Go/No-Go Training Changes Food Evaluation in both Morbidly Obese and Normal-Weight Individuals

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Objective: Not responding to appetitive food items in the go/no-go training has been shown to reduce the evaluation of these items in normal-weight university students. In this preregistered study, we administered an identical go/no-go training in both morbidly obese individuals and normal-weight university students, to assess whether findings from laboratory studies on go/no-go training performed in university environments can be translated to clinical settings.

Method: Obese individuals (N = 59, 14 males, M_{age} = 46.10, M_{BMI} = 44.49) and university students (N = 58, 15 males, M_{age} = 23.21, M_{BMI} = 22.64) were trained to consistently respond to certain food items (go) and withhold responses to other items (no-go). Evaluations of the go and no-go items, along with items not used in the training (untrained), were measured both before and after the training.

Results: Before the training, evaluations of go, no-go and untrained items were matched; after the training, go items were evaluated more positively than no-go (p = .031 and p = .002 in obese and normal-weight individuals) and untrained items (p = .003 in normal-weight individuals). Only relatively hungry participants rated no-go items as less attractive than both go and untrained items (no-go devaluation effect). More important, effects of the training on food evaluation did not differ between the two participant groups.

Conclusions: Obese and normal-weight individuals showed similar responsivity to the go/no-go training on food evaluation, suggesting that insights from laboratory studies may be translated to clinical settings to develop effective interventions to regulate food intake.

Key words: *food, eating, obesity, go/no-go training, response inhibition*

Public Health Significance Statements:

This translational study shows that the go/no-go training, in which people consistently respond to certain food items and withhold responses toward other food items, changes food evaluation in both morbidly obese individuals and normal-weight university students. Direct comparisons suggest many similarities but also some differences between the two groups. This information is useful for understanding whether developing cognitive training tasks in university environments is a useful approach to arrive at clinical interventions to help people regulate their eating behavior.

Go/No-Go Training Changes Food Evaluation in both Morbidly Obese and Normal-Weight Individuals

The world population is putting on weight. Since 1980, the prevalence of worldwide obesity has more than doubled, resulting in 39% of the world's adult population being overweight (body mass index above 25 kg/m^2) and 13% being obese (body mass index above 30 kg/m^2) in 2014. Elevated body mass index (BMI) is a major risk factor for non-communicable diseases such as cardiovascular diseases and diabetes, which combined account for around 50% of all non-communicable disease deaths each year (World Health Organisation, 2016).

Informing people about the health-harming consequences of a high BMI, however, does not seem sufficient to halt this worrisome trend (Marteau, Hollands, & Fletcher, 2012). This may be because many unhealthy behaviors underlying this global obesity epidemic, such as lack of physical exercise or over-consumption of energy-dense foods (World Health Organisation, 2016), are not the result of careful deliberation on the consequences of these behaviors, but rather carried out automatically without much reflection (Marteau et al., 2012). For instance, many people nowadays live in a food-rich environment and are constantly exposed to appetitive foods, especially those that contain much sugar and fat (Swinburn et al., 2011). Exposure to such high-calorie unhealthy foods may automatically trigger people to choose and consume them, despite their intentions to eat more healthily (Stice, Lawrence, Kemps, & Veling, 2016; Stroebe, van Koningsbruggen, Papies, & Aarts, 2013). To help people keep a healthy diet in such an obesogenic food environment, interventions that target the impulsive and automatic processes of eating are needed.

In the current project, we focus on one such behavioral intervention, called the food-specific go/no-go training (the GNG training; for recent meta-analyses and reviews, see Allom, Mullan, & Hagger, 2016; Jones et al., 2016; Jones, Hardman, Lawrence, & Field, 2017; Veling, Lawrence, Chen, van Koningsbruggen, & Holland, 2017). In the GNG training, people are trained to consistently withhold their responses toward certain appetitive food items when a no-go cue is presented (i.e., no-go items), and consistently respond to other food or non-food items when a go cue is presented (i.e., go items). Recent research has consistently shown that inhibiting responses toward appetitive food items leads to decreased explicit evaluations of no-go items compared to go items and items not presented during the training (untrained items; Chen et al., 2016; Chen, Veling, Dijksterhuis, & Holland, 2017; note that the training fails to induce stimulus devaluation when evaluation is measured with implicit association tests, see Jones et al., 2016). Furthermore, both adults and children consumed less of certain foods immediately after the training if these food items had been paired with response inhibition in the training (Folkvord, Veling, & Hoeken, 2016; Houben, 2011; Houben & Jansen, 2011, 2015; Lawrence, Verbruggen, Morrison, Adams, & Chambers, 2015; see also Veling, Aarts, & Papies, 2011 for evidence that the effect on food intake may persist over at least one day). Food items associated with response inhibition were also chosen less often for consumption after training (Porter et al., 2017; Veling, Aarts, & Stroebe, 2013a, 2013b). Lastly, participants who practiced withholding responses to appetitive high-calorie foods in the GNG training on multiple sessions lost more weight in the short-term (Lawrence, Sullivan, et al., 2015; Veling, van Koningsbruggen, Aarts, & Stroebe, 2014), suggesting that the GNG training changed actual eating behavior outside the laboratory.

