Changing value through cued approach: an automatic mechanism of behavior change

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It is believed that choice behavior reveals the underlying value of goods. The subjective values of stimuli can be changed through reward-based learning mechanisms as well as by modifying the description of the decision problem, but it has yet to be shown that preferences can be manipulated by perturbing intrinsic values of individual items. Here we show that the value of food items can be modulated by the concurrent presentation of an irrelevant auditory cue to which subjects must make a simple motor response (i.e., cue-approach training). Follow-up tests showed that the effects of this pairing on choice lasted at least 2 months after prolonged training. Eye-tracking during choice confirmed that cue-approach training increased attention to the cued items. Neuroimaging revealed the neural signature of a value change in the form of amplified preference-related activity in ventromedial prefrontal cortex.

A basic tenet of economic theory is that choices are a reflection of the values that the decision maker places on the available options[1], but it is well known that these values can change with experience, time and context. Research in psychology over the past century has focused on reinforcement as the main mechanism to influence value[2,3], whereas research in behavioral economics has focused on factors such as the description of the decision problem (e.g., framing[4–6]). These studies have shown that choices are influenced by how options are described, how preferences are elicited and by the context of other available options[5,7,8], but they have not attempted to directly perturb the underlying basic values of individual items. Other work has shown that choice itself influences preference[9–11], and that preferences can also be modulated by mere exposure to items[12,13] and by embodied approach/avoidance responses[14–16]. Here we demonstrate a new mechanism by which value can be modulated in a lasting manner simply through cued approach to a stimulus using a combination of behavioral, eye-tracking and functional-neuroimaging methods.

Our approach was influenced by previous research demonstrating that, by modulating the time spent viewing items[17], manipulations of attention can influence choice[18,19]. It has likewise been shown that focusing attention at behaviorally relevant points in time, regardless of the attended item, can 'boost' memory for visual scenes[20,21]. We examined whether association of a food item with an irrelevant cue and motor response can modulate subsequent choices to consume the item.

In each of the studies reported below, we asked participants to fast for 4 h before visiting the laboratory. Upon arrival, they participated in an auction (the Becker-DeGroot-Marschak (BDM) procedure)[22,23] (Fig. 1a) that measured willingness to pay (WTP) for each of 60 snack food items; we informed participants that the auction would be played for real consumption at the end of the experiment. We sorted items based on WTP and split the items into sets of higher-valued and lower-valued items to allow assessment of differential effects based on individual item preferences. Participants underwent cue-approach training in which they observed images of individual food items presented for 1 s (Fig. 1b) and were instructed to press a button as fast as possible (before the image disappeared) only when they heard a tone (i.e., Go trials). We adjusted the tone-presentation delay using a staircase procedure to ensure that the task remained difficult. Sixteen items (8 high-value and 8 low-value) were consistently associated with a tone. There was no feedback to the participants regarding the success of the button press in the allotted time window. We presented the entire set of items 8, 12 or 16 times across the different studies. In each study we presented each item the same number of times, thus controlling for any potential mere-exposure effects[12,13]. In a probe phase that followed training, we presented participants with pairs of items that were matched (Supplementary Fig. 1) for the initial utility of the items (to allow isolation of the cue-approach effect, Fig. 1c) but differed by whether they had or had not been associated with a cue during training (i.e., one Go and one 'NoGo' item). We asked participants to choose one item per trial for a chance to consume that item at the end of the study. We randomly selected one trial and honored the choice on that trial. If training had no effect, participants should be indifferent between the two items and choose them equally often. After the probe phase, we repeated the initial auction (Fig. 1d) to test whether the expressed monetary value of individual items changed after training (both auctions were played out together such that only one bid was chosen).

Figure 1 Task procedure. (**a**) Participants were endowed with three dollars and told that after making a series of auction-based choices, they would have an opportunity to use these $3 to buy a snack. During the auction phase, participants were presented with 60 items, one at a time, on a computer screen. They bid by moving a mouse cursor along an analog scale that spanned from 0 to 3 at the bottom of the screen. The auction was self-paced, and the next item was presented only after the participant placed the bid. (**b**) During training, participants were instructed to press a button when they heard a tone (occurring after a variable delay based on a staircase) but before the image disappeared from the screen (1 s after it appeared). Images appeared on the screen one at a time, and ~25% of items were associated with a tone. Trials were separated by a jittered intertrial interval (ITI) with a mean duration of 3 s. GSD, Go-signal delay. (**c**) During the probe, participants were instructed to choose one of two items that appeared on the screen to the right and left of a central fixation cross. Participants were told that a single trial would be selected and honored for real consumption, meaning they would receive the food item they chose on that particular trial. Participants had 1.5 s to make their choice, and trials were separated by a variable intertrial interval with a mean duration of 3 s. RT, reaction time. (**d**) The auction described in **a** was repeated at the end of the experiment.
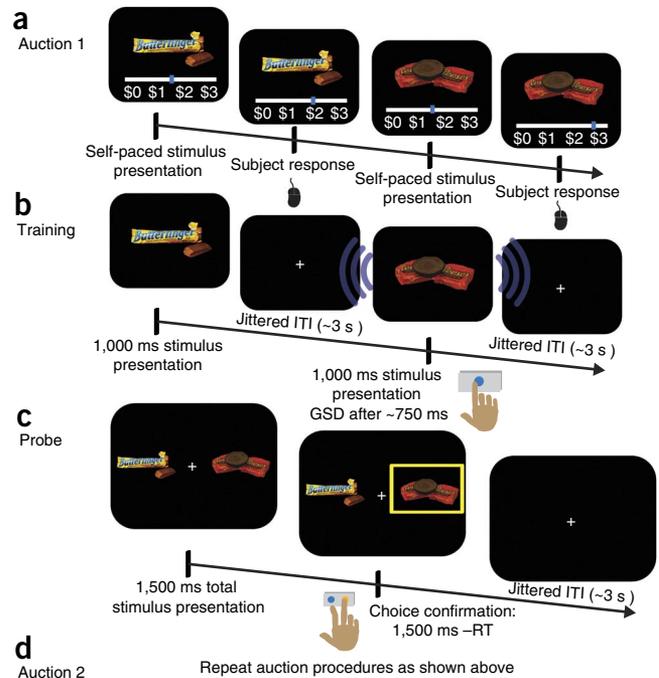
RESULTS

Cue-approach binary-choice effects

We varied the length of training from the initial study (which included 12 repetitions of all 60 snack food items) to test whether fewer (8 repetitions, study 2) or more (16 repetitions, study 4) repetitions would have a different effect on choice. In all four independent samples (studies 1 through 4, total $n = 102$ participants, **Fig. 2a** and **Supplementary Table 1**), we found a consistent effect of cue-approach training on choices during the probe phase for high-value item pairs: participants chose high-value Go items on 60–65% of trials ($P = 0.00006$–0.008; 63% across samples 1–4, $P < 0.0001$ two sided repeated measures logistic regression). There were no differences in this effect between the different samples (all pairwise comparisons, P values > 0.6, two sided repeated measures logistic regression). This occurred even though participants had never been presented with these items in pairs previously, nor were they externally reinforced for pressing the button during training. We did not find an increase of Go-item choices in low-value pairs (except for a marginally significant effect in study 1 (58%, $P = 0.054$, two sided repeated measures logistic regression) and a weak effect across studies 1–4 (55% $P = 0.032$, two sided repeated measures logistic regression)).

The increase in choice for Go items was significantly higher for high-value versus low-value pairs ($P < 0.001$ across the cue-approach studies 1–4, two sided repeated measures logistic regression). The fact that the effect was not consistent across high-value and low-value pair trials suggests that choosing Go items was not a general strategy adopted by participants at probe (e.g., owing to demand characteristic) but rather that cue-approach training was selectively more effective for higher-value items.

