Memory for Individual Items is Related to Non-Reinforced Preference Change

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Abstract

It is commonly assumed that memories contribute to value-based decisions. Surprisingly, most theories of value-based decision-making do not account for memory influences on choice. Recently, new interest has emerged in the interactions between these two fundamental processes, mainly using reinforcement-based paradigms. Here, we aimed to study the role memory processes play in non-reinforced preference change. We used the cue-approach training (CAT) paradigm, that is specifically designed to influence choices without external reinforcements. Instead, the paradigm uses the mere association of cued items with a speeded motor response. Previous studies with this task showed that a single training session induces a long-lasting effect of enhanced preferences for high-value trained stimuli, that is maintained for several months. We hypothesized that CAT influences memory accessibility for trained items, leading to enhanced accessibility of their positive associative memories and in turn to preference changes. In two pre-registered experiments, we tested whether memory for trained items was enhanced following CAT, in the short- and long-term, and whether memory modifications are related to choices. We found that memory was enhanced for trained items and that better memory was correlated with enhanced preferences at the individual item level, both immediately and one month following CAT. Our findings show, for the first time, that memory plays a central role in value-based decision-making, even in the absence of external reinforcements. These findings contribute to new theories relating memory and value-based decision-making and set the ground for the implementation of novel behavioral interventions for long-lasting behavioral change.

Introduction

Value-based decision-making and memory are both extensively studied processes in cognitive psychology and cognitive neuroscience (Fellows, 2017). Most theories of value-based decision-making have focused on processes related to the incremental learning of value following external reinforcement, but have not explicitly addressed the role of memory per se. Thus, fundamental questions remain regarding interactions between memory and value-based decisions.

Several recent empirical studies have begun demonstrating interactions between episodic memory and value-based decision-making. One-shot memory for past events has been shown to bias value-based decisions (Duncan & Shohamy, 2016) and memory accessibility has been shown to affect people's risk preferences (Kusev, van Schaik, & Aldrovandi, 2012). Choice behavior and fMRI signals during value-based decision-making were better explained by episodic memory for individual past choices than by a standard reinforcement learning model (Bornstein, Khaw, Shohamy, & Daw, 2017). Another study has found that during sampling of episodic memories of previous choices, the retrieved context influenced present choices, deviating from the predictions of standard reinforcement learning models (Bornstein & Norman, 2017). Furthermore, it has been shown that choices are influenced by value that is spread across memories from rewarded stimuli to associated items that were never experienced directly with reward (Wimmer & Shohamy, 2012). At the neural level, the ventromedial prefrontal cortex (vmPFC) and the hippocampus both have been shown to play a role in memory processes and value-based decisions (Weilbächer & Gluth, 2017).

All these studies highlighted the interaction between memory and value-based decision-making involving external reinforcements. However, everyday life involves decisions and associations that are not directly reinforced. Thus, it remains unclear if memory plays a general role in value-based decision-making even without external reinforcements. Therefore,

in the current study, we aimed to isolate the role memory processes play in value-based decision-making in the absence of external reinforcements.

We used a non-reinforced behavioral change paradigm, named cue-approach training (CAT). In this task, associating images of items with a neutral cue and a speeded motor response results in a consistent preference enhancement which is maintained for months (Botvinik-Nezer, Salomon, & Schonberg, bioRxiv; Salomon et al., 2018; Schonberg et al., 2014). During CAT, images of items are consistently paired with a neutral cue and a speeded motor response (*'Go items'*), while other items are presented without the cue nor response (*'NoGo items'*). One training session with several presentations of all items leads to long-lasting preference changes, measured as the likelihood of choosing Go over NoGo items that had similar initial subjective values (Schonberg et al., 2014). Results from over 30 samples with this task have demonstrated a replicable and long-lasting effect on various types of stimuli, including snack food items, fruits and vegetables, unfamiliar faces, fractal art images and positive affective images (Bakkour, Botvinik-Nezer, et al., 2018; Bakkour, Lewis-Peacock, Poldrack, & Schonberg, 2017; Botvinik-Nezer et al., bioRxiv; Salomon et al., 2018; Veling et al., 2017; Zoltak, Veling, Chen, & Holland, 2017), revealing the potential of the CAT paradigm as an experimental platform for value-based decision-making without external reinforcements.

Two main features of CAT make it a prime tool to test the influence of memory on choices: First, CAT has been shown to induce a long-lasting behavioral change for up to six months following a single training session of less than one hour (Salomon et al., 2018). Second, CAT has been found to induce consistent preference modifications for higher valued positive stimuli, especially for snack food items (Botvinik-Nezer et al., bioRxiv; Schonberg et al., 2014) and also to neutral and positive but not negative affective stimuli (Salomon et al., 2018). This differential effect could be linked to enhancement of positive but not negative episodic memories.

In the current work, we utilized the CAT paradigm to test the hypothesis that episodic memory processes drive choices even in the absence of external reinforcements. Our proposed theoretical model (see Figure 1) suggests that preference change following CAT results from a boost in memory encoding of positive Go items, which in itself is a consequence of enhanced perceptual processing of Go items (Botvinik-Nezer et al., bioRxiv; Schonberg et al., 2014). We hypothesized that the enhanced encoding of Go items, as well as the greater perceptual activation in response to them, increases accessibility of attributes and associations of these specific Go items (Anderson, 1983; Bhatia, 2013).

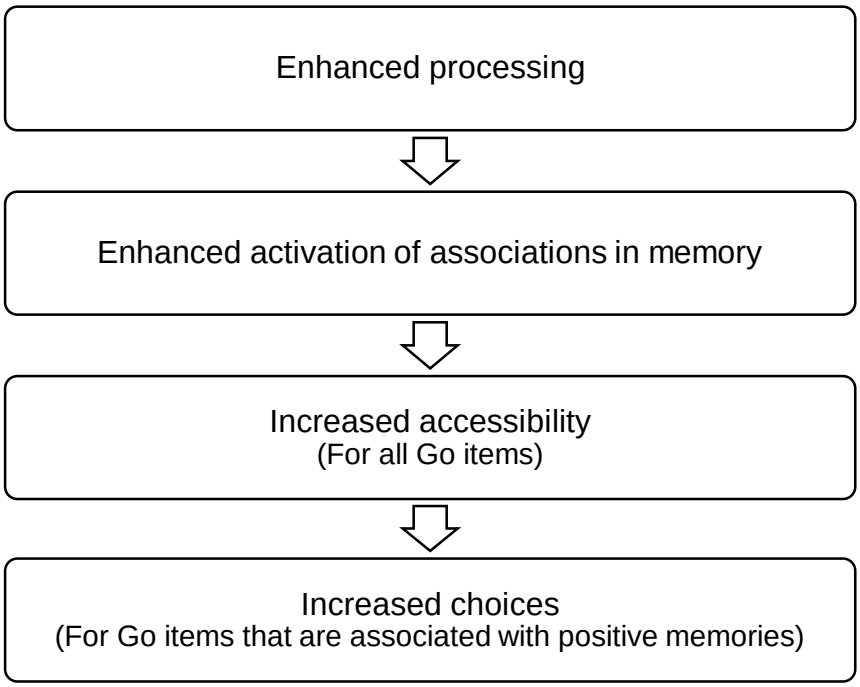

Figure 1. Proposed mechanism of the CAT effect, based on memory modifications.

In order to test memory for individual items, in the current work we introduced a memory recognition task following CAT. In two independent pre-registered experiments and one pilot experiment, memory was evaluated following a long (16 repetitions) or short (a single exposure) CAT training session, before the probe phase that evaluated post-training preferences. We pre-registered our predictions that responses in the memory recognition task will be both faster and more accurate for Go compared to NoGo items. Furthermore, we

hypothesized that preference changes, reflected in the binary choice phase, are due to the enhanced accessibility of memory associations of the Go items, which tips the scales in favor of the Go items. Therefore, we pre-registered our prediction that better remembered Go items will be chosen over worse remembered NoGo items. These hypotheses were tested both in the short-term (immediately or a few days after CAT) and in a one-month follow-up. The findings from this study could shed light on the general role memory plays in preference formation and modification, even in the absence of external reinforcements.

General Methods

Data Sharing

All of our data and codes are shared on GitHub (https://github.com/rotemb9/CAT_memory_paper). Pre-registrations can be found on the Open Science Framework (OSF: Experiment 1: https://osf.io/53vwa/; Experiment 2: https://osf.io/h9rwk/).

Participants

A total of N = 95 participants took part in this study, each completed one of the three experiments: Experiment 1 n = 35; Experiment 2 n = 35; pilot experiment (see Supplementary materials) n = 25; see Table 1 for a demographic description of each experimental sample. We pre-registered the sample sizes of Experiment 1 (https://osf.io/53vwa/) and Experiment 2 (https://osf.io/h9rwk/). A power analysis performed with our previous CAT samples, yielded a minimal n = 20 for detecting the choice effect with 80% power and alpha = .05. However, since the current experiments focused on memory, which was not similarly tested before with CAT, and also taking into account that some participants would probably not return to the follow-up session, we chose to pre-register a larger sample size of n = 35 for each experiment.