Different theoretical accounts have been proposed to explain the effects of GNG training on changing responses to food items. First, the training may reduce evaluation of no-go food items via response conflict. According to the Behavior Stimulus Interaction theory (i.e., the BSI theory; Chen et al., 2016; Veling, Holland, & van Knippenberg, 2008), exposure to appetitive food items triggers automatic approach tendencies toward the foods, which need to be inhibited when the foods are presented together with no-go cues in the GNG training. The approach tendency toward the foods and the response inhibition process leads to response conflict. The negative affect elicited by the conflict (Dreisbach & Fischer, 2015) is then attached to the no-go food items, leading to subsequent decreased evaluation of these items (Veling et al., 2008). Second, repeatedly inhibiting responses towards no-go items during GNG training may lead to the formation of stimulus-stop associations (Best et al., 2016; Bowditch, Verbruggen, & McLaren, 2016; Houben & Jansen, 2015; Verbruggen & Logan, 2008). When these no-go items are next encountered outside the training, these learned stimulus-stop associations may evoke response inhibition reflexively. Furthermore, since action and valence are closely coupled, such that response inhibition is associated with punishment while action is associated with reward (Guitart-Masip et al., 2012; Guitart-Masip, Duzel, Dolan, & Dayan, 2014), the valence of no-go items may also be reduced via their associations with automatic response inhibition. In line with this account, the effectiveness of the training is positively related to the proportion of successful response inhibition in the training (Jones et al., 2016), presumably because successfully inhibiting responses leads to stronger stimulus-stop associations. Note that these explanations are not necessarily mutually exclusive. They may jointly explain the effects of GNG training, or different aspects of the training effects.

Although the findings mentioned above suggest that the GNG training may be a promising tool to help change people's unhealthy eating behaviors by modifying responses to food items, an important limitation is that most previous work was conducted in controlled laboratory settings where participants were undergraduate students with healthy body weight

(BMI between 18.5 and 25 kg/m^2). Conducting controlled experimental studies in laboratory settings is important for understanding the underlying mechanisms of the training (for discussion on how biases in experiments may be related to the effect sizes of cognitive bias modification on substance addiction, see Cristea, Kok, & Cuijpers, 2016), and keeping a healthy diet is also without doubt important for individuals with healthy weight. However, it is at least equally important to see whether the GNG training similarly changes eating behaviors of overweight and obese individuals in clinical settings, as this group is in a more dire need of an effective intervention to regulate their eating behaviors. A recent meta-analysis (Allom et al., 2016) included 14 studies that investigated the effect of response inhibition trainings (with the GNG training as a widely used paradigm) on eating behaviors, and all 14 studies used undergraduate students or community samples with healthy body weight as participants. One notable exception is Lawrence, Sullivan, et al., 2015, where mostly overweight individuals were recruited and the training was found to be effective for them. Furthermore, a multi-faceted food-training program (including the GNG training) on obese and overweight individuals has shown that the intervention reduced body fat over a 4-week period (Stice, Yokum, Veling, Kemps, & Lawrence, 2017).

However, to the best of our knowledge, to date there is no study that directly compares laboratory studies conducted on undergraduate students in university environments, to studies with overweight and obese individuals in clinical settings. Hence, it is unclear whether the findings from laboratory studies can be directly translated into clinical settings. Clinical samples differ from undergraduate students not only in terms of body weight, but also in many other aspects, such as age, or educational background. Such differences may influence how people perform a training task, and/or influence which psychological processes are recruited during the execution of the task, posing the question whether previous laboratory findings based on undergraduate students are generalizable to clinical samples in clinical settings.

On the one hand, overweight and obese individuals may benefit more from the training compared to undergraduate students, as overweight and obese individuals in general have lower inhibitory control capacity (Lavagnino, Arnone, Cao, Soares, & Selvaraj, 2016) and may hence have more to gain from the training (although a recent study failed to observe such a correlation between inhibitory control capacity and training effectiveness in a normal-weight sample, see Chen et al., 2017). On the other hand, their hyper-responsiveness to food may also impair their performance in the GNG training, rendering the training less effective (Adams, Lawrence, Verbruggen, & Chambers, 2017; Jones et al., 2016). A direct comparison between university students and obese individuals will therefore allow us to evaluate whether developing behavioral training tasks in university laboratories with undergraduate students would be a useful approach to arrive at clinical interventions that can help people regulate their responses to food in clinical settings.

In the current research, we administered the same GNG training in both normal-weight and morbidly obese individuals, to directly compare these two groups in two different settings. Normal-weight individuals were mostly undergraduate students from Radboud University in Nijmegen, the Netherlands, and they were tested in the psychology laboratory. Morbidly obese individuals were recruited from the Nederlandse Obesitas Kliniek (NOK, Dutch Obesity Clinic). The NOK is an outpatient clinic with treatment program for obese (BMI > 35 kg/m^2) and morbidly obese (BMI > 40 kg/m^2) patients who will undergo bariatric surgery. In addition to the bariatric procedure, patients also undergo group counseling by a multidisciplinary team, which starts before the surgery and is focused on behavioral change. Obese individuals were tested in the clinic. In short, both groups were trained to consistently respond to certain food items and withhold responses to other food items in the GNG training. Evaluations of the go and no-go items, along with items not used in the training, were assessed both before and after the training. In addition to the GNG training and food evaluation tasks, we also assessed participants' memory of the stimulus-response associations in a memory recall task (as an index of how well they learned the stimulus-response associations from the GNG training), their hunger level, time since last food intake, and demographic information such as BMI, age and gender, to explore whether any potential differences between the two groups could be attributed to differences on these measures.

Note that we used food evaluation as the outcome measurement of the training, to test the basic devaluation effect of no-go food items in the two different settings. Food evaluation is also practically relevant, as it has been related to other behavioral measurements, such as food choice (Veling et al., 2013a) and weight loss (Lawrence, Sullivan, et al., 2015). Although the ultimate aim of the training is often to help people lose weight, using body weight as the outcome measurement in this particular case would be problematic, because of the large difference in body weight between the two groups before the training and the fact that the obese group will undergo bariatric surgery to lose weight after the training.

In line with previous work (Chen et al., 2016, 2017), when the evaluation of no-go items decreased more strongly than both go items and items not used in the training (i.e., untrained food items, see Method below), the effect was defined as the no-go devaluation effect. Preregistrations containing planned sample size, exclusion criteria and analyses plans, materials used in the experiments, data and analysis scripts can be found on Open Science Framework[1].

The Ethics Committee of the Faculty of Social Sciences at Radboud University reviewed the study and granted ethical approval, and all participants provided written informed consent.

