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When Mere Action Versus Inaction Leads to Robust Preference Change

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Understanding the formation and modification of preferences is important for explaining human behavior across many domains. Here we examined when and how preferences for food items can be changed by linking mere action versus inaction to these items. In 7 preregistered experiments, participants were trained to consistently respond to certain food items (go items) and not respond to other items (no-go items) in a go/no-go training. Next, to assess preferences, they repeatedly chose between go and no-go items for consumption. Decision time during the choice task was manipulated and measured. Immediately after training, participants chose go items more often for consumption when choosing under time pressure, for both high-value and low-value choice pairs. Preferences were reliably changed in favor of go items for choices between unhealthy foods, between healthy foods, and between healthy and unhealthy foods. Furthermore, preference change was still observed one week after training, although the effect size largely decreased. Interestingly, when participants made choices without time pressure, the effect became weaker and statistically nonsignificant. These results suggest that preference change induced by mere responding versus not responding is constrained to situations where people take little time to make decisions, and the effect is relatively short-lived. By showing the reliability, generalizability and boundary conditions of the effect, these findings advance our understanding of the underlying mechanisms of go/no-go training, provide more insights into how the training can be effectively applied, and raise new theoretical questions on how mere action versus inaction impacts preferences.

Keywords: preference, food choice, go/no-go task, stimulus-response association, behavioral change

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Everyday life presents numerous occasions in which we need to indicate our preferences by making choices. From the mundane situations of deciding which clothes to wear and what foods to eat, to more important decisions such as which job to take and where to live, preferences are expressed in all the choices that we make in various life domains. It is therefore important to understand how preferences are formed and may be modified.

While some preferences are innate (e.g., preferences for sugary, salty and fatty foods; Breslin, 2013), we humans can also acquire new preferences and modify existing ones (including some innate preferences) by learning from experiences. One prominent form of learning is reinforcement learning, in which different courses of action lead to either reward or punishment (Sutton & Barto, 1998). After an organism learns the contingencies between its responses and the rewarding or punishing outcomes, responses that lead to reward become preferred and are more likely to occur again than responses that lead to punishment (*the law of effect*; Thorndike, 1911). The principles of reinforcement learning play an important role in the creation and modification of preferences, and have been

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implicated in many recent models of decision-making (e.g., Dayan & Niv, 2008; Doya, 2008; Rangel, Camerer, & Montague, 2008).

Interestingly, some recent work suggests that simple responses that are not reinforced by reward or punishment may also lead to preference change (Schonberg et al., 2014). For instance, consistently responding to certain objects (e.g., pressing a key on a keyboard; go items) and withholding responses toward other objects (no-go items) have been shown to create preferences for go items over no-go items under some conditions (Bakkour et al., 2016; Schonberg et al., 2014; Veling, Chen, et al., 2017; Zoltak, Veling, Chen, & Holland, 2018). Notably, no reward or punishment was delivered after the go/no-go responses in these experiments, suggesting that manipulating nonreinforced go/no-go responses toward objects can change people's preferences. However, it is unclear whether mere action versus inaction per se, or other processes that accompany the execution or restraint of responses (e.g., attentional process), lead to the preference change effect. Understanding the role of mere action versus inaction in the modification of preferences is important, as human behaviors, despite their apparent diversity, can be reduced into two fundamental categories: the execution of behavioral responses, or the absence thereof (Guitart-Masip, Duzel, Dolan, & Dayan, 2014). In the current research, we are hence interested in when and how linking mere action versus inaction to objects in the absence of other potentially confounding factors can influence people's preferences for these objects.

Different tasks have been used to manipulate responding versus not responding to objects, such as the stop-signal training (SST; Lawrence, Verbruggen, Morrison, Adams, & Chambers, 2015; Wessel, O'Doherty, Berkebile, Linderman, & Aron, 2014), the cue-approach training (CAT; Schonberg et al., 2014), and the go/no-go training (GNG; Veling, Holland, & van Knippenberg, 2008). In all three trainings, participants are presented with images of different objects and asked to execute or withhold a simple response (e.g., press a key on a keyboard) depending on a cue (or the absence of cue) that is presented in close temporal proximity with the image. The pairing between an item and a response cue is often consistent, so that for some items participants always respond, while for other items they always do not respond during the training.

Importantly, some procedural differences exist between the trainings. In SST, no-go trials are accompanied by a no-go cue, while no cue is presented on go trials. The training contains more go trials than no-go trials. The reverse is true for CAT: only go cues are used, and the training contains more no-go trials than go trials. Because of these differences between the go and no-go trials in SST and CAT, effects of SST and CAT on preferences may not be completely explained by mere action versus inaction. For instance, effects of CAT on preferences have been explained by sustained attention rather than by mere motor responses (Bakkour et al., 2016). In contrast, the go and no-go trials in GNG are closely matched. Both go trials and no-go trials in GNG are accompanied by a cue that signals to respond or not respond, respectively. Furthermore, GNG generally includes an equal number of go and no-go trials. We therefore used GNG in the current research to assess whether mere action versus inaction can impact preferences.

Although manipulating go/no-go responses toward objects with GNG has been shown to change people's preferences (Porter et al., 2018; Veling, Aarts, & Stroebe, 2013a, 2013b), the mechanisms underlying the preference change effect have remained unclear. In the current research, we investigated three important theoretical questions concerning the effect of GNG on preferences, namely (a) whether the effect would be influenced by the amount of decision time used to indicate one's preference; (b) the durability of the preference change effect; and (c) whether the initial reward value of objects would moderate the effect. As explained below, answering these three questions provides insights into when merely responding versus not responding to objects can lead to preference change, and advances knowledge on the underlying mechanisms that give rise to this effect.

Decision Speed

Decision speed, or information processing speed in general, features prominently in decades of theorizing on judgment and decision-making (Kahneman, 2011). Based on processing speed, some models have dichotomized mental processes into one of two distinct types, one that is fast and impulsive, and one that is slow and reflective (e.g., the reflective-impulsive model; Strack & Deutsch, 2004). Other models have treated processing speed as a continuum where more time allows for the integration of more information into a decision process (e.g., Berkman, Hutcherson, Livingston, Kahn, & Inzlicht, 2017; Forstmann, Ratcliff, & Wagenmakers, 2016; Krajbich, Armel, & Rangel, 2010). Both types of models converge on the idea that decisions differ as a function of decision speed, with fast decisions based on more basic information that is readily accessible. For instance, when making food choices, fast choices tend to be more strongly based on basic features such as tastefulness rather than more complex features such as healthfulness (Friese, Hofmann, & Wänke, 2008; Sullivan, Hutcherson, Harris, & Rangel, 2015).

GNG has been proposed as a useful behavior change intervention, because it may change behavior under conditions where people do not take much time to think about their responses. Specifically, the reflective-impulsive model (Strack & Deutsch, 2004) has been used as a theoretical framework to explain the effects of GNG (e.g., Veling, Aarts, & Papies, 2011; Veling, van Koningsbruggen, Aarts, & Stroebe, 2014). According to the reflective-impulsive model, repeatedly executing certain responses toward objects in people's daily lives (e.g., approach and consume palatable foods) may lead to the acquisition of associative links between the objects and responses. Once acquired, the associative links can strongly impact people's behavior when time is limited and people do not carefully reflect on their behaviors (e.g., the mere perception of palatable foods may trigger approach tendency; Seibt, Häfner, & Deutsch, 2007). To change people's behavior then, GNG can be used to modify these learned associative links, so that behavior is changed even when people do not carefully reflect on their behaviors. However, evidence for this claim is lacking, as to date no study compared the effects of GNG between situations where people can think about what to do and situations where this opportunity for reflection is reduced.

To complicate matters, some findings seem to suggest the opposite, that GNG influences behavior when there is sufficient time to think about one's responses. Specifically, responding or not responding to objects has been shown to reliably change evaluations of these objects (i.e., no-go items are evaluated less positively than go or untrained items), when evaluation was assessed with explicit self-reports (Chen, Veling, Dijksterhuis, & Holland, 2016, Chen, Veling, Dijksterhuis et al., 2018; Doallo et al., 2012; Frischen, Ferrey, Burt, Pistchik, & Fenske, 2012; Lawrence, O'Sullivan et al., 2015; Veling et al., 2008). In these studies, participants had unlimited time to indicate their evaluations. In contrast, a meta-analysis indicates that when evaluations are assessed with the implicit association test, a reaction time (RT) measure that encourages speeded responses (Greenwald, McGhee, & Schwartz, 1998), no effects of GNG on evaluation are found (Jones et al., 2016). These results thus seem to suggest that GNG changes behavior in situations where there is enough time to reflect on one's responses.

It is thus unclear whether preference change induced by GNG would be weaker or stronger depending on the amount of decision time available for making choices. GNG may modify associations with objects (e.g., associations between objects and basic affective or motor responses), which may be quickly incorporated into a decision process (Berkman et al., 2017; Strack & Deutsch, 2004). In that case, effects of GNG may be more visible when people have little time to indicate their preferences. Alternatively, GNG may modify one's explicit knowledge about go or no-go items, such as explicit evaluations or knowledge about the contingencies between specific items and responses, which may require more time to be incorporated into a decision. This would mean that the effects of GNG might be stronger when there is more time for making choices. To gain insight into this question, we examined whether the effect of GNG on preferences depends on how much time people have for making choices, and for this we manipulated the amount of decision time available in the choice task. Since decision time varies on a continuum, we also conducted an exploratory analysis, in which decision time was used as a continuous predictor of choice.

The Durability of Preference Change

The second important question concerns the durability of the effects induced by GNG. A recent meta-analysis on the effects of GNG and SST on health behavior showed that when behavior was assessed one to seven days after training, the overall effect size was already smaller than immediately after training (Allom, Mullan, & Hagger, 2016). However, because different measures were often used at different time points, it is unclear whether this decrease in effect size truly reflects the decay of the training effects, or is due to the different measurements employed to assess behavior. To overcome this problem, and to have an objective measure of the effect size of the potential decay, we measured preference both immediately after training and one week later in the current research, with the same behavioral measurement.

Note that the seemingly short-term influence of GNG on behavior stands in stark contrast to preference change induced by CAT, which has been shown to be highly durable in retest sessions performed 1 to 6 months after training (Salomon et al., 2018; Schonberg et al., 2014). Strikingly, in a 6-month follow-up study in Salomon et al. (2018), participants still preferred go items around 60% of the time, showing a decrease of merely four percentage points compared with immediately after training. One explanation for this potential difference in the longevity of training effects by GNG and CAT are the different processes via which the trainings influence behavior. Another explanation may be the different dependent measurements used in these two lines of research. Till now, almost all studies with CAT have used choice as the dependent measurement (Bakkour et al., 2016; Salomon et al., 2018; Schonberg et al., 2014; Veling, Chen et al., 2017; Zoltak et al., 2018), whereas studies with GNG have employed a wide range of behavioral measures, with choice occasionally measured as the outcome of training (Porter et al., 2018; Veling et al. 2013a, 2013b). This methodological difference makes the comparison between GNG and CAT difficult. In the current research, we focused on the effect of GNG on choices, and used the same choice task that has been used in previous work on CAT. Our aim was to provide a high-quality dataset on the effect of GNG on choices, which can then allow a comparison between the results obtained by CAT and GNG. Such a comparison will provide insights into which task works better to induce long-term preference change.

The Role of Reward Value

The third question concerns whether the effect of GNG on preferences would be moderated by the reward value of objects. This question is interesting as it potentially pits two accounts that explain the effects of GNG against each other (for a recent theoretical review, see Veling, Lawrence, Chen, van Koningsbruggen, & Holland, 2017). According to the first account, the behavior stimulus interaction theory (BSI theory, Veling et al., 2008), appetitive items automatically trigger approach tendencies that need to be inhibited when a no-go cue is presented. The response conflict resulting from approach tendency and response inhibition is negative (Dreisbach & Fischer, 2015; Fritz & Dreisbach, 2013). The negativity is then attached to no-go items through repeated pairings, thereby decreasing the reward value of (Chen et al., 2016; Veling et al., 2008) and the preference for no-go items.