All participants had normal or corrected-to-normal vision and hearing and provided signed informed consent to participate in the experiment in return for monetary compensation.

Participants were asked to refrain from eating and drinking anything but water for one hour prior to each visit in the laboratory. The study was approved by the ethics committee of Tel Aviv University.

Table 1
Demographic Information

	Sample size (Excluded)	Females (percent)	Age *M* (*SD*)	Follow-up	
				Sample Size	Interval *M* (*Range*)
Experiment 1	35 (4)	26 (74%)	24.63 (5.26)	30	34.3 (28-46)
Experiment 2	35 (3)	25 (71%)	24.69 (4.61)	-	-
Pilot Experiment	25 (2)	14 (56%)	25.52 (3.24)	14	45.7 (27-68)

Stimuli

Stimuli in this study comprised of colored images of familiar local Israeli snack food items. Images depicted the snack package and the snack itself on a homogenous black rectangle sized 576 x 432 pixels. The stimuli dataset was created in our laboratory and is available online (http://schonberglab.tau.ac.il/resources/snack-food-image-database/). To promote incentive compatible behavior, when participants entered the laboratory they were presented with a cabinet containing the real snacks and the items were available for actual consumption at the end of the experiment.

Procedures

The experiment was run on a 21.5 inch iMAC computer with Matlab version 2014b (Mathworks, Inc. Natick, MA, USA), the Psychtoolbox (http://www.psychtoolbox.org/) and Python-based Pygame package (Python version 2.7).

The general design included an auction (used to obtain subjective willingness to pay), training, a recognition task and a binary choice task (see Figure 2). The tasks, besides the recognition task, were similar to previous studies with CAT (Salomon et al., 2018; Schonberg et al., 2014). The variants of the design for each experiment are described below.

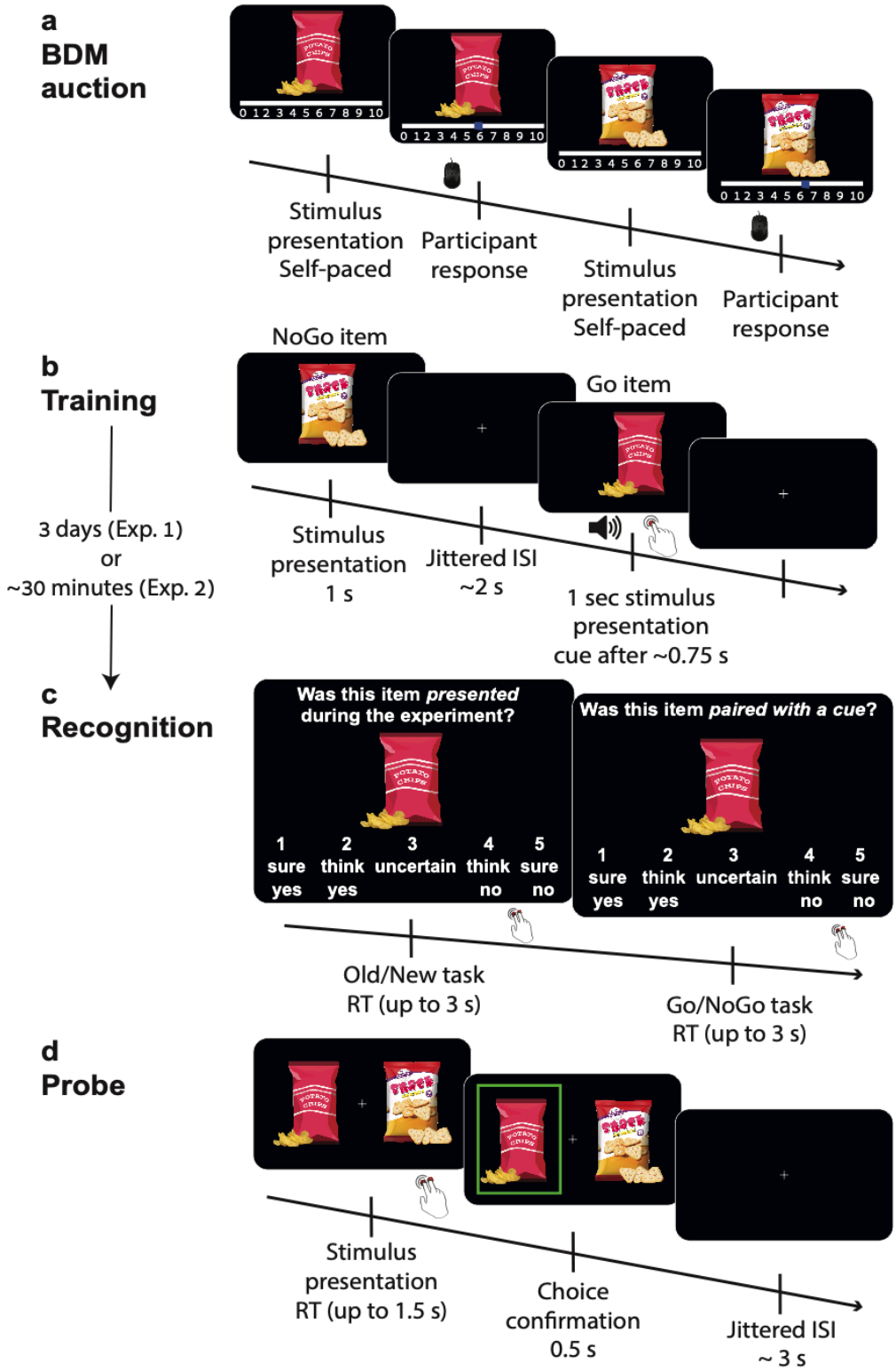

Figure 2. Outline of the experimental procedures. (a) Initial preferences were evaluated using the Becker-Degroot-Marschak (BDM) auction procedure. (b) Cue-approach training (CAT): Go items were associated with a neutral auditory cue and a speeded response. (c) Recognition memory task. (d) Probe: Participants chose between pairs of Go and NoGo items of similar initial value.

Subjective preferences evaluation (see Figure 2a). First, subjective preferences for the snack food items (60 items in Experiment 1 and the Pilot Experiment, and 80 items in Experiment 2) were evaluated using a Becker-DeGroot-Marschak (BDM) auction procedure (Becker, DeGroot, & Marschak, 1964). Participants were first endowed with 10 Israeli Shekels (ILS; equivalent to ~2.7$ US). During the auction, snack food items were individually presented on the screen in a random order. The task was self-paced. Participants were asked to indicate how much money they are willing to pay for each item, using the mouse cursor along a continuous visual analog scale, ranging from 0 - 10 ILS. Participants were informed in advance that at the end of the experiment, the computer will randomly choose one of the items and will generate a counter bid. In case the bid placed by the participant exceeds the computer's bid, she or he will be required to buy the item for the computer's lower bid price. Otherwise, the participant will not buy the item and will keep the allocated 10 ILS. Instructions explicitly mentioned that the best strategy for this task was to indicate the actual willingness to pay (WTP) for each item.

Item selection. For each participant, items were rank-ordered based on the subjective WTP values. Items were split to high-value (above the median) and low-value (below the median) items. One set of items within each value category was used as Go items, while another set of items, with identical mean ranks, was used as NoGo items (see Supplementary Table 1). These sets of items were counter-balanced across participants. This item selection procedure allowed us to present choices of high-value Go versus high-value NoGo items, as well as choices of low-value Go versus low-value NoGo items, with similar initial WTPs, in the probe binary phase. Of the items presented during training, 30% were Go items (12 out of the 40 items in Experiment 1 and the Pilot Experiment; 24 out of the 80 items in Experiment 2).

Training (see Figure 2b). During the training session, individual items were presented on the screen one by one for one second each. We instructed participants to press the 'b' button

on the keyboard as fast as they could whenever an auditory Go-cue was heard. Unbeknownst to participants, the cue was consistently paired with Go items and not with NoGo items. The neutral auditory cue, consisted of a 180 ms-long sinus wave function, was initially heard 750 ms after the stimulus onset. Aiming for a success rate of ~75% (successful button press before the image disappeared from the screen), we updated the delay between the stimulus onset and cue onset with a ladder technique, such that the delay was increased by 16.67 ms following a successful trial and decreased by 50 ms following a missed trial. We used a jittered inter-stimulus interval (ISI) from a truncated exponential distribution, ranging from one to six seconds (one second interval) and an average duration of two seconds.

Recognition (see Figure 2c). The recognition task was added to the paradigm in order to test our proposed mechanism. The recognition task was performed either three days (Experiment 1) or ~30 minutes (Experiment 2) after training, and again in the follow-up session. In this task, all items that would be included in the subsequent Go-NoGo binary choice probe pairs, as well as an equal number of new items, were presented on the screen one at a time. Participants responded for two consecutive questions: (1) Was the item presented during the experiment and (2) was the item paired with a cue during training. Participants responded using a five-point confidence scale (1 - sure yes, 2 - think yes, 3 - uncertain, 4 - think no, 5 - sure no) within a maximal time frame of three seconds.

