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The influence of visual attention on memory-based preferential choice

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ABSTRACT

Many decisions rely on past experiences. Recent research indicates that people's choices are biased towards choosing better-remembered options, even if these options are comparatively unattractive (i.e., a memory bias). In the current study, we used eye tracking to compare the influence of visual attention on preferential choice between memory-based and non-memory-based decisions. Participants completed the remember-and-decide task. In this task, they first learned associations between screen locations and snack items. Then, they made binary choices between snack items. These snacks were either hidden and required recall (memory-based decisions), or they were visible (non-memory-based decisions). Remarkably, choices were more strongly influenced by attention in memory-based compared to non-memory-based decisions. However, visual attention did not mediate the memory bias on preferential choices. Finally, we adopt and expand a recently proposed computational model to provide a comprehensive description of the role of attention in memory-based decisions. In sum, the present work elucidates how visual attention interacts with episodic memory and preference formation in memory-based decisions.

1. Introduction

Imagine you are planning to go to the supermarket during a short break from work to buy a snack. The supermarket is vast and you do not have the time to go through all the shelves. To save time, you recall potential snack options (e.g., chocolate bars, pretzels), together with their locations, from your memory, and choose which one to buy before you even leave the office. As in this example, many of people's every-day decisions rely critically on episodic memory.

Accordingly, there is a growing body of research on decisions from memory (Bordalo, Gennaioli, & Shleifer, 2020; Fechner et al., 2016; Gluth, Sommer, Rieskamp, & Büchel, 2015; Hoffmann, von Helversen, & Rieskamp, 2014; Sali, Anderson, & Courtney, 2016; Shadlen & Shohamy, 2016; Weilbächer & Gluth, 2017; Wimmer & Büchel, 2016). In previous studies (Gluth et al., 2015; Kraemer, Fontanesi, Spektor, & Gluth, 2020; Mechera-Ostrovsky & Gluth, 2018; Weilbächer, Kraemer, & Gluth, 2020), we have investigated the role of memory in preferential choice by asking participants to recall pairs of options and to choose between these memorized options (subsequently referred to as *remember-and-decide* task). The critical decisions in this task are those between a successfully remembered and a forgotten option. In all our studies, we found that people prefer remembered options even when their subjective value is below average. Neuroimaging analyses (Gluth et al., 2015) further indicate that this *memory bias* is mediated by increased effective connectivity between the hippocampus and the ventromedial prefrontal cortex. Yet, it remains an open question what cognitive mechanisms give rise to this memory bias and why people tend to prefer better-remembered options.

In the current study, we investigated whether the memory bias can be attributed to interactions between memory and attention. Attention has been shown to play a crucial role in preferential (and perceptual) choice, as people tend to choose items that they have looked at longer (Cavanagh, Wiecki, Kochar, & Frank, 2014; Fiedler & Glöckner, 2012; Gluth, Kern, Kortmann, & Vitali, 2020; Krajbich, Armel, & Rangel, 2010; Orquin & Mueller Loose, 2013; Stewart, Gächter, Noguchi, & Mullett, 2016) leading to an *attention bias*. Furthermore, research on the interplay of attention and memory has shown that when people are asked to recall information, they tend to fixate on the location where that information was previously presented, a phenomenon known as *looking-at-nothing* (Richardson & Spivey, 2000; Scholz, Mehlhorn, & Krems, 2016; Scholz, von Helversen, & Rieskamp, 2015). This finding suggests that the memory bias in choice may be mediated by attention. More

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specifically, better-remembered items might be looked at more than forgotten items, leading to an advantage for those items in the choice process.

On the other hand, in memory-based choices, attention might overall play a more prominent role because participants can rely less on the options' subjective values, as they do not see them directly, but have to retrieve them from memory. In this case, the necessity to retrieve options might enhance the influence of visual attention, independent of the recall success. Recent work suggests that looking more at an option amplifies its subjective value (Smith & Krajbich, 2019). In our remember-and-decide task, people are presented with two equally salient white squares and try to recall the identities and their value to find the better option. We hypothesize that the choice process is mediated by attention: looking longer at a particular area makes that option more attractive and more likely to be chosen in memory-based compared to non-memory based choice.

To test these predictions, we conducted an eye-tracking experiment in which participants completed an adapted version of the remember-and-decide task (Fig. 1). In this task, participants first learned the association between choice options (i.e., snack items) and locations. Then, they were asked to indicate their preferred option in binary decisions. In two-thirds of trials (subsequently referred to as *memory trials*), participants had to recall the choice options from memory. The remaining third of trials served as *control trials*, in which the options were displayed on the screen. After the decision phase, the memory for each option was probed via cued recall. During the learning and decision phases we used eye-tracking to record participants' eye movements.

To better understand the cognitive process underlying the role of attention in memory-based decisions, we applied and adapted a recently proposed computational model that integrates eye-movement data into the choice process. The Gaze-weighted Linear Accumulator Model [GLAM; Thomas, Molter, Krajbich, Heekeren, & Mohr, 2019] is based on the attentional Drift Diffusion Model [aDDM; Krajbich et al., 2010 Krajbich & Rangel, 2011] and describes how the value of the presented choice options and the gaze proportion of each option determine decisions. GLAM is a multi-alternative sequential sampling model (Busemeyer, Gluth, Rieskamp, & Turner, 2019), and thus makes joint predictions of response times and decisions for two or more choice options. It has been shown to offer very robust parameter estimates, which makes it a suitable tool to compare parameters across our different conditions of memory- and non-memory-based decisions.

Our results provide evidence for an even stronger influence of attention on preference formation in memory-based decisions, as participants' tendency to prefer the option they looked at longer was enhanced in memory trials as compared to control trials. Computationally, this difference mapped onto different estimates of the parameter that quantifies the influence of attention on preference formation in memory and control trials. However, we did not observe longer dwell time on remembered (compared to forgotten) items, so that attention does not appear to mediate the memory bias on preferential choice.