Repeatedly not responding to an object can also create stimulus-stop associations (Best et al., 2016; Verbruggen, Best, Bowditch, Stevens, & McLaren, 2014; Verbruggen & Logan, 2008). Once formed, response inhibition can be automatically triggered and interferes with responses toward no-go items, for instance reducing the frequency or vigor of responses. Because preference is often expressed with certain responses (e.g., pointing at or grabbing a preferred object), inhibiting responses toward no-go items may hence reduce preferences for no-go items.

These two accounts make different predictions for whether GNG will lead to preference change for low-value items. According to the BSI theory, no-go response changes preferences only when the item possesses high reward value, as response conflict only arises when people have strong initial approach tendencies (Chen et al., 2016; Veling et al., 2008). The stimulus-stop association account, on the other hand, does not assume a causal role of response conflict and predicts preference change for both high-value and low-value items. Most previous work till now has used positive items in the training, and focused on evaluation rather than preference. In the few cases where the effect of GNG on evaluation of neutral or negative items was examined, results were mixed (Chen et al., 2016; Chen, Veling, Dijksterhuis, & Holland, 2018; Frischen et al., 2012; Veling et al., 2008). Systematically examining whether GNG changes preference for low-value items, in addition to high-value items, will therefore be theoretically informative in distinguishing the two accounts.

The Present Research

To address the three questions outlined above, we conducted seven experiments. In all experiments, participants were trained to consistently respond to certain food items (both of high value and of low value; go items) and withhold their responses toward other food items (no-go items) in GNG. After the training, they repeatedly chose between go and no-go items in a food choice task for consumption, with either limited (1.5 s for each choice; Experiments 2, 4–7; see Schonberg et al., 2014; Veling, Chen, et al., 2017) or unlimited time (Experiments 1 and 3). The durability of preference change was explored by measuring preferences both immediately following training and 1 week later (Experiments 4–6). For a summary of the key design features across all experiments, see Table 1. Food choice was selected as the main dependent variable, to enable comparisons with previous work (Schonberg et al., 2014; Veling et al., 2013b). A second reason for targeting food choice is that many people nowadays are struggling with making healthy food choices. With the rising rate of overweight and obesity worldwide (World Health Organization, 2016), our ability to address the obesity epidemic depends on our understanding of how food choices may be changed.

For the sake of transparency, we preregistered all seven experiments. Preregistrations containing planned sample sizes, analysis plans, and directional hypotheses can be found at https://osf.io/zy9w3/. Experimental materials (stimuli and Python scripts), raw data, and analyses scripts are also available. For deviations from preregistrations and the reasons for deviations, see Footnotes 1 and 2.

At the start of the project, we predicted preference change for high-value items when people have unlimited time. This prediction was based on the findings that GNG reliably devalued high-value items when evaluation was measured with explicit self-report without time pressure (Chen et al., 2016; Veling et al., 2008). To preview the results, we found that GNG led to preference change for both high-value and low-value items when decision time was limited, but not when people chose with unlimited time. Preference change was still observed one week after training, but the effect size was smaller than immediately after training. Our theoretical stance was adjusted based on the observed results during the project. Specific predictions can be found in the introduction for each experiment and in the preregistrations.

Experiment 1: Slow Choice

In Experiment 1, we investigated the effect of GNG on preference when people had unlimited decision time. As mentioned above, a priori we expected GNG to lead to preference change for high-value items. For low-value items, we expected no effect. We also measured the value of food items after training with an auction task, in which no time limit was implemented. In line with previous work of GNG on evaluation (Chen et al., 2016; Chen, Veling, Dijksterhuis et al., 2018; Veling et al., 2008), we expected reduction in the reward value of no-go items compared with go items, but again only for high-value items.[1]

Method

Sample size. Previous work on the effect of GNG on food evaluation estimated the effect size of devaluation to be around Cohen's $d_z = 0.537$ (Chen et al., 2016). Assuming the effect of GNG on preference is similar to that on evaluation, we used this estimate as the expected effect size. Power analysis with G*Power 3 (Faul, Erdfelder, Lang, & Buchner, 2007) suggested 30 participants for achieving 80% power (alpha level of 0.05, paired-samples t test). We therefore planned to recruit 30 participants for Experiment 1. In Experiments 1 and 2, mostly undergraduate students at the University of Amsterdam were recruited as participants. In Experiments 3–7, mostly undergraduate students at Radboud University were recruited. Repeated participation was not allowed, to ensure that each experiment would contain different samples. The ethics committee at the department of psychology at the University of Amsterdam and the ethics committee at the Faculty of Social Sciences at Radboud University provided ethical approvals. All participants provided written informed consent before participating in the experiments.

Participants. Thirty-one participants[2] took part in Experiment 1. Based on the preregistered exclusion criteria (a) participants who were not between 18- and 26-years-old; (b) participants who bid less than 25 cents on more than 40 food items in the first auction task; and (c) participants whose accuracy on go or no-go trials in the training was 3 *SD* below sample mean *and* below 90%, seven participants were excluded, leaving 24 participants in the final sample. For an overview of exclusion based on each criterion for all experiments, see Table S1 in the online supplemental materials.

[1] Experiments 1 and 2 were conducted simultaneously, by assigning participants to one of the two conditions in a counterbalanced order. For the sake of consistency with other experiments reported in the current article, we refer to them as two separate experiments. The preregistration for Experiments 1 and 2 contained some inconsistency. In the introduction of the preregistration, we discussed previous work showing that the training effect is more pronounced for items that are perceived to be more appetitive (in line with the BSI theory discussed in the main text). In the Hypotheses section of the preregistration, we accordingly predicted an effect on choices for the high value pairs in the slow choice condition (i.e., Experiment 1), but not for the low value pairs. For the fast choice condition (i.e., Experiment 2), we did not have directional hypotheses. However, regarding the effect of GNG on item value as measured by the auction task, we predicted an effect for both Experiment 1 and 2, but failed to mention that this effect was predicted only for high-value items. Furthermore, in the Analysis Plan part of the preregistration we failed to mention these predictions, and instead described data analyses in an exploratory manner. In the main text, we present directional hypotheses in line with the ones outlined in the Hypotheses part (plus that the effect on the auction task was only expected for high-value items), to stay close to the BSI theory that we subscribed to while conducting the first two experiments. Note that these predictions are actually *not* in line with the results we observed. Furthermore, the preregistration failed to mention that in the choice task with time limit (i.e., Experiment 2), when participants failed to choose within 1.5 s, the image would be replaced by a prompt saying "Choose Faster!" for 500 ms. This prompt was actually used when conducting the experiments. The Method section in the main text now correctly mentions the use of this prompt when time limit was used in the choice task.

[2] The number of participants recruited exceeded the planned sample size by one in Experiment 1, 2, and 7. This is because participants registered for the experiments via an online participation system, and despite the experimenters' close monitoring, the number of sign-ups exceeded the planned sample size before the sign-up portal could be closed. In the interest of retaining all data, we decided to not discard the data from the extra one participant for these three experiments. An overview of planned sample size and exclusion of participants for all experiments can be found in Table S1 in the online supplemental materials.

Table 1
Summary of Experimental Designs

Experiment	Stimulus	Go/No-Go proportion	Training length	Decision speed	Delay (range)
Exp. 1	Snacks	75%/25%	8	Slow	—
Exp. 2	Snacks	75%/25%	8	Fast	—
Exp. 3	Candies	50%/50%	6	Slow	—
Exp. 4	Candies	50%/50%	6	Fast	12.4 (7–19)
Exp. 5	Candies	50%/50%	10	Fast	8.1 (7–14)
Exp. 6	Candies	50%/50%	14	Fast	8.3 (7–14)
Exp. 7	Snacks, fruits, and vegetables	50%/50%	10	Fast	—

Note. Go/No-Go proportion = the proportion of Go trials and the proportion of No-Go trials in the training. Training length = the number of repetitions for stimuli in training. Decision speed = fast: 1.5-s time limit; slow: no time limit.

Materials. Sixty images of high-calorie snacks (e.g., chips, cookies, chocolate bars, candies etc.) were selected from previous work (Veling, Chen et al., 2017). On each image, both the packaging and content were clearly visible against black background. All snacks were available in local supermarkets and familiar to participants. The tasks were programmed in PsychoPy (Peirce, 2007) and executed individually for each participant.

Procedure.

Preparation. Participants were asked to not eat anything for at least 3 hr before coming into the lab (drinking water was allowed). Upon arrival, they were asked to verbally report the last time of food consumption to the experimenter. Those who did not adhere to the fasting requirement were asked to reschedule the experiment.

Pretraining auction. Participants first received 2 euros (1 euro, 50 cent, 20 cent, 2*10 cent, and 2*5 cent) from the experimenter to bid in an auction task based on the Marschak-DeGroot-Becker procedure (Becker, DeGroot, & Marschak, 1964), which has been used to assess the willingness to pay (WTP) for snacks in previous work (Schonberg et al., 2014; Veling, Chen et al., 2017). For each of the 60 snacks, they were asked to place a bid by moving a mouse cursor along an analog scale that ranged from 0 to 2 euro (see Panel A of Figure 1). They were told that at the end of the experiment, the program would randomly pick one snack and generate a bid for the selected snack. If their bid was higher than the bid from the computer, they could buy the snack at the computer's bid. To reduce the number of snacks we needed to purchase, we had a selection of snacks in the lab and the program picked one snack out of this reduced selection. For a more detailed description of the auction rules, see the OSF repository.

Item selection. After participants placed bids for all 60 snacks, the program rank ordered the snacks from the highest WTP to the lowest. Eight relatively high-value items (ranked from eight to 15) and eight relatively low-value items (ranked from 46 to 53) were selected for each participant and divided into the go and no-go condition in a counterbalanced manner. This division procedure ensured that the average WTP of go and no-go items was matched before training, for high-value and low-value items separately. Another eight items (four relatively high-value and four relatively low-value) were further selected into the no-go condition and used on the filler trials in the choice task (see Food Choice section below). In total, 16 snacks were assigned to the no-go condition, and the remaining 44 to the go condition. For the selection procedure, see Figure S2 in the online supplemental materials.

Go/no-go training. Participants then received the GNG (Panel B of Figure 1). In the training, one snack image was presented on each trial. One-hundred milliseconds after image onset, a beep was played via headphone. Two different beeps were used as the go and no-go cue, respectively (frequencies 1000 Hz and 400 Hz, duration 300 ms; the assignment of beeps as go and no-go cues was counterbalanced across participants). If the played beep was a go cue, participants needed to press the B key on the keyboard as fast as possible; if it was a no-go cue, they should not respond. In both conditions, the images stayed on screen for 1 s to control for exposure time. The intertrial interval randomly varied between 1.5 and 2.5 s, in steps of 100 ms. Participants first received a practice block of eight trials, during which an incorrect response was followed by an error message (X in red) for 500 ms. The images used in the practice block were not used in the experimental blocks. In the experimental blocks, no performance feedback was provided after each trial, but the overall accuracy was provided after every two blocks. Each image was randomly presented once in each experimental block, and the whole training consisted of 8 blocks, resulting in 480 trials in total.