Method

Planned Sample Sizes. At the time of conducting the experiment with morbidly obese individuals, we estimated the effect size of devaluation induced by the GNG training to be Cohen's $d_z = 0.543$, based on previous work in which a highly similar procedure was used (Chen et al., 2016). A-priori power analysis with G*Power indicated that 28 participants were needed to achieve 80% power with an alpha level of .05 and with paired-samples *t* test as the planned analysis (Faul, Erdfelder, Lang, & Buchner, 2007). We planned to recruit 40 participants to leave room for potential exclusion. However, when clients in the clinic were approached, more than expected showed interest to participate. In total 62 clients from the clinic participated in the study. For the experiment with normal-weight individuals (which was executed after the experiment in the clinic), we therefore also planned to recruit 60 participants, which exceeded the required sample size and was comparable to the sample size of obese group.

Procedure. Participants from both groups followed the same experimental procedure as described below. The only difference was that obese individuals participated during a break of their treatment program in a computer room within the clinic, with a maximum number of 10 participants each time. Since the experiment was scheduled during a break of their program, it was not possible to ask the participants to fast for a few hours (cf. Chen et al., 2016). Normal-weight individuals (mostly undergraduate students at Radboud University) were recruited via the online participation system of the university. Normal-weight participants (who were also not asked to fast to keep this aspect comparable with the obese participants) were tested individually in cubicles and compensated with either course credits or money. Thus, the two groups performed the tasks in quite different environments, which allowed us to examine whether the laboratory-developed task works similarly in a relevant field setting.

Pre-Training Rating. Participants were first presented with eighty pictures of various appetitive food items, one by one. The pictures were selected from the food-pics database (Blechert, Meule, Busch, & Ohla, 2014). Each picture was presented once in the middle of the screen, with the question "*How attractive does this food item look to you?*" presented above the food picture. For each picture, participants gave a rating by clicking on a 200-point slider (from -100 = *Not at all* to 100 = *Very much*; the cursor always started at the middle point, i.e., 0). The slider and the question were chosen so that the current experiment would closely follow previous work that employed this procedure and found no-go devaluation effects across multiple experiments (Chen et al., 2016, 2017). The food picture remained on screen until participants clicked on a '*Continue*' button below the slider to advance to the next trial. The task was self-paced and participants could respond at their own speed. The order of pictures was randomized.

Ranking and Item Selection. After participants rated all 80 pictures, the program rank ordered all pictures from the highest rating to the lowest for each participant. The 54 pictures with the highest ratings were selected and divided into go, no-go and untrained condition (every 3 pictures were assigned into the 3 conditions in a counterbalanced order). This selection procedure was used to create 3 sets of 18 pictures, with the average rating of each set matched (for the average ratings in each condition, see Table 1).

Go/No-Go Training. The pictures selected into the go and no-go conditions were then used in the GNG training. On each trial, a food picture was first presented in the middle of the screen. One hundred milliseconds after picture onset, a colored border was presented around the picture. We used two different colors (blue and grey) and the color served as the go and no-go cue. The assignment of different colors as go or no-go cue was counterbalanced across participants. If the color was a go cue, participants were instructed to respond as fast as possible, by pressing the *B* key on keyboard; if the color was a no-go cue, participants should withhold their response and should not press any key. In both cases, the picture remained on screen for 1 second, and the inter-trial interval randomly varied between 1.0 and 1.5 seconds, in steps of 100 ms. Before the experimental blocks, participants received a practice block with 10 trials to get familiar with the task. An error message was provided for 2 seconds if they made a mistake during practice. Pictures used in the practice block were not used in the experimental blocks. In the experimental blocks, no error message was provided. The whole training consisted of 6 blocks, with each of the 18 go pictures and 18 no-go pictures randomly presented once in each block, resulting in 216 trials in total.

Post-Training Rating. The rating task was then repeated, but this time with only the 54 selected pictures. Participants again indicated how attractive each food appeared to them at that moment on a 200-point slider[2].

Memory Recall. Participants then received a memory recall task. Each of the 36 pictures previously used in the GNG training was presented one by one. For each picture, they were asked to press the B key if they thought they responded to the picture in the training, and press the N key if they thought they did not respond. Each picture remained on screen until participants made a response. The memory recall task was self-paced and proceeded at participants' own speed, and the order of presentation was randomized.

Demographics and Other Questions. Participants filled out their age, gender, current hunger level (*-100 = Not hungry at all; 100 = Very hungry*) and how many hours ago they consumed food. Normal-weight individuals also reported their height and weight for the calculation of BMI. The BMI information of the obese individuals was obtained from the clinic after obtaining their consent. Their BMI was calculated based on objectively measured weight and height. At the end of the experiment, all participants were debriefed, compensated (for student participants) and thanked.

Results

Analyses were conducted using R (R Core Team, 2017) and the jmv package for R (Selker, Love, & Dropmann, 2018).

Participants. In total, 62 participants in the obese group and 60 participants in the normal-weight group took part in the experiment. Based on the preregistered exclusion criterion (accuracy on go or no-go trials 3*SD* below sample mean and below 90%), 3 participants from the obese group and 2 participants from the normal-weight group were excluded. The final sample consisted of 59 participants from the obese group and 58 participants from the normal-weight group. For a summary of participant characteristics, see Table 1.

Performance in Go/No-Go Training. Performance of obese individuals was directly compared to the performance of normal-weight individuals using Welch two-sample *t*-tests. For a summary of performance in the GNG training, see Table 1. Overall, accuracies on go and no-go trials did not differ significantly between two groups, $t(63.72) = -1.64$, $p = .105$, and $t(82.51) = -0.68$, $p = .498$, respectively. Obese individuals, however, responded more slowly on go trials than normal-weight individuals, $t(108.22) = 11.27$, $p < .001$. The slower responses in obese individuals may have different causes such as more distraction during the training due to group testing, or the fact that obese individuals in our study may be less familiar with this kind of computer task, or due to some difference in demographics (e.g., age).

