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The Role of Attention in Explaining the No-Go Devaluation Effect: Effects on Appetitive Food Items

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Evaluations of stimuli can be changed by simple motor responses such that stimuli to which responses are consistently withheld tend to be evaluated less positively than other stimuli. The exact mechanism that underlies this *no-go devaluation* effect is still unknown. Here we examine whether attention to the stimuli during training contributes to the devaluation effect. Participants received a go/no-go training in which 2 go items or 2 no-go items were simultaneously presented, and attention to 1 of the items was cued before participants executed or withheld a simple motor response (press a key on a keyboard). Next, explicit evaluations of these stimuli and untrained stimuli were assessed. Across 2 experiments we observed a predicted no-go devaluation effect, that is, a decrease in evaluations for items that have not been responded to. Furthermore, as predicted, selectively cueing attention toward stimuli during go/no-go training amplified differences in subsequent evaluations between go and no-go stimuli. Confirmatory analyses showed that the devaluation effect for cued no-go stimuli was not statistically significantly stronger than that for uncued no-go stimuli within each experiment. However, combining the data of both experiments showed moderate evidence (p = .023, BF_{+0} = 5.88) for stronger devaluation of cued no-go stimuli compared with uncued no-go stimuli. We conclude that attention to stimuli during go/no-go training contributes to revaluation processes of stimuli via motor actions, and that this knowledge is relevant for a better understanding of the underlying mechanism of the training and to optimize go/no-go training for practical use.

Public Significance Statement

This study suggests that responding or not responding to food items can respectively increase or decrease liking of these items, particularly when people attend closely to them. This finding is important to optimize applied response training tasks to change people's responses to food items.

Keywords: go/no-go training, devaluation, attention, inhibition, food

Supplemental materials: http://dx.doi.org/10.1037/xhp0000659.supp

The role of stimulus evaluation in driving human behavior can hardly be overstated. For instance, many decisions, such as those for food, are strongly influenced by evaluations of the different options (Krajbich, Armel, & Rangel, 2010). Hence, it is important to understand how evaluations of stimuli are acquired and can be changed. Interestingly, stimulus evaluation is not statically hard-wired in the brain, but is malleable through basic learning processes. For instance, presenting a stimulus in close spatial or temporal proximity of a negative or positive cue can change the subsequent evaluation of the stimulus (evaluative conditioning; for a review and meta-analysis see De Houwer, Thomas, & Baeyens, 2001; Hofmann, De Houwer, Perugini, Baeyens, & Crombez, 2010). Recent work suggests that evaluations of stimuli can also be changed by associating them with simple go or no-go motor responses (Z. Chen, Veling, Dijksterhuis, & Holland, 2016; for a review see Jones et al., 2016). Here, we aim to learn more on how motor responses can change stimulus evaluations.

One widely used paradigm to manipulate simple go and no-go responses toward stimuli is the go/no-go training (GNG). During GNG participants consistently respond to some stimuli when a go cue is presented (i.e., go stimuli) and withhold responses toward other stimuli when a no-go cue is presented (i.e., no-go stimuli). After the training, people tend to evaluate the no-go stimuli less positively compared with both go stimuli and untrained stimuli that are not included in the training (e.g., Z. Chen et al., 2016; Kiss, Raymond, Westoby, Nobre, & Eimer, 2008; Veling, Holland, & van Knippenberg, 2008). However, little is known about how the training creates this so-called *no-go devaluation effect*. Here, we test the possible role of attention in driving this effect. In the following, we will first describe the bidirectional relationship

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between attention and evaluation and then how it relates to no-go devaluation and associative evaluative learning.

Attention and Evaluation—A Bidirectional Relationship

A number of experiments have investigated the relationship between attention and evaluations. Interestingly, this relationship appears to be bidirectional (Raymond, Fenske, & Tavassoli, 2003; Shimojo, Simion, Shimojo, & Scheier, 2003). On the one hand, stimuli with high reward-values tend to draw attention toward them (Koenig, Kadel, Uengoer, Schubö, & Lachnit, 2017; though this might be due to the arousal they evoke rather than value directly; see Vogt, De Houwer, Koster, Van Damme, & Crombez, 2008), while, on the other hand, directing attention toward a stimulus during a choice increases its value. This change in value due to attention focus occurs when people focus on a stimulus voluntarily (Krajbich et al., 2010; Shimojo et al., 2003) as well as when attention is manipulated toward a stimulus (Armel, Beaumel, & Rangel, 2017). Interestingly, research suggests that stimulus values can also be increased by attention even when stimulus value is irrelevant, such as during a visual search task, a phenomenon referred to as *mere selection* (Janiszewski, Kuo, & Tavassoli, 2013).

Importantly, manipulating attention toward stimuli cannot only positively impact stimulus valuation, but can also *decrease* stimulus value when the stimuli interfere with a focal task. For instance, in visual search tasks, attending to stimuli increased their evaluated cheerfulness whereas stimuli that interfered with the search for targets (i.e., distractors) decreased in cheerfulness-ratings (Raymond et al., 2003). This phenomenon is referred to as *distractor-devaluation* (for a review see Fenske & Raymond, 2006). Though the specific mechanism behind distractor-devaluation has been debated (Dittrich & Klauer, 2012), recent work suggests there is good evidence for the so-called *devaluation-by-inhibition* hypothesis (e.g., De Vito, Al-Aidroos, & Fenske, 2017; Martiny-Huenger, Gollwitzer, & Oettingen, 2014) which states that this effect can best be explained by the fact that devaluation of task-irrelevant stimuli eases task execution (De Vito et al., 2017; Raymond, Fenske, & Westoby, 2005). This is, when stimuli interfere more strongly with a focal task and hence need to be inhibited more strongly, they need more devaluation to ensure that they stop interfering with the focal task. Indeed, distractor-devaluation is stronger when distractors are spatially close to targets (Martiny-Huenger et al., 2014; Raymond et al., 2005) and therefore exert greater interference with the task of correctly identifying the target (Cutzu & Tsotsos, 2003; Hopf et al., 2006). Interestingly, devaluation effects have not only been observed for distractors in visual search tasks, but also in other kinds of tasks where it is important to respond only to targets and not to distractors such as in the think/no-think task (De Vito & Fenske, 2017).

Devaluation-by-Inhibition and No-Go Devaluation

To explain no-go devaluation then, one could view no-go items as distractors from the focal task of responding during GNG. Specifically, as the focal task in GNG is to only react to go items while not responding to no-go items, it might be beneficial to devalue no-go items. This should especially be the case for high-value items, as they have been shown to elicit stronger go responses compared with less valuable items (Z. Chen, Veling, Dijksterhuis, & Holland, 2018; see also M. Chen & Bargh, 1999). Interestingly, behavior-stimulus-interaction (BSI) theory (Veling et al., 2008) also predicts that no-go devaluation would especially occur for high-value no-go stimuli that trigger strong approach tendencies. According to this theory, withholding a response toward a high-value stimulus leads to a response conflict (i.e., between approach toward the high-value stimulus and stopping), which is inherently related to the experience of negative affect (Dreisbach & Fischer, 2012, 2015) that gets linked to the stimulus.

Thus, we think that BSI theory and a devaluation-by-inhibition account are compatible as they both predict devaluation of high-value no-go stimuli, but from a slightly different angle. While BSI theory emphasizes interference on no-go trials during GNG as a conflict between a predominant approach reaction toward high-value stimuli and withholding a response, the devaluation-by-inhibition account stresses that high-value no-go stimuli might interfere with the focal task of responding.

Associative Evaluative Learning

The devaluation-by-inhibition account and BSI theory explain when stimuli presented during a task are devalued. Another interesting question is how decreased evaluations of no-go stimuli continue to exist even after a task is completed. It seems likely that some kind of associative or propositional learning process can explain this. For example, evaluations of stimuli can be influenced by learning processes such as through evaluative conditioning (De Houwer et al., 2001). In evaluative conditioning paradigms, the value of a neutral stimulus (conditional stimulus [CS]) is changed by paring it with an affectively or emotionally laden second stimulus (unconditioned stimulus [US]; De Houwer, 2007; e.g., Hermans, Baeyens, Lamote, Spruyt, & Eelen, 2005). Evaluative conditioning (EC) has been extensively studied and many promoting and boundary conditions of EC effects have been identified (Hofmann et al., 2010). Interestingly, it has been found that attention toward the stimuli during the conditioning procedure is an important determinant of whether evaluation of the CS will be influenced (Field & Moore, 2005). Moreover, attention needs to be directed at the spatial-temporal relation between CS and US rather than either of the items in isolation to induce EC (Stahl, Haaf, & Corneille, 2016). Attention is thus guiding learning when the value of a neutral CS is changed in EC.