Food choice. Participants then received a food choice task (Panel C of Figure 1). On each trial, two snacks were presented side by side, and participants chose by pressing the U (left) or the I (right) key. They were told that at the end of the experiment, one trial would be randomly selected and they would receive the snack chosen on the selected trial. Two rigged trials were added to the end of the choice task, with snacks that were available in the lab, so that we did not need to purchase all 60 snacks. The choice task consisted of two types of trials, the experimental trials and the filler trials. On the experimental trials, the two snacks had matched value (both high or both low, 32 unique pairs in total); one was paired with go responses in the training, whereas the other was paired with no-go responses. On the filler trials, both snacks were paired with go or no-go responses; one had high value, whereas the other had low value (32 unique pairs in total). Different items were used on the experimental trials and the filler trials. Each pair was presented twice to counterbalance the left-right position. The whole task consisted of 128 trials (excluding the two rigged trials). Participants received unlimited time for each choice. After participants chose, the chosen item was surrounded by a yellow frame for 500 ms as confirmation. The intertrial interval varied between 1.0 and 2.0 s, in steps of 100 ms.

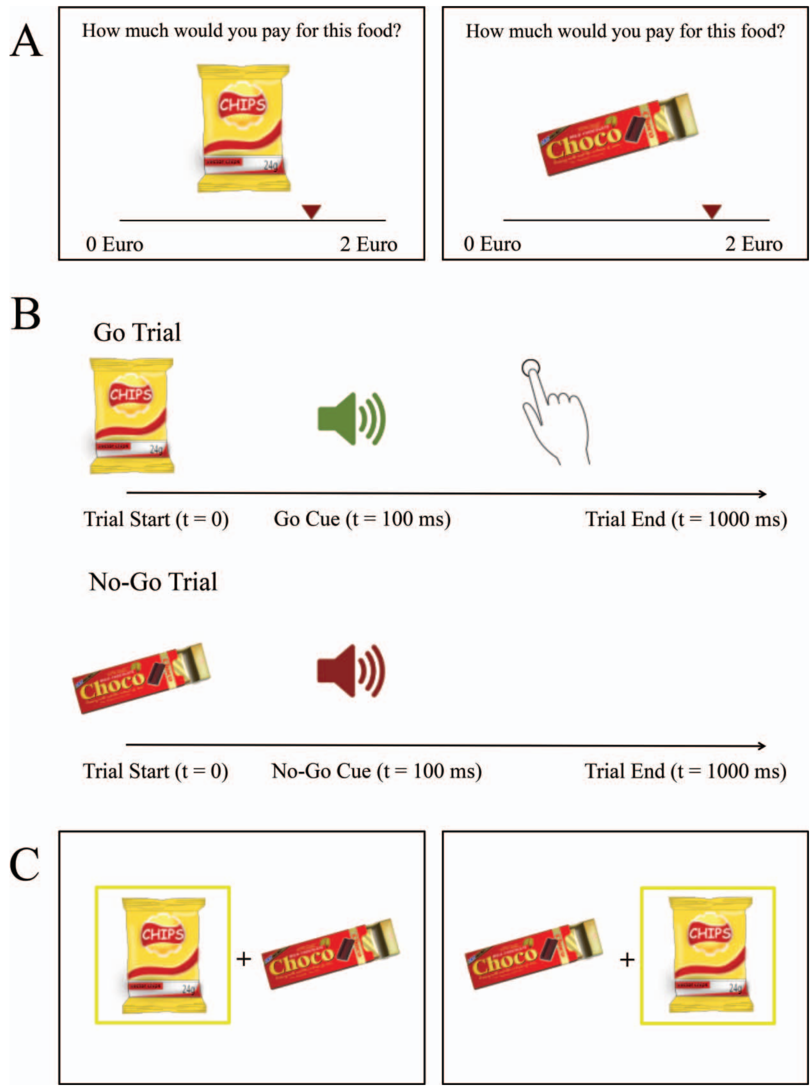

Figure 1. Sequence of main experimental tasks. (A) Auction task in Experiment 1, 2, and 7; rating task in Experiments 3–6; (B) The go/no-go training; (C) Binary choice task, with (Experiments 2 and 4–7) or without (Experiment 1 and 3) time limit. In Experiments 4–6, binary choice task (C) was repeated in retest session. Images are for illustration. For the stimuli and the scripts used in the experiments, see the OSF repository. See the online article for the color version of this figure.

Memory recognition. A memory recognition task was included to assess participants' memory of the snack-response contingencies. For each snack, they indicated whether it had been paired with pressing B (i.e., go response) or not (i.e., no-go response) during GNG.

Posttraining auction. To measure changes in food value, participants then received a second auction task, with the same auction rules as the one they received before the training.

Demographics. Finally, participants filled out demographic information such as height, weight, whether they were currently on a diet, current hunger level (−100 = *not hungry at all*; 100 = *very hungry*), number of hours since last food consumption, and the restraint eating scale (van Strien, Herman, Engels, Larsen, & van Leeuwe, 2007). Age and gender were reported when the experimental program was started. After answering the demographic questions, all participants received one snack based on a trial selected from the choice task (i.e., one of the two rigged choice trials). If they won the auction, they received a second snack. Participants were then debriefed, compensated, and thanked.

Results

Main analyses (repeated-measures logistic regression and multilevel models) were conducted with the lme4 package in R (Bates, Maechler, Bolker, & Walker, 2015; R Core Team, 2017). For a summary of participant demographics (Table S2), performance in GNG (Table S3), and performance in the memory recognition task (Table S4), see the corresponding tables in the online supplemental materials. An exploratory analysis on the development of GNG performance across blocks is also reported in the online supplemental materials.

Food value. To check the selection procedure, the average WTP of the items selected for the experimental choice trials (eight high-value and eight low-value items, divided into go and no-go condition) was calculated for each participant, and then submitted to repeated-measures ANOVA with training condition (go vs. no-go) and value level (high vs. low) as independent variables. As can be seen from Table 2, participants were willing to pay more for high-value items than for low-value items. More importantly, the main effect of training condition was not significant, indicating that the selection procedure succeeded in selecting go and no-go items with matched WTP before training.

To see whether the training influenced the value of snacks, a repeated-measures ANOVA was conducted, with measurement time (before vs. after training), value level (high vs. low) and training condition of items (go vs. no-go) as the independent variables, and the average WTP before and after training as the dependent variable. The interaction effect between measurement time and training condition of items was close to, but did not reach statistical significance, $F(1, 23) = 3.92$, $p = .060$, $\eta^2 = .002$. Before the training, there was no significant difference in WTP between go and no-go items; after the training, participants were willing to pay more for the go items ($M_{\text{high}} = 1.083$, $SD = 0.43$; $M_{\text{low}} = 0.437$, $SD = 0.35$) than for the no-go items ($M_{\text{high}} = 0.982$, $SD = 0.48$; $M_{\text{low}} = 0.429$, $SD = 0.36$), although this main effect of training condition on posttraining WTP was not statistically significant, $F(1, 23) = 3.64$, $p = .069$, $\eta^2 = .007$. Although after training, the value difference between go and no-go items was numerically larger for high-value items ($M_{\text{diff}} = 0.101$) than for low-value items ($M_{\text{diff}} = 0.008$), the interaction effect between value level and training condition on posttraining WTP, however, was not statistically significant, $F(1, 23) = 1.82$, $p = .190$, $\eta^2 = .005$.

Food choices. Choices from the experimental trials, where go items were paired with similarly valued no-go items, were analyzed with repeated-measures logistic regression.[3] Overall, participants did not choose go items more often than chance level, mean proportion of go choices = 53.0%, odds ratio (OR) = 1.14, 95% CI [0.87, 1.50], $p = .327$ (see Figure 2, upper panel). Contrary to our expectation, for both the high-value and low-value choice pairs, participants did not choose go items significantly more often than no-go items, mean proportion of go choices = 55.1%, OR = 1.26, 95% CI [0.90, 1.78], $p = .183$ and mean proportion = 50.9%, OR = 1.06, 95% CI [0.56, 2.00], $p = .869$, respectively. Although numerically participants did choose go items more often for the high-value pairs than for the low-value pairs, the difference was not statistically significant, OR = 1.19, 95% CI [0.55, 2.59], $p = .653$ (Figure 2, lower panel).

On the filler trials, participants chose between high-value and low-value items, where both items were paired with go or no-go responses in the training. Repeated-measures logistic regression showed that participants chose high-value items more often than chance level, mean proportion of choosing high-value items = 83.7%, OR = 9.69, 95% CI [5.06, 18.57], $p < .001$ (see Figure 3). For a summary of the choices on the experimental and filler trials, as well as the median choice RTs in each experiment, see Table 3. For brevity we will not discuss the result on decision time per experiment, but will instead analyze the data from all experiments combined in the end.

Discussion

Contrary to our predictions, participants did not choose go items more often when they had unlimited decision time. Furthermore, the proportion of go choices did not differ significantly between high-value and low-value pairs. This absence of effect on the experimental trials cannot be explained by participants' indifference or lack of motivation, as they showed a strong preference for high-value items on the filler trials that were intermixed with the experimental trials. Results on posttraining value were in the expected direction, but did not reach statistical significance.

Due to the large number of excluded participants, the final sample consisted of 24 participants. The experiment may therefore have been underpowered. This potential problem of insufficient power was addressed in later experiments (Experiments 3–7) by doubling the sample size. Next, we continue with the investigation on the role of decision time and report the effect of GNG on preference when people made choices with time limit in Experiment 2.

Experiment 2: Fast Choice

In Experiment 2, participants made choices under time limit (1.5 s for each choice) after training. A priori we did not have directional hypothesis for whether GNG would influence such fast choices. For the posttraining auction task with no time limit, similar to Experiment 1, we expected a devaluation effect for high-value no-go items, but not for low-value no-go items.

Method

Participants. Thirty-one participants participated in Experiment 2. Based on the preregistered exclusion criteria (a). participants who were not between 18- and 26-years-old; (b) participants who bid less than 25 cents on more than 40 food items in the first auction task; (c) participants whose accuracy on go or no-go trials in GNG was 3 *SD* below sample mean *and* below 90%, two participants were excluded, leaving 29 participants in the final sample.

Procedure. The procedure of Experiment 2 was identical to Experiment 1, except that in the choice task participants had 1.5 s for each choice. If they did not choose in time, the current pair of snacks would be replaced by a prompt saying "Choose Faster!" for 500 ms. The missed trial would be presented again at a later point until they chose in time. If participants chose in time, the chosen snack was surrounded by a yellow frame for 500 ms as confirmation.

Results

Food value. To investigate the effect of GNG on food reward value, we carried out a repeated-measures ANOVA on WTP

[3] Note that we preregistered repeated-measures logistic regression as the planned analysis, while in power analysis we used paired-samples *t* test as the planned analysis when calculating power. This inconsistency was resolved from Experiment 3 on. See Footnote 4 for a power simulation based on repeated-measures logistic regression.