Probe (see Figure 2d). In the probe phase, we tested participants' preferences following CAT, using a binary choice task. On each trial, participants were presented with a pair of items from the same value category (both either high-value or low-value), one Go item (i.e. consistently paired with the cue and button-press during training) and one NoGo item (i.e. not paired with the cue and button press during training). On each trial, participants were given 1.5 seconds to choose the item they preferred, by pressing the button 'u' (to choose the left item) or the button 'i' (to choose the right item) on the keyboard. Participants were told in advance

that at the end of the experiment, one trial will be randomly drawn by the computer and that they will receive the item they chose on the randomly drawn trial. The ISIs were sampled from a truncated exponential distribution, ranging from 1 - 12 seconds (one second interval) and an average duration of three seconds.

Exclusion criteria

Participants that completed one of the experiments were excluded if they placed bids lower than 1 ILS (~ $0.27 US) on more than 40 items during the BDM auction (Salomon et al., 2018; Schonberg et al., 2014); reached a ladder lower than 200 ms at least once during training, pressed the button without a cue on more than 5% of NoGo training trials (more than 5% false alarm rate) and/or did not press the button following a cue on more than 10% of Go training trials (more than 10% misses). These exclusion criteria were listed in the pre-registration of experiments 1 and 2.

Analysis

All analyses were performed using R version 3.3.3.

Recognition. We predicted that Go stimuli will be better remembered compared to NoGo items (regardless of value category), reflected in higher accuracy (hit rate) and faster response times (RTs) in the old / new recognition task. We only included items that were presented during the probe task in pairs comparing high-value Go versus high-value NoGo or low-value Go versus low-value NoGo items, to ensure that both the number and the mean rank of Go and mean rank of NoGo items within each value category are equal.

Responses in the recognition task were transformed to a binary scale (correct / incorrect), with “uncertain” responses counted as incorrect answers. Missed responses were excluded from analysis. Then, we tested the prediction regarding the hit rate with a one-sided logistic regression with the outcome (correct / incorrect) as the dependent variable and the item type (Go / NoGo) and value category (high-value / low-value) as independent variables. The

prediction regarding the RTs was tested with a one-sided linear mixed model with the RT as the dependent variable and the item type (Go / NoGo) and value category (high-value / low-value) as independent variables. In the RT analysis, we included only correct responses, since RT for wrong responses is not an indication of memory strength. Participants were modelled as a random effect in both models.

To test for the differential effect at the level of memory modification (i.e. whether Go items are better remembered over NoGo items to a greater extent in pairs of high-value compared to low-value items), in a hierarchical regression, we tested the significance of the interaction between item type (Go / NoGo) and value category (high-value / low-value).

Choices. We predicted that the CAT effect observed in previous studies will be replicated, such that participants will significantly choose high-value Go over high-value NoGo items (Bakkour et al., 2017; Botvinik-Nezer et al., bioRxiv; Salomon et al., 2018; Schonberg et al., 2014; Veling et al., 2017). Similar to previous studies with the cue-approach task, we tested this prediction using a one-sided logistic regression, comparing the odds of choosing Go items against chance level (log-odds = 0; odds ratio = 1), independently for each value category (high-value / low-value), with the participants as a random effect. An interesting aspect of CAT, demonstrated in previous studies with snack food items, was that its effect is greater in choices of high-value Go over NoGo items, than in choices of low-value Go over NoGo items (Botvinik-Nezer et al., bioRxiv; Schonberg et al., 2014). Therefore, similar to previous studies, we further tested whether there was a differential effect of higher proportions of Go items choices on high-value compared to low-value probe pairs, with one-sided logistic regression.

Relationships between memory and choices. We hypothesized that high-value Go items are preferred over high-value NoGo items because they are more accessible in memory and their positive associations accumulate faster to choices. Therefore, we predicted that binary

choices will be related to memory for the specific alternatives on a trial-by-trial basis, such that better memory for the Go compared to the NoGo item will be related to Go item choices.

We tested this prediction with two logistic models predicting choices of Go items based on the old / new recognition results: one model with the independent variables accuracy for the Go item (1- Go remembered / 0- Go not remembered) and the inverse accuracy for the NoGo item (1- NoGo not remembered / 0- NoGo remembered); and a second model with the *ΔRT* (RT NoGo minus RT Go; only for probe trials in which both items were correctly remembered). In the accuracy model, we further tested the joint accuracy effect (of both remembering the Go item and forgetting the NoGo item). We used hierarchical regression analysis of variance to compare a logistic model without the accuracy regressors (i.e. only the intercept) to a logistic model with the accuracy regressors (i.e. intercept and accuracy regressors).

According to our suggested model, better remembered items should be preferred over worse remembered items when associated memories are positive. Therefore, we predicted that this relationship will be stronger for high-value compared to low-value items. We tested this prediction by running the logistic regression model with the main effect of value category (high-value / low-value) and the interaction between the value category and the recognition variables. To test this hypothesis, in the accuracy model we added three additional independent variables: (1) value category; (2) interaction between the accuracy for the Go item and the value category; (3) interaction between the inverse accuracy for the NoGo item and the value category. In addition, we further tested the interaction of value category with the joint accuracy effect (of both remembering the Go item and forgetting the NoGo item) using hierarchical regression analysis of variance, comparing a logistic model with accuracy and value category regressors only, to a logistic model also including the interactions. In the RT model, we tested the interaction with hierarchical logistic regression modelling the outcome (whether Go item was chosen or not) with three regressors: (1) ΔRT (i.e. positive values indicate better memory

for the Go compared to the NoGo item); (2) value category and (3) interaction between ΔRT and value category. Participants were modelled as a random effect in all models.

Exploratory analyses. In addition to our pre-registered analyses, we performed the following exploratory analyses (see Supplementary Materials): (1) Comparing RT between Go and NoGo items for incorrect responses (Misses), in order to validate our RT memory effects; (2) comparing hit rate and RTs between Go and NoGo items in the recognition Go / NoGo task; and (3) comparing the confidence levels in the old / new recognition task between Go and NoGo items.

Deviation from pre-registration. It should be noted that the statistical models used were correctly pre-registered for Experiment 2 but not for Experiment 1, where we pre-registered we will use t-tests and correlation tests in the recognition analysis and in the analysis of relationships between memory and choices, respectively. However, prior to data analyses, we consulted with an expert statistician and decided to use the more accurate logistic and linear models that are described above (and were correctly pre-registered for Experiment 2, during data collection of Experiment 1).

Experiment 1

In the first pre-registered experiment, we tested whether memory was enhanced for Go compared to NoGo items following CAT and whether memory was related to choices. This experiment included three sessions: Session 2 was completed exactly three days after Session 1 and tested memory involvement in the (relatively) short-term effect of CAT. The Follow-up Session, testing the long-term effects, was performed about one month following Session 1.

Methods

In Experiment 1, we added a recognition task three days following CAT (i.e. in Session 2). The recognition task was added three days and not immediately following CAT to avoid a ceiling effect that was present in previous experiments in our lab when the recognition task

was performed immediately following the probe task (Botvinik-Nezer et al., bioRxiv; Salomon et al., 2018).

Thirty-five valid participants completed the first two sessions, of them *n* = 30 returned for an additional follow-up session, about one month after Session 1 (mean = 34.3 days, *SD* = 5.04 days, range = 28 - 46 days; demographic statistics are reported in Table 1). Four additional participants were excluded based on pre-registered exclusion criteria: two bid less than one ILS on more than 40 items (BDM exclusion criteria) and two reached a ladder lower than 200 ms during training and also pressed the button when not needed (false alarms) on more than 10% of training trials. One participant completed only one probe block (i.e. one instead of two repetitions of each probe pair). This participant was included in the analysis; however, the results do not change when this participant is excluded from the analysis.

Session 1. Upon arrival, we evaluated participants' initial preferences for 60 snack food items with a BDM auction (Figure 2a). Then, they completed 16 repetitions of CAT. In each training repetition, 40 items were presented in a random order (Figure 2b).

Session 2. Exactly three days after Session 1, participants returned to the laboratory for Session 2. They completed the recognition task (Figure 2c), probe task (Figure 2d) and an additional BDM auction (Figure 2a).

The recognition task included 56 items: 28 new items that were not previously presented during the experiment and 28 old items that were previously presented during the experiment (these would later be used in the probe phase - 24 stimuli in the Go versus NoGo pairs and four additional items from the "sanity check" probe pairs).

Following the recognition task, modifications of preferences were evaluated in a probe task. The probe task consisted of a set of binary choices, in which each of the six high-value Go items was pitted against each of the six high-value NoGo items (6 X 6 = 36 comparisons) and each of the six low-value Go items was pitted against each of the six low-value NoGo

items (6 X 6 = 36 comparisons). Thus, overall there were 72 unique pairs of Go versus NoGo item comparisons. We also included "sanity check" probe pairs, in which high-value NoGo items were pitted against low-value NoGo items. Each unique comparison was repeated twice during the experiment (once in each of two task blocks), resulting in overall 144 Go-NoGo probe trials.

