effect of value difference on choice was different between conditions, $\chi^2(3)$ = 6.16, p = .10. Specifically, value difference did not seem to make CAT more effective when the difference between items was low in the low cued condition compared to the both uncued condition (estimate = −2.86, SE = 0.37)[5] (see Figure 3).

Choice and reaction time. Zoltak et al. (2018) previously demonstrated that participants chose low value items slower compared to high value items, suggesting that choices for low value items are not mere mistakes. That is, when participants would have accidentally pressed a key associated with the low value alternative, as a result of learning to respond quickly to those items as a result of CAT, they would likely choose those items very quickly compared to when they chose the high value option. The alternative explanation, using the attentional drift diffusion model (aDDM) as applied to binary choice (e.g., Krajbich et al., 2010), may predict that participants would take more time to choose low value options compared to the high value ones, since the speed with which the decision threshold would have been reached would be influenced by the value of the particular item. Hence, thresholds would be reached faster when participants would choose high value items, compared to when they would choose low value ones.

[1] z = 3.93, OR = 1.25, 95% CI = [1.12, 1.41], $\chi^2(1) = 14.53$, $p < .001$.

[2] z = −5.63, OR = 0.52, 95% CI = [0.41, 0.65], $\chi^2(1) = 31.84$ $p < .0001$.

[3] z = −1.24, OR = 1.14, 95% CI = [0.92, 1.41], $\chi^2(1) = 1.51$, $p = .22$.

[4] z = −8.99, OR = 0.10, 95% CI = [0.03, 0.11], $\chi^2(1) = 88.05$, $p < .0001$.

[5] z = −7.76, OR = 0.24, 95% CI = [.027, .127], $\chi^2(1) = 2.39$, $p = .12$.

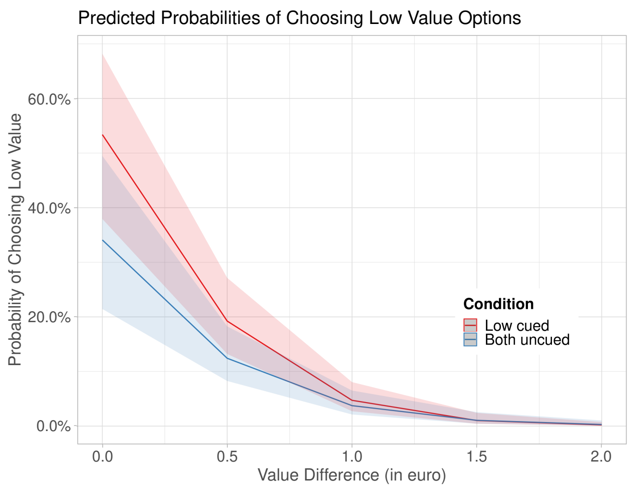

Figure 3: *Predicted Probabilities of Choosing Low Value Options over High Value Options as a Function of Value Difference between the Options and Condition.* Plot shows marginal effects of interaction terms in model described in the main text. Shaded regions represent 95% confidence intervals.

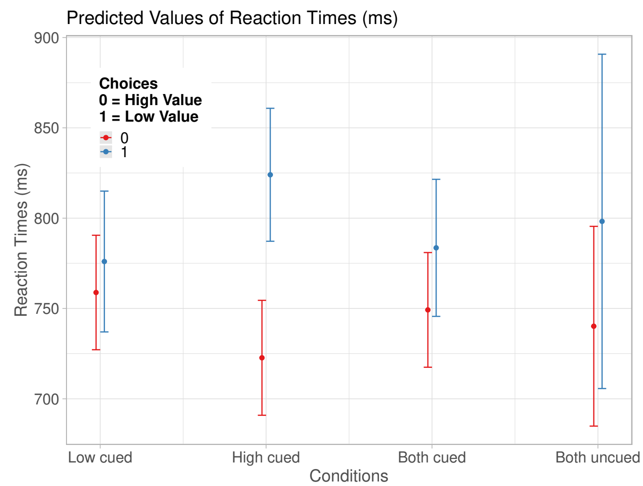

Figure 4: *Predicted Values of Reaction Times (in milliseconds).* Red colour represents response times for high value options and blue colour represents response times for low value options. Error bars, S.E.