We should emphasize that all items used were palatable junk food items. In an additional study (study 7) in which all items were below the median auction value (**Supplementary Fig. 2**), we still observed a cue-approach effect (**Supplementary Fig. 3**) for the higher-valued items in this set, which suggested that the difference in cue-approach effects between high-valued and low-valued items may be relative to the overall distribution of value in the training set; alternatively, there may be a nominal value threshold below which the effect does not occur.
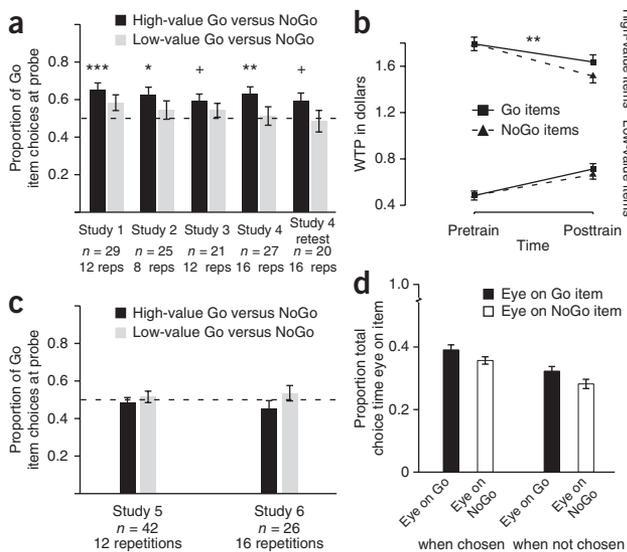

Figure 2 Behavioral results for cue-approach and cue-avoidance studies. (**a**) Proportion of choices of the Go item in pairs of high-value Go versus NoGo and low-value Go versus NoGo items for each of the four cue-approach studies (1–4) as well as for study 4 retest. Number of repetitions reflect number of individual stimulus presentations during training. Significance level reflects odds of choosing the Go versus NoGo item. (**b**) WTP before and after training for Go and NoGo separately for items in the probe high-value Go versus high-value NoGo pairs (top) and low-value Go versus low-value NoGo (bottom) pairs. The sample includes all participants from studies 1–4 of cue approach. Significance level reflects interaction for time by item type (Go or NoGo) in a repeated-measures linear regression. $n = 102$ participants. (**c**) Proportion of choices of the Go item in pairs of high-value Go versus NoGo and low-value Go versus NoGo (light gray) items for the two cue-avoidance studies. (**d**) Proportion of total choice time during probe that gaze position was on the high-value Go or NoGo item in a pair for trials when Go or NoGo items were chosen separately. The sample is a subset of study 4 ($n = 18$ participants). Eighteen participants had their eye positions recorded with an eye tracker while performing the cue-approach task. Significance levels reflect repeated measures linear regression. Effects for **d** are discussed in Results. Error bars, s.e.m. (**a**,**c**) and within-subject s.e.m. (**b**,**d**).
$^{***}P < 0.0001$, $^{**}P < 0.001$, $^{*}P < 0.01$, $^{+}P < 0.05$ (two-sided tests).

Cue-approach auction effects

As mentioned above, we repeated the initial auction (**Fig. 1d**) to test whether the expressed monetary value of individual items changed after training (both auctions were played out together such that only one bid was chosen). We found evidence that nonreinforced training influenced the value of individual items. We selected high-valued and low-valued items on the basis of their relatively extreme values in the initial auction, and thus both high-valued and low-valued items showed overall regression to the mean (**Fig. 2b**). Across samples 1–4, the high-value Go items retained their value better (i.e., showed less regression to the mean) than the high-value NoGo items (delta between high-value Go and NoGo = 12.2 cents, $P = 0.0006$ combined across samples 1–4, two sided repeated measures linear regression). For the low-value items there was also regression to the mean for both Go and NoGo items (delta between low-value Go and NoGo = 4.9 cents less, $P = 0.12$, two sided repeated measures linear regression). When we analyzed data for both auctions using repeated-measures linear regression with Go/NoGo and value (high/low) factors and a participant-grouping factor, there was a main effect of Go/NoGo ($P < 0.0001$, two sided repeated measures linear regression), and the interaction term of high/low by Go/NoGo was marginally significant for the second auction bids when accounting for the first auction bids ($P = 0.053$, two sided repeated measures linear regression).

This suggests that cue-approach training also influenced subjective values of Go versus NoGo items (as expressed by relative changes in WTP) differently for high-value and low-value items. Previous work has demonstrated effects of choice on preferences (see refs. 9,10 for the underlying neural mechanisms), which extend for long periods of time[24]. Thus, it is likely that the binary choices influenced the auction. In an additional sample collected without a probe phase (study 9) there was not a significant effect on the second auction (**Supplementary Table 2**). Direct comparison of this greater retention of the original values of high-value Go items compared to high-value NoGo items between the two samples that showed this effect (study 2 and study 4) with the no-probe study 9 showed a marginal difference for study 4 versus study 9 ($P = 0.0592$, two sided repeated measures linear regression) and for study 2 versus study 9 ($P = 0.0471$, two sided repeated measures linear regression). When combining samples 1–4 and comparing them to study 9, the comparison was not significant ($P = 0.1$, two sided repeated measures linear regression). This hints that 'pre-post' auction differences might reflect the effects of choice during the probe phase. A fuller understanding of the factors that modulate these changes in value will require additional empirical work.

Cue-avoidance and cue without approach

To test the mechanism underlying the cue-approach effect, we ran two additional independent samples (**Fig. 2c**) on a cue-avoidance task, which is a functional mirror of the cue-approach manipulation. The entire procedure was identical to that described in **Figure 1**, except for the training phase. In this phase, rather than asking participants to press the button only when they heard the sound, we asked the participants to press the button every time they saw an image, unless they heard a sound. We titrated the timing of the sound using a ladder technique similar to that in a standard stop-signal task[25]. In this version, the cue appeared at exactly the same frequency as studies 1–4 but served as an inhibition or avoidance cue rather than an approach cue, similar to the 'automated inhibition' version of the stop-signal task[26,27]. In a probe phase identical to that described above, we found no difference between choices of Go and NoGo items (for choice of high-value Go: 48% ($P = 0.5$, two sided repeated measures logistic

regression) and 45% ($P = 0.3$, two sided repeated measures logistic regression) in studies 5 (with 12 repetitions of all items) and 6 (with 16 repetitions of all items), respectively; for choice of low-value Go: 52% ($P = 0.7$, two sided repeated measures logistic regression) and 53%, ($P = 0.4$, two sided repeated measures logistic regression)). Furthermore, in a direct comparison between the pooled samples of the cue-approach version (studies 1–4, $n = 102$ participants) and the pooled sample of the cue-avoidance version (studies 5 and 6, $n = 68$ participants), we found that the choices of the high-value Go items were significantly greater for the cue-approach task ($P < 0.0001$, two sided repeated measures logistic regression between subjects) but not for the low-value Go items ($P = 0.28$, two sided repeated measures logistic regression between subjects).

To test whether a motoric action is necessary for the cue-approach effect, we performed an additional study (study 8) in which we repeated the same procedure without requiring any motor responses. Participants heard the cue at times yoked to those of study 4 participants but were not required to make any motor responses. We did not find any effects during the probe phase (**Supplementary Fig. 3**) of study 8 (P values > 0.3, two sided repeated measures logistic regression). There was a significant difference for choices of high-value Go items between study 4 and study 8 ($P = 0.002$, two sided repeated measures logistic regression) but not for low-value Go items ($P = 0.7$, two sided repeated measures logistic regression). These results suggest that the motor response is crucial for the cue-approach effect.

Eye gaze during training

We examined whether the observed effects were due to greater observation times during training and thus modulation of the mere-exposure effect[28,29]. We tested the gaze time during training on part of the samples for which sufficient eye-tracking data were collected: on 12 participants from the imaging sample (study 3), on all participants in the last run of the longer-training cue-avoidance study (study 6) and on all participants for the study with cues but no approach (study 8). We did not find any significant differences in gaze times (P values > 0.1, two sided repeated measures linear regression) across all of training nor on the last training run in any of these studies (**Supplementary Table 3**).

It should be noted that there were no significant behavioral-choice effects in any of these studies (nor within the subsample of 12 participants from study 3), and thus these gaze data cannot entirely rule out an effect of gaze differences. To examine this question further, we performed a regression of gaze time for each item and subsequent choices for the corresponding item during probe for each of these studies. This was possible because there was variance in choices of individual items even though there was no mean difference in choices between Go and NoGo items. We found no significant effect of gaze time (P values range between 0.06 to 0.48, two sided repeated measures logistic regression; **Supplementary Table 3**) either for Go items and/or for the interaction of choices of Go versus NoGo items in any of these samples. Furthermore, the fact that participants observed the items for almost their entire presentation times in all of these studies (and for similar periods of time at the end of training) suggests that it is unlikely that the observed effects are driven by differences in gaze duration. Additional work is necessary to conclusively test whether gaze differences are related to choices during probe.