Follow-up Session. About one month after Session 1, participants returned to the lab and completed the Follow-up Session, which included the same tasks as in Session 2.

Results

Recognition. Overall, participants largely showed the pre-registered predicted pattern of behavior in both sessions: participants better remembered Go compared to NoGo items and there was no interaction with the value category.

Session 2. (for full statistics see Supplementary Table 2). *Overall performance.* The mean hit rate of participants was 86.31% (*SD* = 10.33%). The mean correct rejection rate was 70.53% (*SD* = 17.60%). The mean d' was 1.824 (*SD* = 0.747). The mean RT was 1.458 (*SD* = 0.262) seconds for hits, 1.796 (*SD* = 0.504) seconds for misses, 1.589 (*SD* = 0.351) seconds for correct rejections and 1.840 (*SD* = 0.366) seconds for false alarms.

Hit rate. Overall, as predicted and pre-registered, hit rate in the old / new recognition task was significantly higher for Go (*M* = 88.51%) compared to NoGo (*M* = 84.97%) items (*one-sided p* = .047, *odds ratio* = 1.425, 95% *CI* [0.942, 2.157], logistic regression; see Figure 3a), while it was not higher for high-value (*M* = 86.30%) compared to low-value (*M* = 87.40%) items. No interaction was found between the value category (high-value / low-value) and item type (Go / NoGo; *two-sided p* = .434).

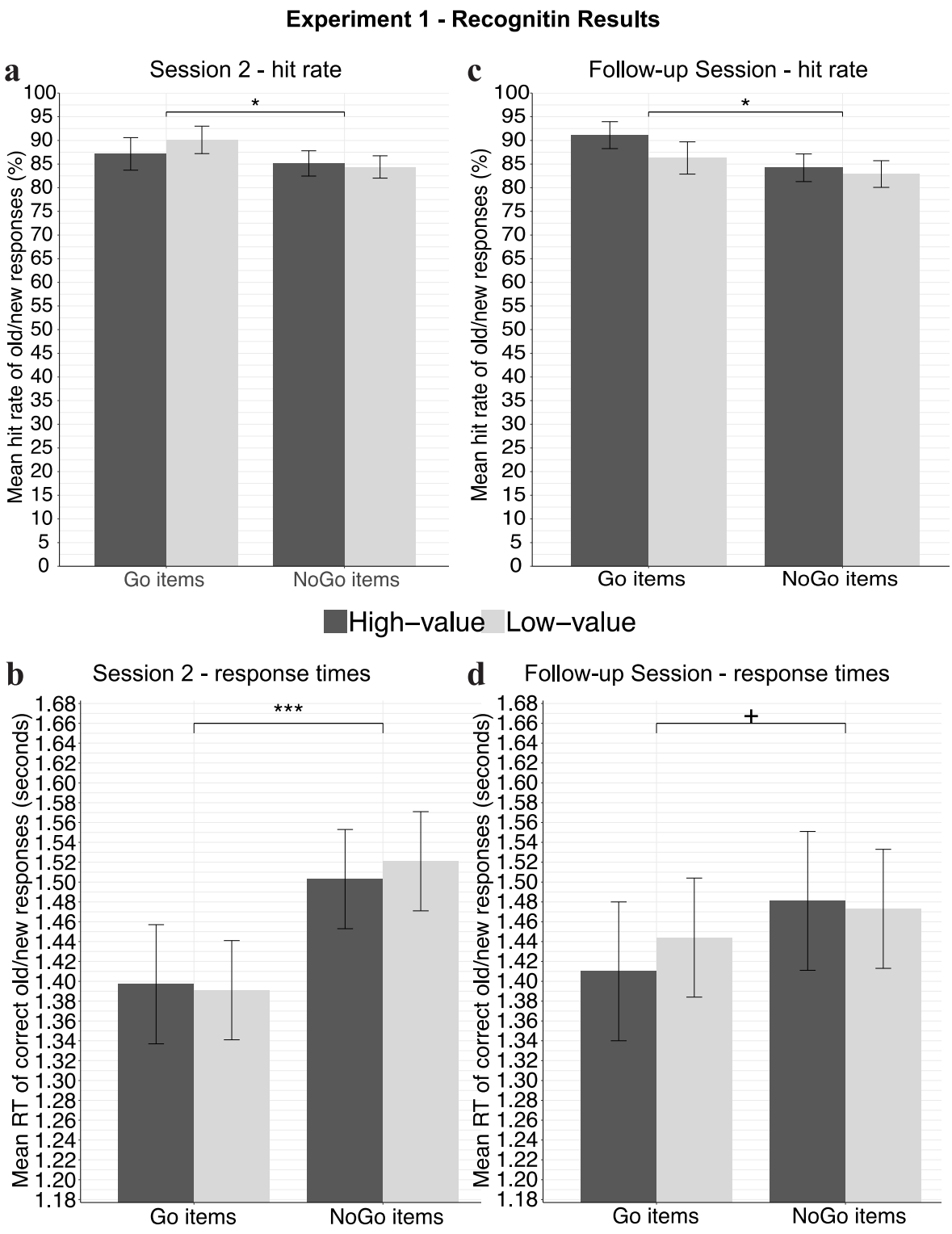

Figure 3. Recognition results of Experiment 1. The mean hit rate (a,c) and response times (b,d) of each participant were calculated and then averaged across participants. Error bars represent standard error of the mean across participants. Asterix represent one-sided statistical significance; + $p < .07$, * $p < .05$, ** $p < .01$, *** $p < .001$

Response times. In accordance with our pre-registered predictions, RTs in the recognition task were significantly faster for Go (*M* = 1.392 seconds) compared to NoGo (*M* = 1.514 seconds) items (*one-sided p* < .001, *estimated mean difference* = -0.126, linear mixed model; see Figure 3b). We did not find RT differences between high-value (*M* = 1.448 seconds) and low-value (*M* = 1.454 seconds) items (*one-sided p* = .422, *estimated mean difference* = -0.006) nor an interaction between the value category and item type (*two-sided p* = .549).

Follow-up Session. (for full statistics see Supplementary Table 2). In this session, we tested the relationships between memory and choices in the long-term, one month following CAT.

Overall performance. The mean hit rate of participants was 84.47% (*SD* = 11.76%). The mean correct rejection rate was 61.15% (*SD* = 19.85%). The mean d' was 1.454 (*SD* = 0.742). The mean RT was 1.456 (*SD* = 0.314) seconds for hits, 1.633 (*SD* = 0.446) seconds for misses, 1.603 (*SD* = 0.326) seconds for correct rejections and 1.749 (*SD* = 0.336) seconds for false alarms.

Hit rate. As in Session 2 and in accordance with our pre-registered predictions, hit rate in the old / new recognition task was significantly higher for Go (*M* = 88.81%) compared to NoGo (*M* = 83.53%) items (*one-sided p* = .016, *odds ratio* = 1.632, 95% *CI* [1.044, 2.550], logistic regression; see Figure 3c) and not significantly higher for high-value (*M* = 87.57%) compared to low-value (*M* = 84.77%) items (*one-sided p* = .143, *odds ratio* = 1.272, 95% *CI* [0.818, 1.980]). As in Session 2, there was no interaction between the value category and item type (*two-sided p* = .436).

Response times. A general trend of faster RTs for Go (*M* = 1.422 seconds) compared to NoGo (*M* = 1.477 seconds) items was observed, but only with marginal significance (*one-sided p* = .059, *estimated mean difference* = -0.049, linear mixed model; see Figure 3d). RTs were

not significantly faster for high-value (*M* = 1.442 seconds) compared to low-value (*M* = 1.455) items (*one-sided p* = .313, *estimated mean difference* = -0.015). There was no interaction between the value category and item type (*p* = .637).

Choices - all sessions (see Figure 4; for full statistics see Supplementary Table 3). As predicted and pre-registered, participants significantly chose high-value Go over high-value NoGo items, both three days after CAT (*M* = 61.67%, *one-sided p* < .001, *odds ratio* = 1.745, 95% *CI* [1.647, 1.849], logistic regression) and one month after CAT (*M* = 59.62%, *one-sided p* < .001, *odds ratio* = 1.546, 95% *CI* [1.464, 1.632]). They also significantly chose low-value Go over low-value NoGo items three days after CAT (*M* = 58.16%, *one-sided p* = .009, *odds ratio* = 1.487, 95% *CI* [1.387, 1.594]) and marginally in the one-month follow-up (*M* = 54.95%, *one-sided p* = .066, *odds ratio* = 1.244, 95% *CI* [1.164, 1.330]).