Stimulus Evaluation. To check whether the ratings of go, no-go and untrained items were matched before the training, we first performed repeated-measures ANOVA, with training condition as within-subject factor, group as between-subject factor and the average ratings before the training as the dependent variable. The main effect of training condition was not significant, $F(2, 230) = 0.18$, $p = .833$, $\eta_p^2 = .002$, suggesting that the ratings of go, no-go and untrained items were indeed matched before the training (see Table 1). The main effect of group, and the interaction effect between group and training condition on pre-training ratings, were also not statistically significant, $F(1, 115) = 0.01$, $p = .924$, $\eta_p^2 < .001$, and $F(2, 230) = 1.67$, $p = .191$, $\eta_p^2 = .014$, respectively.

For each training condition, a difference score was calculated by subtracting the average rating before the training from the average rating after the training. Note that analyses on the difference scores were equivalent to adding time (i.e., pre- vs. post-training) as an extra independent variable when ratings were used as the dependent variable. We use difference scores as the dependent variable to simplify the interpretation of the results, as we do not need to break down interaction effects with time. In both groups, the difference scores were negative (obese group, $M_{\text{go}} = -8.45$, $SD_{\text{go}} = 11.42$, $M_{\text{no-go}} = -11.48$, $SD_{\text{no-go}} = 10.53$, $M_{\text{untrained}} = -10.18$, $SD_{\text{untrained}} = 9.93$; normal-weight group, $M_{\text{go}} = -7.47$, $SD_{\text{go}} = 11.08$, $M_{\text{no-go}} = -12.79$, $SD_{\text{no-go}} = 11.88$, $M_{\text{untrained}} = -11.79$, $SD_{\text{untrained}} = 11.27$), indicating that in general the ratings of the selected items decreased after the training. This general decrease in evaluation is likely due to regression to the mean.

More important, to assess the change in evaluation induced specifically by the training and explore potential differences between the two groups, the difference scores were submitted to repeated-measures ANOVA, with training condition as a within-subject factor and group as a between-subject factor. The main effect of condition was significant, $F(1.89, 217.32) = 10.35$, p

$< .001$, $\eta_p^2 = .083$. The main effect of group, and the interaction effect between group and condition, were not significant, $F(1, 115) = 0.14$, $p = .709$, $\eta_p^2 = .001$, and $F(1.89, 217.32) = 1.11$, $p = .330$, $\eta_p^2 = .010$, respectively. Pairwise comparisons showed that the difference between go and no-go items, and the difference between go and untrained items, were statistically significant, $t(116) = 3.97$, $p < .001$, Hedges's $g = 0.366$, 95% CI [0.106, 0.625], and $t(116) = 3.23$, $p = .002$, Hedges's $g = 0.297$, 95% CI [0.038, 0.556], respectively. The difference between untrained and no-go items was not statistically significant, $t(116) = 1.36$, $p = .177$, Hedges's $g = 0.125$, 95% CI [-0.133, 0.383].

Due to the difficulty in interpreting non-significant results with null hypothesis significance testing, we also conducted Bayesian analysis to assess evidence in support of the null hypotheses (Dienes, 2014). Bayesian repeated-measures ANOVA implemented in BayesFactor package for R (Morey, Rouder, & Jamil, 2014) showed that the Bayes factors for the main effect of group and for the interaction effect were 0.250 and 0.148, respectively (the Bayes factor for the main effect of training condition was 314.8). In other words, the data is 4 times (1/0.250 = 4) more likely under the null model than under the model with the main effect of group, and 6.77 times (1/0.148 = 6.77) more likely under the model without the interaction effect than under the model with the interaction effect. These two Bayes factors suggest that the observed data provided support for the absence of the main effect and the absence of the interaction effect between group and training condition. Despite the differences between two groups in terms of BMI, age, educational background and testing environments, these results suggest that the GNG training similarly changed food evaluations for both morbidly obese and normal-weight individuals. However, contrary to previous findings (Chen et al., 2016, 2017), after taking the untrained items into account, the overall effect could be better explained as a go valuation effect (i.e., less decrease in evaluations of go items over time) rather than a no-go devaluation effect (i.e., more decrease in evaluations of no-go items over time).

Although the previous analysis showed that there was no difference between the obese and the normal-weight group, it may still be interesting and useful to learn the effect sizes of the training within each group. We therefore also carried out repeated-measures ANOVA for each group separately, as outlined in our preregistrations. For the obese group, the main effect of training condition was close to but did not reach statistical significance, $F(2, 116) = 2.76$, $p = .067$, $\eta_p^2 = .045$, whereas the effect was statistically significant for the normal-weight group, $F(1.77, 100.72) = 8.31$, $p < .001$, $\eta_p^2 = .127$. In the obese group, only the difference between go and no-go items reached statistical significance, $t(58) = 2.21$, $p = .031$, Hedges's $g = 0.286$, 95% CI [-0.080, 0.653]. The difference between untrained and no-go items, and the difference between go and untrained items, were not statistically significant, $t(58) = 1.04$, $p = .304$, Hedges's $g = 0.134$, 95% CI [-0.231, 0.499], and $t(58) = 1.38$, $p = .174$, Hedges's $g = 0.178$, 95% CI [-0.187, 0.544], respectively. For the normal-weight group, the difference between go and no-go items, and the difference between go and untrained items, were significant, $t(57) = 3.34$, $p = .001$, Hedges's $g = 0.435$, 95% CI [0.063, 0.807] and $t(57) = 3.14$, $p = .003$, Hedges's $g = 0.410$, 95% CI [0.038, 0.781], respectively. The difference between untrained and no-go items was not statistically significant, $t(57) = 0.870$, $p = .388$, Hedges's $g = 0.114$, 95% CI [-0.255, 0.482]. Note that although the significance patterns were slightly different between the obese group and the normal-weight group, the previous analyses involving group as a factor suggest that there was no main effect of group or an interaction between group and training condition. The overall pattern was therefore highly comparable between these two groups (see Figure 1 for results).