The role of attention during GNG in modifying evaluations of go and no-go items has not yet been examined. Note that GNG is different from EC as the evaluation of no-go items is assumed to change by pairing them with an inhibitory response rather than by pairing them with another negative stimulus (e.g., a no-go cue or instruction to stop; Z. Chen et al., 2016). However, no-go devaluation can still be described in terms of operant evaluative conditioning where negative affect is an outcome of an inhibitory motor response. This negative affect is in turn transferred to an item that is present when the inhibitory response was performed (De Houwer, 2007; Eder, Krishna, & Van Dessel, 2019).

In light of work on the devaluation-by-inhibition hypothesis, and work on EC, it can be predicted that increasing attention to no-go items may increase the no-go devaluation via two mechanisms. First, by enhancing attention to no-go items, these items may interfere even more with the task to respond to go items compared with when no attention manipulation is employed (De Vito et al., 2017). Moreover, any negative affect elicited by interference may become more strongly tied to the no-go stimulus when people attend closely to the trial (Stahl et al., 2016).

The Present Research

To investigate the role of attention in no-go devaluation effects, we combined GNG with an attentional cueing paradigm (Posner, 1980). Specifically, instead of presenting one high-value stimulus at a time during GNG, as is usually done, we now presented two high-value stimuli simultaneously on each go or no-go trial, and cued people's attention to one of the stimuli. We predicted that enhanced attention toward a no-go item would strengthen devaluation (i.e., compared with the other nonattended to no-go item) as, in line with a devaluation-by-inhibition account, attention toward no-go items might enhance interference (De Vito et al., 2017) and as previous research suggests that attention facilitates associative learning during GNG (Best, Lawrence, Logan, McLaren, & Verbruggen, 2016; see also Criaud & Boulinguez, 2013).

Three experiments investigated the research question in a controlled laboratory environment at Radboud University. For all studies, planned sample sizes, hypotheses, materials, analyses, and expected results were preregistered and the anonymized data have been uploaded on the Open Science Framework (OSF) at https://osf.io/bk5dg/. We conducted three experiments but report only two experiments in detail in the current article (Experiments 1 and 2), and, for the below mentioned reasons, explain the other experiment (Experiment 0) in detail in the online supplemental materials.

In Experiment 0, we used a different attention manipulation than in Experiments 1 and 2. In Experiment 0, to manipulate attention, we used a task-irrelevant cue. Specifically, participants performed a GNG in which two stimuli were simultaneously presented on each go or no-go trial, and participants either executed or withheld a simple motor response (i.e., pressing the B key on keyboard). To manipulate attention, one of the stimuli shortly moved. Thus, the attentional cueing was not linked to the training (i.e., participants' responses were completely determined by the go and no-go signals, but not the attentional cueing) and participants were not informed about the attentional cueing procedure at all in the instructions. We observed that this attentional cueing failed, as participants could not identify which item had been linked to attentional cueing above chance level as measured after the training (in fact their memory recognition for cued stimuli was significantly below chance level; 38% correct, $p < .001$). This result is in line with the observation of the experimenter that participants occasionally remarked not noticing *any* attentional cueing.

Therefore, to increase the salience of the attention manipulation, we increased the cue intensity, and also changed the task instruction to make the cue task-relevant. Participants received information about the existence of the attentional cue and were also instructed to identify the location of the cued item. Thus, rather than cueing automatic selective attention, the attention manipulation in the experiments reported in this article are action-relevant in that the cue is directly related to the response on go trials. Based on the work discussed above about the devaluation-by-inhibition hypothesis, this action-relevant cueing is more directly related to the nature of cueing in visual search where identifying target items is strictly task-relevant (e.g., Janiszewski et al., 2013) than the task-irrelevant cue that we used in Experiment 0 (see Fu, Fan, Chen, & Zhuo, 2001 for a discussion on possible differences between ways of cueing attention).

Experiment 1

To examine our research question, we closely based our procedures on earlier work that found robust effects of GNG on stimulus evaluation (Z. Chen et al., 2016). It is important to note that this previous work suggested that no-go devaluation effects only occur for very appetitive (or high-value) items (but see later work by Z. Chen, Veling, Dijksterhuis, et al., 2018). For that reason, we also focused on appetitive items here. As in earlier GNG research, the main procedure consisted of a pretraining evaluation of food items, GNG, and a posttraining evaluation. Importantly, to study the role of attention, we developed an alternative version of GNG. In traditional GNG, participants are presented with one food-item at a time on a computer screen and receive an auditory go- or no-go signal creating go items and no-go items respectively (e.g., Z. Chen et al., 2016). However, there were two major differences between the GNG employed here and traditional GNG.

First, on each experimental trial, two items were presented on the screen at the same time. The reason to adapt GNG in this way was to enable us to administer an attention cue through a classical attentional cueing (AC) manipulation (Posner, 1980; Posner, Snyder, & Davidson, 1980). In AC paradigms, two stimuli are presented on a computer screen, and before stimulus presentation, the location at which one of the pictures is presented is preceded by a peripheral cue that draws attention toward that location. Due to the AC, the stimulus at the cued location receives more attention than the stimulus on the opposite location (Posner, 1980). Alternative versions of AC paradigms exist in which attention is triggered by vibrating movements of the target-stimulus itself instead of an additional cue (Hudson & Skarratt, 2016; Pratt, Radulescu, Guo, & Abrams, 2010). AC paradigms have been used extensively in cognitive and social psychology to attract a person's focus of attention toward a location on which an item is presented (Frischen, Bayliss, & Tipper, 2007). It has been shown that AC improves detection of the cued stimulus (Fu et al., 2001; Posner et al., 1980) and facilitates memory and associative learning tasks compared with stimuli on the opposite side of the cued stimulus (Blask, Walther, Halbeisen, & Weil, 2012; Pashler, Johnston, & Ruthruff, 2001).

Therefore, by administering an AC for one of the two stimuli in GNG, it is assumed that the cued item receives more attention compared with the stimulus on the opposite side of the screen, thereby creating *cued* items and *uncued* items. The AC used in the current experiment was a short trembling movement administered for the first 100 ms after the two items appeared on the screen and that stopped once the go or no-go signal was presented. Presenting the AC before the go/no-go signal was meant to enhance attention for the cued item at the moment of presenting the response signal, while still making it possible for participants to focus their attention on the uncued item afterward.

The second difference from traditional GNG was that, instead of responding by pressing a single key on go-trials, participants needed to press one of two different keys, depending on the side of the screen that the cued item was presented on (see also Lawrence, O'Sullivan et al., 2015). Thereby, we ensured that participants needed to look at the screen to perform the task correctly. Altogether the experiment included five different stimulus-conditions. Cued go- and no-go items, and uncued go- and no-go items were present in a fully crossed 2 × 2 within-subject design. In addition, untrained items, that is, items present in the pre- and postevaluation but not included in GNG and the memory task, were included to disentangle possible increases in evaluation of go items from decreases in evaluation of no-go items. We preregistered the following hypotheses:

> *Hypothesis 1:* Replicating earlier work by Z. Chen, Veling, Dijksterhuis, and Holland (2016) we predicted to find a no-go devaluation effect; that is, no-go items would more strongly decrease in evaluation from before to after GNG than both go items and untrained items.

> *Hypothesis 2:* Cueing attention toward no-go items would result in a stronger no-go devaluation from pre- to post-GNG compared with no-go items that do not receive an AC.

Method

Power analysis. We conducted a simulation-based power-analysis in R (R Core Team, 2016; a detailed description of the simulation can be found in the online supplemental material, Section 2 and the R script is available on the OSF), as power-analyses for complex multilevel models that we employ here are not readily implemented in available software-packages for power-analyses. Due to the absence of better estimates, the parameters for the power-analysis were partly based on the results from Experiment 0 while the effect size estimation was based on previous GNG research (Z. Chen et al., 2016) at $d = 0.50$ for Hypothesis 1. As there was no previous data for the effect size for Hypothesis 2, we estimated the difference between cued and uncued items to be $d = 0.25$, that is, uncued items will be devalued half as strong as cued items. The simulation showed that for a power of 80%, 43 participants would be needed. We sampled five additional participants to prevent power-decline when preregistered exclusion criteria need to be applied.