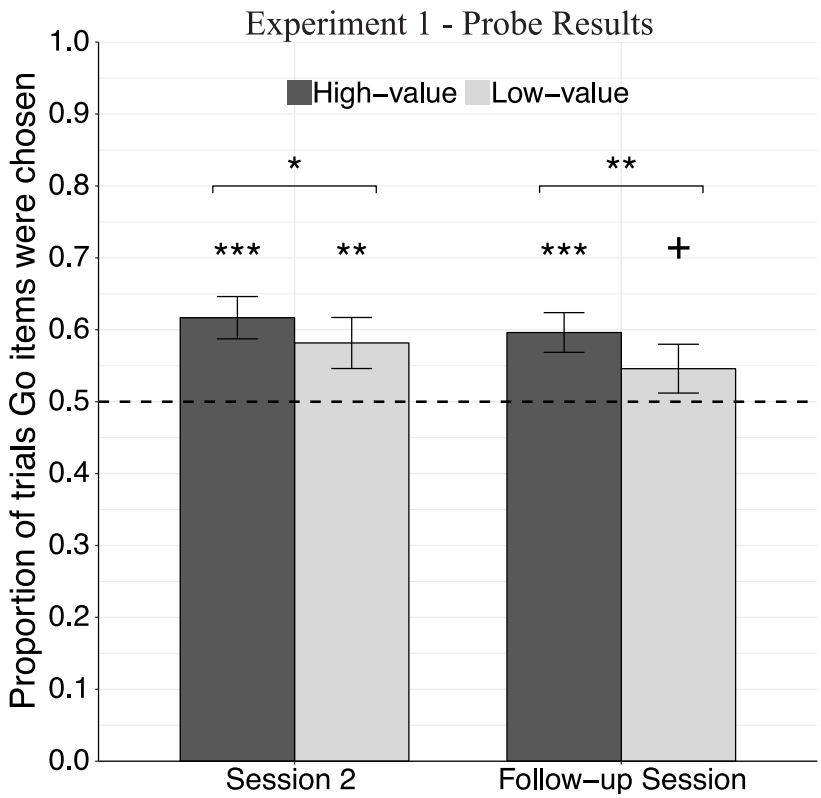

Figure 4. Probe results of Experiment 1. Mean proportions of choosing the Go item (calculated for each participant and then averaged across participants) are presented with error bars representing standard error of the mean. Dashed line indicates 50% chance level. Asterisks represent statistical significance of a one-sided logistic regression analysis; + *p* < .07, * *p* < .05, ** *p* < .01, *** *p* < .001.

The proportion of Go item choices was significantly higher for high-value compared to low-value probe pairs, both in Session 2 (p = .022) and the Follow-up Session (p = .002). These results replicate previous findings with CAT (Botvinik-Nezer et al., bioRxiv; Salomon et al., 2018; Schonberg et al., 2014).

Relationships between memory and choices. Our main analysis focused on the relationships between memory and choices at the individual item level.

Session 2. (see Supplementary Table 4). We tested the relationship between memory for the specific items and choices made in the subsequent probe in Session 2. Based on our suggested model, we predicted that these relationships will be significantly positive for choices between high-value items. We further predicted a significant interaction between memory and the pair value category (high-value / low-value).

The relationship between forgetting the NoGo item and choosing the Go item was significantly positive for choices between high-value items (*one-sided p* < .001, *odds ratio* = 2.279, 95% *CI* [1.706, 3.044]) and for choices between low-value items (*one-sided p* = .015, *odds ratio* = 1.356, 95% *CI* [1.030, 1.785]). Although this relationship was stronger for high-value pairs, the interaction between forgetting the NoGo item and the pair value category was not significant (*one-sided p* = .103).

The relationship between accurately remembering the Go item and choosing it over the NoGo item was not significant for choices between high-value items (*one-sided p* = .319, *odds ratio* = 1.078, 95% *CI* [0.789, 1.472]) and was negative for choices between low-value items (i.e. when the low-value Go item was accurately remembered, it was chosen less; *one-sided p* = .937, *odds ratio* = 0.757, 95% *CI* [0.530, 1.081]). The interaction between accurately remembering the Go item and the pair value category was significant (*one-sided p* = .003).

As predicted, the relationship between both remembering the Go item and forgetting the NoGo item and choosing the Go item (see Figure 5a) was significantly positive for choices

between high-value items (*one-sided p* < .001) and for choices between low-value items (one-*sided p = .014)*. However, the effect was significantly stronger for high-value compared to low-value items (*one-sided p = .006).*

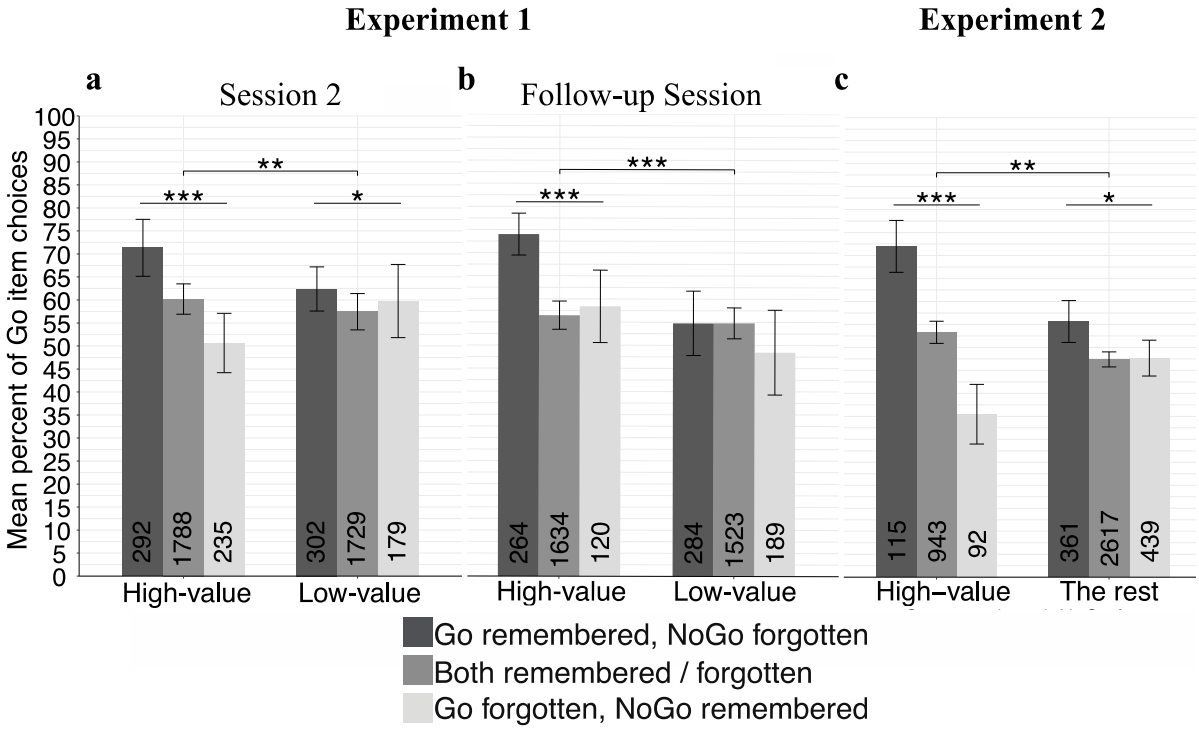

Figure 5. The relationships between recognition memory and choices, in (a) Experiment 1, Session 2 (performed three days after Session 1); (b) Experiment 1, Follow-up Session (~30 days after Session 1); (c) Experiment 2. Mean percent of Go item choices as a function of recognition memory with error bars representing standard error of the mean. The number of trials, summed across participants, is presented at the bottom of each bar. Asterisks represent statistical significance (one-sided logistic regression) of the joint effect of remembering the Go item and forgetting the NoGo item for each value category; * $p < .05$, ** $p < .01$, *** $p < .001$.

The relationship between the recognition ΔRT and choices (see Figure 6a) of high-value Go over high-value NoGo items was significantly positive (i.e. when the RT for the NoGo item in the recognition task was longer than the RT for the Go item, the Go item was chosen more in the probe task; *one-sided p* = .036, *odds ratio* = 1.211, 95% *CI* [0.984, 1.490]). This relationship was also positive but not significant for low-value probe pairs (*one-sided p* = .158, *odds ratio* = 1.113, 95% *CI* [0.903, 1.371]). Although this relationship was stronger for

high-value items, the interaction between the ΔRT and value category was not significant (*one-sided p* = .114).