Self-Reported Hunger as Potential Moderator. Next, we carried out exploratory analyses to explore the discrepancy between the current results (i.e., a go valuation effect) and previous findings (i.e., a no-go devaluation effect, Chen et al., 2016). A notable difference between the current study and the previous experiments is that in the previous experiments participants were required to fast for at least 3 hours before taking part. This was done because previous work has shown that the no-go devaluation effect induced by the GNG training was stronger for participants with relatively high appetite (by recruiting participants before lunch vs. after lunch, Veling, Aarts, & Stroebe, 2013a, 2013b). This moderation is explained by assuming that participants with relatively high appetite show stronger approach tendencies toward appetitive food items. According to the BSI theory (Veling et al., 2008), the resulting response conflict is therefore also stronger, leading to a stronger devaluation effect. To explore whether appetite moderates the strength of no-go devaluation effect in the current study, we explored the role of self-reported hunger. Since no differences in food evaluation were found between the normal-weight and obese groups, we performed analysis on collapsed dataset.

A repeated-measures ANOVA on the difference scores of pre- and post-training ratings was performed, with training condition (go vs. no-go vs. untrained) as the within-subject factor, group (normal-weight vs. obese) as the between-subject factor, and self-reported hunger added as a covariate. The interaction effect between training condition and hunger was significant, $F(1.88, 213.81) = 3.65$, $p = .030$, $\eta_p^2 = .031$. When participants were relatively not hungry (hunger rating one standard deviation below mean), the differences between go and no-go items, untrained and no-go items, and untrained and go items, were all not significant, *estimate* = 1.98, $SE = 1.47$, $z = 1.35$, $p = .363$; *estimate* = -1.09, $SE = 1.17$, $z = -0.93$, $p = .622$; and *estimate* = -3.07, $SE = 1.33$, $z = -2.31$, $p = .053$, respectively (see left panel of Figure 2). Importantly, when participants were relatively hungry (hunger rating one standard deviation above mean), the differences between go and no-go items and between untrained and no-go items were statistically significant, *estimate* = 6.35, $SE = 1.47$, $z = 4.34$, $p < .001$, and *estimate* = 3.40, $SE = 1.17$, $z = 2.90$, $p = .011$, respectively. The difference between untrained and go items was not statistically significant, *estimate* = -2.95, $SE = 1.33$, $z = -2.23$, $p = .066$ (see right panel of Figure 2). Thus, relatively hungry participants exhibited the no-go devaluation effect, similar to what has been observed in previous work (Chen et al., 2016, 2017).

Memory of Stimulus-Response Associations as Potential Moderator. At the end of the experiment, participants received a memory recall task to assess their learning of the stimulus-response associations. Previous work has shown that merely remembering the stimulus-response associations without engaging in the training is not *sufficient* to induce the devaluation effect (Experiment 5, Chen et al., 2016). Motor responses, or more precisely, the inhibition of response tendencies on no-go trials, are therefore required for the devaluation effect. Nonetheless, learning stimulus-response associations may contribute to the effect of the training on stimulus evaluations. Recent work indeed suggests that differences in learning stimulus-response associations may explain the presence and absence of the no-go devaluation effect with different experimental procedures (Chen et al., 2017). Therefore, we explored whether the two groups differ in learning stimulus-response associations, and directly tested whether the learning of stimulus-response associations moderates the effects.

Signal detection analysis was used on the memory recall data to disentangle the discriminability and bias components in recognition memory (Macmillan & Creelman, 2004). In the terminology of signal detection theory, a hit was defined as a go item correctly identified as go, a false alarm was defined as a no-go item identified as go, a correct rejection was defined as a no-go item correctly identified as no-go, and a miss was defined as a go item identified as no-go. Hit rate and false alarm rate were calculated for each participant. Proportions of 0 and 100% were converted to 1/(2N) and 1-1/(2N), respectively, where N is the number of trials on which the proportion was based (Macmillan & Creelman, 2004). Proportions after applying such edge correction method were used to calculate indices of discriminability and bias (d' and β, using the R code provided by Pallier, 2002). Using another edge correlation method as recommended by Macmillan & Creelman, 2005, namely adding 0.5 to all counts before calculating the hit and false alarm rates, or using the non-parametric indices of discriminability and bias, does not change the results reported below.

Welch's two sample *t*-tests suggest that obese individuals showed lower discriminability ($M_{\text{obese}} = 0.38$, $SD_{\text{obese}} = 0.71$) than normal-weight individuals ($M_{\text{control}} = 1.45$, $SD_{\text{control}} = 1.13$), $t(95.71) = -6.15$, $p < .001$, Hedges's $g = -1.11$, 95% CI [-1.525, -0.736]. Furthermore, obese individuals also showed lower bias ($M_{\text{obese}} = 1.00$, $SD_{\text{obese}} = 0.38$) than normal-weight individuals ($M_{\text{control}} = 1.37$, $SD_{\text{control}} = 0.70$), $t(86.76) = -3.52$, $p < .001$, Hedges's $g = -0.646$, 95% CI [-1.022, -0.270]. The results on discriminability suggest that overall normal-weight individuals learned the stimulus-response associations better than obese individuals.

The discriminability index was then added as covariate to the repeated-measures ANOVA on difference scores, with training condition and group as independent variables. The interaction effect between discriminability and training condition was significant, $F(2, 228) = 11.38$, $p < .001$, $\eta_p^2 = .091$. When participants did not learn the associations well (discriminability index one standard deviation below mean), they showed neither go valuation nor no-go devaluation effect (see Figure 3, left panel). The differences between go and no-go items, between go and untrained items, and between untrained and no-go items, were all statistically not significant, *estimate* = 0.10, *SE* = 1.39, $z = 0.07$, $p = .997$; *estimate* = - 0.58, *SE* = 1.24, $z = 0.47$, $p = .887$; and *estimate* = 0.67, *SE* = 1.21, $z = 0.56$, $p = .842$, respectively. When participants learned the associations relatively well (discriminability index one standard deviation above mean), they showed a strong go valuation effect (see Figure 3, right panel). More specifically, pairwise comparison showed significant difference between go and no-go items, and between go and untrained items, *estimate* = 8.24, *SE* = 1.39, $z = 5.91$, $p < .001$, and *estimate* = 6.60, *SE* = 1.24, $z = 5.32$, $p < .001$, respectively. The difference between untrained and no-go items was not statistically significant, *estimate* = 1.64, *SE* = 1.21, $z = 1.36$, $p = .362$. The bias index did not significantly interact with training condition, $F(1.87, 213.51) = 1.83$, $p = .166$, $\eta_p^2 = .016$.