Eye gaze during probe

Recent work shows that participants spend more time fixating on an item before choosing it compared to unchosen alternatives[17] and that high-value items draw attention[30], which reflects the role of

Figure 3 Imaging results from the probe phase. (**a**) Parametric effect of the number of times each high-value Go item was chosen during probe. (**b**) The difference in the parametric effect of the number of times each item was chosen during probe between high-value Go and high-value NoGo items. This analysis was only run in an a priori mask of mPFC that encompassed the medial PFC by combining Harvard-Oxford atlas regions (frontal pole, frontal medial cortex, paracingulate gyrus and subcallosal cortex) falling between $x = 14$, $x = -14$ and $z < 0$. x-y-z values reported in standard Montreal Neurological Institute (MNI) space. Heatmap color bar ranges from z-stat = 2.3 to 3.3. Map in **a** was cluster-corrected at a whole-brain level. $P < 0.05$, two sided linear regression.

attentional mechanisms in value computation and choice behavior[31]. Eye-tracking data collected on a subset of sample 4 (16 repetitions, $n = 18$ participants) during the probe phase was consistent with this. We calculated the proportion of time participants spent viewing a particular item as the total amount of time the gaze position was within the bounds of a food item on the screen, divided by the reaction time. In a repeated-measures linear regression comparing proportion of time spent viewing an item against Go/NoGo and chosen/unchosen factors (with two grouping factors of item presentations and participants), we found a main effect of chosen/unchosen ($P < 0.0001$, two sided repeated measures linear regression) and Go/NoGo ($P = 0.002$, two sided repeated measures linear regression) (**Fig. 2d**). Thus, participants tended to spend a larger proportion of the total gaze time on the chosen versus unchosen item during the choice window regardless of whether it was a Go item (proportion = 39% versus 28%, $P < 0.0001$, two sided repeated measures linear regression) or NoGo item (proportion = 36% versus 32%, $P = 0.01$, two sided repeated measures linear regression) (**Fig. 2d**), consistent with the previous results[17].

We found a significant difference in gaze time between unchosen Go versus NoGo items ($P = 0.04$, two sided repeated measures linear regression; **Fig. 2d**), which showed that cue-approach training drove attention toward the Go items in the subsequent decision-making phase even when participants did not choose these items. This may reflect increased salience of Go items[32]. In additional analyses we found a positive association between the pre-post training difference in bids and the proportion of time spent viewing an item during the choice phase ($P = 0.029$, two sided repeated measures linear regression), which linked the observed gaze bias[18] directly to changes in preference.

Long-term behavioral maintenance

To examine the long-term maintenance of the cue-approach effect, we invited participants to return to the lab after their initial visit to perform a second probe phase. We found that, after an average of 66 d (range 41–87 d), participants in the sample with the longest training (16 presentations) showed continued preference for the high-value Go over NoGo items ($n = 20$ participants, $P = 0.04$, two sided repeated measures logistic regression, proportion 60%).
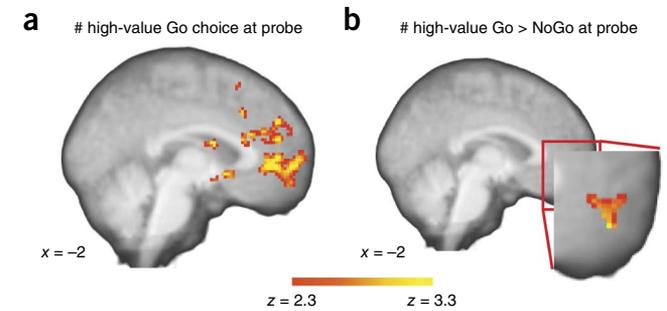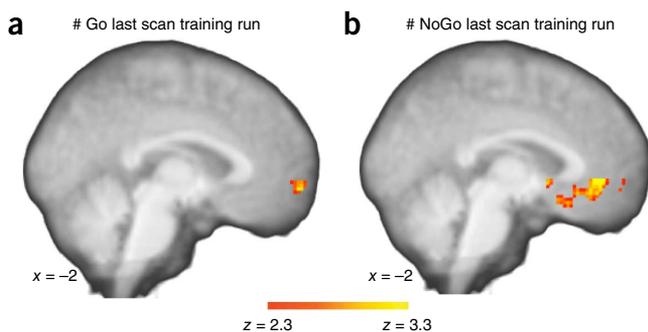
Long-term maintenance was also present in the eye-tracking data; an analysis of eye-tracking data during the follow-up probe showed a main effect of Go/NoGo ($P = 0.0001$, two sided repeated measures linear regression), though in this case the effect was only present for chosen items (**Supplementary Fig. 4**). This suggests that longer cue-approach training may have effects that last over months. We found no such effect in any of the other samples with shorter training.

In an additional sample (study 7), we repeated the probe after 1 week and 1 month (**Supplementary Fig. 3**); the cue-approach effect on choices remained significant (P values < 0.0001, two sided repeated measures logistic regression) at both delays for the higher-valued items (which were below the median auction value in this sample). Further studies will be needed to verify how much additional training may be necessary to ensure long-term maintenance and for how long this effect lasts.

Imaging results during probe and training

The foregoing behavioral and eye-tracking results provide converging evidence that cue-approach training increased the subjective value of cue-associated Go items. To investigate the neural signature of this value change, we performed training and probe while participants were scanned with fMRI in study 3 ($n = 21$ participants, items presented for 12 repetitions). Previous studies[23,33–35] establish that the ventromedial prefrontal cortex (vmPFC) is crucial for encoding decision values, and therefore we focused our analysis on this region during the probe phase. During the probe phase, we tested whether the greater preference for the chosen Go items was reflected in blood oxygenation level–dependent (BOLD) signals. The pairs during probe were matched for their pretraining preference; the effectiveness of this procedure is highlighted by the lack of difference in choices of Go and NoGo items in the cue-avoidance studies (studies 5 and 6) and no-approach study (study 8). We defined the post-training preference for each item as the number of times each item was chosen during the probe phase (out of eight presentations) and used this value as a parametric regressor for the chosen item on each trial (Go or NoGo). Consistent with the common involvement of the vmPFC and ventral and mediodorsal striatal regions in representation of subjective value, activity in these regions was positively associated with number of times chosen for high Go items (**Fig. 3a**; for all activation peaks see **Supplementary Table 4**). Further, we found that the association between BOLD response and preference was stronger (more

Figure 4 Imaging results from the last training run. (**a**,**b**) Modulation of number of times each high-value Go item was chosen (**a**) and NoGo item was chosen (**b**) during probe. This analysis was only run in an extensive mask of mPFC that encompassed the medial PFC by combining Harvard-Oxford regions (frontal pole, frontal medial cortex, paracingulate gyrus and subcallosal cortex) falling between $x = 14$, $x = -14$ and $z < 0$. Heatmap color bar ranges from z-stat = 2.3 to 3.3. Maps were cluster-corrected within a priori mask of mPFC, as in **Figure 3b**. $P < 0.05$, two sided linear regression.

positive) in vmPFC for high-value Go items compared to high-value NoGo items during probe when we limited the analysis to an extensive area of the vmPFC (**Fig. 3b**). Thus, the enhanced preference for high-value Go items was also reflected in the neural signature of a stronger relation between vmPFC activity and preference. A previous study[36] involving real versus hypothetical choices shows that the signal in brain regions including vmPFC is amplified during real choices, which can be attributed to increased attention during real choices. We did not find any neural signature for a value change for the low-value Go items (versus either baseline or low-value NoGo items), consistent with the lack of a behavioral effect on the low-value items.