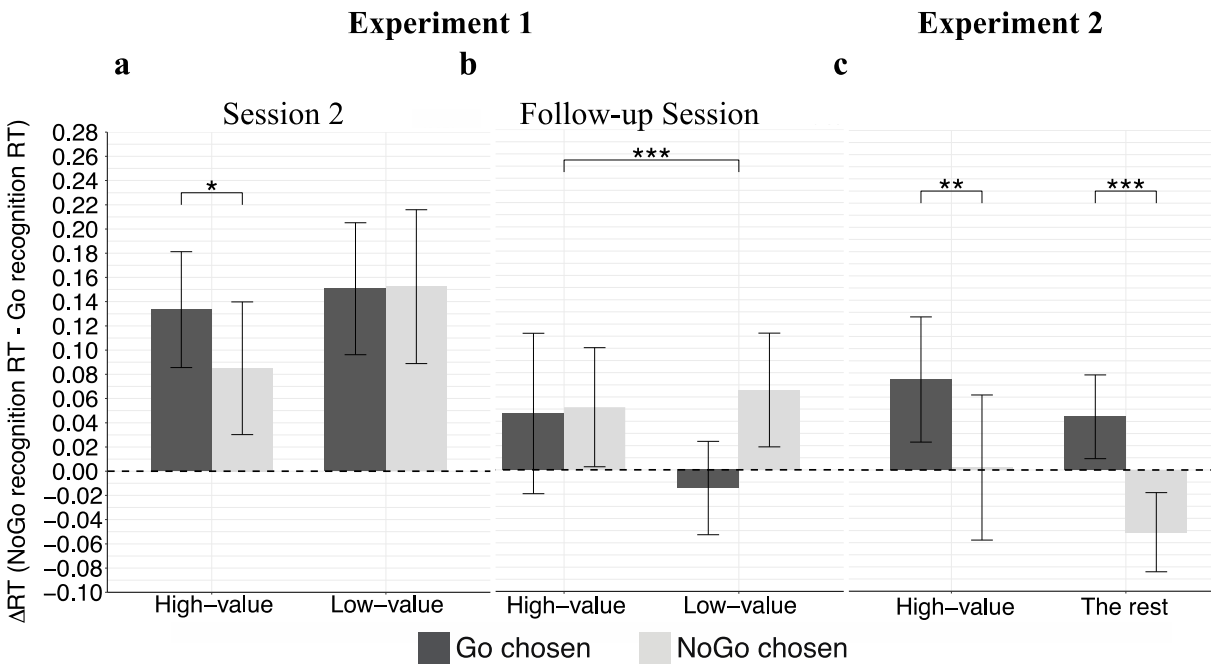

Figure 6. The relationships between recognition ΔRT and choices in (a) Experiment 1, Session 2 (performed three days after Session 1); (b) Experiment 1, Follow-up Session (performed ~30 days after Session 1); (c) Experiment 2. Mean ΔRT values (in seconds) are presented for choices of Go items and for choices of NoGo items, within each value category. Error bars represent standard error of the mean. Asterisks represent statistical significance of one-sided logistic regression; * $p < .05$, ** $p < .01$, *** $p < .001$.

Follow-up Session. (see Supplementary Table 5). The relationship between forgetting the NoGo item and choosing the high-value Go over the high-value NoGo item was significantly positive (*one-sided p* < .001, *odds ratio* = 2.757, 95% *CI* [2.027, 3.749]). This relationship was weaker but also significantly positive for low-value items (*one-sided p* = .046, *odds ratio* = 1.264, 95% *CI* [0.962, 1.660]). The interaction between forgetting the NoGo item and the value category was significant (*one-sided p* < .001).

The relationship between accurately remembering the Go items and choosing them over the NoGo items was not significant, for choices between high-value items (*one-sided p* = .130, *odds ratio* = 0.793, 95% *CI* [0.530, 1.187]) nor for choices between low-value items (*one-sided p* = .483, *odds ratio* = 1.007, 95% *CI* [0.730, 1.390]). The interaction between accurately

remembering the Go items and the value category was, counter to our hypothesis, more positive for low-value compared to high-value items (*one-sided p* = .950).

The relationship between both remembering the Go item and forgetting the NoGo item and choosing the Go item (see Figure 5b) was significantly positive for choices between high-value items (*one-sided p* < .001) and not significant for choices between low-value items (*one-sided p = .121)*. This relationship was significantly stronger for high-value compared to low-value items (*one-sided p* < .001*)*.

The relationship between the ΔRT and choices (see Figure 6b) of high-value Go over high-value NoGo items was positive but not significant (*one-sided p* = .267, *odds ratio* = 1.068, 95% *CI* [0.868, 1.315]). This relationship was negative for low-value probe pairs (i.e. when the ΔRT between the low-value NoGo and the low-value Go item was larger, the Go item was less chosen; *one-sided p* = .999, *odds ratio* = 0.709, 95% *CI* [0.565, 0.888]). The interaction between the ΔRT and value category was significant (*one-sided p* < .001).

Discussion

In Experiment 1, similar to previous studies, we found enhanced preferences towards Go items, both three days and one month following CAT. Similar to previous studies with snack food items (Botvinik-Nezer et al., bioRxiv; Schonberg et al., 2014), the CAT effect was stronger in high-value than in low-value probe choices (Figure 4).

In line with our pre-registered suggested model, we found enhanced memory for Go compared to NoGo items (reflected as higher hit rate and faster RTs), both in the short- and in the long-term. This is the first direct evidence for enhanced memory accessibility of Go versus NoGo items following CAT, suggesting that memory modifications are involved in the underlying mechanism of the CAT effect.

Most importantly, since our model hypothesized that each choice is related to the memory for the specific items in the presented pair, we tested whether choices were related to

the memory for the specific items on each binary choice pair. As predicted, we found evidence showing that memory was indeed related to the specific choices. Choices of the Go items over the NoGo items were more likely when the individual Go item was remembered and the NoGo item was forgotten. Furthermore, these relationships were generally more positive for choices between high-value items compared to choices between low-value items. These results are in line with our hypothesis, that for higher valued items, better remembered Go items will be chosen over worse remembered NoGo items.

Experiment 1 was also the first experiment with CAT where choices were first tested three days (and not immediately) after training. In previous experiments there was always a probe phase on the same day of training and then subsequent probes up to six months after the initial training. The results of Experiment 1 show that training directly influences choices for at least a few days after training, therefore suggesting that the long-term duration of the CAT effect is less likely to be driven by previous choices via a mere choice effect (Sharot, Fleming, Yu, Koster, & Dolan, 2012).

Experiment 1 showed that choices following CAT are related to memory at the individual item level. Therefore, we decided to increase the number of trained and tested items, as well as to decrease the number of training runs. Our goal was to increase the variance across items, in pre-training preferences, post-training memory and post-training choices, to further examine the relationships between memory and value-based choices at the individual item level.

Experiment 2

The findings of Experiment 1 suggested that choices following CAT were related to memory at the individual item level. To further examine these relationships, in Experiment 2 (pre-registered on OSF: https://osf.io/h9rwk/), we sought to increase the variance of memory scores across items and allow a better examination of the memory effects on individual items. To do

so, we doubled the number of trained and tested items, and for the first time, we decreased the number of training repetitions to a single one.

Methods

Experiment 2 included n = 35 valid participants. Three additional participants were excluded based on the pre-registered BDM exclusion criteria. Upon arrival, participants completed a BDM auction with 80 items (instead of 60 items as in Experiment 1), Then, participants completed the training task, which was similar to Experiment 1, besides two important modifications: First, each item was only presented once (instead of 16 repetitions in Experiment 1). Second, 80 (instead of 40) items were presented during training. Out of the 80 items, 12 items were high-value Go items and 12 items were low-value Go items (compared to six high-value Go and six low-value Go items in Experiment 1).

After training, participants completed a filler task during which they ranked fractal art images, unfamiliar faces and familiar faces (of local politicians), as well as the familiarity of the familiar faces. The filler tasks lasted about 30 minutes. Following the filler tasks, participants completed a recognition task, similar to the one performed in Experiment 1, but with a larger total number of 160 items - 80 old and 80 new items.

Then, participants completed the probe task. Since we doubled the number of trained items, we also doubled the number of probe comparisons. Probe Go-NoGo choices included four value categories: high, medium-high, medium-low and low value (for the exact ranks of each value category see Supplementary Table 1). Each category included 36 unique choices between the six Go items pitted against six NoGo items of identical mean rank. Thus, overall each probe block included a total of 144 unique Go versus NoGo choices. Twelve “sanity check” probe trials (i.e. choices between high-value and low-value NoGo items) were also presented, as in Experiment 1.

Finally, participants completed a familiarity task for the items, in which they ranked the familiarity of each snack food item. However, the results of this task are beyond the scope of this study.

Results

Recognition (see Supplementary Table 6). In contrast to our predictions, participants did not remember the Go compared to the NoGo items more accurately following one training run.

Overall performance. The mean hit rate of participants was 85.63% (*SD* = 11.34%). The mean correct rejection rate was 81.6% (*SD* = 12.48%). The mean d' was 2.403 (*SD* = 1.829). The mean RT was 1.384 (*SD* = 0.214) seconds for hits, 1.558 (*SD* = 0.290) seconds for misses, 1.436 (*SD* = 0.239) seconds for correct rejections and 1.752 (*SD* = 0.349) seconds for false alarms.

Hit Rate. In contrast to Experiment 1 and to our pre-registered prediction, in Experiment 2 the hit rate in the old / new recognition task was not higher for Go (*M* = 84.67%) compared to NoGo (*M* = 85.78%) items (*one-sided p* = .759, logistic regression; see Supplementary Figure 1a), but was significantly higher for higher value categories (*one-sided p* = .004). There was no interaction between the value category (high / medium-high / medium-low / low value) and item type (Go / NoGo; *two-sided p* = .570).