Discussion

In the current research, both morbidly obese and normal-weight individuals were trained to consistently respond to certain food items and withhold responses toward other food items, in a clinical setting and a controlled laboratory setting, respectively. Between-group comparisons suggest that the two groups behaved strikingly similarly to the employed experimental procedures, despite the differences in testing environments (group versus individual testing) and participant characteristics (BMI, age). (a) First, both groups rated the food items as equally attractive before the training. (b) They also performed equally well in the GNG training as measured by the error rates. (c) Furthermore, the GNG training similarly changed evaluations of food items in both groups. The go food items were evaluated more positively than both no-go and untrained food items after the training, indicating overall a go valuation effect. Differences between groups were observed for go reaction times and performance in the memory recall task.

These observed similarities between two very different participant groups in responsiveness to the GNG training suggest that the approach taken by many previous studies, namely developing the GNG training task in controlled university laboratories and later on translating the findings into clinical interventions in different settings, is a reasonable way of developing effective behavioral interventions (Allom et al., 2016; Jones et al., 2016). That is, our results show that changes in stimulus evaluation induced by the GNG training in university laboratories may result in similar changes when obese participants are tested in clinical settings. The GNG training can thus be further optimized in controlled laboratory studies, and translated into clinical interventions at a later stage, once the effect of the training proves to be strong and durable in the laboratory. This approach is efficient, as testing the training task in university laboratories is often relatively cheap and convenient. Overweight or obese individuals may eventually perform the training in clinics or at home, which could be a useful complement to traditional treatment programs.

It is important to emphasize that overall we found a go valuation effect (i.e., after the training, go items were evaluated more positively compared to no-go and untrained items), but not the no-go devaluation effect. The absence of the no-go devaluation effect in the current research may seem surprising in light of previous work that used almost the same materials and procedures and has reliably found the no-go devaluation effect (Chen et al., 2016). One important difference between these previous experiments and the current research is that in previous work participants were always asked to not eat anything during the three hours before participating in the experiments (Chen et al., 2016), whereas in the current research it was not possible to ask participants to fast. This procedural difference may explain the discrepancy between the current research and the previous findings (Chen et al., 2016). Specifically, participants with a relatively high appetite may have stronger approach tendencies toward appetitive food items, and hence, the resulting response conflict when they inhibit their responses on the no-go trials may be stronger. This may lead to a larger decrease in food evaluation induced by the GNG training compared to when people are relatively satiated (Veling et al., 2013a, 2013b). In line with this post-hoc explanation, the exploratory analysis showed that self-reported hunger moderated the effect of training, such that relatively hungry participants rated no-go items less positively than both the go and untrained items, in line with the no-go devaluation effect observed in previous work (Chen et al., 2016, 2017; Veling et al., 2008). This finding suggests that in future examinations of the possible no-go devaluation effect among obese individuals, care should be taken such that the training is conducted when participants are relatively hungry. This conclusion, however, should be treated with caution, as it is based on exploratory analyses, and self-reported time since last food intake did not moderate the training effects (see Footnote 3). Future work needs to more extensively replicate and investigate this effect in preregistered studies before drawing strong conclusions.

Go valuation effects have been observed in previous work, where participants responded rapidly or frequently to go items (Chen et al., 2016, 2017). Post hoc, our current finding on the go valuation effect is in line with the theoretical account that action and valence are closely coupled, such that inaction is associated with punishment and action (i.e., go responses) is associated with reward (Guitart-Masip et al., 2012, 2014). Related, recent work on a different food training paradigm (the cue-approach training, see Bakkour et al., 2016; Schonberg et al., 2014; Veling et al., 2017) has shown that rapidly responding to go items led to choices for these go items over no-go items, and potentially also increased the reward value of go items (Schonberg et al., 2014). The fact that food items can be made more attractive by linking them to a simple motor response is interesting and potentially useful. Although this go valuation effect was shown here for food items that were already attractive, other experiments have revealed that the effect can also occur for food items that are relatively unattractive (Chen et al., 2016, 2017). Future work may use this go valuation effect by presenting low-calorie healthy food items on go trials, to see whether responding to these healthy food items may increase people's liking for them.

We also explored the role of memory of the cue-food contingencies in relation to the food evaluations using signal detection analysis. Overall, obese participants showed lower discriminability and lower bias scores than normal-weight participants. The discriminability score moderated the training effect, such that individuals who learned the stimulus-response associations relatively well showed a strong go valuation effect, whereas those who did not learn the associations well did not show any effect. The bias score did not moderate the training effects. The nature of the learning process in the GNG training, and why some individuals learned the associations better than others, however, is not entirely clear. Some individuals learned the associations better, maybe because they paid more attention to the training (Best et al., 2016) and/or they were more familiar with this kind of computer tasks. Future work may test whether revealing the structure of the training (i.e., consistent mapping between a stimulus and a certain response) would lead to better learning of the associations, and thereby stronger behavioral effects. This knowledge will be useful in practical settings where researchers strive to improve the effectiveness of the training.