We also examined training-related changes in fMRI signals. There were no differences in stimulus-driven activations when we compared the fMRI activity related to onset of Go items at the end of training versus the beginning of training, which perhaps reflected the fact that no choices were required (participants simply pressed a button when they heard a tone). Previous studies show value-related activations in the absence of choice[37] and therefore for all subsequent analyses we used as a parametric regressor the same preference indicator as in the probe phase, i.e., the number of times each item was chosen during probe. In the last run of training, vmPFC response (using the prehypothesized anatomical mask for the region) was associated with number of choices on the later probe for both Go and NoGo items (separately) (**Fig. 4**; for all activation peaks, see **Supplementary Table 5**). However, there were no significant differences between the preference-related effect for Go and NoGo items during the last run, and no preference-related effects for either item type during the first run of training. This suggests that the mere exposure to the items for both Go and NoGo items increased their values in a relatively similar way.

DISCUSSION

Previous research has focused on the roles of experience, time and context in modulating decision values[2–6]. The present work is, to our knowledge, the first to show that the subjective value of goods (measured both by choice and by WTP) can be modified through simple cue-approach exposure without external reinforcement or any other explicit manipulation of value. Our converging results using behavioral and neuroimaging methods provide insight into an automatic mechanism that directly perturbs the values of items by driving attention toward those items. We suggest that the cue-approach manipulation enhanced the attention devoted to the processing of the items and thus amplified the value signals of the items. This is further exemplified by the fact we obtained this effect only for the higher-valued items in the training set, even when these high-value items were below the median auction value (in study 7). We found that the auditory cue by itself was not sufficient for the behavior change and that the change was not due to viewing-time differences during training. It is plausible that a motor approach signal was activated during the probe phase, but the effect of training on auction responses, which required an entirely different response, speaks against this alternative. Results of the cue without approach and the lack of effects in the cue-avoidance studies all suggest that the cue-approach effect is not merely an attentional or salience effect but rather that it reflects the combination of the cue with the motor-approach response. Other researchers[38,39] have managed to train participants to avoid choices of food items, albeit in a different experimental setup with close to 100% stopping rates. This suggests that the failed stop trials in our studies (which targeted 75% successful inhibition) may have obscured the effect. Additional studies will be needed to test this. Future studies will also need to test whether the choice effects reported here generalize from the specific trained pictures to other stimuli representing the same or similar items.

In conclusion, our findings suggest that cue-approach training can potentially serve as a 'nudge'[40] working at the level of enhancing attention to and memory for items in order to modify choices. This is especially important given the failures of many current interventions aimed at changing unhealthy habits based on effortful self-control[41].

METHODS

Methods and any associated references are available in the online version of the paper.

Note: Any Supplementary Information and Source Data files are available in the online version of the paper.

AUTHOR CONTRIBUTIONS
T.S., A.B. and R.A.P. designed the experiment, T.S., A.B., A.H.M., L.N. and J.P. conducted the experiment, T.S., A.B., A.H.M. and J.A.M. analyzed the data, and T.S., A.B. and R.A.P. discussed the results and wrote the paper.

COMPETING FINANCIAL INTERESTS
The authors declare no competing financial interests.

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ONLINE METHODS

Participants. 252 healthy subjects participated in nine studies using three versions of a task (see **Supplementary Table 1** for sample details). No statistical test was run to determine sample size a priori. The sample sizes we chose are similar to those used in previous publications, and our replications used similar sample sizes after our first successful result.

All participants had normal or corrected-to-normal vision, no history of psychiatric diagnoses, neurologic or metabolic illnesses, no history of eating disorders, had no food restrictions and were not taking any medications that would interfere with the experiment. Additionally, participants who were scanned (study 3) were free of any metal implants or any other contraindications for MRI. Participants were told that the goal of the experiment was to study food preferences and were asked to refrain from eating 4 h before arrival to the laboratory[23]. All participants gave informed consent, and the study was approved by the internal review board at the University of Texas at Austin.

Experimental procedure. The general task procedure is presented in **Figure 1**. Participants first underwent an auction (**Fig. 1a**), then a training task (**Fig. 1b**), then a probe (**Fig. 1c**) and finally a repeat of the auction (**Fig. 1d**). Stimulus presentation and behavioral data acquisition were implemented in Pygame[42] for the auction and Matlab (MathWorks) with Psychotoolbox[43–45] for the training and probe phases.

Auction. First, participants took part in an auction[22,23] (**Fig. 1a**) in which photographs of 60 appetitive junk food items[23] were presented in random order. We followed the BDM procedure[22,23] in which participants were endowed with three dollars and told that they would have an opportunity to use them to buy a snack at the end of the session. During the auction, participants were presented with one item at a time on a computer screen. They placed their bid by moving the mouse cursor along an analog scale that spanned from 0 to 3 at the bottom of the screen. The auction was self-paced, and the next item was presented only after the participant placed his or her bid. This procedure has been shown to reliably provide a measure of WTP per item[23]. Two participants from cue-approach study 1, one from study 3 and two from study 4 were excluded because there was not enough range in bids for those participants to properly categorize the stimuli using the method explained in the next section. In the cue-avoidance study, three participants were excluded from study 5 and two from study 6 because they bid less than $0.25 on more than 40 items; in studies 7 and 8, we also excluded one participant in each sample owing to auction exclusion criteria. These exclusions ensured a sufficient number of highly valued items that were different enough from lower-valued items.

Item selection. Items were ranked based on WTP, where item 1 had the highest WTP and so forth until item 60, which had the lowest WTP. We then chose eight items as higher-valued (ranked 8–15) and eight items as lower-valued (ranked 46–53). Out of each of these eight items, four were associated with an auditory cue to later served as Go items and four were not associated with the cue to later served as NoGo items (**Supplementary Fig. 1**). This selection procedure ensured pairing of high-value Go with high-value NoGo items and low-value Go with low-value NoGo items. These pairs made up of two items of similar WTP later presented at probe (see below) such that participants should a priori be indifferent in a choice between them based on initially stated values. To maintain ~25% cue frequency (8 of 30 high and 8 out of 30 low) as is usually done in stop-signal tasks[25], we chose an additional 4 high-value items (out of the items ranked 16–23) and an additional 4 low-value items (out of the items ranked 38–45) that were later used in high-value Go versus low-value Go comparisons and high-value NoGo versus low-value NoGo comparisons during probe (data not shown).

For study 7 (*n* = 26 participants), we only used the lower-value 30 items for training and selected items ranked 38–45 as the higher-value items (**Supplementary Fig. 2**).

Cue-approach training. The task is functionally opposite to the stop-signal task[25]. On each trial, images of the food items were presented on the screen for 1 s followed by an intertrial interval of an average 3 s (range 1–12 s, **Fig. 1b**). Item presentation was randomized within a block of 60 trials. Participants were instructed to press a button on the keyboard as fast as they could, but only when they heard a tone. Their task was to press the button before the items

disappeared from the screen. The items that were chosen as Go items were consistently associated with the tone. In study 1 we initiated the tone at 650 ms after the item was presented on the screen (Go-signal delay, GSD) and then updated the GSD using a ladder technique; we increased the GSD by 17 ms if participants pressed the button before the item disappeared, whereas the GSD was reduced by 50 ms if the participants pressed the button after the item disappeared (always after 1 s). We chose this 3:1 ladder titration ratio to ensure a 75% success rate in button presses. In study 1 (*n* = 29 participants) and study 3 (*n* = 21 participants) all 60 food items were presented 12 times each during training. In study 2 they were presented 8 times and in study 4 (*n* = 27 participants) they were presented 16 times. The order of presentation within the 60 items was randomized, and all items were presented before the next set started. After two presentations of all items the participants received a short self-paced break before continuing to the next run. In studies 2, 3 and 4, we initiated the ladders at 750 ms as the results from study 1 showed a convergence around that number.

Cue-avoidance training. Item selection was identical to the procedure for cue-approach training. This task is highly similar to the trained-inhibition version of the stop-signal task[26,27]. All components and timings of this task were identical to the cue-approach training except for two details. First, in this task, participants were instructed to press the button as fast as they could every time they saw an item, unless they heard a tone. Second, as this task was designed to optimize the difficulty of stopping, the stop-signal-delay was initiated at 250 ms. We used a similar 3:1 ratio for ladders titration in this task; we decreased the ladder by 50 ms if participants did not stop on time and increased it by 17 ms if they did manage to stop. In study 5 (*n* = 42 participants) all items were presented 12 times and in study 6 (*n* = 26 participants) all items were presented 16 times.