Participants. Forty-eight participants between 18 and 34 years were recruited through the SONA Research Participation System of Radboud University. Four participants were excluded due to incompatibilities between Python versions, causing the script to raise an error. Moreover, three participants had to be excluded because they did not respond correctly at least 90% of the time during GNG (preregistered criterion). Thus, 41 participants were included in the analyses (32 females, nine males, $M_{age} = 22.63$, $SD_{age} = 4.21$). In line with previous work participants were asked to fast for 180 min before coming to the laboratory. This was done to increase the chance that participants would find food items rewarding. However, as we could only check adherence with self-report measures, we decided not to exclude participants based on adherence to this instruction ($n = 4$; hence it is not mentioned as an exclusion criterion in the preregistration). The average reported duration of food abstinence prior to participation was 4.3 hr. The experiments in this project received ethical approval from the institutional review board and all participants provided written informed consent.

Materials. The experimental procedure was implemented in Python 2.7, with the main components executed in PsychoPy (Version 1.82.01; Peirce, 2007). Eighty highly palatable food pictures of snacks, dishes, fruits, and vegetables from the food-pics database (Blechert, Meule, Busch, & Ohla, 2014) were selected as stimuli. The experiment was presented on a Windows 7 computer, equipped with a 24-in. widescreen monitor. The evaluation procedure and the GNG are adapted from Z. Chen et al. (2016). The go/no-go signals were played on over-ear headphones.

Procedures. The experiment consisted of five parts, presented in the following order: pretraining evaluation of the pictures, GNG, posttraining evaluation, and a memory task. Figure 1 displays a graphical overview of the procedure.

Pretraining evaluation. Before GNG, participants received a self-paced evaluation task in which they rated 80 palatable food pictures on perceived attractiveness by using a 200-point slider (0 = *not at all,* 200 = *very much*). As we were interested in the change in evaluation for high-value pictures only, the pictures were ranked by evaluation and the 50 top-rated pictures were selected for the following tasks. The selected pictures were divided into five sets of 10 pictures with matched average evaluation for each group. Four sets were randomly assigned into the four experimental conditions, that is, each item type (go vs. no-go) by attention condition (cued vs. uncued) combination. The remaining set was used as untrained items, which were included in the pre- and postrating but not in the GNG.

Go/no-go training. Each trial in the GNG started with a fixation-cross presented in the middle of the screen for 1,000 ms. Afterward, the fixation-cross disappeared and two food pictures were presented side by side. One of the two pictures (left or right) was slightly moving up and down quickly to attract visual attention (i.e., AC manipulation). The other picture did not move and is referred to as the uncued picture.

The movement of the cued picture lasted for 100 ms and stopped simultaneously with the presentation of the go/no-go signal. Two auditory tones were used as the go and no-go signal (frequency: 300 Hz or 700 Hz, duration 300 ms; the assignment of the tones was counterbalanced across participants). When hearing the go-signal, participants were instructed to indicate which of the pictures was moving by pressing the corresponding arrow-key (left vs. right arrow key) on the keyboard as fast as possible before the picture disappeared. When hearing the no-go signal, they were instructed to not press any key until the picture disappeared by itself. Independent of the response, the pictures remained on the screen for 1,000 ms in total. No performance feedback was provided. The intertrial interval was 1,500 ms. See Phase C in Figure 1 for an illustration of a trial.

Before the experimental blocks, participants received a practice block with 18 trials to get familiar with the task. To start the experimental blocks, their response accuracy needed to be above 90% in the practice block. If participants failed twice, they were told to contact the experimenter, who then checked whether they thoroughly understood the instructions. Afterward, they could practice again and start the experimental blocks. The training consisted of 10 experimental blocks, with 20 trials in each block. The whole training took approximately 20 min.

Posttraining evaluation. After the training, participants rated the 40 items that were included in the training and the 10 untrained

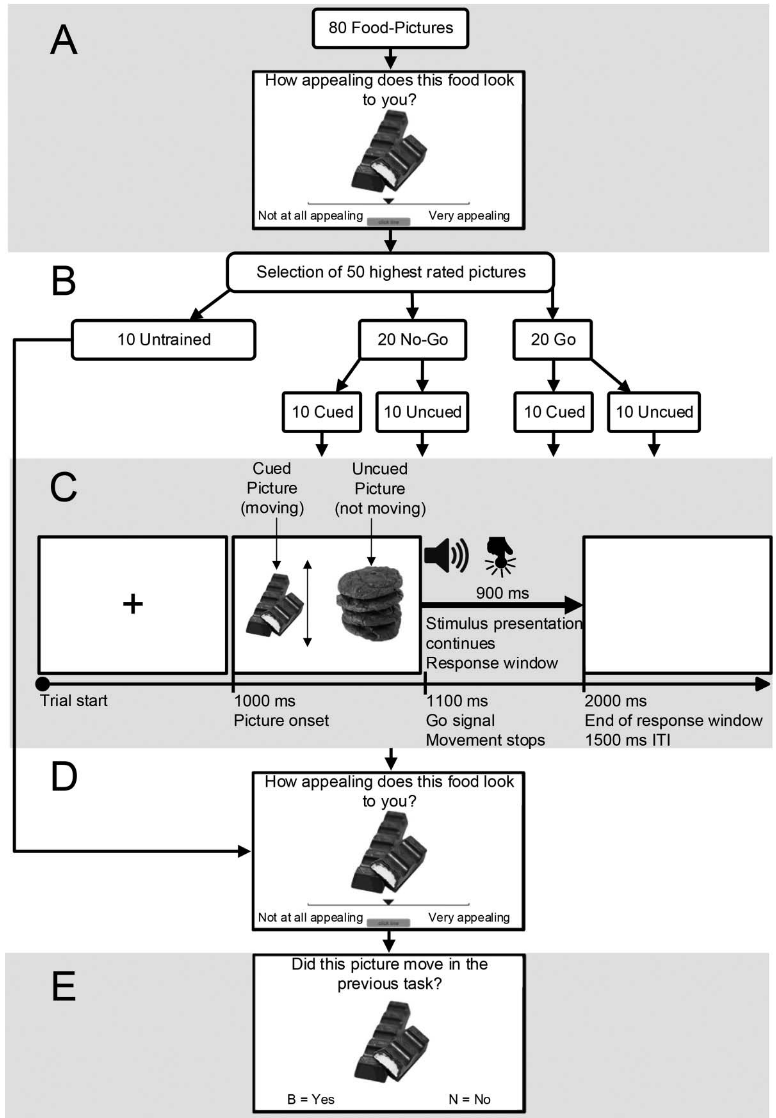

Figure 1. Graphical display of the experimental procedure. (A) Pretraining evaluation of 80 food-pictures on how appealing they look. (B) Sorting and selection of pictures. The 50 highest rated pictures from the pretraining evaluation are selected and divided into the four combinations of AC and item type conditions and an untrained baseline, which are matched on pretraining rating. (C) Example of a cued go-trial. The left picture is cued by slightly moving it up and down for the first 100 ms of picture presentation. Afterward, the movement stops and the go-cue is presented simultaneously. From this point, the participant has a 900-ms response-window to press the left or right arrow-key. After the response-window, the picture disappears and a blank screen (intertrial interval) is presented for 1,500 ms. (D) Posttraining evaluation; the 50 selected items are evaluated again in the same way as in (A). (E) The memory task, asking participants to recall whether items moved or not, that is, whether they were cued.

items again, using the same scale and with the same instructions as in the pretraining evaluation.

Memory task. After the second evaluation, participants received a surprise memory task, which was not mentioned in the instructions before to not induce the idea that the GNG would be a memory test. In this task, participants had to indicate whether each of the 40 pictures from the GNG had been cued, that is, had moved during training, or not. The results of the memory task are discussed in Section 5 of the online supplemental material.