Response times. Contrary to our predictions, RTs were not significantly faster for Go (*M* = 1.380 seconds) compared to NoGo (*M* = 1.383 seconds) items (*one-sided p* = .463; see Supplementary Figure 1b), nor significantly faster for higher value items (*one-sided p* = .209). The interaction between item type and value category was not significant (*two-sided p* = .883).

Choices (for full statistics see Supplementary Table 7). In the high-value probe choices (equivalent to those of Experiment 1), participants significantly chose Go over NoGo items (*M* = 54.41%, *one-sided p* = .035, *odds ratio* = 1.209, 95% *CI* [1.152, 1.270], logistic regression;

see Supplementary Figure 2) after one training run. However, participants did not show preferences modification for the Go items in the other value categories.

Relationships between memory and choices (see Supplementary Table 8). In Experiment 2, we tested the relationships between choices and memory within each of the four value categories. Since preferences were only changed for high-value items, we combined the other three categories (i.e. "The rest". See Supplementary Table 9 for statistics of each of these value categories) in our analysis. We tested the interactions between memory and value category by modelling the value category as high-value compared to the rest of the categories.

The relationship between forgetting the NoGo item and choosing the Go item was significantly positive both for choices between high-value items (*one-sided* $p < .001$, *odds ratio* = 2.519, 95% *CI* [1.636, 3.879], logistic regression) and for choices in the rest of the value categories combined (*one-sided* $p = .007$, *odds ratio* = 1.298, 95% *CI* [1.056, 1.596]). The interaction between forgetting the NoGo item and the value category was significant (*one-sided* $p = .006$).

The relationship between accurately remembering the Go item and choosing it over the NoGo item was significantly positive for choices between high-value items (*one-sided* $p = .002$, *odds ratio* = 1.831, 95% *CI* [1.200, 2.793], logistic regression) and not significant for choices in the rest of the value categories combined (*one-sided* $p = .279$, *odds ratio* = 1.059, 95% *CI* [0.874, 1.284]). This relationship was significantly stronger for high-value items compared to the other value categories (*one-sided* $p = .003$).

The relationship between memory (both remembering the Go item and forgetting the NoGo item) and Go items choices (see Figure 5c) was significantly positive, both for choices between high-value items (*one-sided* $p < .001$) and for choices between items from the rest of the value categories combined (*one-sided* $p = .020$). This relationship was significantly stronger for high-value compared to the other value categories (*one-sided* $p = .001$).

The relationship between the ΔRT and choices of Go over NoGo items (see Figure 6c) was significantly positive for the high-value items (*one-sided p* = .003, *odds ratio* = 1.448, 95% *CI* [1.110, 1.887], logistic regression) as well as for the rest of the value categories combined (*one-sided p* < .001, *odds ratio* = 1.344, 95% *CI* [1.164, 1.551]). The interaction between the ΔRT and value category was not significant (*one-sided p* = .232).

Discussion

In Experiment 2, we tested the relationship between choices and memory for individual items with a larger number of items compared to previous experiments and following one repetition of CAT. Even after a single training run, we found a preference modification effect for items in the high-value category. Contrary to our pre-registered predictions, we found no evidence for better memory of Go items in comparison to NoGo items. These results imply that one training run might be sufficient to change preferences for the most valued Go items (a change which was significant but weak compared to previous CAT samples), but not sufficient to induce an effect of enhanced memory across items.

Replicating the results of Experiment 1, in line with our pre-registered hypotheses, we found strong relationships between better memory for the Go items and choices of these items over the less remembered NoGo items, mainly for high-value items (the value category in which the choice effect was found). The larger number of Go and NoGo items used in the recognition and probe tasks in this experiment compared to previous ones (48 items in the current experiment versus 24 or less in previous experiments), allowed us to more generally test the relationships between memory for specific items and choices. These results provide additional evidence in support of our suggested model, by replicating, in a different design, the finding that better-remembered Go items following CAT are also chosen more often.

General Discussion

Preferences as memories (PAM) is a framework that suggests that the retrieval of relevant knowledge from memory is the basis used to compare options and make a choice between them (Weber & Johnson, 2006). This framework explains the associative nature of preferences, as well as known characteristics of preferences such as instability and semantic framing-effects. However, the role of memory processes in value-based decision-making as well as the cognitive and neural mechanisms by which memory influences decisions are not yet fully understood (Fellows, 2017; Shadlen & Shohamy, 2016; Weilbächer & Gluth, 2017).

Here, we tested the relationships between memory and behavioral change of choices without external reinforcements using the CAT paradigm. This paradigm has been shown to reliably change preferences for items using the mere-association of images with a neutral cue and a speeded button press response.

We hypothesized that the cognitive mechanisms underlying the CAT effect are based on modifications of memory accessibility. We suggested that memory for Go items will be enhanced following CAT. Therefore, we predicted better recognition memory for Go compared to NoGo items following CAT in the short- and long-term, and that the better memory of Go items would lead to greater preferences for high-value Go items during probe.

We tested our suggested mechanism and predictions in two pre-registered experiments based on an additional pilot experiment. In Experiment 1, we tested these predictions with a recognition and a subsequent probe task, performed three days after CAT. Similar to other studies with CAT (Bakkour, Botvinik-Nezer, et al., 2018; Bakkour et al., 2016, 2017; Botvinik-Nezer et al., bioRxiv; Salomon et al., 2018; Schonberg et al., 2014; Veling et al., 2017; Zoltak et al., 2017), we found enhanced preference for Go items following CAT. High-value Go items were preferred over high-value NoGo items three days as well as one month following CAT (Figure 4). Low-value Go items were also preferred over low-value NoGo items, but to a significantly lesser extent. As our model predicted, we also found a significant memory

enhancement, reflected as higher hit rates and faster RTs in the recognition task for Go compared to NoGo items, both in the short- and long-term (Figure 3). Moreover, we found that memory for individual items was positively related to choices of Go over NoGo high-value items, both when memory and choices were tested three days as well as one-month after CAT (Figures 5 and 6).

Based on the findings of Experiment 1, we concluded that CAT affects memory, and thus choices, at the individual item level. Therefore, in Experiment 2, we increased the number of items to more widely explore the variability of the effect across items. We decreased the number of training repetitions to one, in order to test whether one run is sufficient to affect memory and preferences. We found that even a single training run is sufficient to induce preference modification in the highest value category tested. Overall, memory was not significantly enhanced for Go compared to NoGo items. Nonetheless, we found significant relationships between memory and choices: better remembered Go items were more likely to be preferred over worse remembered NoGo items in the binary probe phase. The absence ofoverall memory modifications might have been the result of lack of consolidation in such short time scales (memory was tested about 30 minutes after CAT).

Prior to these experiments we conducted a pilot experiment (see Supplementary Materials), which was similar to Experiment 1, but with an additional probe task performed at the end of Session 1. In this pilot sample we found positive relationships between memory for individual Go items and choices of these items over worse remembered NoGo items. Unlike previous studies, there was no overall CAT effect in the pilot experiment. The effect on memory was relatively weak and was found only when comparing the RTs, possibly due to a ceiling effect in recognition memory performance in this experiment. Nevertheless, the existence of a link between memory and choices at the individual item level in the Pilot

Experiment indicates that even when the main effects of both choices and memory are absent, individual choices are still related to memory for the individual items.

We interpreted faster RTs for Go compared to NoGo items in Experiment 1 and the Pilot Experiment as an indication of better memory for Go items, in accordance with our pre-registered model and predictions. However, an alternative explanation for these findings might be that the association of Go items with motor responses during training resulted in a conditioned response of pressing when Go items are presented, leading to faster RTs for these items irrespective of memory strength. To disentangle these two hypotheses, we performed exploratory analyses on the recognition data from Experiment 1 and the Pilot Experiment (the two experiments where RTs in the recognition task were faster for Go compared to NoGo items). We tested whether responses were faster for Go items even when they were incorrect (see Supplementary Exploratory Analyses). No significant difference was found between RTs for Go compared to NoGo items in incorrect old / new recognition trials, but the interaction between item type (Go / NoGo) and response accuracy (correct / incorrect) was not significant. However, in the old / new recognition task, the number of incorrect responses was very low, which may have limited the interaction analysis. Therefore, we also tested response times in the Go / NoGo recognition task (see Supplementary Exploratory Analyses). While correct responses were significantly faster for Go items in correct responses, they were non significantly slower for incorrect responses. Importantly, the interaction between item type (Go / NoGo) and response accuracy (correct / incorrect) was significant, indicating that RTs were faster for Go items only in correct responses. These findings suggest that the faster RTs for Go compared to NoGo items in the old / new recognition task are indeed an indication of better memory for these items.