Cue without approach. For study 8 we followed the same procedure as in the cue-approach training but did not ask the 31 participants to press the button when they heard the tone. We used yoked ladders from study 4.

Probe. After the completion of training, participants filled in a computer-adapted version of the Barratt impulsiveness scale (BIS)-11 questionnaire[46]. They were then told that they would next perform a new task (**Fig. 1c**) where they would be presented pairs of items. They were told that a single trial would be drawn at random at the end of the session and their choice on that trial would be honored (i.e., they would receive the item that they had chosen on that trial at the end of the experiment and will stay to consume it in the lab).

Pairing procedure. We presented unique pairs of items during the probe phase. The main goal of our analysis was to test how the cue-approach or avoidance training affected participants' preferences between items that had similar initial value. We presented items from the same value category (high or low with similar WTP rankings) such that one item was associated with the cue during training and the other was not (**Supplementary Fig. 1**). Participants were presented with 16 unique pairs (each of the four Go items were paired with each of the four NoGo items) for each value category. If the manipulation did not affect participants' valuation of the items then they should be indifferent between them. Participants were also presented with two additional pair types made up of high-value Go versus low-value Go and high-value NoGo versus low-value NoGo items. These pairs served as 'sanity checks' to ensure that the initial WTPs truly represented participants' values (the results of these comparisons are not reported, but in all cases the expected differences between choice of high- and low-valued items were observed).

No-probe version. In study 9 we did not include the probe phase for 25 participants.

Trial timing. At trial onset, the two items in a pair were presented directly to the right and left of a fixation cross (**Fig. 1c**). Participants had 1.5 s to respond with either of two buttons on the keyboard corresponding to the left or right locations on the screen. The chosen item was highlighted with a green rectangle around it. The choice confirmation remained on the screen for 500 ms until a fixation-cross appeared during the intertrial interval for an average of 3 s (range 1–12 s). If the participants did not choose within the allotted time, a message appeared on the screen asking them to please choose faster followed by the intertrial fixation cross

and the next trial began. Each of the 64 unique pairs was presented twice across the two probe runs. The order and left-right locations of the items on the screen were randomized across participants and across the two runs.

Questionnaires. As mentioned above, the BIS-11 (ref. 46) questionnaire was administered between training and probe (no significant correlations were found with the proportion of choices of high-value Go items, $P > 0.3$, two sided Pearson correlation). At the end of the session, when participants remained in the lab to consume the food item, they received several additional questionnaires, which are beyond the scope of this manuscript.

Probe behavior. To test whether cue-approach (or cue-inhibition) training induced a preference change, we performed a repeated-measures logistic regression using the lmer function from the lme4 library in R (ref. 47) to compare the odds of choosing the Go to NoGo items against equal odds for the high-value and low-value pairs separately. We also performed a repeated-measures linear regression to test for differences in reaction time (RT) for choices of Go and NoGo items for the high-value and low-value pairs separately (data not shown).

Probe eye-tracking. Eye-tracking data were acquired using an Eyelink-1000 SR-Research eye tracker. Usable data were obtained on 18 participants from cue-approach study 4. Gaze position was categorized as being either within the x-axis boundaries of the fixation cross, within the x-axis boundaries of the stimulus on the right of the fixation cross or on the left of the fixation cross. The proportion of the trial time spent looking at the right or left items on each trial was calculated. We examined the difference in the proportion of total trial time spent looking at the Go item versus the NoGo item, when the participant chose the high-value Go or the high-value NoGo item separately using repeated measures linear regression. We also examined the difference in the proportion of time spent looking at the Go versus the NoGo item when that item was not chosen using repeated-measures linear regression. We also looked at the main effect of Go/NoGo item assignment as well as the main effect of chosen/unchosen on the proportion of choice time spent viewing an item during probe phase using repeated measures linear regression including the two factors Go/NoGo and chosen/unchosen with two grouping factors (for item presentation and participant).

Auction. Repeated-measures linear regression was used to test the two-way interaction between time (pretraining auction and post-training auction) and condition (Go and NoGo) within each value category separately. This interaction tests whether the change in WTP over time is different for Go and NoGo items. P values for the effects in the mixed models were calculated using the Kenward-Rogers approximation for degrees of freedom[48]. In order to better account for regression to the mean, we looked at the main effect of factor Go/NoGo item assignment as well as its interaction with value (high-value versus low-value items) on WTP at the second, post-training auction while accounting for WTP on the first, pretraining auction using repeated-measures linear regression with a grouping factor for participant.

We also investigated the influence of the change in WTP from pre- to post-training auctions on the proportion of choice time spent viewing a particular item during the probe phase accounting for Go/NoGo item assignment using repeated-measures linear regression with a grouping factor for participant.

Retest. We recontacted all participants and requested that they return to the lab. Participants were requested to fast for 4 h similar to the original experiment. In this follow-up session, 20 participants performed the auction and then probe phase with the same pairings as the one they had originally performed on their first visit to the lab.

Imaging version. We performed study 3 of the cue approach experiment while 21 participants were scanned with fMRI. In this version, participants used an MRI-compatible response pad to enter their response. They filled in the computer-adapted version of the BIS-11 (ref. 46) using the MRI-compatible button box before the probe phase while inside the scanner.

fMRI acquisition and analysis. Imaging data were acquired on a 3T Skyra MRI scanner (Siemens) with a 32-channel head coil. Functional data were acquired using a T2*-weighted echo planar imaging sequence (repetition time (TR) = 2,000 ms, echo time TE = 30 ms, flip angle (FA) = 60°, field of view (FOV) = 256, acquisition matrix of 128×128. Forty eight oblique axial slices with a 2-mm inplane resolution were positioned 30° off the anterior commissure-posterior commissure line to reduce the frontal signal dropout[49] and spaced 2 mm with a 0.5 mm gap to achieve full brain coverage). Slices were acquired using the multi-band sequence[50] (acceleration factor = 2, parallel imaging factor iPAT = 2) in an interleaved fashion. Higher-order shimming was used to reduce susceptibility artifacts. Each of the training runs consisted of 194 volumes and each of the probe runs consisted of 164 volumes. In addition to functional data, a single three-dimensional high-resolution full brain image acquired using a magnetization prepared rapid gradient echo (MPRAGE) pulse sequence (TR = 1,900 ms, TI = 900 ms, TE = 2.43 ms, FA = 9°, FOV = 25 cm^2) was acquired for brain masking and image registration.

Raw imaging data in DICOM format were converted to NIFTI format and preprocessed through a standard preprocessing pipeline using the FSL package[51] version 5. Functional image time series were first aligned using the MCFLIRT tool to obtain six motion parameters that correspond to the x-y-z translation and rotation of the brain over time. Second, the skull was removed from the T2* images using the brain extraction tool (BET) and from the high-resolution T1 images using Freesurfer[52,53]. Spatial smoothing was performed using a Gaussian kernel with a full-width half maximum (FWHM) of 5 mm. Data and design matrix were high-pass filtered using a Gaussian-weighted least-squares straight line fit with a cutoff period of 100 s. Grand-mean intensity normalization of each run's entire four-dimensional data set by a single multiplicative factor was also performed. The functional volumes for each participant and run were registered to the high resolution T1-weighted structural volume using a boundary-based registration method[54] implemented in FSL5 (BBR). The T1-weighted image was then registered to the MNI152 2 mm template using a linear registration implemented in FLIRT (12 degrees of freedom). These two registration steps were concatenated to obtain a functional-to-standard space registration matrix.