2. Method

All processed data and data analysis files of this study can be found on the Open Science Framework website (osf.io/fvqhu/).

2.1. Participants

A power analysis with G*Power [version 3.1.9.2; (Faul, Erdfelder, Lang, & Buchner, 2007)] indicated that a sample size of $n = 32$ is required to identify the memory bias in preferential choice (one sample *t*-test, one-tailed, power = 0.95, medium effect size Cohen's d = 0.6). A total of 51 participants started the experiment and we continued data collection until complete data was obtained from 40 participants (data from 11 participants had to be excluded; 5 participants did not show up for the second session, 3 were excluded due to technical problems, 2 could not be eye-tracked, 1 aborted the study). In addition, the data of one participant was excluded from the analyses because there were too few critical trials with one remembered and one forgotten option (see section data exclusion). In our behavioral analysis we thus included $n =$ 39 participants (women = 29, age: range 18–46, $M = 24.08$, $SD = 5.34$, BMI: range 16.92–35.08, $M = 22.16$, $SD = 3.27$). Participants performed two sessions differing only in the decision phase on the *remember-and-decide task* (more details see section experimental procedures). From the 39 included participants, 20 participants completed first a parallel presentation session and one week later a sequential presentation session,[1] and vice versa for the other 19 participants. In the parallel session, choice options were presented simultaneously on the screen (see details in Section 2.4). All participants had normal or corrected-to normal vision with glasses. The study was approved by the Institutional Review Board of the Faculty of Psychology, University of Basel, and all participants gave written informed consent. For their participation, they received either course credit or 5 Swiss Francs (CHF) per 15 min. In addition, they had the opportunity to get two snack bonuses per session (see the Section 2.4.2).

2.2. Apparatus

Participants were seated in front of a 24-in. computer screen (resolution 1680 × 1050 pixel), instructed to move as little as possible during the main experiment and to sit comfortably. If necessary the chair or the screen were moved to optimize eye tracking (with an ideal distance between participant and screen of 60 to 80 cm). Stimulus presentation and creation of choice sets were realized using MATLAB Version R2016a and its toolbox Cogent 2000 (version 1.33). The screen resolution was set to 1280 × 1024 pixel. An SMI RED 500 eye-tracking device was used to record participants' gaze positions at a sampling rate of 500 Hz.

For the main *remember-and-decide* task participants performed 24 rounds in four blocks of approx. 20 min each with a mandatory break after every sixth round. We included the breaks to avoid participants getting tired and unfocused, therefore we asked participants to either leave the room or to stand up and move around during that time. The eye-tracking recording software (iView X™ SDK version 3.6) was controlled via MATLAB using remote commands. The eye tracker sampled data of both eyes at 500 Hz during the encoding and the decision phases. The calibration procedure consisted of a five-point calibration followed by a four-point validation. The calibration procedure was repeated after each break or in case a fixation criterion was not reached while participants had to fixate on a fixation cross centered on the screen. The fixation criterion tested whether the collected eye-tracking data sample deviated >200 pixels left/right/top/down from the screen's centroid within ten independent data samples (a data sample contains 100 data points collected every millisecond, consisting of the x and y coordinates of the left eye's gaze).

2.3. Selection of stimulus material

Prior to running the study, we conducted a pilot experiment of approximately 15 min to select a suitable set of food snack items. A separate group of participants ($n = 21$, women = 15, age: range 18–29, $M = 21.86$, $SD = 2.5$) rated 60 snacks on the dimensions familiarity, distinctiveness, representativeness (of their snack category), and subjective value on a discrete scale from 0 to 10. Snacks were grouped into six categories (bars, bonbons, chocolate, wine gums, nuts, salty snacks). From these 60 snacks, 48 were then selected for the current study, mainly on the basis of familiarity and subjective value (e.g., snack items that were unfamiliar to many participants were excluded). The mean ratings for the 48 remaining snacks for the four dimensions were:

[1] Here we report findings from the former only. Details concerning the sequential session can be found in Appendix D.