In order to test whether we can replicate the previous findings by Zoltak et al. (2018), we analysed our reaction time data using a linear mixed effects model using the "lmer" function of the lme4 package (Bates, Maechler, Bolker & Walker, 2013) in R (R core team, 2017). Response times were centered and log transformed, and our model included a fixed intercept and fixed effects for condition (high cued vs. low cued vs. both cued vs. both uncued) and choice (high value vs. low value). Additionally, we included an interaction term between condition and choice. The repeated measures nature of the data was modelled by including a per-participant random adjustment to the fixed intercept ("random intercept"). All p values were computed using the S-method, as implemented by the function *mixed* in the package "afex" (Singmann et al., 2018). All post hoc comparisons were done using the package "emmeans" (Lenth, Singmann, Love, Buerkner & Herve, 2019) using the Tukey HSD adjustment. we found a significant effect of condition, F (3, 386.92) = 5.65, p <.001, a significant effect of choice, F (1, 3895.88) = 24.52, p < .001, as well as a significant interaction between condition and choice, F (3, 3866.98) = 3.21, p = .02. However, a follow up Tukey test revealed that only the low cued and high cued conditions differed significantly, estimate = −.109, z-ratio = −2.807, p = .03 (see Figure 4). Participants were, on average, fastest to choose the high value option in the high cued condition and, on average, slowest to choose the low value option in the high cued condition and these reaction times differed significantly, when compared to the low cued condition.

Eye tracker data. First, in order to demonstrate that participants looked longer at the item they chose (Krajbich et al., 2010) and therefore to indirectly validate our eye tracking measurement, we analysed the proportion of looking time at the low value item using a linear mixed effects model using the "lmer" function of the lme4 package (Bates, et al, 2013). The fixed effects structure included a fixed intercept and fixed effect for choice. To account for the repeated measures nature of the data we also included a per-participant random adjustment to the fixed intercept ('random intercept'). All p values were computed using the KR-method, as implemented by the function *mixed* in the package "afex" (Singmann et al., 2018). There was a significant effect of choice, β = .299, F (1, 2283.56) = 49.66, p < .001, indicating that participants looked longer at the items they chose, thus replicating choice gaze patterns established in previous literature (e.g., Schonberg et al., 2014).

Next, in order to test our main hypothesis and to see whether participants looked longer at the low valued item in the cued low condition compared to the both uncued condition, we analysed the proportion of looking time again using a linear mixed effects model. The fixed effects structure included a fixed intercept and fixed effects as well as interaction terms for the two conditions (cued low vs. both uncued) and value difference. Value difference was centered. To account for the repeated measures of our data we included a per-participant random adjustment to the fixed intercept ('random intercept'). Following the suggestion of an anonymous reviewer we also included reaction times, which have been log transformed and centered, in the model to control for their effect on looking times. All p values were computed using the S-method, as implemented by the function *mixed*

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Table 2: Average proportion of looking times at the low valued items across all conditions.

Condition	Mean	S.D.	S.E.	Median
Both uncued	0.472	(0.346)	0.011	0.448
Low cued	0.463	(0.346)	0.011	0.448
High cued	0.467	(0.348)	0.011	0.449
Both cued	0.462	(0.350)	0.011	0.450

in the package "afex" (Singmann et al., 2018). Post hoc comparison were done using the package "emmeans" (Lenth et al., 2019) using the Tukey HSD adjustment. We did not find any significant effects of condition (β = .018, F (3, 3871.20) = .19, p = .90), specifically when conducting a follow up Tukey test we did not find that participants looked longer at the low valued item in the low cued condition compared to the both uncued condition (estimate = .028, z-ratio = .633, p = .92). We also did not find a significant effect of value difference (β = .013, F (1, 225.41) = 0.00, p = .96). Thus, our results did not confirm our main eye-gaze hypothesis.[6] For descriptive statistics see Table 2.