Questionnaires and demographics. The final part of the experiment was identical to Z. Chen et al. (2016). Participants filled out a restraint eating scale (Herman & Polivy, 1980), answered questions about their (current) eating habits and an open question about their idea of the study's purpose. The questions were irrelevant to the current research but were included for possible future exploratory purposes.

Results

All confirmatory analyses were conducted in the statistical software R (Version 3.3.2; R Core Team, 2016) using ANOVA's. Note that we preregistered mixed-effects models for Experiment 1. As we encountered severe convergence issues while fitting the models (for this reason we preregistered ANOVA's for Experiment 2), we report the results from repeated-measures ANOVA's here for the sake of consistency with Experiment 2 and readability. Results from all mixed-model analyses and a detailed discussion about problems while fitting the models can be found in Section 3 of the online supplemental material. For all tests, the two methods yielded the same results in terms of statistical significance (though the mixed-effects models were sometimes simplified) except when this is explicitly indicated.

Descriptives. The average evaluation of all 80 items on the prerating on the 200-point scale was $M = 121.56$ ($SD = 47.93$). For only the 50 items included in the training or the untrained baseline items, means and standard deviations were $M = 147.80$ ($SD = 30.03$) for the preevaluation and, $M = 134.58$ ($SD = 38.78$) for the postevaluation. The overall difference between pre- and postevaluation of the included items was $M = -13.23$ ($SD = 30.45$). Note that this decrease in value can partly be attributed to regression to the mean, as only the highest-rated items were included in the training. This is a commonly observed finding when items are selected based on receiving a high prerating (e.g., Z. Chen et al., 2016). Moreover, on average, participants gave a correct response in the training on 97% of the trials during GNG.

Hypothesis 1. To test the first hypothesis, whether no-go items will be devalued more strongly than go and untrained items, we investigated the change in evaluation from pre- to post-GNG across GNG-conditions, that is, the item type (go vs. no-go vs. untrained) by time (pre- vs. post-) interaction. The two main effects of item type and time were significant with $F(1, 80) = 8.85$, $p < .001$, $\eta_p^2 = .181$ and $F(1, 40) = 42.93$, $p < .001$, $\eta_p^2 = .518$, respectively. The interaction was significant, $F(1, 80) = 10.40$, $p < .001$, $\eta_p^2 = .206$, showing that devaluation was different across the three item type conditions. The pattern of results is depicted in Figure 2.

As predicted, planned pairwise comparisons of the time by item type interaction with subsets of the data including only the relevant item type levels revealed that no-go items ($M_{dif} = -16.58$, $SD_{\text{dif}} = 35.10$) were devaluated more strongly than go items ($M_{dif} = -11.13$, $SD_{\text{dif}} = 33.52$), $F(1, 40) = 11.39$, $p = .002$, $\eta_p^2 = .222$, and untrained items ($M_{dif} = -10.73$, $SD_{\text{dif}} = 31.97$), $F(1, 40) = 17.06$, $p < .001$, $\eta_p^2 = .299$. There was no significant difference between untrained and go items, $F(1, 40) = 0.10$, $p = .751$, $\eta_p^2 = .003$.

Hypothesis 2. To assess whether attention condition (cued vs. uncued) influenced devaluation within no-go items, their change in evaluation from pre- to post-GNG was compared across AC conditions. The AC by time interaction within no-go items was significant, $F(1, 40) = 4.50$, $p = .040$, $\eta_p^2 = .101$ in the ANOVA approach. However, in this case, the preregistered mixed-effects model was not significant ($p = .066$). For this reason, we conclude that, even though the cueing-conditions differ in the expected directions (i.e., descriptively cued no-go items were devalued more than uncued no-go items), this effect did not reach statistical significance. Moreover, there was a significant main effect of time,

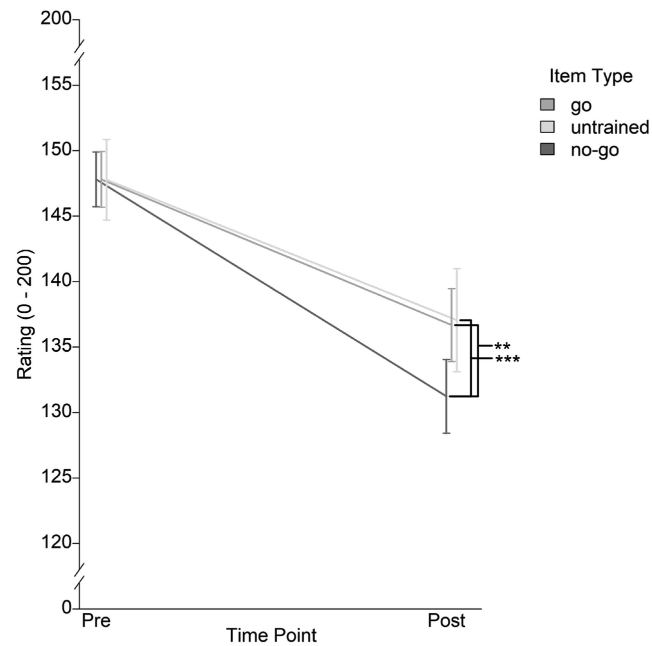

Figure 2. Evaluations of the items at pre- and post-GNG as a function of GNG-condition in Experiment 1. Error bars stand for adjusted 95% confidence intervals. The slopes of no-go items differ significantly from go- and untrained items. ** $p < .01$. *** $p < .001$.

$F(1, 40) = 63.94$, $p < .001$, $\eta_p^2 = .615$, and a main effect of AC condition, $F(1, 40) = 5.13$, $p = .029$, $\eta_p^2 = .114$. See Figure 3 for a graphical depiction of the results.

Explorative analyses. To further explore the relationship between attention and evaluation not only for no-go items but also go items, an ANOVA with item type (go vs. no-go), attention condition (cued vs. uncued) and time (pre vs. post) as independent variables was run, yielding a significant three-way interaction, $F(1, 40) = 6.45$, $p = .015$, $\eta_p^2 = .139$.

Follow-up comparisons revealed that there was a significant difference in terms of value-change from pre- to posttraining between cued go and no-go items, $F(1, 40) = 15.17$, $p < .001$, $\eta_p^2 = .275$, while uncued items were not significantly different between the go and no-go conditions, $F(1, 40) = 0.52$, $p = .474$, $\eta_p^2 = .013$. Moreover, there were significant differences between the untrained items and both cued and uncued no-go items, $F(1, 40) = 23.54$, $p < .001$, $\eta_p^2 = .370$ and $F(1, 40) = 4.53$, $p = .040$, $\eta_p^2 = .102$, respectively. The latter result, however, was not confirmed with mixed-models where the difference between uncued no-go items and the untrained items was not significant ($p = .20$). All other differences were nonsignificant, showing that no-go devaluation was present for cued no-go items and that there might be devaluation of uncued no-go items compared with untrained items as well, though the evidence is certainly weaker. These findings suggest that cueing does influence the difference in evaluation between go and no-go items, although only in an exploratory fashion.

As an anonymous reviewer pointed out to us, it is often found that response errors are related to negative affect (Chetverikov, Jóhannesson, & Kristjánsson, 2015). Thus, even though the

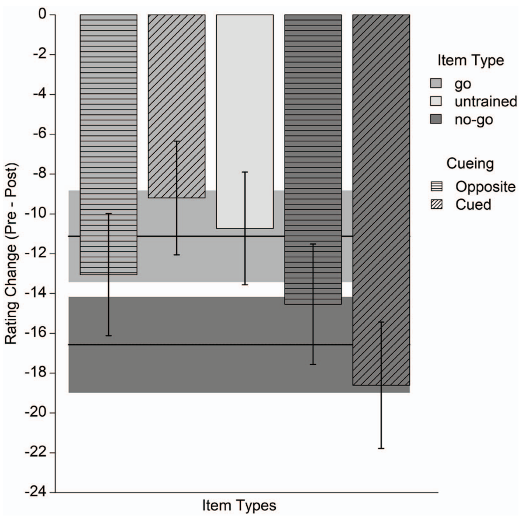

Figure 3. Bars represent changes in evaluation (postrating minus prerating) in Experiment 1 per item type, with longer bars indicating stronger decrease in value. Error-bars denote 95% confidence-intervals per group, adjusted for within-subject variation according to Rouder and Morey (2005). Horizontal lines indicate average changes for go and no-go items, pooled over AC conditions. Shaded areas of respective item-type color around the horizontal lines represent respective adjusted 95% confidence intervals.