Table 2
Value of Go and No-Go Items Before Training

Experiment	High value: Go	High value: No-Go	Low value: Go	Low value: No-Go	Go vs. No-Go
Exp. 1	1.11 (.30)	1.11 (.29)	.29 (.29)	.29 (.29)	$F(1, 23) = 1.38$, $p = .252$
Exp. 2	1.16 (.30)	1.16 (.31)	.43 (.31)	.43 (.30)	$F(1, 28) = .01$, $p = .931$
Exp. 3	1.58 (.32)	1.58 (.32)	.35 (.37)	.36 (.37)	$F(1, 59) = 1.87$, $p = .176$
Exp. 4	1.58 (.30)	1.58 (.29)	.27 (.29)	.28 (.29)	$F(1, 62) = .09$, $p = .764$
Exp. 5	1.52 (.24)	1.52 (.23)	.40 (.31)	.41 (.30)	$F(1, 56) = 1.58$, $p = .214$
Exp. 6	1.53 (.29)	1.53 (.28)	.37 (.32)	.38 (.32)	$F(1, 58) = 2.46$, $p = .123$
Exp. 7	.92 (.41)	.91 (.41)	.78 (.45)	.78 (.44)	$F(1, 69) = .15$, $p = .696$

Note. In Experiment 7, the high value level refers to unhealthy foods, and the low value level refers to healthy foods. Standard deviations are reported in parentheses.

before and after training, with measurement time (before vs. after training), value level (high vs. low), and training condition of items (go vs. no-go) as independent variables. The interaction effect between measurement time and training condition of items was statistically significant, $F(1, 28) = 4.52$, $p = .043$, $\eta^2 = .001$. While before the training, there was no difference in WTP between go and no-go items (see Table 2), after the training, the main effect of training condition was statistically significant, $F(1, 28) = 4.68$,

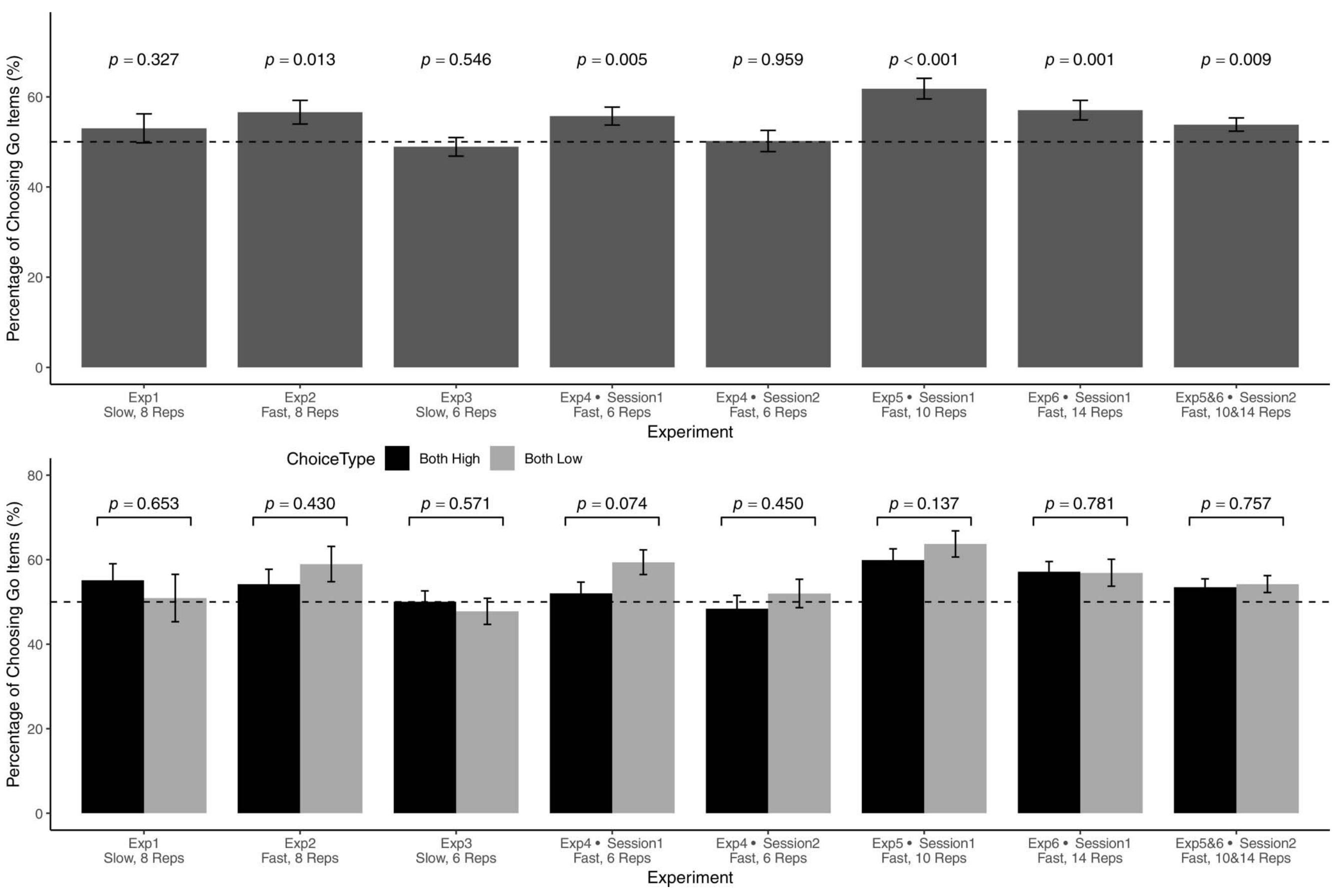

Figure 2. Probability of choosing go items on experimental trials in Experiments 1–6, combining (upper panel) and separating (lower panel) high-value and low-value choice pairs. Slow indicates choices made without time limit and fast indicates choices made within 1,500 ms. Reps indicates how many times the go and no-go items were presented in the training. The *p* values in the upper panel are calculated from repeated-measures logistic regression comparing the overall probability of choosing go items against the 50% chance level. The *p* values in the lower panel are calculated from repeated-measures logistic regression comparing the probability of choosing go items between high-value and low-value pairs. Error bars stand for standard errors of mean proportions.

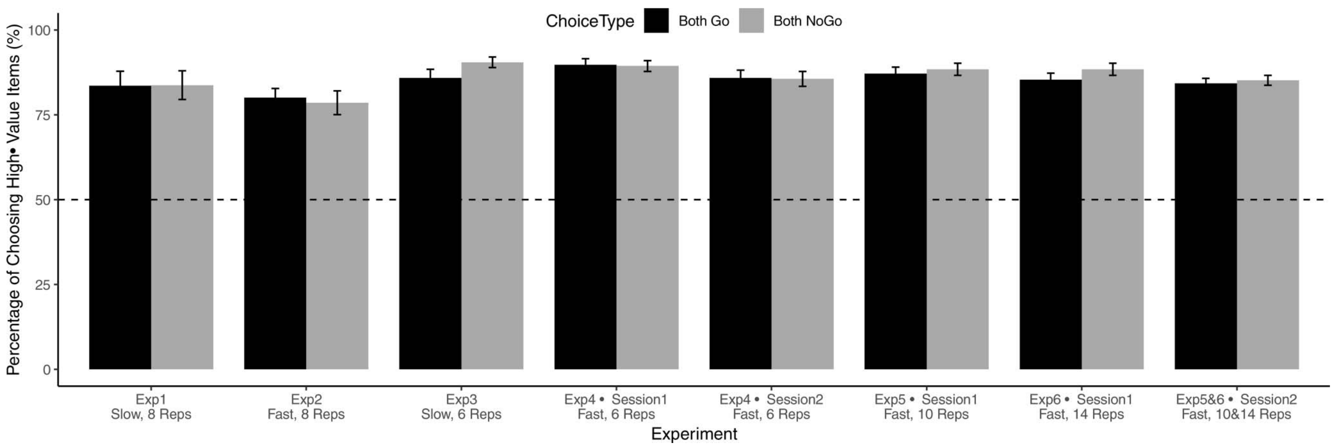

Figure 3. Probability of choosing high-value items on filler trials in Experiments 1–6, separated for both go and both no-go pairs. Slow indicates choices made without time limit and fast indicates choices made within 1,500 ms. Reps indicates how many times the go and no-go items were presented in the training. Error bars stand for standard errors of mean proportions.

p = .039, η^2 = .004. Participants were willing to pay more for go items (M_{high} = 1.094, SD = 0.40; M_{low} = 0.579, SD = 0.42) than for no-go items (M_{high} = 1.080, SD = 0.38; M_{low} = 0.512, SD = 0.35). However, the training was not more effective for high-value items, as the interaction effect between training condition and value level on posttraining WTP was not statistically significant, $F(1, 28)$ = 0.66, p = .424, η^2 = .002. If anything, the value difference between go and no-go items was numerically larger for low-value pairs (M_{diff} = 0.067) than for high-value pairs (M_{diff} = 0.014) after the training, opposite to the initial prediction.

Food choices. When choosing with time limit, participants overall chose go items significantly more often, mean proportion = 56.6%, OR = 1.32, 95% CI [1.06, 1.64], p = .013. Furthermore, participants chose go items more often for low-value pairs than for high-value pairs (Figure 2, lower panel), but the difference was not statistically significant, OR = 1.24, 95% CI [0.73, 2.11], p = .430. On the filler trials, participants chose high-value items more often, mean proportion = 79.3%, OR = 4.78, 95% CI [3.34, 6.83], $p < .001$ (see Figure 3). This shows that even under such strict time limit (see Table 3 for median choice RTs), participants still could assess the value of the snacks and make value-based decisions.

Discussion

GNG increased people's preferences for go items when they chose quickly. The initial value of snacks did not seem to moderate the effect, as participants chose go items similarly often for high-value pairs and for low-value pairs (if anything, they seemed to choose go items more often for low-value pairs). These fast choices were meaningful choices, as participants were well informed that they were choosing snacks for real consumption. In addition, on the filler trials participants overall preferred high-value over low-value items, suggesting that they could make value-based decisions within the strict time limit of 1.5 s.

GNG also influenced the value of go and no-go items as assessed by the auction task. Participants were willing to pay more for the go snacks than for the no-go snacks after training, while before the training the two were matched in WTP. Similar to the findings on choices, this effect was not moderated by the reward

Table 3
Percentages of Choosing Go Items on Experimental Trials and of Choosing High-Value Items on Filler Trials

	Experimental trials			Filler trials		
Experiment (decision speed)	HV pairs	LV pairs	Median choice RT	Go pairs	No-Go pairs	Median choice RT
Exp. 1 (slow)	55.1% (19.4%)	50.9% (27.5%)	1142.6 (409.8)	83.6% (20.8%)	83.7% (20.7%)	908.8 (290.2)
Exp. 2 (fast)	54.2% (19.0%)	58.9% (22.5%)	744.9 (107.9)	80.1% (14.3%)	78.6% (18.7%)	715.7 (95.9)
Exp. 3 (slow)	50.1% (19.9%)	47.8% (24.0%)	1460.0 (703.4)	85.9% (19.8%)	90.5% (12.0%)	1119.7 (484.6)
Exp. 4 (fast)	52.0% (21.0%)	59.4% (23.1%)	749.0 (106.2)	89.8% (13.9%)	89.4% (12.6%)	681.6 (89.8)
Exp. 4—Retest (fast)	48.4% (21.4%)	52.0% (23.0%)	700.5 (104.6)	85.9% (15.3%)	85.6% (15.1%)	647.3 (93.6)
Exp. 5 (fast)	59.9% (20.4%)	63.7% (23.3%)	742.0 (115.7)	87.2% (14.0%)	88.4% (13.6%)	691.5 (100.8)
Exp. 6 (fast)	57.2% (18.3%)	56.9% (24.6%)	748.6 (103.2)	85.3% (14.9%)	88.4% (13.6%)	701.8 (92.7)
Exp. 5 and 6—Retest (fast)	53.5% (21.2%)	54.2% (21.3%)	697.0 (98.1)	84.2% (16.3%)	85.2% (15.4%)	659.3 (90.4)
Exp. 7 (fast)	62.1% (20.9%)	60.8% (21.7%)	704.0 (142.9)	—	—	—

Note. HV pairs = High-value pairs; LV pairs = Low-value pairs. Choice RTs are reported in ms. Standard deviations are reported in parentheses.

value of items. If anything, value change induced by training was larger for low-value items than for high-value items, which is not in line with the BSI theory. However, because the second auction task was conducted after the choice task, this change in value could either be caused by GNG, or by the choice task preceding the second auction task. The current design does not allow us to disentangle these two possibilities, and we will focus on the effect of GNG on choice rather than value in the remainder of this article.