Although these present results are interesting, some limitations with the current work still warrant more future research. First, the training effects were relatively weak. Future research may look at factors that can further increase the effectiveness of the training. For instance, exploratory analyses on self-reported hunger and memory of stimulus-response associations suggest that conditions that increase participants' appetite and those that facilitate stimulus-response learning may increase the effectiveness of the training. These factors can be potential candidates for future investigations. Second, we only included food evaluation as the outcome measurement. Although change in food evaluation via the GNG training has been related to weight loss in previous work (Lawrence, Sullivan, et al., 2015), it remains interesting to see whether the training changes actual eating behavior and eventually body weight in the long term, especially for obese individuals. Note also that in the current research, we measured explicit evaluations of food items. As mentioned before, a recent review suggests that when stimulus evaluation is assessed with implicit association tests, the training may not induce devaluation (Jones et al., 2016). Future work may examine whether the training changes implicit evaluations, and how and when GNG changes implicit and explicit evaluations respectively. Related, in the current research we directly trained participants' responses towards (images of) specific food items. However, our environment is also filled with non-food cues that have been associated with food, such as symbols of fast food chains, food advertisements, or very visible environmental cues for food such as snacking machines. Previous work has shown that such food-associated cues may elicit food seeking even when people were satiated (Watson, Wiers, Hommel, & De Wit, 2014), and severely obese individuals were particularly sensitive to cues that have been associated with high-calorie food (Watson, Wiers, Hommel, Gerdes, & de Wit, 2017). In light of these findings, it is interesting for future research to explore whether training people's responses toward such food-associated cues could also change their eating behaviors. Finally, the obese individuals in the current research were all motivated to lose weight, and were about to undergo surgery. This raises the question whether the effect may generalize to obese individuals with relatively low motivation to lose weight (Veling et al., 2014). All these questions need to be more systematically addressed in future work.

To conclude, in the current research we adopted a translational approach and directly compared two groups in different settings. The results showed that both groups performed well in the GNG training, and the GNG training changed food evaluation in the same direction for both normal-weight and morbidly obese individuals. More specifically, after the training, participants rated go items as more attractive than both no-go and untrained items. Furthermore, participants who learned the stimulus-response associations relatively well showed a strong go valuation effect, and those who were relatively hungry showed a typical no-go devaluation effect. These results are encouraging, as they suggest that the theoretical insights gained from controlled laboratory studies with undergraduate students can be translated into more practical settings with clinical samples, despite the differences in participant characteristics and testing environments. Our research therefore serves as a step in bridging the gap between laboratory research and work in more applied settings. More future work is needed, both fundamental and translational, to help develop effective interventions to combat obesity.

Footnote

1 - https://osf.io/cb89f/?view_only=c8f0d38dce5e4c0e8d8d8767d306cb00

2 - At the end of *Post-Training Rating*, participants also rated the attractiveness of 10 non-food images (hammers, tapes etc.). This task was included to back up the cover story, which was that the current study was about people's evaluation of both food and non-food objects in their daily life. Data from this task will not be further discussed.

3 - Note that in previous work, appetite was manipulated by recruiting participants before and after lunch (Veling et al., 2013a, 2013b), whereas the self-reported appetite did not correlate with the no-go devaluation effect (Veling et al., 2013a). In the current research, participants also reported time since last food intake (in hours). Time since last food intake, however, did not moderate the training effects. Misunderstanding of the question among some of the participants (i.e., reporting the exact time of last food intake, instead of hours since last food intake) makes the interpretation of the results difficult. Future work may look into how appetite can be accurately assessed with self-reports and which measurement may best moderate the effects.

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Table 1. Summary of Demographics, Performance in the Go/No-Go Training and Food Evaluations for Obese and Normal-Weight Group

Parameter	Obese Group	Normal-Weight Group	Group Difference
Female/Male	45/14	43/15	$\chi^2(1) = 0.003$, $p = .958$
Age	46.10 (11.46)	23.21 (5.08)	$t(80.1) = 14.0$, $p < .001$
BMI	44.49 (5.56)	22.64 (2.96)[a]	$t(89.0) = 26.5$, $p < .001$
BMI Range	34.0 – 60.0	18.4 – 32.3[a]	-
Go Accuracy (%)	97.85 (7.11)	99.41 (1.57)	$t(63.7) = -1.6$, $p = .105$
NoGo Accuracy (%)	97.94 (3.71)	98.31 (1.74)	$t(82.5) = -0.7$, $p = .498$
Go RT (ms)	445.80 (52.37)	349.00 (39.83)	$t(108.2) = 11.3$, $p < .001$
Go Pre-Rating	36.93 (24.67)	37.14 (18.20)	$t(106.7) = -0.1$, $p = .959$
NoGo Pre-Rating	36.84 (24.65)	37.33 (18.18)	$t(106.7) = -0.1$, $p = .904$
Untrained Pre-Rating	36.84 (24.50)	37.30 (18.13)	$t(106.9) = -0.1$, $p = .909$
Go Post-Rating	28.48 (26.03)	29.67 (21.10)	$t(111.0) = -0.3$, $p = .787$
NoGo Post-Rating	25.36 (24.70)	24.54 (21.87)	$t(113.8) = 0.2$, $p = .849$
Untrained Post-Rating	26.66 (25.55)	25.51 (22.08)	$t(113.2) = 0.3$, $p = .795$

Note: M = male; F = female; BMI = body mass index (kg/m^2); Standard deviations are reported in parentheses. a: One participant did not report his or her weight. BMI was calculated for the remaining 57 participants.