response-accuracy during GNG was quite high with 97% correct responses, it is important to rule out the possibility that response errors might explain the reported changes in evaluation. Therefore, in line with previous work on devaluation-by-inhibition (e.g., De Vito et al., 2017), we repeated the analyses reported above with a subset of the data that only included evaluations of items that have not been associated with response-errors (i.e., responding toward no-go or not responding toward go items) in any of the 10 times they were presented during the training. For Hypothesis 1, the reanalysis yielded very similar results to those reported above with $F(1, 80) = 9.32$, $p < .001$, $\eta_p^2 = .189$ for the overall-interaction, $F(1, 40) = 12.62$, $p < .001$, $\eta_p^2 = .240$ for the follow-up test of go versus no-go items, $F(1, 40) = 11.50$, $p = .002$, $\eta_p^2 = .223$ for no-go versus untrained items and $F(1, 40) < 0.01$, $p = .980$, $\eta_p^2 < .001$ for go versus untrained items. For Hypothesis 2, we found similar results as well, again showing a significant difference between cued and uncued no-go items for the repeated-measures ANOVA, $F(1, 40) = 5.47$, $p = .025$, $\eta_p^2 = .120$. After excluding items associated with response errors, the effect was now significant for the mixed-effects model as well, $F(1, 26.75) = 4.52$, $p = .043$.

Discussion

Confirming Hypothesis 1, we did fully replicate earlier GNG findings (Z. Chen et al., 2016), showing that no-go items are devaluated more strongly than go and untrained items. This is interesting, as this task is the first to show that GNG effectively decreases evaluations of no-go foods even when two pictures are presented at the same time. Hypothesis 2 was not confirmed. Although the means were in the predicted direction, our confirmatory analysis did not show a significant difference between cued and uncued no-go items. However, explorative analyses suggest that cueing did affect evaluations, as the difference between cued go versus cued no-go items was significant whereas this was not the case for uncued items. Moreover, the difference between cued no-go and uncued no-go items was in the predicted direction, and reached significance with a nonpreregistered ANOVA approach, and when no-go stimuli associated with commission errors and go stimuli associated with omission errors during the training were excluded. Together, this suggests that attention might indeed be necessary for no-go devaluation to occur, but that a statistical difference between cued and uncued no-go stimuli might have been difficult to obtain.

For this reason, we conducted a direct replication of Experiment 1, in which we considerably increased the sample size to have higher statistical power for the predicted difference between cued and uncued no-go items. Moreover, based on Experiment 1, we preregistered to find an interaction of Time × Cueing Condition × Item Type, and we changed our statistical approach.

Experiment 2

Experiment 2 was a direct replication of Experiment 1 with increased sample size. We had the following predictions:

Hypothesis 1: We expect a significant three-way interaction of Time (pre vs. post) × Cueing Condition (cued vs. uncued) × Item Type (go vs. no-go). Specifically, the evaluation-change from pre- to postmeasure will be stronger for cued go versus no-go items than uncued go versus no-go items.

Hypothesis 2: Cued no-go items will significantly decrease more in value from pre to post compared to untrained items.

Hypothesis 3: Cued no-go items will decrease more in value from pre to post than uncued no-go items.

Method

The materials and procedures of Experiment 2 were identical to Experiment 1.[1] The only difference was the increased sample size of 80 participants, according to a power-analysis assuming a medium-sized effect for the difference between cued and uncued no-go items (rather than assuming $\eta_p^2 = .101$ from Experiment 1 as it might be overestimated). Participants from either of the previous experiments were not allowed to take part. Five participants were excluded due to technical problems or preregistered exclusion criteria and were therefore resampled (preregistered). Moreover, as the analyses in Experiment 1 often suffered from convergence issues that were related to the random-term for food items not having enough observations in some cells, we changed the preregistered analyses to a 2 × 2 repeated-measures ANOVA with an error-term for the participant-level but not the food-item level. Note that this choice reflects a trade-off between choosing the best statistical analysis available (i.e., mixed-effects models) versus changing our design. Specifically, to stick with a fully crossed random structure in the mixed-model (or an f1 × f2 test in

[1] Experiment 2 contained an additional binary choice-task between items included in the training at the very end for exploratory purposes.

ANOVA terms), we need a sufficient number of observations per Attention × Item Type combination not only per participant but also per food-item. As we have no control over the items participants like the most and are therefore selected for the training, this means that we cannot a priori determine the condition that items are distributed to. To solve this, one could include the same food items for each participant instead of selecting the highest-value items only. At the time of conducting the study, however, we chose for a direct replication of the experimental design of Experiment 1. The advantage of this decision, in hindsight, is that we can combine the data of experiments more easily as we will report later (and where we could also successfully apply mixed-effects models). Nevertheless, mixed-effects models were again conducted as well whenever possible to check the robustness of the results. The results from those analyses can be found in the online supplemental material, Section 3. Moreover, any discrepancies between the analyses in terms of statistical significance are explicitly reported in the article.

Results

When examining the assumptions for the ANOVA, we identified outliers on the model residuals, the mean-rating scores, and the difference scores between pre- and postrating using a 3-*SD* outlier criterion (deviating more than 6 *SD* units) as well as a median absolute deviation (MAD) criterion (deviating more than 8 MAD units; Leys, Ley, Klein, Bernard, & Licata, 2013). An inspection of the raw scores showed that one person gave the highest possible rating to almost half the items on the pretraining measure while giving the lowest possible rating to most of those items in the post measure. Note that this implies that within the duration of the experiment, the person changed his or her opinion about the food items from extremely positive to extremely negative. As we consider this response-pattern implausible (based on our previous work with this kind of task in which we never encountered this in more than 13,000 food ratings; e.g., Z. Chen et al., 2016), we post hoc excluded this case for further analysis. The results including the outlier are available in Section 3 of the online supplemental materials and differ substantially from the results with the outlier included in some cases.

Descriptives. The average evaluation of the 50 items included in the training, was $M = 151.00$ ($SD = 29.56$) for the preevaluation and, $M = 140.53$ ($SD = 36.10$) for the postevaluation. The overall difference between pre- and postevaluation was $M = -10.46$ ($SD = 26.87$). On average, participants gave a correct response in the training on 97% of the trials. For an overview of evaluation-changes for the different item types see Figure 4.

Hypothesis 1. As predicted, we found a significant Time × Cueing Condition × Item Type interaction, $F(1, 78) = 9.97$, $p = .002$, $\eta_p^2 = .113$, indicating that attention cueing influenced the change in evaluation of go and no-go items in different ways. As predicted, the change in evaluation is stronger between cued items than uncued items ($M_{dif} = -5.35$; see Figure 5). Follow-up analyses revealed that there was a significant difference between cued go and no-go items, $F(1, 78) = 25.76$, $p < .001$, $\eta_p^2 = .248$, while the difference between uncued go and no-go items was not significant, $F(1, 78) = 3.36$, $p = .071$, $\eta_p^2 = .041$.

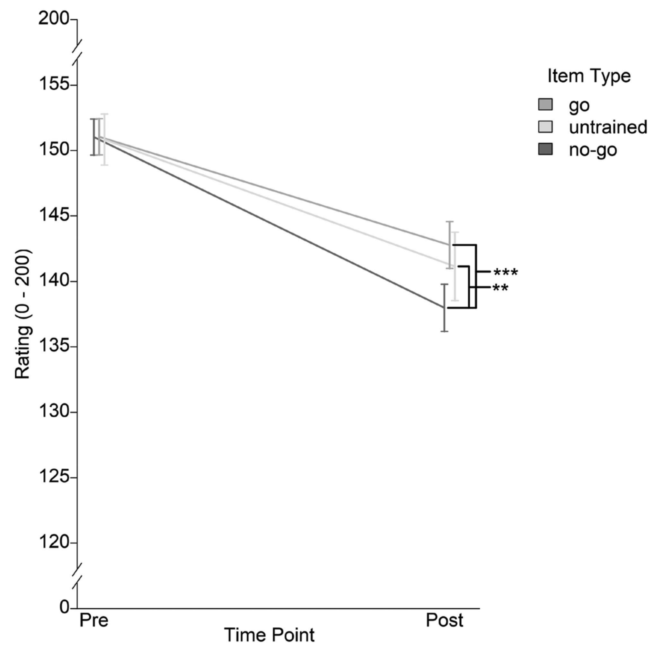

Figure 4. Evaluations of the items at pre- and post-GNG as a function of GNG-condition in Experiment 2. The slopes of no-go items differ significantly from go- and untrained items. ** $p < .01$. *** $p < .001$.