3 General Discussion

In line with previous research (Krajbich et al., 2010; Schonberg et al., 2014; Veling et al., 2017), and authenticating participants' choices as valid preferences, our participants overall showed a preference for high value food items over low value food items, with the mean proportion of choices for low value foods being below 25% in each condition (see Figure 1). Next, in line with our main behavioural hypothesis, we showed an increase in the proportion of choices for low value items over high value items, when the low value item was cued compared to when both items were uncued. The effect of CAT in increasing choices for cued low value items versus uncued high value items was not obtained when compared to the both cued condition. These behavioural results replicate our previous findings (Zoltak et al., 2018).

With regard to our exploratory analyses, initially we found that the average value difference between the choice alternatives in the low cued versus both uncued condition was negatively correlated with the effectiveness of CAT. Thus, CAT appeared more effective to increase the probability of choosing low value options when the difference in value between two options was smaller (see also Zoltak et al., 2018). However, this relation was not found with item-based analyses. More specifically we did not find evidence in our model that value difference makes CAT more effective when the difference between items was low in the low cued condition compared to the both uncued condition. Due to these inconclusive results, we refrain from speculating on the role that value difference plays in CAT effectiveness. More research is needed to determine whether CAT may be more suited to influence choices for low over high items for a) participants who tend to have relatively small value differences between the bid items to start with, and/or b) participants who tend to generally bid within a narrow spread, which could indicate a general lack of strong preferences.

Second, with regard to the response time analysis, we found that response times differ as a function of choice and condition, and that participants are on average slower when choosing low value options compared to high value options (see Figure 3). However, this difference was statistically significant only between the low cued and high cued condition. The fact that participants were fastest to choose high value options in the high cued condition is not surprising, as CAT may have boosted the participants natural preference and choice of the high value options, therefore providing us with a limited number of observations (and reaction times) in which they actually choose a low value item. Therefore, further research is needed to see whether there is indeed a robust difference in response time between cued low and high value options.

With regards to our eye-tracking analysis we replicated previous findings (e.g., Krajbich et al., 2010; Krajbich & Rangel, 2011; Schonberg et al., 2014) showing that participants spend more time fixating on the chosen item compared to the unchosen alternative. To test whether CAT directs attention towards cued low value options that are pitted against uncued high value ones, we additionally compared the proportions of looking time at low value options between cued low and both uncued trials. Interestingly, and against our hypothesis and previous suggestion (Zoltak et al., 2018), we found no evidence that the behavioural effect on choice can be explained by enhanced attention to cued items. We now discuss two possible reasons for the absence of this effect.

First, it could be that our measurement of the gaze patterns was not sensitive enough to pick up any meaningful gaze patterns because of the cuing manipulation. Note, however, that the eye-tracker did show differences between gazes toward chosen (mostly high value) versus unchosen (mostly low value) items, suggesting that the equipment was sensitive to detect differences in participants' gaze patterns in a meaningful way. Nonetheless, we examined visual attention toward low value items presented near high value items, which may weaken any effects of cuing on visual attention compared to when two items of equal value are presented as was done in the previous study (Schonberg et al., 2014). In other words, it may be easier to detect effects of visual attention as a function of food value or food choice than as a function of cuing, especially when two food items differ in value.

[6]Excluding RTs from the model led to the same conclusions.