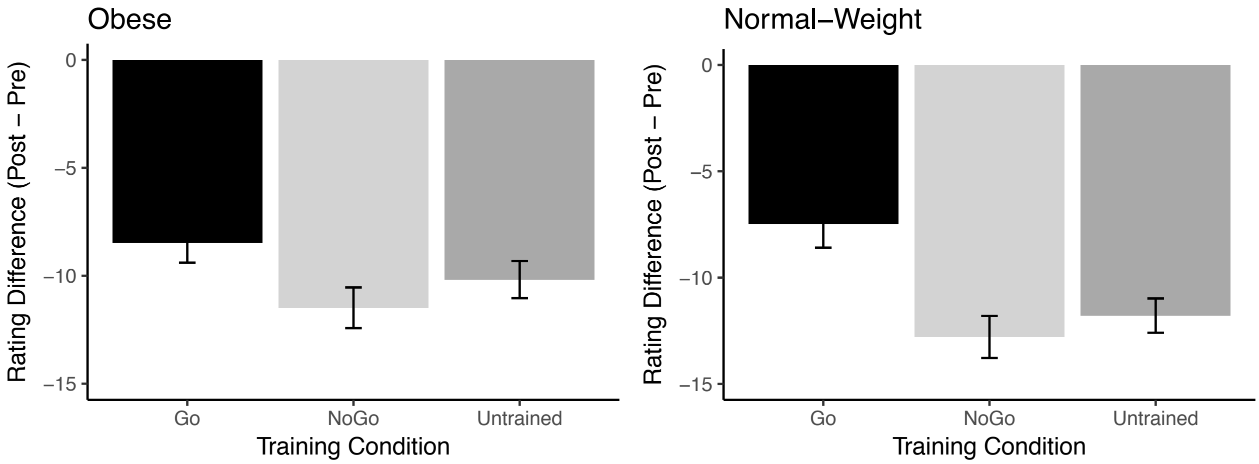

Figure 1. Change in Food Evaluation Induced by the Go/No-Go Training in Obese (left panel) and Normal-Weight (right panel) Individuals. Error bars stand for within-subject standard errors of mean.

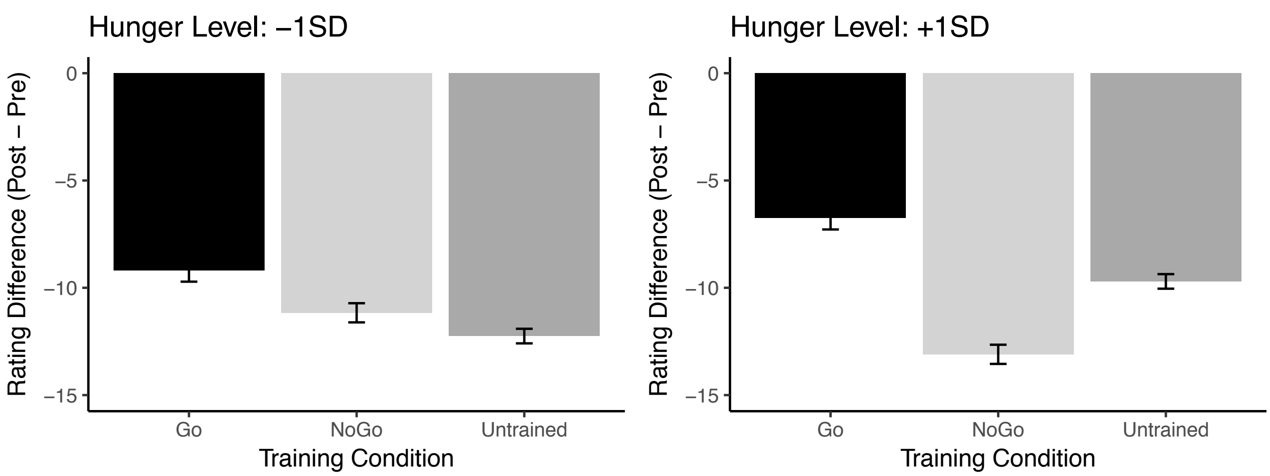

Figure 2. Change in Food Evaluation Induced by the Go/No-Go Training in Participants with Low (one standard deviation below mean; left panel) and High Self-Reported Hunger (one standard deviation above mean; right panel). Error bars stand for within-subject standard errors of mean.

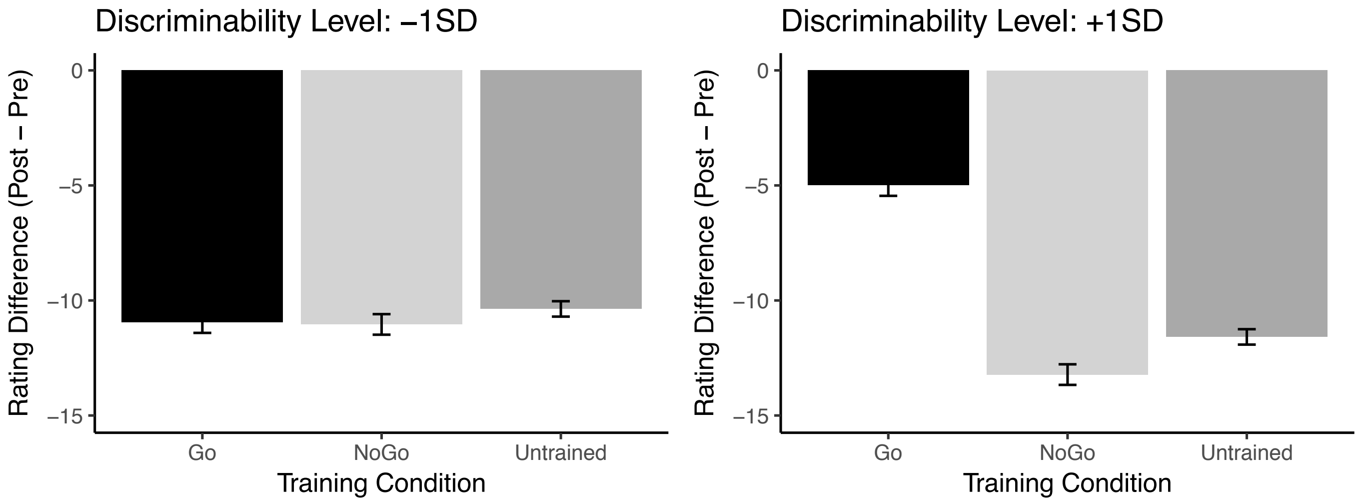

Figure 3. Change in Food Evaluation Induced by the Go/No-Go Training in Participants with Low (one standard deviation below mean; left panel) and High Discriminability Score (one standard deviation above mean; right panel). Error bars stand for within-subject standard errors of mean.

Data Transparency Statement:

No part of the data in this manuscript has been published before. This manuscript is currently not under consideration of any other journals.