Imaging analysis. We focused our analysis on the probe phase to examine the neural signature of value change. We used a general linear model (GLM) for the probe phase that included seven regressors for each of the four trial types: for high-value Go versus high-value NoGo, (i) onsets of trials when high-value Go items were chosen with fixed duration of 0.87 s, which was the average RT across all trials across all subjects; (ii) to explore the preference for each item (**Fig. 3a**), we used the demeaned total number of choices (on all probe trials where this item appeared) of the chosen item as a parametric modulator of the above onset regressor (the same average RT was used as duration as above); (iii) to account for the difference in pretraining WTP between the items in each pair we added the WTP difference as a parametric modulator with the same onsets and durations as regressor #1. All of the above three regressors were added for the trials when participants chose the NoGo item in a pair. To account for RT differences between choices of the Go and NoGo items we added a regressor with the onsets of all high-value Go and NoGo trials but as the modulator we added the demeaned RT across all these trials. We defined the same seven regressors for the probe trials that compared low-value Go to low-value NoGo and also high-value Go versus low-value Go and high-value NoGo versus low-value NoGo, which resulted in a total of 28 regressors (four trial types times 7) and an additional regressor for missed trials of all types. We included the six motion regressors described above, framewise displacement (FD) and RMS intensity difference from one volume to the next (DVARS)[55] as confound regressors. We also modeled out trials with FD and DVARS that exceeded a threshold of 0.5 by adding a single time point regressor for each 'to-be-scrubbed' volume[56]. All regressors were entered at the first level of analysis and all (but the added confound regressors) were convolved with a canonical double-gamma hemodynamic response function. The temporal derivative of each regressor (but the added confound regressors) was included in the model. The model was estimated separately for each participant for each run.

To test which regions showed a greater modulation by the preference for an item we contrasted the parametric modulator of the chosen high-value Go items (regressor (ii) above) with the same regressor for the high-value NoGo items (**Fig. 3b**). We masked this contrast by our pre-hypothesized vmPFC region. The mask encompassed the medial PFC by combining Harvard-Oxford regions (frontal pole, frontal medial cortex, paracingulate gyrus and subcallosal cortex) falling between $x = 14$, $x = -14$ and $z < 0$.

Four participants were excluded from the imaging analysis because their parametric modulator of choices was zeroed out. One chose all high-value Go items at exactly the same proportion and three chose all high-value NoGo items at the same proportion during probe. Thus, the parametric modulator was perfectly correlated with the intercept regressor (column of 1 s) resulting in a rank-deficient design matrix.

For all group analyses we averaged across individual subjects to perform a one-sample t-test to obtain the overall effects for the group. All reported statistical maps were corrected at the whole-brain level using a cluster-based Gaussian random field correction for multiple comparisons, with an uncorrected cluster-forming threshold of $z = 2.3$ and corrected extent threshold of $P < 0.05$, except for the comparison between modulation of high-value Go and high-value NoGo during probe, which was corrected only for the medial PFC mask.

Training. The GLM during the training phase included 4 regressors for each Go item broken down by subsequent four probe trial types (high-value Go versus high-value NoGo, low-value Go versus low-value NoGo, high-value Go versus Low-value Go and high-value NoGo versus low-value NoGo): (i) onsets of the Go trial, modeled with a fixed duration of 1 s; (ii) same onset and duration but modulated by subsequent number of choices during probe; (iii) same onset and duration but modulation by initial WTP; (iv) same onset and duration but modulated by the Go-signal delay for that trial. Thus there were four different Go trials and for each there were four regressors yielding a total of 16 regressors. Then for each of the different types of the NoGo trials there were three regressors similar to above except the modulation by the Go signal delay as there was no signal in the NoGo trials. Thus, there were four different NoGo trials and for each there were three regressors yielding a total of 12 regressors. To account for RT differences between all trials we added a regressor with the onsets of all Go trials and the modulator was the demeaned RT across all these trials. We further added a missed trial regressor for high-value Go and low-value Go and two regressors for an erroneous response for high-value and low-value NoGo. There were a total of 33 regressors. We added the same covariates as in the probe design matrix: we included the 6 motion regressors described above, along with framewise displacement (FD) and RMS intensity difference from one volume to the next (DVARS)[55] as confound regressors.

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Supplementary Material for:

Changing value through cued approach: An automatic mechanism of behavior change

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1
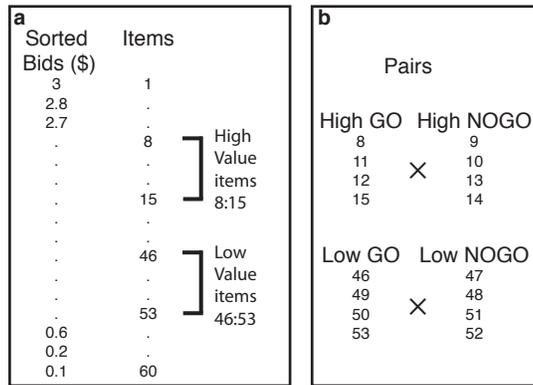
Supplementary Figure 1: Diagram of the sorting and pairing procedure used for studies 1 through 6, 8 and 9.
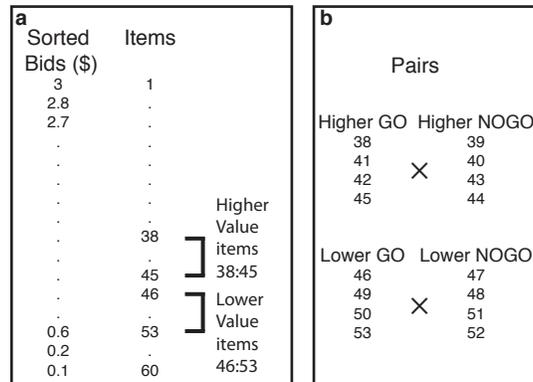
Supplementary Figure 2: Diagram of the sorting and pairing procedure used for Study 7.

2

Proportion of GO item choices at probe
during additional cue-approach studies
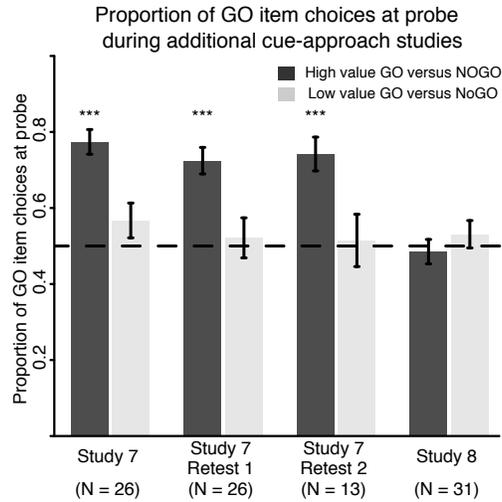
Supplementary Figure 3: Proportion of choices of the GO item in pairs of high value Go versus NoGo (dark grey) and low value Go versus NoGo (light grey) items for each of Study 7, Study 7 Retest 1 (1 week after original training), Study 7 Retest 2 (1 month after original training) as well as Study 8 (where participants heard a tone, but were not required to press a button). The larger effect size in Study 7 may be due to the fact that in this study only 30 items were presented during training. This will need to be examined in future studies to control for the difference in chosen items below the median.

Proportion of total choice time eye on item
during high Go vs. NoGo probe trials
for subset of sample 4 Retest (N = 17)
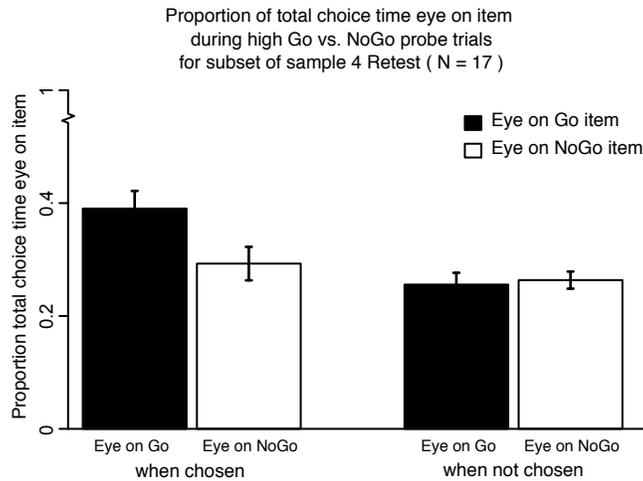
Supplementary Figure 4: Proportion of total choice time during retest probe that gaze position was on the high Go (black) or high NoGo (white) item in a pair for trials when Go or NoGo items were chosen separately. The sample is a subset of Study 4 Retest. Seventeen participants had their eye positions recorded with an eye tracker while performing a probe on average two months after cue-approach training. Effects are discussed in the text. Error bars reflect within subject SEM.