Experiment 3: Slow Choice

In Experiment 3, we aimed to repeat and extend Experiment 1, by recruiting more participants, and using different stimuli and a different task for measuring value. Because the results of Experiment 1 and 2 were not in line with our initial predictions, for this experiment a priori we did not have directional hypotheses.

Method

Sample size. In Experiment 3, we planned to recruit between 60 and 65 participants. This increase in sample size was motivated by the observation that due to the exclusion of participants, the final sample size was smaller than the planned sample size in Experiments 1 and 2. Doubling the sample size left more room for potential exclusion. In Experiments 1 and 2, paired-samples *t* test was used as the planned test in power analysis, whereas when analyzing the choice data, repeated-measures logistic regression was used. To resolve this inconsistency, we simulated data to evaluate the power of repeated-measures logistic regression with 60 participants. Power simulation suggested that with 60 participants, we have around 90% power at an alpha level of .05, with repeated-measures logistic regression as the planned test and Cohen's *d* of 0.5 as the expected effect size. Details on the power simulation can be found in Footnote 4.[4]

Participants. Sixty participants took part in the experiment, and no participant met the preregistered exclusion criterion (accuracy on go or no-go trials in the training 3 *SD* below sample mean *and* below 90%). For why we only used GNG performance as the exclusion criterion in the current experiment, see Footnote 5.[5]

Materials and procedure. Experiment 3 was similar to Experiment 1, except a few changes. First, instead of using snacks, we used images of 60 different candies (e.g., gummies, hard candies, nougats, chocolate, etc.). All candies were purchased from local candy stores and familiar to participants. Each type of candies was placed on a white plate against gray background, and arranged to occupy a similar amount of area on the plate.

Second, instead of using an auction task, in Experiment 3 we used a rating task in which participants reported how much they wanted to eat each of the candies at that moment by using a 200-point scale (0 = *not at all*; 2 = *very much;* see Krajbich et al., 2010, where a similar question was used to probe the value of food items). Because of the small amount of candies on each image (e.g., two nougats, six gummy bears), monetary bids may not be sensitive enough to the variation in reward value as participants might bid relatively low for all items. We therefore used the rating task instead when candies were used as stimuli (Experiments 3–6). The auction task was used again in Experiment 7 where snacks, fruits, and vegetables were used as stimuli.

Third, in Experiments 1 and 2, all 60 images were used in the training. The GNG contained more go trials (around 75%) than no-go trials (around 25%). In Experiment 3, only the 32 selected images were used in the training: of which 16 were paired with no-go responses and 16 with go responses. The GNG in Experiment 3 and all following experiments thus contained an equal number of go and no-go trials (see Table 1 for an overview). This change enabled us to better isolate the effect of mere action versus inaction on preferences. The selection procedure in Experiment 3 was the same with the one used in Experiment 1 and 2, except that all unselected items were not used. See Figures S2 in the online supplemental materials for the selection procedure.

Lastly, GNG included six blocks (instead of eight) in Experiment 3, resulting in 192 trials in total. In Experiment 3 and all the following experiments, participants did not receive a rating or auction task after training. In short, in Experiment 3 participants received the following tasks in order: rating task, GNG, food choice task without time limit, memory recognition task and demographic questions.

Results

In line with Experiment 1, on the experimental trials, participants did not choose go items more often, mean proportion = 48.9%, OR = 0.95, 95% CI [0.79, 1.13], $p = .546$. The difference between high-value and low-value pairs was not statistically significant, OR = 0.90, 95% CI [0.62, 1.30], $p = .571$. Although we used different stimuli and a different task to assess food value, on the filler trials participants still preferred high-value items, mean proportion = 88.2%, OR = 19.06, 95% CI [11.46, 31.71], $p < .001$, suggesting that they still made value-based choices and that self-reported wanting is a valid measure of food reward value.

[4] For the power simulation, we first defined a beta distribution with Shape Parameters 3 and 2 as the population distribution of the underlying probability of choosing go over no-go items. The mean of this beta distribution is 60%, and the *SD* is 20%, which is comparable with what we observed in the fast choice condition in Experiment 1. Furthermore, this population distribution corresponds to Cohen's *d* of 0.5, which is also close to previous meta-analyzed effect size (Allom et al., 2016). After defining the population distribution, we simulated 10,000 experiments: For each experiment, we randomly sampled 60 data points from the population distribution, and these data points corresponded to the underlying probabilities of choosing go items for 60 subjects. For each subject, we further generated 64 trials with the Bernoulli distribution (0 = no-go, 1 = go; each subject's probability of choosing go items was used as P(1)). Repeated-measures logistic regression was conducted on each simulated experiment. Overall, in about 90% of the 10,000 experiments, the intercepts were significantly higher than 0 at the .05 level. In other words, the current setup has about 90% power to detect the effect.

[5] Note that in Experiments 3 to 7, we removed the exclusion criterion that participants who was not between 18- and 26-years-old would be excluded, and instead used age between 18 and 35 as an eligibility criterion when recruiting participants. The exclusion criterion on age was initially used in Experiment 1 and 2 to ensure homogenous samples for each experiment, which would then enable the comparison of results across experiments. We used a slightly larger age range to facilitate the recruitment of participants for later experiments, while still making the samples homogenous and similar. Furthermore, we also removed the exclusion criterion that participants who bid less than 25 cents on more than 40 snack items would be excluded (except in Experiment 7, where an auction task was again used to assess value of food items). This exclusion criterion is more relevant when an auction task is used, as participants may underbid in order to keep the monetary reward. This strategy is no longer applicable when they are asked to indicate how much they would like to consume different food items, as was the case in the remaining experiments, except Experiment 7.

Discussion

Using a larger sample size, we did not find an effect of GNG on slow choices. The absence of effect in Experiment 1 was thus replicated. This again could not be explained by participants' indifference or lack of motivation, as the choices on the filler trials were clearly guided by the value of candies. Again, there was no significant difference between choices with high-value pairs and with low-value pairs. However, to show that this absence of effect was not due to any procedural changes from Experiments 1 and 2 to Experiment 3 (i.e., difference in stimuli used, tasks for assessing value, length of training), but a genuine moderation effect by decision time, it is important to show the effect of GNG on preferences with time limit again, with the same setup. In Experiment 4, we used the setup from Experiment 3 but added the 1.5-s time limit on choices, to see whether the results from Experiment 2 could be replicated.

Experiment 4: Fast Choice

Experiment 4 was a replication and extension of Experiment 2. We predicted that after training, participants would choose go items more often. Because no significant difference between high-value and low-value pairs had been observed, we did not have a specific hypothesis concerning whether the reward value of items would moderate the effect.

Method

Sample size. As in Experiment 3, we planned to recruit between 60 and 65 participants.

Participants. Sixty-three participants took part in the experiment, and none of them met the preregistered exclusion criterion (accuracy on go or no-go trials in the training 3 *SD* below sample mean *and* below 90%).

Materials and procedure. The procedure of Experiment 4 was the same as Experiment 3, except that in the choice task participants had 1.5 s for each choice.

Results

Replicating the results of Experiment 2 and in line with our prediction, participants chose go items more often on experimental trials, mean proportion = 55.7%, OR = 1.28, 95% CI [1.08, 1.52], $p = .005$. Descriptively, the effect was stronger for low-value pairs than for high-value pairs, but the difference was not statistically significant, OR = 1.40, 95% CI [0.97, 2.03], $p = .074$. On the filler trials, participants again chose high-value items more often, mean proportion = 89.6%, OR = 12.92, 95% CI [9.55, 17.47], $p < .001$.

Discussion

Using a larger sample size and a slightly different procedure, results from Experiment 2 were replicated: Participants preferred go items when choosing under time pressure. Although not in line with our predictions (we predicted an effect for slow choices with high-value items in Experiment 1), the results from the first four experiments were quite consistent. GNG changed people's preferences when they chose quickly, but not when they had more time to decide. Furthermore, item reward value did not seem to moderate the effect. Direct comparisons between high-value and low-value pairs did not show significant difference in all four experiments. In the remaining experiments, we therefore did not have directional hypotheses for item reward value. The effect of item reward value will be explored in the final exploratory analyses with data from all experiments combined.

Experiment 4: Retest—Fast Choice

In all four experiments presented till now, participants received the choice task immediately after training. It was unclear whether the training-induced preference change would still be observed after some delay. To explore this question and estimate the effect size of potential decay, participants from Experiment 4 were invited back to the lab at least 1 week after training, and received the same choice task again (i.e., with time limit of 1.5 s). This experiment was exploratory in nature and we did not have directional hypotheses.

Method

Sample size. Sample size could not be determined a priori as it depended on how many of the 63 participants from Experiment 4 would respond to the invitation for the retest session.

Participants. In total, 47 participants responded to the invitation and took part in the retest session. The average delay between the training and the retest session was 12.4 days (SD = 3.1, range = [7, 19]).

Materials and procedure. Participants were required to not eat anything for at least 3 hr. They received a same food choice task as the one they received in the first session, with 1.5-s time limit. After the choice task, they received the same memory recognition task, and reported their current hunger level (−100 = *not hungry at all*; 100 = *very hungry*) and hours since the last time of food consumption. They then received one bag of candies based on a trial selected from the choice task, and were compensated and thanked.

Results

Participants did not choose go items more often on the experimental trials, mean proportion = 50.2%, OR = 1.01, 95% CI [0.83, 1.22], $p = .959$. This proportion of go choices was significantly smaller than that immediately following training, OR = 0.86, 95% CI [0.76, 0.98], $p = .024$. For an exploratory analysis on the decay of the effect as a function of the delay between two sessions, see the online supplemental materials. The difference between high-value and low-value pairs was again not statistically significant, OR = 1.18, 95% CI [0.77, 1.83], $p = .450$. On the filler trials, participants still preferred high-value items, mean proportion = 85.7%, OR = 8.39, 95% CI [6.09, 11.57], $p < .001$.

To explore the consistency of choices on experimental trials between two sessions, choices in Session 1 (i.e., whether the chosen item was a go or no-go item) were used to predict choices in Session 2 with a repeated-measures logistic regression. For the trials where participants chose go items in Session 1, they were more likely to choose go items again in Session 2 (mean proportion of go choices = 69.5%, SD = 15.3%), compared with the trials where they chose no-go items in Session 1 (mean proportion of go choices = 27.4%, SD = 14.0%), OR = 7.40, 95% CI [5.83, 9.40], $p < .001$. In other words, on average participants made the same choices for about 70% of the trials, suggesting that their choices were fairly consistent.

Discussion

By administering the same choice task to participants one week after training, we explored to what extent the effect of GNG on preference was durable. Overall, the training effect showed a large decrease, to the extent that participants did not choose go items more often in the retest session. This seemed to suggest that GNG did not have durable influence on preference. However, the consistency in choices revealed by the exploratory analysis suggested that preference change after 1 week might be observed if we could (a) increase the effect size of training-induced preference change and (b) increase sample size to have sufficient power for detecting a small effect. In Experiment 4, all items were repeated six times in training. One way to increase the effectiveness of training may be to increase the number of repetitions in training. In the next two experiments we increased both the number of repetitions and the sample size to (a) explore the effect of training length on the effectiveness of training and (b) see whether the training could influence delayed preference with more statistical power.

Experiment 5 and 6: Fast Choice

Experiments 5 and 6 were conducted with three aims: (a) to examine the reliability of the effect of GNG on fast choices with two more replications; (b) to explore whether the number of repetitions in training would influence its effectiveness, by presenting each item 10 times in GNG in Experiment 5 and 14 times in Experiment 6; and (c) to examine the delayed effect with a larger sample. We predicted that participants would prefer go items immediately after training, in both Experiment 5 and 6. Anticipating a small delayed effect, we a priori decided to combine data from both experiments when examining the delayed effect. For this combined dataset, we predicted that participants would choose go items more often than no-go items.