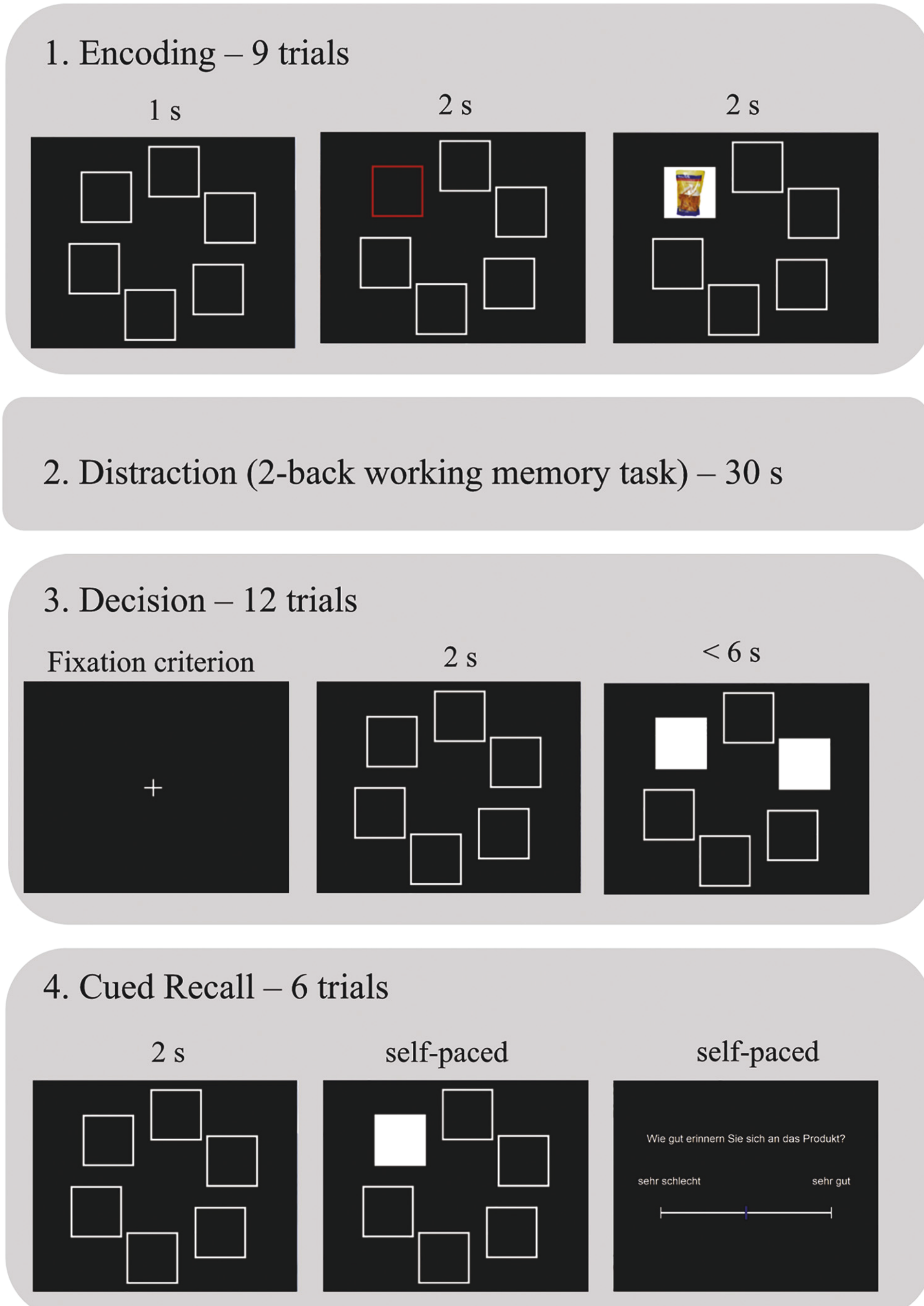

Fig. 1. Experimental paradigm (*remember-and-decide task*). An example round of the task is shown. Each round consists of four phases. In the first phase participants encode the association of snack items and screen locations. The second phase is a 2-back task to overwrite working memory. Third, participants perform binary preferential choices. Critically, only locations but not items are shown, so that the items need to be recalled from memory. Fourth, participants are asked to recall the name of each item and to rate their memory strength (English translation of the text on the slide: "How well do you remember the product?" The answer ranges from "very poorly" to "very well").

familiarity ($M = 7.01$, $SD = 2.02$), subjective value ($M = 6.17$, $SD = 1.23$), distinctiveness ($M = 6.11$, $SD = 1.42$) and representativeness ($M = 8.43$, $SD = 1.09$).

2.4. Experimental procedures

After participants gave their written informed consent and confirmed not having eaten in the previous 4 h, they were familiarized with the snacks. Then participants were given the written instructions. Afterwards they sat down in front of the computer and typed in demographic information (age, gender, education, job, height, weight). Next, they were asked to indicate how hungry they felt at that moment using a continuous rating scale from 0 (not hungry) to 10 (very hungry). Subsequently participants were shown all 48 food snacks together with their names on the screen. Participants were asked to memorize the names for the recognition phase of the remember-and-decide task. Participants were then asked to indicate for all food snacks how much they would like to eat them at the end of the study on a continuous scale ranging from 0 (not at all) to 10 (very much). They rated each snack twice, the first time with the slider bar starting in the middle (i.e., at a rating of 5), the second time with the slider bar starting at their first rating (such that they were given the opportunity to adjust their initial rating). This second rating was then used as the participant's subjective value of each snack.

Based on participants' ratings, choice trials were generated using the following algorithm. As in previous studies (Gluth et al., 2015; Mechera-Ostrovsky & Gluth, 2018), we excluded the 6 highest-rated snacks to minimize the influence of value on memory (since best options are remembered much better than other options). From the remaining 42 snacks, we created 24 sets of six snacks, one set for each of the 24 rounds of the main task. Snacks were split into 3 value levels (low, medium, and high), with 14 snack items per value level. Two low-value, two medium-value, and two high-value were chosen randomly as the six snacks per round. Each snack was then allocated to one position on the screen (see Fig. 1). For the 12 decision trials, 12 out of 15 possible combinations of two snacks were selected randomly. The number of decisions between snacks that were both shown 2× during encoding, both shown 1×, or one shown 2× and the other 1× was equal (three times each). Some snacks were repeated during the experiment, but the algorithm ensured that the number of repetitions of snacks across runs was minimized as much as possible to avoid intrusions. After the choice trials had been generated, participants performed the main task with two training rounds.

2.4.1. Remember-and-decide task

The remember-and-decide task (Fig. 1) had 24 rounds, each consisting of four phases: encoding (9 trials), distraction (30 s), decision (12 trials) and cued recall (6 trials). Out of the 24 rounds, 16 (i.e., 192 decision trials) were memory rounds (with items being covered during the decision phase), while the remaining 8 rounds (i.e., 96 decision trials) were control rounds (with items being depicted during the decision phase). Therefore, memory and control rounds differed with respect to the decision phase only.

During the encoding phase participants learned the association between 6 food snacks and their location on the screen. The six squares (i.e., option locations) were arranged on a circle with their centroid being equidistant from the screen center. The squares had a side length of 280 pixels. To allow a choice between left and right squares, the squares were arranged so that there was always one option more on the right and the other more on the left. This was achieved by rotating the squares on a circle (with a radius of 360 pixels) by 35 degrees. Encoding consisted of 9 trials, with the first 6 trials showing each snack once at its location, one snack at a time. Afterwards, 3 randomly selected snacks were presented a second time, again one snack at a time. After an option appeared on the screen, participants had to indicate whether the snack was salty (key Q) or sweet (key P).

The n-back phase was a 2-back task used to overwrite participants' working memory before the decision phase. Participants saw a number for 1 s and had to press the space bar if the current number was identical to the second-last seen number. Numbers ranged from 0 to 9. A total of 30 numbers were presented each round, such that each distraction phase lasted for 30 s.