An interesting aspect of CAT with snack food items is that it affects choices of high-value Go over NoGo items more than choices of low-value Go over NoGo items (Botvinik-

Nezer et al., bioRxiv; Salomon et al., 2018; Schonberg et al., 2014). This effect was suggested to indicate that CAT may induce value scaling, rather than a fixed-increment value enhancement (McGuire & Kable, 2014). Alternatively, we suggest that this differential effect is due to the greater number of positive memories associated with high-value versus low-value snacks. Our proposed model (Figure 1) suggests that memory is enhanced for both high-value and low-value Go items following CAT. When presented with binary choices of high-value items, the memories associated with Go items that are activated are usually positive, resulting in a preference for these items. When choosing between low-value items, activated associations are not necessarily positive since these items are subjectively less preferred to begin with (but not necessarily disliked). Therefore, choices of low-value Go over low-value NoGo items following CAT are significantly less consistent.

Overall, the findings of the current study were in line with our pre-registered hypotheses. When choices were affected, memory was enhanced for Go compared to NoGo items. Memory was enhanced for both high-value and low-value Go items, suggesting that the differential effect of CAT on preferences was not the result of a stronger memory enhancement for high-value Go compared to low-value Go items. Most importantly, when examining memory for each of the items in each specific binary choice, we found that better memory for the Go compared to the NoGo items was related to choices of Go over NoGo items more positively for high-value compared to low-value choice pairs.

One of the main unexplained observations in value-based decision-making is that harder decisions (e.g. between options with similar subjective values) take longer (Krajbich, Armel, & Rangel, 2010; Milosavljevic, Malmaud, Huth, Koch, & Rangel, 2010). In perceptual decision-making, perceptual evidence accumulates with time and a decision is made once a given threshold of evidence has been reached (Gold & Shadlen, 2007; Shadlen & Kiani, 2013). However, during value-based decision-making, it is unclear what consumes the time to

decision. Recently, it has been proposed that these decisions are based on retrieval of accumulated evidence from episodic memory (Bakkour, Zylberberg, Shadlen, & Shohamy, bioRxiv; Shadlen & Shohamy, 2016). The findings of the current study indicate strong relationships between enhancement of memory accessibility and choices even in the absence of external reinforcements. In the framework of evidence accumulation from episodic memory during value-based decision-making, the relationships we found between choices and memory accessibility may be driven by a faster rate of evidence accumulation from memory in favor of the better remembered Go items.

Our findings provide the first evidence for the involvement of memory accessibility in value-based choices even in the absence of external reinforcements. These findings are important for revealing the role of memory in value-based decision-making in general and in isolation of external reinforcements. These results shed light on the mechanism underlying behavioral change following CAT, which offers novel avenues for long-lasting behavioral change interventions for maladaptive behaviors such as eating disorders and addictions.

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Competing interests

The authors declare no competing interests.

References

Anderson, J. R. (1983). A spreading activation theory of memory. *Journal of Verbal Learning and Verbal Behavior*, *22*(3), 261–295. http://doi.org/10.1016/S0022-5371(83)90201-3

Bakkour, A., Botvinik-Nezer, R., Cohen, N., Hover, A. M., Poldrack, R. A., & Schonberg, T. (2018). Spacing of cue-approach training leads to better maintenance of behavioral change. *PLoS ONE*, *13*(7), 1–39. http://doi.org/10.1371/journal.pone.0201580

Bakkour, A., Leuker, C., Hover, A. M., Giles, N., Poldrack, R. A., & Schonberg, T. (2016). Mechanisms of Choice Behavior Shift Using Cue-approach Training. *Frontiers in Psychology*, *7*(March), 1–12. http://doi.org/10.3389/fpsyg.2016.00421

Bakkour, A., Lewis-Peacock, J. A., Poldrack, R. A., & Schonberg, T. (2017). Neural mechanisms of cue-approach training. *NeuroImage*, *151*(September), 92–104. http://doi.org/10.1016/j.neuroimage.2016.09.059

Bakkour, A., Zylberberg, A., Shadlen, M. N., & Shohamy, D. Value-based decisions involve sequential sampling from memory. *bioRxiv*, 269290. http://doi.org/10.1101/269290

Becker, G. M., DeGroot, M. H., & Marschak, J. (1964). Measuring utility by a single-response sequential method. *Behavioral Science*, *9*(3), 226–232. http://doi.org/10.1002/bs.3830090304

Bhatia, S. (2013). Associations and the accumulation of preference. *Psychological Review*, *120*(3), 522–543. http://doi.org/10.1037/a0032457

Bornstein, A. M., Khaw, M. W., Shohamy, D., & Daw, N. D. (2017). Reminders of past choices bias decisions for reward in humans. *Nature Communications*, *8*(May), 1–9. http://doi.org/10.1038/ncomms15958

Bornstein, A. M., & Norman, K. A. (2017). Reinstated episodic context guides sampling-based decisions for reward, *20*(7). http://doi.org/10.1038/nn.4573

Botvinik-Nezer, R., Salomon, T., & Schonberg, T.. Enhanced bottom-up and reduced top-down fMRI activity is related to long-lasting non-reinforced behavioral change, 1–42. bioRxiv

Duncan, K. D., & Shohamy, D. (2016). Memory states influence value-based decisions. *Journal of Experimental Psychology: General*, *145*(11), 1420–1426. http://doi.org/10.1037/xge0000231

Fellows, L. K. (2017). The Neuroscience of Human Decision-Making Through the Lens of Learning and Memory. In *Current topics in behavioral neurosciences* (Vol. 37, pp. 231–251). http://doi.org/10.1007/7854_2016_468

Gold, J. I., & Shadlen, M. N. (2007). The Neural Basis of Decision Making. *Annu. Rev. Neurosci.*, *30*, 535–574. http://doi.org/10.1146/annurev.neuro.29.051605.113038

Krajbich, I., Armel, C., & Rangel, A. (2010). Visual fixations and the computation and comparison of value in simple choice. *Nature Neuroscience*, *13*(10), 1292–8. http://doi.org/10.1038/nn.2635

Kusev, P., van Schaik, P., & Aldrovandi, S. (2012). Preferences induced by accessibility: Evidence from priming. *Journal of Neuroscience, Psychology, and Economics*, *5*(4), 250–258. http://doi.org/10.1037/a0030289

McGuire, J. T., & Kable, J. W. (2014). Go means green. *Nature Neuroscience*, *17*(4), 489–

90. http://doi.org/10.1038/nn.3680

Milosavljevic, M., Malmaud, J., Huth, A., Koch, C., & Rangel, A. (2010). The Drift Diffusion Model can account for the accuracy and reaction time of value-based choices under high and low time pressure. *Judgment and Decision Making*, *5*(6), 437–449.

Salomon, T., Botvinik-Nezer, R., Gutentag, T., Gera, R., Iwanir, R., Tamir, M., & Schonberg, T. (2018). The Cue-Approach Task as a General Mechanism for Long-Term Non-Reinforced Behavioral Change. *Scientific Reports*, *8*(1), 3614. http://doi.org/10.1038/s41598-018-21774-3

Schonberg, T., Bakkour, A., Hover, A. M., Mumford, J. a, Nagar, L., Perez, J., & Poldrack, R. a. (2014). Changing value through cued approach: an automatic mechanism of behavior change. *Nature Neuroscience*, *17*(4), 625–30. http://doi.org/10.1038/nn.3673

Shadlen, M. N., & Kiani, R. (2013). Decision making as a window on cognition. *Neuron*, *80*(3), 791–806. http://doi.org/10.1016/j.neuron.2013.10.047

Shadlen, M. N., & Shohamy, D. (2016). Decision Making and Sequential Sampling from Memory. *Neuron*, *90*(5), 927–939. http://doi.org/10.1016/j.neuron.2016.04.036

Sharot, T., Fleming, S. M., Yu, X., Koster, R., & Dolan, R. J. (2012). Is Choice-Induced Preference Change Long Lasting ? http://doi.org/10.1177/0956797612438733

Veling, H., Chen, Z., Tombrock, M. C., Verpaalen, I. A. M., Schmitz, L. I., Dijksterhuis, A., & Holland, R. W. (2017). Training impulsive choices for healthy and sustainable food. *Journal of Experimental Psychology: Applied*, *23*(2), 204–215. http://doi.org/10.1037/xap0000112

Weber, E. U., & Johnson, E. J. (2006). Constructing Preferences from Memory. *SSRN Electronic Journal*, 1–26. http://doi.org/10.2139/ssrn.1301075

Weilbächer, R. A., & Gluth, S. (2017). The interplay of hippocampus and ventromedial prefrontal cortex in memory-based decision making. *Brain Sciences*, *7*(1).

http://doi.org/10.3390/brainsci7010004

Wimmer, G. E., & Shohamy, D. (2012). Preference by Association: How Memory Mechanisms in the Hippocampus Bias Decisions. *Science*. http://doi.org/10.1126/science.1223252

Zoltak, M. J., Veling, H., Chen, Z., & Holland, R. W. (2017). Attention! Can choices for low value food over high value food be trained? *Appetite*, *124*, 124–132. http://doi.org/10.1016/j.appet.2017.06.010