Hypothesis 2. We predicted that cued no-go items would significantly decrease more in value than untrained items. Indeed, there was a significant difference between the conditions, $F(1, 78) = 12.76$, $p < .001$, $\eta_p^2 = .141$. There was also a nonpredicted significant difference between uncued no-go items and the untrained items, $F(1, 78) = 4.14$, $p = .045$, $\eta_p^2 = .050$. The latter difference was, however, not significant in a mixed-model analysis ($p = .091$).

Hypothesis 3. Finally, we predicted that cued no-go items would be devalued significantly stronger than uncued no-go items. However, again there was no support for the hypothesis of a significant difference between the two conditions, $F(1, 78) = 2.78$, $p = .099$, $\eta_p^2 = .034$, though again, the means differed in the predicted direction.

Explorative analyses. To fully explore the three-way interaction between time cueing condition and item type, we further investigated the pattern of differences between the go-conditions and the untrained condition. We found that while the difference between cued go items and the untrained items was significant, $F(1, 78) = 5.07$, $p = .027$, $\eta_p^2 = .061$, there was no significant difference between uncued go items and untrained items, $F(1, 78) = 0.10$, $p = .756$, $\eta_p^2 = .001$. Moreover, we found a significant difference between cued and uncued go items, $F(1, 78) = 6.01$, $p = .016$, $\eta_p^2 = .072$ (see Figure 5).

Again, we tested whether excluding items associated with erroneous responses would change the reported results. For Hypothesis 1, this did not change the reported results substantially, $F(1, 78) = 12.73$, $p < .001$, $\eta_p^2 = .140$ for the three-way interaction; $F(1, 78) = 27.20$, $p < .001$, $\eta_p^2 = .259$ for cued go versus cued no-go; $F(1, 78) = 3.37$, $p = .070$, $\eta_p^2 = .041$ for uncued go versus uncued no-go. For Hypothesis 2, while the difference between cued no-go

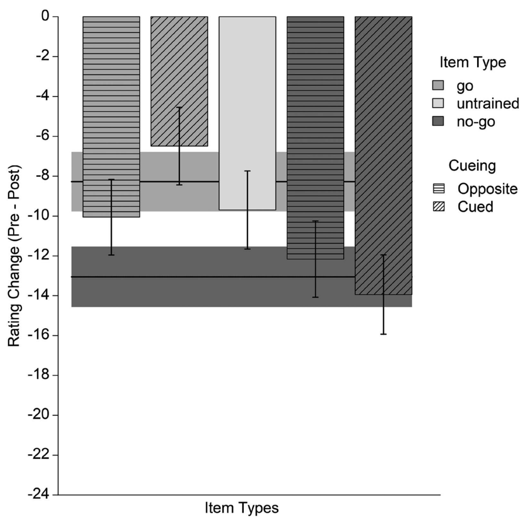

Figure 5. Bars represent changes in evaluation (postrating minus prerating) in Experiment 2 per item type, with longer bars indicating stronger decrease in value. Error-bars denote 95% confidence-intervals per group, adjusted for within-subject variation according to Rouder and Morey (2005). Horizontal lines indicate average changes for go and no-go items, pooled over AC conditions. Shaded areas of respective item-type color around the horizontal lines represent respective adjusted 95% confidence intervals.

versus untrained items did not substantially change, $F(1, 78) = 11.04$, $p = .001$, $\eta_p^2 = .124$, there was no significant difference between uncued no-go items and the untrained condition anymore, $F(1, 78) = 3.09$, $p = .083$, $\eta_p^2 = .038$. Interestingly, excluding erroneous responses did also lead to a significant difference between cued and uncued no-go items (Hypothesis 3; $F(1, 78) = 4.45$, $p = .038$, $\eta_p^2 = .054$).

Analyses on Combined Data

As Experiment 2 was an exact replication of Experiment 1, we combined the data of both experiments for explorative analyses to investigate the robustness of the results and see whether the predicted difference between cued and uncued no-go items would be visible in the combined sample. Moreover, by combining the data we could perform a linear mixed-model analyses that we initially intended to perform (see preregistration Experiment 1) which simultaneously accounts for both random variation within participants and variation on the item level. Descriptive statistics for the combined analysis can be found in Figure 6.

As in Experiment 2 (and the exploratory analysis of Experiment 1), we found support for the hypothesis that there is a larger difference between cued go versus no-go compared with uncued go versus no-go items, $\beta = -0.053$, $F(1, 60.11) = 12.82$, $p < .001$, 95% CI [−0.083, −0.020]. For Hypothesis 2 of Experiment 2 (i.e., lower evaluations for cued no-go compared to untrained), we found $\beta = -0.092$, $F(1, 47.17) = 24.62$, $p < .001$, 95% CI [−0.132, −0.055], and for Hypothesis 3 of Experiment 2 (lower evaluations of cued no-go vs. uncued no-go), we found $\beta = -0.044$, $F(1, 45.81) = 5.57$, $p = .023$, 95% CI [−0.079, −0.007]. Thus, there seems to be a difference between cued and uncued no-go items, but the effect size is smaller than we initially expected and therefore difficult to statistically detect within each separate experiment. Note that in these combined analyses we excluded the outlier from Experiment 2. Including the outlier renders the test for Hypothesis 3 nonsignificant ($p = .083$), the conclusions for the other results do not change. For the full report of the results with outliers see the online supplemental material, Section 4.

To get more insight into the robustness of the effect of cueing on no-go items, we additionally calculated a Bayes factor (BF) for the combined data (cued no-go vs. uncued no-go). This allows us, conditional on the selected prior distributions, to quantify the evidence for the presence of an effect against the evidence of the absence of an effect. Moreover, we can track the BF throughout the sampling process to see how the evidence for or against the hypothesis of stronger devaluation for cued no-go items develops. We used a Cauchy prior ($\gamma = 0.707$) and calculated the one-sided BF_{+0} (evidence for more devaluation of cued no-go items compared with evidence for no effect or a difference in the opposite direction) in a paired *t* test on the difference-scores using the statistical software JASP (v0.8.4.0; JASP Team, 2017). The analysis yielded $\delta = 0.327$, 95% CI [0.092, 0.579], $BF_{+0} = 5.88$, which means that there is around six times as much evidence for the predicted effect than there is for no or a reversed effect. BFs between 3 and 10 are often interpreted as moderate evidence.

Figure 7 (upper panel, left) shows the sequential analysis plot and a robustness check to see how strongly the BF depends on the width of the prior. As it can be seen, the BF was 3 or higher for any sample size larger than 45 participants, varying between 3 and 30 from this point onward. Moreover, the right-hand panel shows that the prior still has a strong influence on the BF, with higher BF for narrow priors, reflecting the fact that the difference between cued

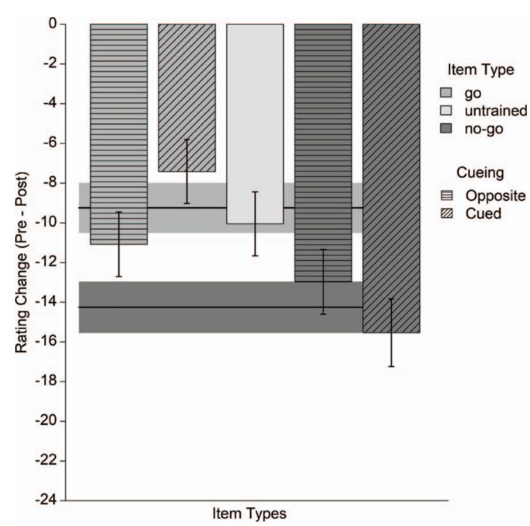

Figure 6. Bars represent changes in evaluation (postrating minus prerating) for the combined data of Experiment 1 and 2. Error-bars denote 95% confidence-intervals per group, adjusted for within-subject variation according to Rouder and Morey (2005). Horizontal lines indicate average changes for go and no-go items, pooled over AC conditions. Shaded areas of respective item-type color around the horizontal lines represent respective adjusted 95% confidence intervals.