In the decision phase, participants chose their preferred snack items. Participants selected the left option by pressing the “Q” key and the right option by pressing the “P” key on the keyboard (options were arranged in a way that one square was always more left and one more right). Participants had to make their choice within 6 s. We restricted the decision time to prevent participants from using the first trial to recall all 6 items before making a choice. The decision phase consisted of 12 trials per round. Therefore, each option was presented in 4 decision trials on average. We tested for the possibility that decision accuracy increased over the course of the 12 trials per decision phase (possibly due to participants remembering options not at their first but second to fourth presentation; see also Gluth et al. (2015)). Note that choice accuracy is defined as the observed proportion with which the participants choose the higher-rated snack (i.e., choice consistency between preference rating and preferential choice). We found that choice accuracy changed significantly (one-way repeated measures ANOVA: $F(11,418) = 3.69$, $p = .036$). A post-hoc multiple pairwise *t*-tests (Bonferroni-corrected for 66 multiple comparisons) suggested that accuracy was only lower in the first compared to the last three trials (10−12) per decision phase. In the memory rounds, snacks were “hidden” behind a white square, while in the control rounds option were directly visible.

Lastly, participants' memory performance was assessed in the cued recall phase. Thereto, participants saw one highlighted position per trial and said the name of the associated snack item aloud. If they could not remember the item, they said aloud “next”. The experimenter confirmed the participant's response by saying “yes”. Participants were not informed about the correctness of their response, as the experimenter did not see the participant's screen and was therefore not aware of the correct answer. After the experimenter confirmed the response, participants pressed the space bar and indicated how well they remembered the specific item (recall certainty) on a continuous visual analogue scale (ranging from very poorly to very good). Items were categorized as forgotten if i) the participant described the product too vaguely (the experimenter could not match what the participant said to one specific product), ii) the participant recalled a wrong item, or iii) the participant did not recall the item at all.

2.4.2. Incentives

After completing the remember-and-decide task, a lottery was performed, in which participants could win up to two snacks. The first snack was drawn from participants' preference ratings, the second from their decisions during the remember-and-decide task. For the preference ratings, two items were randomly selected, and the participant received the higher-rated item. For the decision phase, the lottery algorithm first assessed participants' accuracy in pressing the key “Q” (salty) or “P” (sweet) during encoding and their performance in the 2-back task. If their accuracy was below 70% in either task, the chance to get a snack was set to 70%, otherwise it stayed at 100%. If the algorithm determined the participant to receive a reward, then a decision trial was randomly selected. If the participant made a choice in this trial they received the chosen snack from that trial. If no choice was made, the participant received no snack. These incentive rules were explained to participants prior to performing the task and aimed to motivate participants to perform well.

2.4.3. Familiarity and distinctiveness questions

After completing the remember-and-decide task and receiving their rewards, participants were asked to rate their familiarity with each snack and to judge each snack's distinctiveness. The ratings were entered on a continuous visual analogue scale ranging from −3 to +3 (with the two extremes and the midpoint being highlighted).

2.4.4. Final questions about hunger and strategies

At the end of the experiment, participants rated their current hunger feeling and were asked to report what strategy they used to remember the locations of the snacks. Participants could enter text in an answer box. After completing the second session, participants could provide any comments regarding the entire experiment in an answer box.

2.5. Data exclusion

The following exclusion criteria were applied either to all trial types (memory and control) or only to a subset of trials. Memory trials were further divided into two categories depending on the cued recall: in *remrem* trials both options were recalled (i.e. two *rem*embered options), in *remfor* trials only one option was recalled (i.e. one *rem*embered and one *for*gotten option; these trials are used to assess the memory bias on choice).

2.5.1. Behavioral data exclusion

From the 40 participants that completed both experimental sessions and had complete data sets, we checked the following behavioral exclusion criteria: not more than 30% of misses (no response given) during the decision phase; at least 20 remfor trials of the decision phase; from these 20 trials at least 5 trials with the remembered item being chosen at least 5 trials with the forgotten item being chosen (these criteria assured that the logistic regression analysis of the memory bias could be performed accurately). Due to this minimal number of trials criterion we had to exclude one participant, resulting in $n = 39$ participants.

2.5.2. Eye-tracking data exclusion

For the eye tracking data (fixations only) we focused on data quality first at the fixation level by i) excluding all fixations with a tracking ratio $\leq 60\%$ and ii) by excluding all fixations not to the chosen or unchosen option. Tracking ratio is defined as the number of non-zero gaze positions divided by sampling frequency multiplied by run duration, expressed in percent. On the participant level we excluded participants with ≤ 15 trials in any trial type (control, remrem and remfor). Due to this exclusion procedure the number of trials was reduced, with a total of 8189 trials and $n = 37$ participants remaining for the analysis on gaze influence and the GLAM model fitting. For the included 37 participants we could analyze eye-tracking data for a mean of 88.38 (SD $= \pm$ 9.01; range 61–96) control trials and a mean of 132.95 (SD $= \pm$ 32.15; range 50–180) memory trials. Trials in which both options were forgotten were excluded from data analysis due to their small number ($M = 18.24$, $SD = 14.48$, range 2–57). On average, there were more remrem trials than remfor trials (remrem: $M = 81.86$, $SD = 32.5$, range = 17–153; remfor: $M = 51.08$, $SD = 18.03$, range = 18–88).

2.6. Data analysis

2.6.1. Assessment of the (corrected) memory bias

We were interested in replicating the memory bias on preferential choice (Gluth et al., 2015). Thereto, we performed a logistic regression via maximum likelihood on *remfor* trials. The probability p_i to choose the remembered option i over the forgotten option is given by:

$$p_i = logit^{-1}\left(\beta_0 + \beta_1 \cdot x_i\right), \tag{1}$$

where x_i refers to the standardized subjective value of option i (standardization was done separately for each participant), and β_0 and β_1 refer to intercept and slope coefficients, respectively. The probability that the remembered option will be chosen is estimated by drawing from a Bernoulli distribution with success probability p_i:

$$y \sim \text{Bern}(p_i), \tag{2}$$

This logistic regression analysis was performed on an individual level. A memory bias in the sense of preferring remembered over forgotten options is present if the intercept coefficient of this regression is positive (Gluth et al., 2015). We calculated a *corrected memory bias* by subtracting each participant's average value of their forgotten options from the value of the remembered option before performing the regression analysis. This correction ensured that the memory bias was not solely driven by the possibility that forgotten options were less valuable than remembered options (for more details, see Mechera-Ostrovsky & Gluth, 2018).