4

Study	N	Age (Mean ± SD)	Gender (F/M)	Additional participants excluded	Goal of Study
1	29	22.8 ± 2.8	21/8	2 due to auction	Effect of cue-approach training on choice (12 training runs)
2	25	20.9 ± 2.6	18/7		Effect of cue-approach training on choice- shorter training (8 training runs)
3	21	20.8 ± 3.4	12/9	4 due to scan, 1 due to auction	Neural basis of effect of cue-approach training on choice (12 training runs)
4	27	19.9 ± 2.7	16/11	2 due to auction	Effect of cue-approach training on choice - longer training (16 training runs)
4 Retest	20	20.2 ± 3.0	13/7		Long term maintenance of cue-approach training on choice (16 training runs)
5	42	21.3 ± 2.5	30/12	3 due to auction	Effect of cue-avoidance training on choice (12 training runs)
6	26	18.9 ± 1.2	22/4	2 due to auction	Effect of cue-avoidance training on choice - longer training (16 training runs)
7	26	18.5 ± 2.4	16/10	1 due to auction	Effect of cue-approach training on choice using only lower valued items - longer training (16 training runs)
8	31	21.2 ± 3.5	24/7	1 due to auction, 7 due to time spent viewing item	Effect of cue without approach training on choice (16 training runs)
9	25	21.7 ± 3.1	18/7		Effect of cue-approach training on auction without choice phase - longer training (16 training runs)

Supplementary Table 1: Demographic information for participants in all samples.

Values represent mean ± standard deviation.

5

	High				Low			
	GO		NOGO		GO		NOGO	
	Pretrain	Posttrain	Pretrain	Posttrain	Pretrain	Posttrain	Pretrain	Posttrain
Study 1 (N = 29)	1.72	1.52	1.72	1.44	0.36	0.58	0.35	0.52
	interaction time * go/nogo P = 0.2603				interaction time * go/nogo P = 0.3029			
Study 2 (N = 25)	1.87	1.75	1.87	1.56	0.55	0.82	0.56	0.78
	interaction time * go/nogo P = 0.0048				interaction time * go/nogo P = 0.4430			
Study 3 (N = 21)	1.87	1.65	1.87	1.55	0.47	0.70	0.48	0.62
	interaction time * go/nogo P = 0.2103				interaction time * go/nogo P = 0.2960			
Study 4 (N = 27)	1.74	1.69	1.73	1.50	0.58	0.80	0.58	0.77
	interaction time * go/nogo P = 0.007				interaction time * go/nogo P = 0.6462			
Study 7 (N = 26)	0.70	1.00	0.70	0.76	0.51	0.71	0.51	0.76
	interaction time * go/nogo P < 0.0001				interaction time * go/nogo P = 0.3795			
Study 8 (N = 31)	1.89	1.73	1.90	1.72	0.51	0.71	0.50	0.68
	interaction time * go/nogo P = 0.7720				interaction time * go/nogo P = 0.6443			
Study 9 (N = 25)	1.83	1.62	1.83	1.61	0.58	0.69	0.58	0.67
	interaction time * go/nogo P = 0.8129				interaction time * go/nogo P = 0.5501			

Supplementary Table 2: Average WTP for High and Low, Go and NoGo items during pre-training and post-training auctions for all cue-approach studies (Study 1 through 4 and 7) as well as cue without approach (Study 8) and cue-approach without the probe phase (Study 9). P values reflect the interaction of factors for time (pre- or post-training) and cue-status (Go or NoGo) on WTP separately for High and Low value items.

6

	Study 6 last run (N = 23)	Study 3 12 runs (N = 12)	Study 3 last run (N = 12)	Study 8 16 runs (N = 31)	Study 8 last run (N = 31)
Mean time spent viewing High GO item (ms)	936.3	706.7	642.3	955.1	963.5
Mean time spent viewing High NOGO item (ms)	935.4	704.3	658.3	953.9	936.9
High GO viewing time vs high NOGO viewing time P	0.96	0.92	0.72	0.81	0.13
High GO viewing time per item versus subsequent choices of item P	0.32	0.18	0.88	0.84	0.58
Interaction of viewing time per item versus subsequent choices of item by HighGO/HighNOGO P	0.48	0.91	0.48	0.12	0.06

Supplementary Table 3: Average time spent viewing High Go and High NoGo items for the last run of training in Study 6 (cue-avoidance, we did not collect eye-gaze data during the earlier training runs) as well as last run and all training runs for Study 3 (cue-approach) and Study 8 (cue without approach). P values reflect two-tailed test of the difference in viewing time between High Go and High NoGo items.

7

Contrast	Cluster	Region	Number of voxels in region	Cluster size	x	y	z	Peak z stat
# High GO choice at probe (Fig. 3a)	1	L Frontal Pole	398	1820	8	40	0	3.9
		L Paracingulate Gyrus	241					
		R Paracingulate Gyrus	214					
		R Anrterior Cingulate Gyrus	197					
		R Frontal Pole	171					
		L Anterior Cingulate Gyrus	156					
		L Superior Frontal Gyrus	76					
		R Superior Frontal Gyrus	44					
		L Frontal Medial Cortex	27					
	2	L Caudate	61	397	8	-2	16	4.23
		R Caudate	48					
		R Thalamus	14					
	3	L Accumbens	26	266	-6	2	-12	3.62
		R Subcallosal Cortex	25					
		L Putamen	22					
		L Pallidum	19					
		L Subcallosal Cortex	13					
	4	L Paracingulate Gyrus	81	241	-8	10	46	3.6
		R Paracingulate Gyrus	71					
		L Superior Frontal Gyrus	26					
		L Supplementary Motor Cortex	11					
# High GO > # High NOGO at probe (MPFC mask, Fig. 3b)	1	L Frontal Medial Cortex	55	116	-2	52	-14	3.42
		L Paracingulate Gyrus	24					
		L Frontal Pole	17					

Supplementary Table 4: Regions showing significant activations for imaging contrasts presented in **Fig. 3**. For each cluster, the list shows all regions from the Harvard-Oxford atlas that contained more than 10 active voxels within that cluster, along with the peak X/Y/Z location for the cluster in MNI space.

Contrast	Cluster	Region	Number of voxels in region	Cluster size	x	y	z	Peak z stat
# High GO, training last run (MPFC mask, Fig. 4a)	1	L Frontal Pole	44	98	-4	60	-6	3.34
		R Frontal Pole	39					
		L Frontal Medial Cortex	12					
# High NOGO, training last run (MPFC mask, Fig. 4b)	1	R Paracingulate Gyrus	156	561	2	38	-6	3.83
		R Subcallosal Cortex	106					
		L Paracingulate Gyrus	75					
		L Subcallosal Cortex	65					
		R Cingulate Gyrus, anterior division	54					
		R Frontal Pole	31					
		L Cingulate Gyrus, anterior division	26					
		R Frontal Medial Cortex	25					
		L Frontal Medial Cortex	12					
		L Frontal Pole	11					

Supplementary Table 5: Regions showing significant activations for imaging contrasts presented in **Fig. 4**. For each cluster, the list shows all regions from the Harvard-Oxford atlas that contained more than 10 active voxels within that cluster, along with the peak X/Y/Z location for the cluster in MNI space.

of a study demonstrating that incorporating clustering into the connectivity can also introduce spontaneous transitions between different firing regimes[14].

As with all computational models the network studied by Ostojic[1] incorporates potentially important simplifications, including the fact that the synapses sum linearly (there is no saturating driving force). But perhaps one of the most important assumptions of the model is that the units are spontaneously active. Thus, in a sense, the burstiness is not an emergent property of the network because each unit in isolation is essentially 'tonically bursting'. Rather, it may be the pattern of inhibition-induced pauses in tonic activity that creates the heterogeneous state. In addition,

strictly speaking, the patterns do not arise autonomously from the internal dynamics of the network as with actual cortical networks, in which self-perpetuating patterns of activity can be observed even *in vitro*[15]. Thus, another question for future studies will be to determine whether Ostojic's results[1] hold for excitation-dominated regimes and whether the network can generate heterogeneous patterns of activity that are driven entirely by the internal dynamics.

COMPETING FINANCIAL INTERESTS
The authors declare no competing financial interests.