Method

Sample size. We planned to recruit between 60 to 65 participants for each experiment.

Participants. Sixty participants took part in Experiment 5, of which three were excluded based on preregistered exclusion criterion (accuracy on go or no-go trials in the training 3 SD below sample mean *and* below 90%). The final sample consisted of 57 participants. Sixty participants took part in Experiment 6, of which one was excluded (same exclusion criterion as in Experiment 5). The final sample consisted of 59 participants.

Materials and procedure. The procedure of Experiments 5 and 6 was the same as Experiment 4, except that the GNG contained 10 blocks in Experiment 5, and 14 blocks in Experiment 6.

Results

As predicted, in both Experiment 5 and 6, participants chose go items more often on experimental trials, mean proportion = 61.8%, OR = 1.74, 95% CI [1.40, 2.16], $p < .001$, and mean proportion = 57.0%, OR = 1.37, 95% CI [1.13, 1.65], $p = .001$, respectively. The differences between low-value pairs and high-value pairs were not statistically significant, OR = 1.37, 95% CI [0.92, 1.83], $p = .137$ in Experiment 5 and OR = 1.05, 95% CI [0.74, 1.49], $p = .781$ in Experiment 6. They also preferred high-value items on the filler trials, mean proportion = 87.8%, OR = 10.74, 95% CI [7.78, 14.84], $p < .001$ in Experiment 5, and mean proportion = 86.9%, OR = 8.79, 95% CI [6.77, 11.41], $p < .001$ in Experiment 6.

Directly comparing Experiment 5 with Experiment 4 showed that participants in Experiment 5 chose go items more often than those in Experiment 4, OR = 1.35, 95% CI [1.03, 1.77], $p = .029$. However, further increasing the number of repetitions did not increase the effect size further. If anything, participants chose go items a bit less often in Experiment 6 than in Experiment 5, OR = 0.79, 95% CI [0.60, 1.04], $p = .093$. There was also no significant difference between Experiment 6 and 4, OR = 1.07, 95% CI [0.82, 1.39], $p = .631$.

Discussion

In line with our predictions and the results from Experiments 2 and 4, the effect of GNG on fast choices immediately following training was replicated when participants received longer training. Although increasing the number of stimulus repetition from six to 10 increased the training effect size, further increasing it to 14 did not make the training more effective. Next, we present results from the retest session, combining data from both Experiments 5 and 6.

Experiment 5 and 6: Retest—Fast Choice

Method

Participants. One-hundred and 15 participants took part in the retest session. Average delay between the two sessions was 8.2 days (SD = 1.8, range = [7, 14]).

Materials and procedure. The procedure was the same with the retest session of Experiment 4.

Results

In line with our prediction, participants preferred go items on the experimental trials, mean proportion = 53.8%, OR = 1.18, 95% CI [1.04, 1.34], $p = .009$. For the delayed effect for Experiment 5 and 6 separately, see the online supplementary materials. This delayed effect was again significantly smaller than the immediate effect, OR = 0.78, 95% CI [0.72, 0.84], $p < .001$. Participants' choices were fairly consistent. They selected go items more often in the retest session if they had chosen the go items in Session 1 (mean proportion = 71.3%, SD = 13.6%), than if they had chosen no-go items before (mean proportion = 30.4%, SD = 17.1%), OR = 7.39, 95% CI [6.25, 8.72], $p < .001$. Comparison between high-value pairs and low-value pairs revealed no statistically significant difference, OR = 1.04, 95% CI [0.82, 1.32], $p = .757$. On the filler trials, high-value items were still chosen more often, mean proportion = 84.7%, OR = 7.57, 95% CI [6.19, 9.27], $p < .001$.

Discussion

As predicted, by increasing the number of stimulus repetition in training and using a larger sample, we observed an effect of training on preference 1 week after training. The effect of GNG on preference therefore seems durable and not limited to immediately following training. Admittedly, the effect size was quite small after one week, and again a significant reduction in effect size was observed, showing that the effect of training has decayed with the passage of time.

In all experiments presented so far, participants were trained to respond to certain high-calorie food items (e.g., snacks, candies) and not respond to other high-calorie food items. In the choice task after training, they chose between two high-calorie food items that were matched on value. This procedure enabled us to isolate the effect of GNG from some confounding factors (e.g., type of food, difference in reward value), but also left an important question unanswered. That is, whether GNG could be used to promote healthy choices, when people choose between healthy and unhealthy foods. Examining this question is not only interesting from an applied perspective, but may also extend the effect of training to a situation where the value of food items is not matched, a situation that has not been examined in the previous experiments.

Experiment 7: Promoting Healthy Choices?

In Experiment 7, participants were trained to respond to certain healthy (i.e., fruits and vegetables) and unhealthy food items, and to not respond to other healthy and unhealthy food items in GNG. After training, they chose between healthy and unhealthy items (among other choices) for consumption, again within 1.5 s. We predicted that participants would choose healthy items more often, when the healthy items were associated with go responses and unhealthy items with no-go responses (i.e., healthy-trained trials), in comparison with when both items were not included in the training (i.e., untrained trials). Note that the untrained choices were included as a baseline to which the healthy-trained choices will be compared. This modification was introduced because a priori the average value of healthy and unhealthy items cannot be matched, hence the choices cannot be compared with the 50% chance level as in previous experiments. We also included choices in which the unhealthy items were paired with go responses and the healthy items with no-go responses (i.e., unhealthy-trained trials). These trials were included to make go and no-go responses toward healthy and unhealthy items equally likely. For the comparison between unhealthy-trained and untrained choices, we did not have directional hypothesis, as the preexisting preference for unhealthy items might make any further increase in unhealthy choices difficult to observe (i.e., ceiling effect). Lastly, participants also made choices between two healthy items and between two unhealthy items, with one paired with go responses and the other with no-go responses. As in previous experiments, the average value of these go and no-go items were matched. For these choices, we expected to replicate previous results, such that participants would prefer go items for these choices.

Method

Participants. For Experiment 7, we planned to recruit 72 participants, which exceeded the sample sizes used in previous experiments and left room for potential exclusion. Seventy-three participants participated. Three participants were excluded based on predetermined exclusion criteria (a) participants who bid less than 25 cents on more than 40 food items in the first auction task, and (b) participants whose accuracy on go or no-go trials was 3 *SD* below sample mean *and* below 90%, leaving 70 participants in the final sample.

Materials. Thirty unhealthy high-calorie snacks were selected from Experiments 1 and 2. Thirty low-calorie food items that were generally considered healthy (i.e., fruits and vegetables; Tilman & Clark, 2014) were selected from previous work (Veling, Chen et al., 2017).

Procedure. Participants were asked to fast for 3 hr before the experiment started. Upon arrival, they received two euros to bid on each of the 60 food items (30 healthy and 30 unhealthy, mixed and randomized). After the auction, the program rank ordered all items from the highest WTP to the lowest, for healthy and unhealthy foods separately. Food items were then selected into different training conditions based on rankings. Eight healthy and eight unhealthy items (ranked from 12 to 19 within the healthy and unhealthy category) were selected into the within-category choice trials. Half of the eight selected items were assigned into the go condition, whereas the remaining half was assigned into the no-go condition. These within-category choices were the same with the experimental choices participants in previous experiments received. On the within-category choice trials, participants chose between two healthy or two unhealthy items with matched WTP, one paired with go responses and the other with no-go responses.

Eighteen healthy and 18 unhealthy items (ranked from three to 11 and from 20 to 28 within the healthy and unhealthy category) were selected for the between-category choices (i.e., choices between healthy and unhealthy items). Crucially, the between-category choices were further divided into three conditions: healthy-trained condition, in which healthy go item was paired with unhealthy no-go item; unhealthy-trained condition, in which healthy no-go item was paired with unhealthy go item; and untrained condition, in which both the healthy and unhealthy item were not used in the training but included in the choice task. Note that the unhealthy-trained condition was included to ensure an equal number of healthy and unhealthy items in both go and no-go trials. This made it difficult to infer the structure of GNG, and ensured that healthy choices could not simply be explained by demand characteristics. When used in applied settings, these unhealthy-trained trials should be omitted to avoid the promotion of unhealthy food choices.

After the selection procedure (for the exact selection procedure see Figures S3 and S4 in the online supplemental materials), the 40 selected items were used in GNG and repeated 10 times. After the training, participants received a choice task with 1.5-s time limit. The choice task consisted of 32 choices between two healthy items, 32 choices between two unhealthy items, 36 unhealthy-trained choices, 36 healthy-trained choices, and 36 untrained choices. Different types of choices were mixed and presented in a random order. After the choice task, participants received a memory recognition task and filled out some demographic questions. Results from the choice task and the auction task were revealed, and participants received one or two food items. They were debriefed, compensated, and thanked.

Results

Food value. For the result of the selection procedure for items used in within-category choices, see Table 2. To check the selection procedure for items used in between-category choices, the average WTP of the items was calculated, for healthy and unhealthy items separately. The WTP was submitted to repeated-measures ANOVA, with item category (healthy vs. unhealthy) and choice trial type (healthy-trained, unhealthy-trained vs. untrained) as independent variables. There was a small nonsignificant difference between healthy and unhealthy items, showing that participants were willing to pay more for unhealthy items, $F(1, 69) = 2.93$, $p = .091$, $\eta^2 = .016$. Crucially, there was no significant interaction with choice trial type, $F(2, 138) = 0.33$, $p = .721$, $\eta^2 < .001$, suggesting that the value difference between healthy and unhealthy items was matched across different types of choices. In other words, any change in preference could not be explained by preexisting value difference between healthy and unhealthy items.

Within-category choices. As predicted, and replicating previous findings, for within-category choices in which participants chose between go and no-go items (both healthy or both unhealthy, with matched WTP), overall they preferred go items, mean proportion = 61.5%, OR = 1.69, 95% CI [1.41, 2.03], $p < .001$. This effect was found for both unhealthy items, mean proportion = 62.1%, OR = 1.85, 95% CI [1.43, 2.39], $p < .001$, and healthy items, mean proportion = 60.8%, OR = 1.74, 95% CI [1.33, 2.29], $p < .001$ (Figure 4, left panel).

Between-category choices. To compare healthy choices between healthy-trained and untrained choice trials, a repeated-measures logistic regression was conducted, with choice trial type as the predictor and whether the chosen item was a healthy item or not as the outcome. As predicted, the main effect of choice trial type was significant, OR = 1.63, 95% CI [1.25, 2.12], $p < .001$, indicating that participants chose healthy items more often on healthy-trained trials (mean proportion of healthy choices = 46.2%) than on untrained trials (mean proportion of healthy choices = 39.4%; see Figure 4, right panel). Similarly, although we did not predict the effect, people chose healthy items less often in unhealthy-trained trials (mean proportion of healthy choices = 32.6%) than on untrained trials, OR = 0.66, 95% CI [0.48, 0.91], $p = .010$.

Discussion

Experiment 7 replicated and extended the previous findings, by showing that GNG modified not only choices between unhealthy items, but also choices between healthy items. Moreover, the training also promoted healthy food choices, when people chose between healthy and unhealthy items. Note that the promotion of healthy food choices by GNG is in a relative sense, but not in an absolute sense. That is, although in all three between-category choice conditions, participants chose healthy items less than 50% of the time (see Figure 4, right panel), their preference for healthy items increased when they chose between a healthy go item and an unhealthy no-go item, in comparison with when both items were untrained (i.e., the increase of healthy choices from untrained condition to healthy-trained condition; see Figure 4, right panel).