Furthermore, we tested two more models with additional predictors. A first model included the (standardized) encoding time (item presented once or twice during the encoding phase of the remember-and-decide task) of the remembered option as predictor. A second model included the (standardized) memory strength (certainty level of item recall assessed during the recall phase of the remember-and-decide task). We included two predictors, for the remembered as well as for the forgotten option. Results are reported in Appendix A.

2.6.2. Pre-processing of eye-tracking data

Raw eye-tracking data (in idf file format) from the decision phase were preprocessed using the software BeGaze Version 3.6.40. Preprocessing included recoding of gaze positions into events (fixations, saccades, and blinks) using the high-speed detection algorithm and default values (i.e., peak velocity threshold 40°/s, minimal fixation duration 50 ms, peak velocity start at 20% of saccade length and end at 80%). AOIs (area of interest) were defined as the six squares where snacks were shown. Fixations outside of the pre-defined AOIs were counted as empty gazes.

Next, we aggregated all fixations at the trial level. Importantly, we computed the gaze proportion (relative dwell time on an option) for option i as follows:

$$\text{gaze proportion}_i = \frac{(0.5 \cdot \text{nonfixation time} + \text{total fixation time}_i)}{\text{response time}} \tag{3}$$

Note that the gaze proportions to the left and right option sum up to 1. We chose this specification of gaze proportion, as we had many trials with a large discrepancy between the total fixation time (left and right option) and the response time due to fixations to irrelevant options or outside of any AOI. Assume, for example, a response time of 4000 ms with the left option being fixated for only 300 ms and the right option for only 700 ms. Thus the total fixation time is 1000 ms. The simple ratio between left and right dwell times would mean that the left (right) option was fixated in 30% (70%) of the trial, disregarding the fact that neither option was fixated for 3000 ms. With Eq. 3, the numbers are 55% (45%) for left (right) and thus less extreme. Thereby, we avoided an over-weighting of small differences in trials with poor recording quality.

Additionally, we tested if the gaze influence persists when using the classical definition of gaze proportion (i.e., fixation duration to one option divided by the total fixation duration), instead of the definition used in Eq. 3. Indeed, the gaze influences did not change, as the sign of the final gaze advantage (difference between the total fixation time to the left option minus the right option) remained unchanged.

2.6.3. Assessment of gaze influence on choice

We sought to replicate previous findings on the influence of attention on decision making (Armel, Beaumel, & Rangel, 2008; Folke, Jacobsen, Fleming, & De Martino, 2017; Gluth et al., 2020; Krajbich et al., 2010; Krajbich & Rangel, 2011), to extend these findings to memory-based decisions, and to test whether the influence of attention is present in memory-based decisions. Thereto, we tested whether the allocation of gaze influences choice probability over and above the influence of value (Thomas et al., 2019). Following previous approaches (Krajbich et al., 2010; Thomas et al., 2019), we first estimated the probability that an option is chosen based on its value (logistic regression). Then, we subtracted this estimated probability from the observed choice (binary variable, 1 = option chosen, 0 = option not chosen). Finally, we averaged the resulting choice probability for trials in which the option had a positive vs. negative final gaze advantage (i.e., difference between the total fixation duration to one option and the total fixation duration to the other option). We estimated this gaze influence separately for each participant and each of the three different conditions: control, remrem, and remfor.

To test for an increased influence of visual attention (gaze) in decisions from memory, we performed a linear mixed effects analysis of the relationship between gaze influence and condition (control, remrem and remfor). As fixed effect, we entered the condition into the model. As random effects, we entered intercepts for the participants. As effect size measure we used R^2. In sum, the model equation was:

$$gaze\ influence \sim condition + (1|participant) + \varepsilon \tag{4}$$

In addition, we performed two post-hoc contrasts, testing whether the control condition differs from the two memory conditions (control - (remrem + remfor)/2), and whether the two memory conditions differ from each other (contrast remrem - remfor).

2.7. Computational modeling procedures

We aimed to investigate how the influence of attention maps onto cognitive processes of memory-based preferential choice. In particular, we were interested in explaining the increased impact of attention in memory-based compared to “regular” non-memory-based decisions.

We applied the Gaze-weighted Linear Accumulator Model (GLAM) proposed by Thomas et al. (2019), who made their code publicly available on GitHub at http://ww.github.com/glamlab/glam. Note that we re-scaled all participants' item rating values to range from 1 to 10 (original values ranged from 0 to 10), so that model parameter values were comparable to the original publication.

2.7.1. GLAM details

The GLAM (Thomas et al., 2019) describes the influence of gaze allocation on the decision process as a linear stochastic race (Tillman & Logan, 2017; Usher, Olami, & McClelland, 2002) and is inspired by the multialternative attentional Drift Diffusion Model (Krajbich & Rangel, 2011). This model represents each choice option with a separate evidence accumulation process, and the option whose accumulator reaches a decision boundary first wins the race and is chosen. One advantage of linear stochastic race models is that they are easy to generalize to tasks with more than two choice options. More relevant for the current study are the additional advantages of GLAM that it can fit parameters robustly, and that it comes as a toolbox with a Bayesian implementation and efficient code leading to fast fitting (Theano implementation).

Detailed specifications of the GLAM are provided in Thomas et al. (2019). Here, we we summarize the model mechanics briefly, with an emphasis on how we adapted it to the present case of memory-based decisions. Each option *i* is represented by a separate noisy accumulator of evidence. As soon as the first accumulator reaches a decision boundary, the corresponding option is chosen. The boundary is set to 1.