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Go means green

Joseph T McGuire & Joseph W Kable

A simple cued-approach training procedure can bias economic choices toward specific goods. It appears to work by drawing overt attention toward trained items, scaling up their judged value.

A bottle of Napa Valley Cabernet is probably tasty, but is it worth $70 to me? Is a fancy cup of coffee worth $7? As a would-be purchaser, I need to translate my subjective and intuitive valuation of a good into units of cold, hard cash. Even for nonmonetary choices, such as whether to read a book or watch TV, I need to be able to assess and compare the values of dissimilar options on a common scale.

Schonberg *et al.*[1] describe a simple manipulation that boosts the value people place on individual goods. The goods in their experiments were snack items (for example, a Butterfinger bar) and the manipulation consisted of 'Go' training. Pictures of 60 different foods appeared one by one on a computer screen, 12 times each over the course of 48 min. Most items just had to be viewed passively, but about a quarter were designated by the experimenters as 'Go items'. Every appearance of a Go item was quickly followed by an auditory signal to make a speeded key press.

In the next stage of the study, participants made binary decisions, picking which of two snack items they would rather receive at the end of the experiment. In pairs consisting of a Go item and a control item, matched for their pretraining value to the participant, Go items were selected 60–65% of the time. Similar

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effects were apparent in a subsequent auction task, in which participants bid an average of about 12 cents more for Go items than for originally equivalent control items.

These are surprising results, as the Go-training manipulation differed markedly from other common strategies for modifying people's preferences. Items were not associated with any new incentive, participants received no additional information, and the Go and control items did not differ in their familiarity or duration of exposure[2]. The manipulation does not appear to target habitual responding[3,4], nor does it alter the framing of decisions[5] or the architecture of the choice environment[6]. Given the unexpectedness of the observed effects, it is important and commendable that the researchers present multiple replications[7], documenting the influence of Go training on binary choice in a total of five independent samples.

A potentially revealing wrinkle is that not all snack items were equally susceptible to the effects of Go training. There was a 'rich-get-richer' effect across items, such that an individual's favorite items received the biggest boost. The strongest effects were seen when comparing initially high-valued items assigned to the Go versus control condition. For initially less-favored items, the differential effect of Go training was small to nonexistent.

The dependence on initial item value helps to argue against the uninteresting possibility that participants might, for some reason, have

selected the Go items on purpose instead of expressing their true preferences. It also helps shed light on how Go training works. One way to make sense of this pattern of effects is to suppose that, instead of adding a fixed increment to an item's subjective value, Go training had an effect more akin to scaling item value by a multiplicative factor (**Fig. 1**). A differential scaling or amplification of subjective value would have the biggest effect if both items were highly valued to begin with.

Amplification-like influences on subjective valuation have been discussed before in characterizing the effects of overt visual attention. A recent theoretical proposal by Krajbich *et al.*[8] holds that choice alternatives loom larger in moment-by-moment value comparisons if they are being visually fixated. Schonberg *et al.*[1] present evidence for a direct connection between Go training and visual fixation. Eye-tracking data revealed that participants spent more time fixating Go items than control items during binary choices, even controlling for the fact that Go items were more frequently selected. This raises the possibility that overt attentional capture may have mediated the effect of Go training on expressed preferences.

In situations in which preferences shift, it is potentially instructive to investigate whether there is a corresponding shift in preference-related brain activity. A natural target for such an investigation is ventromedial prefrontal cortex (VMPFC). VMPFC is one in a small
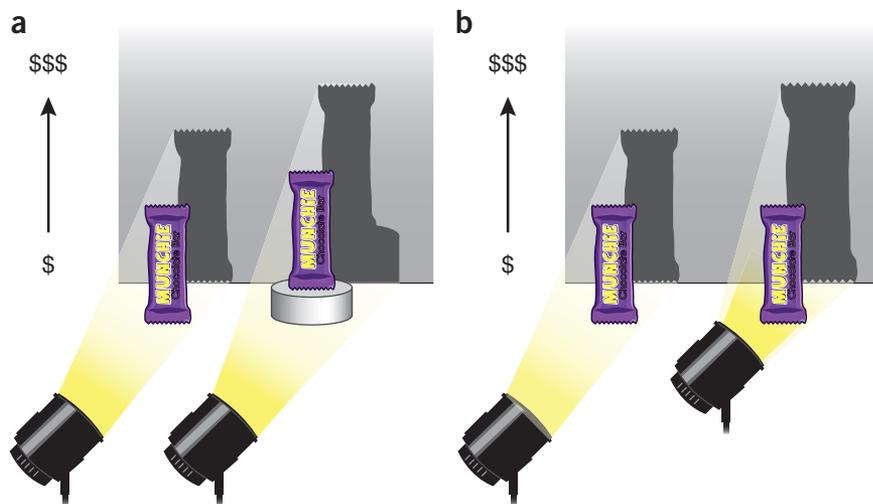
Figure 1 An analogy in which a decision maker's subjective evaluation of an item is represented by the size of the shadow the item casts. (**a**) One way to increase an item's value would be to prop it up (right), raising its value by an additive increment. (**b**) A second way would be to light it from closer up (right), scaling up its value multiplicatively. The reported effect of Go training on item valuation looks more like a scaling effect (**b**) than an additive effect (**a**). The subjective value of Go-trained items appears to be amplified, making these items loom larger in value-based decisions.

Marina Corral Spence

collection of brain regions whose activity in fMRI experiments consistently shows a correlation with the subjective value of choice stimuli[9–11].

Given that participants valued Go items more highly, one possible hypothesis is that Go items would evoke higher VMPFC activity than control items. This is not, however, what the researchers observed. Instead, VMPFC activity showed stronger modulation by value across Go items, even when only considering items that all had high subjective value initially. That is, there was a bigger difference in VMPFC activity between more- and less-preferred Go items than between more- and less-preferred control items. These neuroimaging findings lend further credence to the idea that value signals were amplified, not merely shifted, as a result of Go training.

The significance of these findings stems in part from the potential for translational extensions. This work could hold relevance for people who are interested in altering their own future choices. For example, individuals wishing to lose weight might be interested in a training exercise that could help increase the future appeal of healthy foods. This type of extension would fall in the same broad family as previous efforts to devise a training exercise for alcohol-dependent individuals to increase their future probability of selecting nonalcoholic beverages[12]. Naturally, there are many

steps remaining on the road toward a clinical intervention. One outstanding question is how Go training would generalize to different pictures of the trained items, different items in the trained category and items outside the laboratory. A second important step is to extend the effect to choice items with more complex attribute structure. A bucket of fries and a future lithe figure might both be high-value outcomes, but the choice between them involves starker tradeoffs than a choice between Snickers and Kit Kats. Third, although there is already evidence that the effect can sometimes last a month or more, further research is merited on the factors that govern its durability.

Of more immediate importance, the work by Schonberg et al.[1] stands to inform our theoretical understanding of how preferences are constructed even when no one is trying to alter them. There are several potential mechanisms that might account for the efficacy of Go training in altering valuation, and future work is needed to tease them apart. One possibility is that subjective value is enhanced for items with some kind of motor association or affordance (that is, items with which one could physically interact). If this is the case, the present effect might be related to the previous finding that people place higher monetary valuations on snack items that are presented as real, graspable objects rather

than as pictures[13]. A second possibility would draw links to the literature on embodied approach/avoidance training[12,14]. If the training were altered so that Go cues required a response connoting avoidance, such as pushing the item away, an embodied-cognition perspective might predict a reversal of the observed effect on later choices. A third potential hypothesis would place importance on the predictive relationship between Go items and the imperative cue (the visual onset of the snack item reliably anticipated the cue by about 750 ms). Perhaps participants learn to pay closer attention to Go items because these items furnish information about the timing of a motivationally relevant stimulus. If this hypothesis is correct, then blocking that predictive relationship—say, by adding a generic predictive cue before every Go item—should diminish the efficacy of Go training. Conversely, the effect might still be obtained if an imperative cue followed the visual offset of the Go item.

In sum, Schonberg et al.[1] have reported a new and thought-provoking influence on economic choice and explicit valuation. Their work opens many avenues for future research and lays the groundwork for new insights regarding the fundamental mechanisms of value-based decision making. That's a hard thing to put a price on.

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