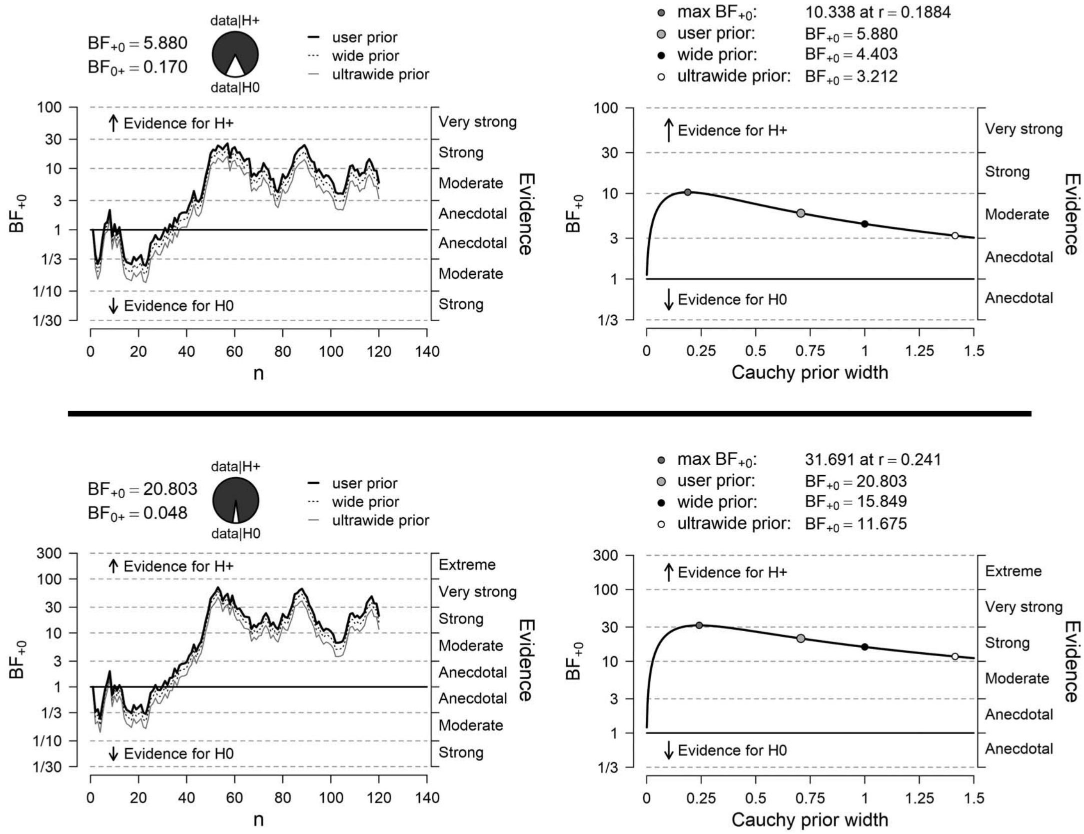

Figure 7. Upper panel. Left: Sequential BF during sampling. The black line indicates the BF conditional on the prior that was used in the analysis, while the dashed line corresponds to a wide prior and the gray line corresponds to an ultrawide prior. For the user prior, the BF varies between 1/3 and 30. Right: The final BF as a function of prior-width, suggesting stronger evidence for an effect as the prior gets more narrow and weaker evidence as the prior gets wider. Lower panel. The same information as in the upper panel for items that were always responded to correctly by a given participant.

and uncued no-go items, even though it is supported by the BF, is small but robust. Again, we analyzed a data-set excluding all items that received erroneous responses yielding $\delta = 0.390$, 95% CI [0.143, 0.636], $BF_{+0} = 20.80$, suggesting strong evidence for a difference between cued and uncued no-go items in this case.

General Discussion

The present experiments tested four hypotheses. The first hypothesis (Experiment 1) that no-go items would be evaluated lower compared with go items and untrained items after GNG was confirmed. This effect was also observed in Experiment 2. This finding speaks to the robustness of the no-go devaluation effect (Z. Chen et al., 2016; Veling et al., 2008) and indicates that this effect can even be observed when two items are presented simultaneously during GNG. There was no confirmatory evidence for the hypothesis examined in both experiments that cued no-go items would be devalued more strongly than uncued no-go items. However, we did find this pattern of results in an exploratory fashion in multiple ways. First, this effect was observed within each experiment when post hoc excluding items to which participants erroneously responded during GNG. Second, we observed this effect when we combined the data of the experiments with a frequentist ANOVA, mixed-effects model, and Bayes factor approach. Altogether, we found moderate evidence in the data in favor of lower evaluations of cued no-go items compared with uncued no-go items. The evidence for an effect in the data was strong when stimuli that were related to erroneous responses were post hoc excluded from the analyses.

The third hypothesis (Hypothesis 2 of Experiment 2) that cued no-go items were evaluated lower than untrained items was confirmed. This suggests that increasing attention to a food item may not necessarily lead to a higher evaluation of this food item (cf. Janiszewski et al., 2013). The fourth hypothesis (Hypothesis 1 of Experiment 2) was that changes in evaluation from pre to post would be stronger for cued go versus cued no-go items than uncued go versus uncued no-go items. This hypothesis was confirmed. We also found this pattern in an exploratory fashion in Experiment 1. Thus, we can conclude that cueing does amplify the difference in evaluation between go and no-go items. The results suggest that this is because cueing impacts both evaluations of go and no-go items. Specifically, exploratory analyses of Experiment 1 and the preregistered analysis of Experiment 2 indicate that both cued and uncued no-go items differed from untrained items, but the effect size was larger for the cued items. Furthermore, the difference between uncued no-go items and untrained items disappeared after excluding items that were incorrectly responded to during GNG in explorative analyses. With regard to the go items, Experiment 2 revealed that cued, but not uncued go items, were rated more positively compared to untrained items. Together, these results suggest that changes in evaluation of go and no-go items are amplified when people attend to these items during the training. This result is important for both theoretical and applied reasons.

From a theoretical perspective, the results are in line with a devaluation-by-inhibition account (De Vito et al., 2017). Specifically, devaluation should be stronger the more an item interferes with a focal task to ease task-execution (Martiny-Huenger et al., 2014; Raymond et al., 2005). In Experiments 1 and 2, an attention cue was employed that was task-relevant. This is, when an item was moving to trigger attention, it also informed people which button to press once a go signal would be presented. Thus, while the cued item was possibly task-relevant, the opposite-cue item became task-irrelevant as soon as the attention cue was presented. The fact that cued no-go items are devalued more strongly in the combined data than uncued no-go items might thus reflect the fact that devaluation is stronger when an item is more interfering with the focal task during go/no-go training.

While we predicted a difference for cued versus uncued no-go items, we did not have a priori predictions for go items as in previous go/no-go training research we did not reliably find effects of responding on evaluations of go items. However, cued go items were rated significantly higher after training than uncued go items and untrained items. It seems possible to explain enhanced evaluation of cued go items with the same mechanism by which we explain devaluation of no-go items, as both these effects may also be viewed as serving the goal of facilitating task execution. More specifically, increasing the value of task-relevant go items may facilitate go responses (i.e., it has been shown that go responses are faster for high compared with low value items; Z. Chen, Veling, Dijksterhuis, et al., 2018), which facilitates task-execution for cued go items. For uncued go items however, even though they are visible while a response is executed, they do not need to be responded to and therefore a change in value for these items would not further facilitate task execution. In other words, task-relevant items that are consistent with the focal task become more positive, while items inconsistent with the focal task (no-go items) become more negative when they are initially (before the no-go signal appears) considered task-relevant because they are cued.

On first sight, our results might seem contradictory to those of Janiszewski, Kuo, and Tavassoli (2013), who found that attentional cueing in a visual search task was *always* related to increased evaluations for cued items (i.e., mere selection) and decreased evaluation for uncued items (i.e., mere neglect), while in the present study, attentional effects depend on the item type. We think that this apparent contradiction represents the fact that Janiszewski et al. (2013) applied a visual search task in which the cued item was always the target while the uncued item was always the distractor. In our cueing procedure, however, the cued item was a *potential* target. For cued no-go items however, this potential target turned out to be a distractor (i.e., a to-be-neglected item) while only cued go items eventually turn out to be legitimate target items. Thus, we think that our findings converge well with this previous research.