First, for each item *i* the relative evidence E_i is being accumulated at each time point *t*:

$$E_i(t) = E_i(t-1) + v \cdot R_i + N(0, \sigma^2), \text{with}\, E_i(0) = 0 \tag{5}$$

Next, the relative evidence R_i' is defined as the difference in the absolute evidence signal A_i:

$$R_i\text{'} = A_i - max_J(A_J) \tag{6}$$

Where A_i is a constant and depends on the option's $value_i$ and on how long an option is fixated ($gaze_i$):

$$A_i = gaze_i \cdot value_i + \ (1 - gaze_i) \cdot \gamma \cdot value_i \tag{7}$$

γ is the gaze bias parameter, determining the amount of downweighting during the biased state. If $\gamma = 1$ there is no gaze bias. This parameter is analogous to the θ parameter in the attentional Drift Diffusion Model (Krajbich et al., 2010). In other words, the absolute evidence signal A_i implements the gaze bias mechanism. Importantly, to estimate the GLAM for our data, which included memory-based and non-memory-based trials, we expanded the original equation for A_i as follows:

$$\begin{aligned} A_i = {} & gaze_i \cdot value_i \cdot remembered_i + \\ & gaze_i \cdot \rho \cdot (1 - remembered_i) + \\ & (1 - gaze_i) \cdot \gamma \cdot value_i \cdot remembered_i + \\ & (1 - gaze_i) \cdot \gamma \cdot \rho \cdot (1 - remembered_i) \end{aligned} \tag{8}$$

where the dummy variable *remembered* indicates whether an option had been recalled (1) or not (0; relevant only to memory trials). Most importantly, we introduce a new parameter ρ, determining the reference value of the forgotten option. If this value is smaller than the true average of all forgotten options, a memory bias is induced, because the remembered option is more likely to be preferred.

To take into account participants' different use of the rating scale, the GLAM adopts a logistic transformation of the relative evidence R_i estimating the scaling parameter τ as follows:

$$s(x) = \frac{1}{1 + e^{-\tau \cdot x}} \tag{9}$$

$$R_i = s(R_i\text{'}) \tag{10}$$

The model has a quasi-analytical solution for the first passage time density.

2.7.2. GLAM variants

We estimated three model variants. The first variant (GLAM_orig) is the original full GLAM (with gaze bias) including four free parameters (v, γ, σ, and τ). As the value of forgotten items in remfor trials, we took the average value of all forgotten options per participant. The second model variant (GLAM_ρ) takes the memory bias on choice into account. Therefore, we added parameter ρ to the model, which represents the value that a participant assigns to forgotten options. Consequently, this model includes five free parameters (v, γ, σ, τ and ρ). The third variant (GLAM_nobias) assumes that gaze does not play a role in the choice process. It is a restricted version of GLAM_ρ with four free parameters (v, σ, τ and ρ) and the gaze bias parameter γ being fixed to 1. We included this model variant, as not all participants may show a gaze influence on choice (see detailed discussion in Thomas et al., 2019).

We first compared the model fits of three model variants quantitatively on the basis of the Widely Applicable Information Criterion (WAIC; Vehtari, Gelman, & Gabry, 2017) and WAIC model weights. The WAIC measure takes model complexity into account. Lower values indicate a better model fit. WAIC-based model weights provide an estimation of how well each model performs relative to the others. We also compared the models qualitatively, by testing their ability to reproduce choice and RT patterns accurately as well as to predict a (potential) influence of gaze on choice and a (potential) memory bias on choice in remfor trials.

2.7.3. Quantitative model comparison

Models were compared based on WAIC and model weights (summing to 1). The model weights were calculated manually with the formula (Wagenmakers & Farrell, 2004):

$$weight_i = \frac{e^{-0.5 \cdot dWAIC_i}}{e^{-0.5 \cdot dWAIC_i} + e^{-0.5 \cdot dWAIC_j} + e^{-0.5 \cdot dWAIC_k}}, \tag{11}$$

with $dWAIC_i$ being the difference in WAIC between the best model (lowest WAIC) and model *i*. The same applies to models *j* and *k*, as we compare three models with each other (GLAM_orig, GLAM_ρ, and GLAM_nobias).

2.7.4. Estimation, simulation and recovery of GLAM

To estimate the model, we sampled four chains with 1000 tuning samples (being discarded) and 2000 posterior samples. Convergence was checked with the following two criteria: Gelman-Rubin statistic ($\widehat{R} < 1.05$) and number of effective samples larger than 100. As parameter estimates we report the maximum a posteriori (MAP) estimates. We fitted the model for all trials per participant. To take different trial types into account, we included a dummy variable coding whether a trial is a control or a memory trial and another dummy variable coding whether the options were remembered or not (relevant to memory trials only). Gaze influence (γ) scaling (τ) parameters were estimated separately per condition (control and memory). Preliminary model fits indicated that the other two parameters (velocity v and noise σ) did not differ significantly per condition (see Appendix C).

The full GLAM (denoted in the following as *GLAM_rho*) has five parameters (v, γ, σ, τ, ρ). We used uninformative, uniform priors:

$$\begin{aligned} & v \sim Uniform(10^{-6}, 0.0003) \\ & \gamma \sim Uniform(-10, 1) \\ & \sigma \sim Uniform(10^{-6}, 0.02) \\ & \tau \sim Uniform(0, 5) \\ & \rho \sim Uniform(-10, 10) \end{aligned}$$

We estimated the GLAM separately to each participant ($n = 37$). The model did not converge for four participants, even when increasing the number of samples substantially. Therefore, we report the model fits of $n = 33$ participants.

Choices and RT for all trials that were included in the parameter estimation were simulated with 50 repetitions each. For every trial, the model used the option values, the gaze distributions and the information, whether options have been recalled or not. To account for a small proportion of "trembling-hand" errors, the simulation produced a random choice and RT between participants' minimum and maximum observed RT with a fixed rate of 5%. Choices and RTs were simulated from the GLAM with a rate of 95%. We additionally performed a parameter recovery to ensure our estimates were reliable. All generating and recovered parameter estimates showed sufficiently high correlations ($r > 0.7$). The recovery results are reported in the Appendix C.