Although the effect of GNG on choices between healthy and unhealthy items has been shown before (Porter et al., 2018; Veling et al., 2013b), the current finding is still noteworthy because of the methodological improvement (i.e., repeated choices for real consumption rather than one-shot hypothetical choice). Furthermore, the inclusion of different types of choices and the 1.5-s time limit (which were not used in previous work) makes it very unlikely that the observed results were due to demand characteristics. The current finding therefore serves as a strong demonstration that GNG can promote healthy food choices.

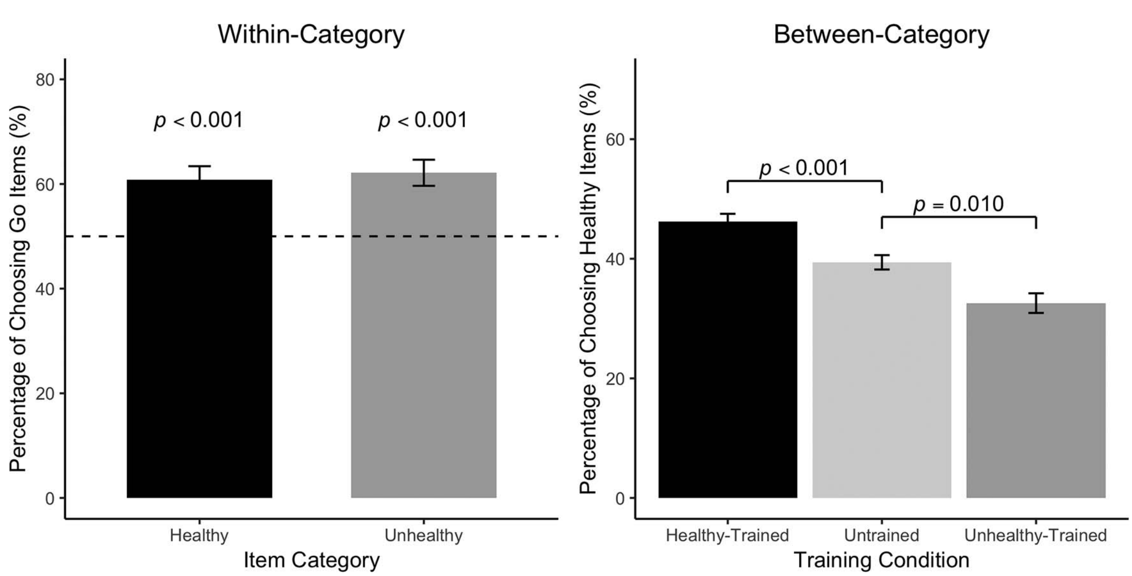

Figure 4. Probability of choosing go items on within-category choices (left panel) and probability of choosing healthy items on between-category choices (right panel) in Experiment 7. *p* values are calculated from repeated-measures logistic regression. Error bars in the left panel stand for standard errors of mean proportions; error bars in the right panel stand for within-subject standard errors of mean.

Furthermore, this finding also suggests that the effect of GNG on preference is not limited to situations where the value of two choice options is closely matched. Rather, the training seems able to overcome value difference (at least to some extent) and increase choices for relatively low-value items. Although no filler choice trials were included, the choices participants made were arguably still value-based, as the overall proportion of healthy choices was below 50%, which mirrors the finding that the average WTP was lower for healthy items than for unhealthy items. The value difference between healthy and unhealthy items was admittedly small and statistically not significant. Future research may look into whether the training changes preference when the value difference is more substantial.

In all experiments reported so far, we consistently found that GNG changed preference, but only when participants chose under time limit. Furthermore, item reward value did not seem to moderate the effect. Next, we conducted exploratory analyses on combined data sets to further explore whether and how decision time and item reward value may moderate the effect.

Exploratory Analyses on Decision Time

To directly compare fast choices with slow choices, data from all choice tasks immediately after training were combined (i.e., Experiments 1–3 and 7 and the first session of Experiments 4–6). Only the trials on which people chose between two similarly valued go and no-go items were included in this analysis. Multilevel logistic regression was used, with trials nested within participants, and participants nested within experiments. Overall, when participants had unlimited time to make choices (Experiments 1 and 3; 84 participants, 5,376 trials), they did not choose go items significantly more often than no-go items, mean proportion = 50.0%, OR = 1.00, 95% CI [0.86, 1.16], $p = .997$. However, when participants chose within 1.5 s (Experiments 2, 4–7; 278 participants, 17,792 trials), they chose go items more often for consumption, mean proportion = 59.6%, OR = 1.48, 95% CI [1.32, 1.66], $p < .001$. The difference between fast and slow choices was statistically significant, OR = 1.47, 95% CI [1.18, 1.82], $p = .001$. These results thus suggest that GNG more effectively influenced fast choices than slow choices. Note that based on these results, it is premature to conclude that slow choices cannot be changed by GNG. In the two experiments on slow choices reported here (Experiments 1 and 3), a relatively small number of stimulus repetitions were used. The possibility remains that with a more extensive training by repeating the stimuli more times, choices made without time limit may eventually also be changed. We are currently conducting another line of research that may provide more insights into this question.

One and a half seconds was used as an arbitrary cut-off value to distinguish between fast and slow choices. However, decision time varies on a continuum. To gain a more nuanced understanding of how decision time influences the effect, we carried out an exploratory analysis by using decision time as a continuous predictor. To reduce the influence of extreme values, for each participant choice trials with extreme RTs were first removed (more than 2.5 absolute deviation from the median; Leys, Ley, Klein, Bernard, & Licata, 2013). For the remaining trials, decision time was standardized for each participant and used as predictor for choices. All random intercepts and random slopes were included. For participants who received the choice task with time limit, longer decision time was associated with fewer choices for go items, OR = 0.88, 95% CI [0.84, 0.92], $p < .001$. For those who received the choice task without time limit, the effect of decision time was not statistically significant, OR = 0.96, 95% CI [0.87, 1.06], $p = .387$. Interestingly, for the retest session in which participants chose with time limit, longer decision time was again related to lower likelihood of choosing go items, OR = 0.91, 95% CI [0.85, 0.96], $p = .002$ (see Figure 5). The pattern of the results remained the same when choice trials with extreme decision times were included.

Exploratory Analyses on Reward Value

In the first six experiments, the effect of GNG on preference was not significantly moderated by item reward value. To more reliably assess whether GNG more effectively changed preferences for high-value items, we combined the choice data from Experiments 1 to 6. Data from Experiment 7 were not included, as item reward value was not manipulated in Experiment 7. Multilevel analysis

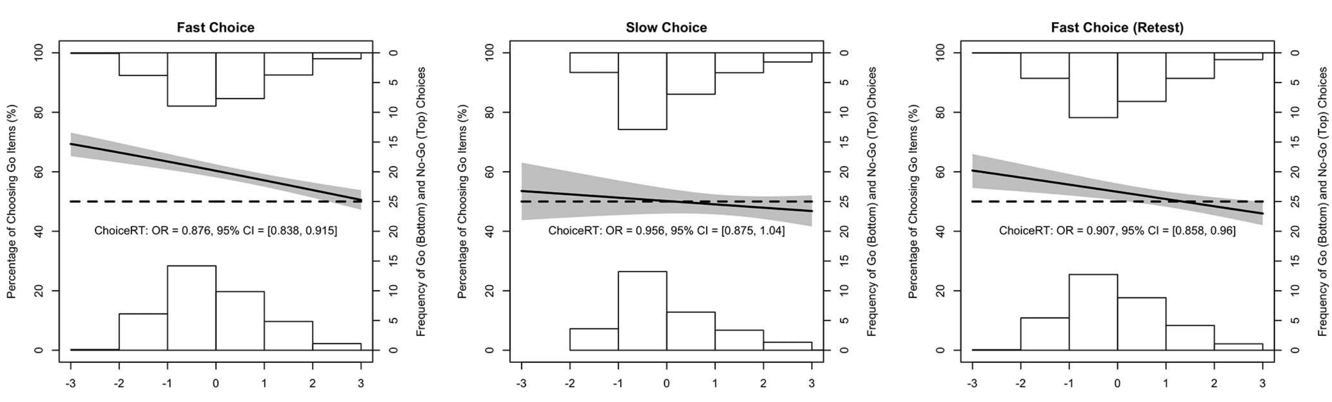

Figure 5. Probability of choosing Go items predicted by decision time (standardized). Trials with extreme RTs were removed (more than 2.5 absolute deviation from the median). Shaded region stands for 95% confidence interval. Heights of bars stand for the average frequencies of choosing go items (bottom) and choosing no-go items (top) within each RT bin.

was used, with trials nested within participants, and participants nested within experiments. Whether the two items presented were of low or high value was used as the predictor, and whether the chosen item was a go or no-go item was used as the outcome. All random intercepts and random slopes were included. For experiments in which participants made choices with time limit (i.e., Experiments 2 and 4–6; 208 participants), they chose go items less often when both items were of high value compared with when both items were of low value, OR = 0.81, 95% CI [0.66, 0.98], $p = .029$. This effect, however, was not found for delayed choices (i.e., retest session of Experiments 4–6; 162 participants), OR = 0.93, 95% CI [0.74, 1.15], $p = .491$, and for choices without time limit (i.e., Experiments 1 and 3; 84 participants), OR = 1.14, 95% CI [0.81, 1.60], $p = .443$.

A key assumption of the BSI theory is that the strength of response conflict is jointly determined by the initial approach tendency and ensuing response inhibition process. In the current research, we selected items based on participants' monetary bids or self-reported wanting, and assumed high-value items evoked stronger impulses than low-value items. To directly test this assumption, items that were used in the experimental choice trials were selected for each participant, and go and no-go trials involving these items were selected from GNG. The results showed that compared with low-value items, participants responded to high-value items more accurately on go trials, $t(291) = 2.66$, $p = .008$, Hedges's $g = 0.155$, 95% CI [−0.008, 0.318], and less accurately on no-go trials, $t(291) = -4.20$, $p < .001$, Hedges's $g = -0.245$, 95% CI [−0.409, −0.082]. Furthermore, on go trials they responded to high-value items more quickly compared with low-value items, $t(291) = -7.45$, $p < .001$, Hedges's $g = -0.435$, 95% CI [−0.600, −0.271] when using median RT, and $t(291) = -8.57$, $p < .001$, Hedges's $g = -0.501$, 95% CI [−0.666, −0.336] when using mean RT. These results are in line with previous findings (Chen, Veling, Dijksterhuis et al., 2018), and suggest that the high-value items indeed triggered stronger impulses to respond than low-value items. However, the impulse-invoking quality of high-value items does not seem to lead to stronger preference change for these items.

General Discussion

In the current research, we conducted seven preregistered experiments to investigate when linking mere action versus inaction to objects would lead to preference change. Three questions concerning training-induced preference change were examined, namely the influence of decision speed, the durability of the effect and the role of item reward value. GNG reliably led to preference change when participants made choices within 1.5 s (Experiments 2 and 4–7), but not when they chose without time limit (Experiments 1 and 3). Within fast choices, they were more likely to choose go items on trials where they chose quickly. Preference change induced by GNG was still observed one week later, although the effect size largely decreased compared to immediately after training. High-value items seemed to invoke stronger go responses than low-value items, but this did not translate into larger preference change for high-value items. Next we discuss the implications of these findings in turn.

Decision Speed

Contrary to our initial prediction, preference change induced by GNG seems to be constrained to fast choices. By repeatedly responding to certain food items and withholding responses toward other items, participants may form associations between food items and simple motor responses (Logan, 1988; Verbruggen et al., 2014) and/or associations between foods items and affective reactions that accompany the responses. For instance, withholding responses may trigger negative affect (Chen et al., 2016; Veling et al., 2008), while responding to food items may elicit positive affect (Guitart-Masip et al., 2014), and the affective reactions may become attached to food items. Although the exact content of the acquired associations is not clear (i.e., whether the food items are associated with simple motor responses or with affective reactions), it seems that the acquired associations can be rapidly retrieved and influence people's choices when they choose quickly under time pressure (Berkman et al., 2017; Forstmann et al., 2016; Strack & Deutsch, 2004). When more decision time is allowed, the transient activation of the learned associations may quickly decay. More decision time may allow for the incorporation of more information into the construction of preferences (Sullivan et al., 2015). As more information is incorporated into a decision process, the influence of the initially retrieved associations may weaken.