Second, although the effect of CAT on choices has been shown repeatedly (e.g., Bakkour et al., 2016; Schonberg et al., 2014; Veling, Chen, et al., 2017), to date only a few experiments examined whether CAT increases visual attention for cued over uncued items (Salomon et al., 2019; Schonberg et al., 2014), and only one experiment showed this effect (Schonberg et al., 2014). Thus, it could also be that this initially reported effect of CAT on visual attention is not so robust as the behavioural effect. This could mean that there may be additional mechanisms that could explain how CAT changes choices. For instance, participants may have learned a response tendency to quickly react to the cued low value items, which could sometimes influence choices for consumption. Although previous work suggests effects of CAT cannot be explained by creation of low level stimulus-response links (e.g., CAT also influences choices when people make choices with their eyes instead of their fingers; Schonberg et al., 2014; see also Bakkour et al., 2016), it is possible that people learn a strong tendency to select the cued items during CAT, which may subsequently influence their decisions for these items irrespective of whether they look at them. However, there is no indication in our data that people are quicker to select low value items that are cued compared to when these items are not cued, which would be predicted by this account. The present research thus raises new questions regarding how CAT influences choices for low value items.

Interestingly, a recent article published by Salomon et al. (2019) has also failed to replicate the original findings of Schonberg et al. (2014), showing that participants did not fixate more on cued stimuli compared to uncued stimuli. In their additional exploratory analysis of gaze patterns during the cue-approach training they found a developing gaze-bias pattern, which manifested itself by longer fixations on the cued stimuli compared with the uncued stimuli during the training. Yet, this difference was not correlated with subsequent choices in the choice task.

To conclude, we have shown that CAT can increase the probability of choosing low value items when people make choices between low and high value items. However, we found no evidence that this behavioural effect can be explained through enhanced visual attention for cued items. More work is thus needed to examine how CAT changes the probability of choosing low value items.

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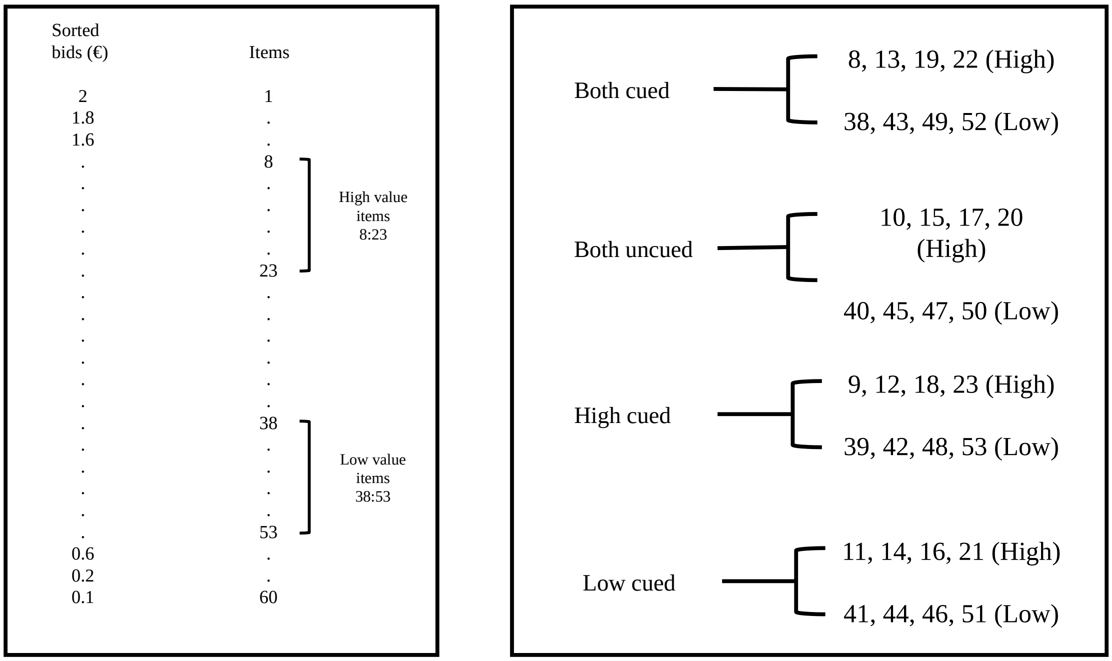
Appendix



Willingness to Pay (WTP) Sorting Procedure and Examples of Choice Pairs. Left panel represents the selection procedure based on WTP. Right panel demonstrates all pairs used in the choice task. For each pair (e.g., cued low) every high value item was paired with every low value item.