2.8. Software

For the linear mixed effects model estimating the gaze influence we used the lme4 package (Bates, Mächler, Bolker, & Walker, 2015) (version 1.1–21) as implemented in R (version version 3.6.1). *P*-values were obtained with the lmerTest package (Kuznetsova, Brockhoff, & Christensen, 2017) version 3.1–0, using Satterwaite approximation. For post-hoc contrasts we used the R package lsmeans (Lenth, 2016) version 2.30.0. The GLAM model versions were implemented in the Python library PyMC3 version 3.6 (Salvatier, Wiecki, & Fonnesbeck, 2016) and fitted using the NUTS (No-U-turn sampler, Hoffman & Gelman, 2011) sampling method for all model variants. In addition, the following python packages were required: NumPy, SciPy, Pandas, Statsmodels, and Theano.

3. Results

3.1. Replication of the memory bias in preferential choice

Our first aim was to replicate the memory bias in preferential choice. Thereto, we regressed the choice of the remembered option in remfor trials on its standardized subjective value. In line with a (corrected) memory bias, the average intercept coefficient was significantly greater than 0 ($t(38) = 3.01$, $p = .002$, $d = 0.49$, see Fig. 2). Thus, people tended to prefer remembered options over forgotten options, controlling for their subjective value.

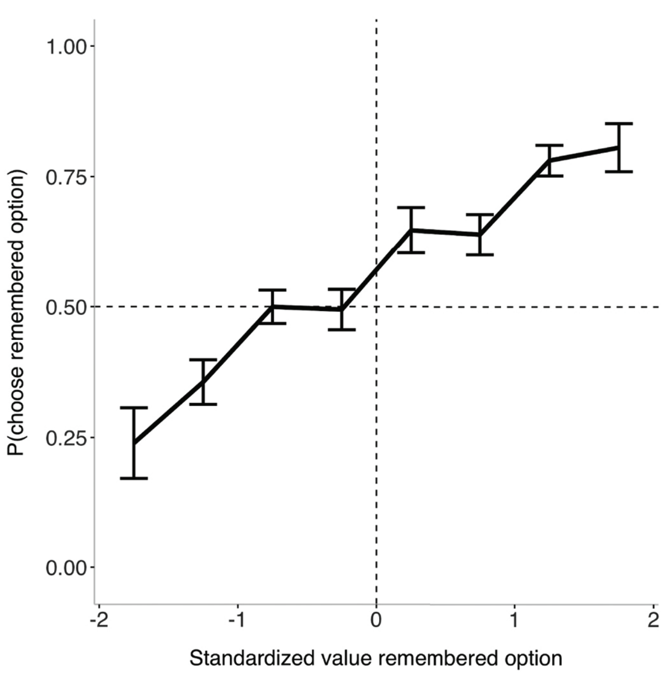

Fig. 2. Corrected memory bias in preferential choice. Probability to choose the remembered option over the forgotten option depending on its standardized subjective value (corrected for the value of all forgotten options). The memory bias is evident by the fact that the point of indifference (50% choice probability) is not at 0 but shifted towards negative (standardized) values. Error bars represent the 95% confidence interval.

3.2. Visual attention influences preferential choices from memory

The effect of gaze influence on choice was significantly greater than zero in all three conditions (control $t(36) = 6.62$, $p < .001$, $d = 1.09$; remrem $t(36) = 8.42$, $p < .001$, $d = 1.38$; remfor $t(36) = 8.14$, $p < .001$, $d = 1.34$). Therefore, we replicated the presence of an *attention bias* in the control condition. Moreover, results from a linear mixed effects model showed that the fixed effect of condition affected the amount of gaze influence ($t(88.95) = 5.35$, $p < .001$, $R^2 = 0.53$) suggesting significant differences between conditions. A further investigation with a post-hoc contrast analysis confirmed the gaze influence to be significantly lower in the control condition compared to the two memory conditions ($t(76.1) = -3.74$, $p < .001$). Moreover, the two memory conditions did not differ from each other ($t(76.1) = -1.16$, $p = .25$, see Fig. 3). These findings indicate that the influence of attention on the formation of preferences was stronger in memory- compared to non-memory-based decisions. Note that the result was independent from the definition of gaze proportion (see Methods).

3.3. Visual attention does not differ between remembered and forgotten options

We predicted that remembered options would receive more attention compared to forgotten options. To test this hypothesis we performed a paired *t*-test to compare the average number and duration of fixations towards remembered and forgotten options in remfor trials. Contrary to our prediction, the eye-tracking data did not provide evidence for a

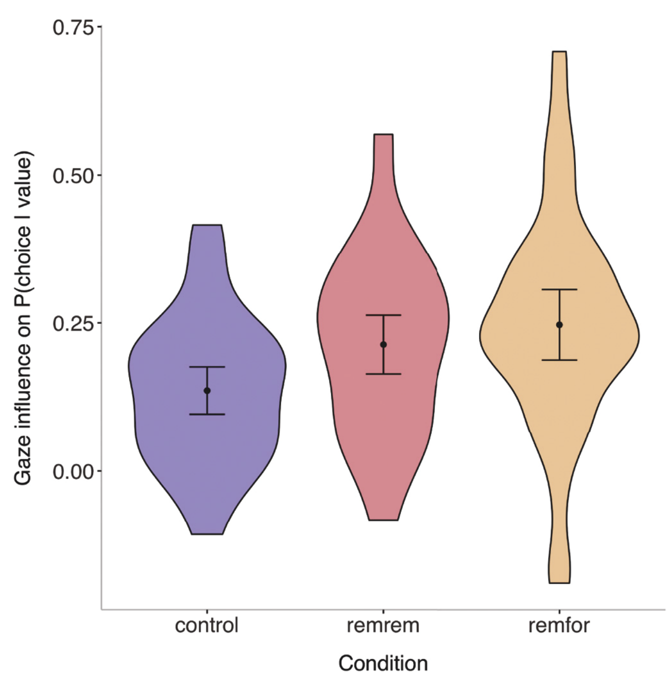

Fig. 3. The influence of attention on choice separately per condition (control, remrem and remfor). The gaze influence quantifies to what degree decisions depend on the gaze difference (left - right) after correcting for the influence of value (estimated with a logistic regression). If one option is being fixated longer, that option has an increased probability of being chosen. This gaze influence is stronger in memory-based decisions compared to control decisions. Black dots represent the mean value and the error bars the 95% confidence interval.