Another interesting observation was that response-errors seemed to attenuate the observed effects. When people responded to no-go stimuli, this may be an indication they considered these no-go stimuli, at least momentarily, as task relevant. As explained above, this may make the stimulus more positive and hence reduce the no-go devaluation effect. This logic converges well with an associative learning account in which the association strength depends on the amount of observations for a certain association but also the strength of the consistency between them (see Jones et al., 2016 for a review). Our findings also suggest similarities with recent studies on the role of attention within the domain of evaluative conditioning. Specifically, findings in the domain of evaluative conditioning suggest an important role of attention in explaining EC effects (e.g., Field & Moore, 2005). For example, it has been shown that evaluative conditioning effects are not found when attentional resources are restricted during the learning phase such as under high cognitive load (Mierop, Hütter, & Corneille, 2017; e.g., Pleyers, Corneille, Yzerbyt, & Luminet, 2009). Also, recent studies revealed no reliable EC effects when the CS were presented parafoveally (Dedonder, Corneille, Bertinchamps, & Yzerbyt, 2014), subliminally (Heycke, Aust, & Stahl, 2017), or in a suppressed manner using Continuous Flash Suppression (Högden, Hütter, & Unkelbach, 2018). Our findings with GNG converge with these results and suggest that attention seems to enhance GNG effects.

Our results further suggest that it might be fruitful for future research to investigate the exact interplay of task relevance, interference and attention in explaining no-go devaluation effects. With the present research design, we cannot distinguish between mere attentional effects that facilitate the coupling of stopping-induced negative affect with no-go items from an explanation that emphasizes cued no-go items as very interfering with the focal task goal. Though the purpose of the trembling pictures was to cue attention, it also indicated which picture needs to be responded to in go-trials. As a result, it remains unclear whether an attention cue that is not directly task-relevant and cues automatic and involuntary attention rather than goal-directed attention would influence evaluations in the same way (for possible differences see, e.g., Fu et al., 2001). Note that we did not find any effects of such a cueing procedure in Experiment 0 (reported in the online supplemental material), which led us to change our cueing procedure. Future work may examine whether task-irrelevant attention cueing influences evaluations of go and no-go stimuli.

Another interesting discussion concerns the mediating role of contingency awareness in these effects. Several studies revealed a strong link between contingency awareness (explicit knowledge of the contingency between US and CS) and the strength of evaluative conditioning (see for an overview Corneille & Stahl, 2018). Therefore, contingency awareness is said to be a crucial mediator in evaluative conditioning (Pleyers, Corneille, Luminet, & Yzerbyt, 2007), but such correlation does not imply causation (see, e.g., Gawronski & Bodenhausen, 2018). In Experiment 2 (for Experiment 1 we did not collect data on this) we also found a correlation between memory for contingencies and the strength of the GNG effect for the cued items, $r(77) = .35$, $p = .001$ (see online supplemental material, Section 5). This raises the question how knowledge of which stimuli are go and which stimuli are no-go is related to the effects on evaluation. For instance, it has been shown that receiving information about which stimuli are to be approached and are to be avoided in an approach-avoidance task might be sufficient to change evaluations of these stimuli (Van Dessel, De Houwer, Gast, Smith, & De Schryver, 2016; Van Dessel, Gawronski, Smith, & De Houwer, 2017). For GNG however, learning which stimuli were go and which were no-go was not sufficient to change stimulus evaluations, when people did not execute the training but only observed it (Z. Chen et al., 2016, Experiment 5). These findings suggest that, even though explicit knowledge on contingencies may be a (strong) correlate of attention during GNG, it may not be the pivotal mediator in GNG devaluation effects. Of course, the role of contingency awareness within GNG should be more explicitly tested in future studies.

The present results are also important from an applied perspective. As noted in the introduction, GNG has received a lot of interest recently as a new and promising intervention to change people's responses to food (Allom, Mullan, & Hagger, 2016; Jones et al., 2016; Turton, Bruidegom, Cardi, Hirsch, & Treasure, 2016). However, GNG does not always have the desired effect (e.g., Turton et al., 2018). This may be, at least partly, because little is still known about the working mechanisms of the training, so that it can be hard to determine whether any minor changes to the training would influence effectiveness, or what the best way is to administer the training. The present results indicate that, when it comes to changing evaluations of food items, it seems important to make sure that people's attention is cued to the food items. Note that this is by no means trivial, as the go/no-go signals are the task-relevant cues, and the food pictures are often task irrelevant (e.g., Veling, van Koningsbruggen, Aarts, & Stroebe, 2014). Thus, people might only focus on the go/no-go signals and not on the pictures. A variant of GNG in which participants react to the location of the picture does therefore provide a promising alternative (e.g., Lawrence, O'Sullivan et al., 2015; Lawrence, Verbruggen, Morrison, Adams, & Chambers, 2015). Although the effect size we found for the difference between cued and uncued no-go items is small, optimizing the training even with small adjustments is important to eventually arrive at more effective training procedures. Moreover, the valuation effects for cued go items might be important for applied work in the food-domain where the goal is to increase low-calorie food evaluations and decrease high-calorie food evaluations at the same time. Future work may more systematically examine whether effects on measures such as food choice or food intake become stronger when people attend more to the pictures during the training.

Another promising direction for future research would be to apply the present procedure to stimuli other than food items, as no-go devaluation has been demonstrated for other motivational stimuli including sexual stimuli (Driscoll, de Launay, & Fenske, 2018; Ferrey, Frischen, & Fenske, 2012) and alcohol (Houben, Havermans, Nederkoorn, & Jansen, 2012). Therefore, it seems possible that the present findings will generalize to other high-value stimuli. Future research should investigate this question more closely.

The present studies also have a number of limitations. Most importantly, we did not directly measure participants' attention. It would be interesting to include more direct measures of attention, such as eye tracking, in future work. It is also important to follow up on the question whether the involuntary and automatic triggering of attention is sufficient for the amplification of evaluation-change that we observed in the present paper, or whether it is necessary for attention to be task-relevant, as one would expect from a devaluation-by-inhibition account. Second, we recruited a rather homogeneous sample of participants at the university, so from an applied perspective it remains to be tested whether similar effects can be found in important target groups. A recent study employed the same GNG among university participants and morbidly obese participants, and did find that these groups are equally sensitive to effects of GNG on food evaluation (Z. Chen, Veling, de Vries, et al., 2018). Last, we only examined explicit evaluations of food items, so it would be interesting to test effects of attention cueing on other outcome measures such as food choice.

Moreover, it might be possible that the mere movement of items attenuated the results of this study. Specifically, it has recently been shown that categorizing items during GNG can influence the effects. Serfas, Florack, Büttner, and Voegeding (2017) demonstrated that GNG leads to more persistent evaluation-changes when go and no-go items belong to meaningful categories (e.g., all healthy items are go, all unhealthy items are no-go). In our design, it is possible that participants categorized items into moving and nonmoving items. As this categorization would not be consistent with the categorization as go versus no-go items and does not convey any meaning beyond the completion of the task, it might have attenuated the effects in this study. Future research should investigate this possibility.

Finally, we want to stress that statistical procedures to analyze complex data structures such as mixed-effects models are rapidly improving and becoming more accessible to researchers, and it has frequently been argued and demonstrated that these approaches are superior to classical ANOVA designs in many situations (e.g., Aarts, Verhage, Veenvliet, Dolan, & van der Sluis, 2014; Baayen, Davidson, & Bates, 2008; Gelman, Hill, & Yajima, 2012). We think preregistered, state-of-the-art, analyses should be the default in psychological science and that researchers should justify their statistical models. However, as the current article demonstrates, more research into specific cases of applying these methods is needed. In our situation for instance, simulation studies investigating the convergence rate of maximal-model structures for crossed random-effects with heterogeneous cell-sizes for one of the nesting levels and their relative performance compared with classical ANOVA methods would help with selecting a proper model specification.

To conclude, the present experiments show that evaluations of go versus no-go items are influenced by a manipulation of attention cueing, and thus suggest that effects of GNG depend on the amount of attention people devote to the food items during the training. This finding sheds new light on the working mechanism of GNG and may be used to optimize future applied training procedures.

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