Interestingly, reliable effects of GNG on evaluation have been found when evaluation was assessed with self-paced explicit rating (Chen et al., 2016; Chen, Veling, Dijksterhuis et al., 2018; Lawrence, O'Sullivan et al., 2015; Serfas, Florack, Büttner, & Voegeding, 2017; Veling et al., 2008). Evaluation is thus susceptible to the influence of GNG when people rate objects without time pressure, whereas preferences are influenced by GNG when people choose quickly under time pressure. One explanation for this inconsistency can be that the thoroughness of information processing may differ between evaluating and choosing food items. When evaluating a food item, people may sample as minimal information as possible, as the accuracy of the evaluation does not have any immediate behavioral consequences. Thus, the affective reactions or the response tendencies triggered by a food item may be sufficient input for one to arrive at an evaluation. More decision time does not lead to the revision of this initial immediate evaluation, as people may not be motivated to take more information into account (e.g., the iterative reprocessing model of evaluation; Cunningham & Zelazo, 2007; Cunningham, Zelazo, Packer, & Van Bavel, 2007). In contrast, when choosing for real consumption, people are more likely to consider all relevant information thoroughly when there is sufficient time. The initial preference for go items induced by GNG may thus decrease when other information (e.g., the caloric content of each food, what one ate before, etc.) enter the decision process.

Essentially, this explanation suggests that decision time itself is not crucial; rather, the effect of GNG on preference depends on whether more information is integrated into a decision process to reduce the influence of GNG. In that case, factors other than decision time that also influence the incorporation of information can also moderate the effect of GNG, such as people's motivation to consider all information (as discussed above) and the opportunity afforded by the situation, such as whether they are under cognitive load or not (Fazio, 1990). These questions need to be explored to further understand how different factors, including decision time, influence the training effects.

The current finding also raises new questions on how to interpret previous findings showing effects of GNG on more distal outcomes such as eating behavior or weight loss that did not manipulate time pressure. For instance, previous work has found that GNG can facilitate weight loss attempts (Lawrence, O'Sullivan et al., 2015; Veling et al., 2014). Based on the present finding, it seems possible that the training may have contributed to weight loss by changing people's fast food decisions, but not or less so when people spend more time to carefully think about what food items to choose. This hypothesis is difficult to test, but has important implications for the application of GNG. For instance, GNG may not work well in tandem with interventions that aim to facilitate weight loss by promoting deliberative decision-making. This may explain why combining GNG with an implementation intention intervention (Gollwitzer, 1999) that reminds people about their weight loss goals so that they are more likely to carefully think about their food choices did not lead to an additive effect on weight loss compared to using one of the two interventions alone (Veling et al., 2014).

Lastly, the finding that effects on preferences are only observed under time pressure argues against the possibility that participants merely apply a simple rule to choose go items during the choice task. The accurate application of a rule would likely benefit from having more time, which would lead to larger preference change with longer decision time. This reasoning suggests preference changes induced by GNG are unlikely due to demand characteristics to choose go items over no-go items.

The Durability of Preference Change

In line with a previous meta-analysis that estimated the effects of GNG across time across different studies (Allom et al., 2016), the effect of GNG on preferences shows a large decrease in effect size from immediately after training to 1 to 2 weeks later. Importantly, by using the same behavioral measure to assess effects over time, the present finding shows that the lack of longevity of GNG-induced effects observed in previous work (Allom et al., 2016) is not simply an artifact of the different behavioral measures used. Rather, behavior change induced by GNG may indeed by relatively short-lived.

In contrast to the relatively short-term effect of GNG, CAT has been shown to induce highly durable preference changes, up to 6 months after training (Salomon et al., 2018). Some procedural features of CAT distinguish it from GNG, such as the inclusion of more no-go trials than go trials, the absence of no-go cues (participants are asked to respond to go cues and not respond when no cue is presented), and the dynamic adjustment of the delay between stimulus onset and the go cues (go cues are presented such that participants manage to respond in time on approximately 75% of the trials). Because of these procedural features, preference change induced by CAT is often not explained by simple motor responses, but by heightened attention that accompanies the execution of go responses (Bakkour et al., 2016; Schonberg et al., 2014). In GNG, go trials and no-go trials are equally frequent and both go and no-go cues are presented, which allows us to examine the effect of mere action versus inaction without other potentially confounding factors. The current findings therefore serve as a strong demonstration that merely responding or not responding to objects can change people's preferences.

In terms of the longevity of the training-induced preference change, GNG and CAT show quite different patterns. Here we explored the effect of GNG 1 to 2 weeks after training, a time frame much shorter than the ones explored in previous work on CAT (from 1 to 6 months; Salomon et al., 2018; Schonberg et al., 2014). However, after this relatively short delay, preference change by GNG already shows a large decrease. For comparison, the effect of GNG 1 to 2 weeks posttraining is numerically smaller than that obtained with CAT 6-months posttraining (Salomon et al., 2018). This large difference in the durability of the effects is consistent with the argument that CAT and GNG lead to preference change via different underlying mechanisms. CAT therefore seems more suitable for long-term preference change. Future work is needed to better understand the different natures of the associations learned during CAT and GNG, and how these associations lead to sustainable changes in preferences.

The Role of Reward Value

We originally predicted that GNG would lead to preference change only for high-value items when participants made choices without time limit, as only high value items require strong inhibition of impulsive responses once a no-go cue is presented (Veling et al., 2008). Contrary to this expectation, we find that GNG more strongly changed preference when participants made choices with time limit, and the effect was not stronger for high-value items. This unexpected result leads to interpretational difficulties with explaining how preferences were changed. For instance, it could be that stimulus-stop associations have been acquired for both high- and low-value items, and that these associations influence preferences for high- and low-value food items alike. Alternatively, it could be that high-value no-go items were devalued (Chen et al., 2016; Serfas et al., 2017; Veling et al., 2008), while low-value go items increased in value (Chen et al., 2016; Chen, Veling, Dijksterhuis et al., 2018). The underlying mechanisms for preference change may differ between high- and low-value items, but the behavioral outcome can remain the same. The current data do not allow us to disentangle these different accounts.

Implications for Applied Behavioral Interventions

Tasks that manipulate simple responses (including GNG) have been shown to influence a range of behavioral outcomes, such as volume of consumption (Bowley et al., 2013; Folkvord, Veling, & Hoeken, 2016; Houben, 2011; Houben, Havermans, Nederkoorn, & Jansen, 2012; Houben & Jansen, 2011, 2015; Jones & Field, 2013; Lawrence, Verbruggen et al., 2015; Veling et al., 2011), and self-selected portion size (Van Koningsbruggen, Veling, Stroebe, & Aarts, 2014). Multiple sessions of training have even been shown to facilitate weight loss in two samples (Lawrence, O'Sullivan et al., 2015; Veling et al., 2014; see also Stice, Yokum, Veling, Kemps, & Lawrence, 2017). Manipulating simple responses toward objects therefore seems feasible as a behavior change intervention.

In light of the interest of using these tasks in applied settings, we explored two questions that are important from an applied perspective. First, we varied the number of stimulus repetition in training (Experiments 4–6) to observe its influence on the effect. Although initially increasing the number of repetition increases the effectiveness of training, further lengthening the training does not lead to more effectiveness. This may be because learning during training is a function of both the number of repetitions and the amount of attention allocated to the training. While increasing repetitions provides more instances to learn, it also makes the training more taxing. To maximize efficiency, training may ideally be provided in multiple sessions to avoid decrease in attention. Spacing the training also has the added benefit of promoting long-term behavior change (Bakkour et al., 2018), which is an important goal for behavior change interventions.

Second, the effect of GNG was examined for choices between healthy and unhealthy foods. To date, preference change as a result of go/no-go responses has mostly been examined for choices between items from the same category (Bakkour et al., 2016; Salomon et al., 2018; Schonberg et al., 2014; Veling, Chen et al., 2017; Zoltak et al., 2018). The current work thus extends the effects of GNG to cross-category choices. However, the task employed here cannot be used in applied settings directly, as it contains healthy and unhealthy items on both go and no-go trials. As the result on the unhealthy-trained condition shows, this may inadvertently create preferences for unhealthy items to which people respond. When used as an intervention, the training should contain only healthy items on go trials, and only unhealthy items on no-go trials (Lawrence, O'Sullivan et al., 2015). This modification may also promote learning on a category level (e.g., healthy food = go; unhealthy food = no-go) rather than on an item level, which may make the effect more generalizable. Generalization of the effect from trained to untrained items is important for the application of GNG, and needs to be further pursued.

Limitations and Future Directions

Due to the lack of untrained items, it is unclear whether preference for go items over no-go items reflects an effect of the go items, an effect of the no-go items, or a combination of both. This difficulty in the interpretation of the results applies not only to the current research, but also to all previous work on CAT, where the same choice task has been used. Future work may pit untrained items with both go and no-go items in the choice task, to directly test whether the effects induced by CAT and GNG are different in nature.

Slow choices seem resistant to the influences of GNG. Interestingly, previous work on CAT has similarly shown that the effect of CAT on preferences is also constrained to situations where people choose under time pressure (Veling, Chen et al., 2017). These findings thus raise the question of whether slow choices can be trained at all. As mentioned earlier, in addition to GNG and CAT, SST has also been used to change behavior, although the results seem mixed (e.g., Houben, 2011; Schonberg et al., 2014). The effect of SST on health behavior change is also smaller than that of GNG in recent meta-analyses (Allom et al., 2016; Jones et al., 2016). Nevertheless, SST is often proposed to strengthen top-down inhibitory control capacity for effortful inhibition of impulses triggered by objects (Houben, 2011). SST may have a stronger influence on choices when there is sufficient time for the top-down suppression of impulses, but this possibility remains to be tested.

Lastly, it is unclear whether the observed results can generalize to other samples, such as overweight or obese individuals. Previous work has shown that repeated GNG with unhealthy food items facilitated weight loss in an overweight community sample (Lawrence, O'Sullivan et al., 2015), suggesting that the effects are not confined to undergraduate students with healthy body weight. Furthermore, a recent study directly compared an undergraduate student sample with a clinical sample of morbidly obese individuals, and found that GNG changes food evaluation in both samples in similar ways (Chen, Veling, Vries et al., 2018). However, important differences were also identified. Student participants learned the stimulus-response contingencies better than the clinical sample, and the learning of stimulus-response contingencies predicted the effect of GNG on evaluation. In light of these findings, the generalizability of the current findings to different samples and contexts may depend on how well individuals can learn from training, which also needs to be further explored.

Conclusion

To summarize, GNG reliably changed people's preference when they made choices with time limit, but not with unlimited time. This effect was still observed 1 week after training. Furthermore, item reward value did not moderate the effect. Overall, these findings are in line with the idea that preferences are dynamically constructed in choice situations (Slovic, 1995). The construction of preferences is influenced by recent learning histories (such as whether one has responded to certain items or not), especially when preferences need to be expressed quickly. By showing the reliability, generalizability, and boundary condition of preference change induced by mere action versus inaction, the current work provides more insight into the underlying mechanism of the effect, how trainings that manipulate responding versus not responding to objects may be used in applied settings, and raise new questions on what people learn from repeated stimulus-response pairings and how these learned content impact preferences.

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