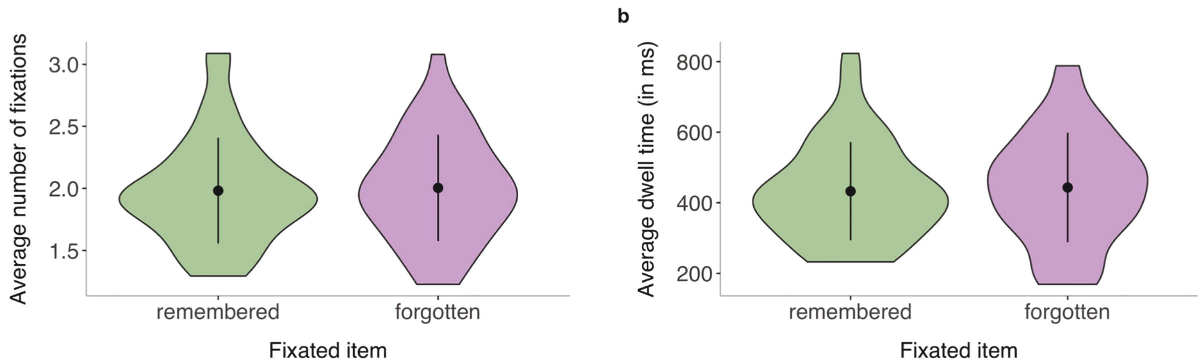

Fig. 4. Mean number of fixations (A) and mean duration of fixations (B) in remfor trials. On average, participants looked similarly often and long to the two options. Black dots represent the mean value and the error bars the 95% confidence interval.

statistically significant difference, neither in terms of the average number of fixations per trial (remembered: $M = 1.98$, $SD = 0.43$, forgotten: $M = 2.00$, $SD = 0.43$; $t(38) = -0.44$, $p = .33$, $d = 0.07$) nor in terms of the average duration of fixations (remembered: $M = 432.71$, $SD = 139.03$ ms, forgotten options: $M = 443.32$, $SD = 155.00$ ms; $t(38) = -0.72$, $p = .24$, $d = 0.12$, see Fig. 4).

3.4. Fixation properties

Similar to previous work combining eye-tracking and computational modeling (Krajbich et al., 2010; Sepulveda et al., 2020), we also compared important fixation properties separately for the three conditions (control, remrem, and remfor; see Fig. 5). Indeed, the control condition differed from the two memory conditions (remrem and remfor) with respect to various measures. First, with respect to the number of fixations, a two-way repeated measures ANOVA revealed a statistically significant interaction between value difference and condition, ($F(6.02, 132.37) = 2.47$, $p < .001$). Post-hoc tests confirmed that the effect of condition was significant at each value difference, indicating fewer fixations in memory-based compared to control decisions (Bonferroni adjusted p-values: $p < .001$, see Fig. 5A). Second, participants had on average shorter middle fixation durations in control compared to memory trials ($F(10,120) = 1.00$, $p < .01$; see Fig. 5B). Third, there were main effects of fixation type ($F(1.52, 56.17) = 18.97$, $p < .001$) and condition ($F(1.39, 51.37) = 30.97$, $p < .001$) but no significant interaction on the mean duration of first, middle, and last fixations (Fig. 5C). Fourth, when looking at the probability to choose the last fixated item as a function of value difference (i.e., value of the last-fixated minus value of the other option), we observed that the choice curve was shifted upwards in memory compared to control trials (especially when the value of the last-fixated option was lower than the value of the other option). This is in line with the above-mentioned result of a particularly strong influence of attention on the formation of preferences in memory-based decisions. We performed a multinomial logistic regression analysis for each participant individually, then (analogously to our analysis for the memory bias) we tested for a significant effect of the estimated coefficients with two-tailed t-tests against 0. The results confirmed the presence of a significant effect of the condition remfor ($t(38) = 3.82$, $p < .001$, $d = 0.61$) and remrem ($t(38) = 4.13$, $p < .001$, $d = 0.66$, see Fig. 5D) on the probability to prefer the last-fixated option. The effect of value was also significant ($t(38) = 18.88$, $p < .001$, $d = 3.02$).

In Fig. 6, we also report the fixation properties for remfor trials only, separated by fixations on the remembered vs. the forgotten option. Consistent with the results reported above (Section 3.3), we observed no significant differences between remembered and forgotten options with respect to number of fixations (Fig. 6A) or fixation duration (Fig. 6B and C). However, there was a significant effect of remembering an item (vs. forgetting it) on the probability to prefer the last-fixated option ($t(38) = -2.50$, $p = .02$, $d = 0.40$, Fig. 6D). That is, if the last-fixated option was the remembered option, participants were more likely to choose that option compared to if it was the forgotten option. Note that this finding is consistent with the proposal that people assign a reduced subjective value to forgotten options. The effect of value was also significant ($t(38) = 10.82$, $p < .001$, $d = 1.73$).

3.5. Modeling gaze and memory influences on choice

To elucidate the computational processes underlying the interaction between visual attention and memory-based decision making (and in particular the increased influence of gaze on choice in memory-based decisions), we applied the recently proposed GLAM Thomas et al. (2019), a sequential sampling model that takes eye-movement data into account.

3.5.1. Quantitative and qualitative model comparison

We first compared the three model variants quantitatively via the WAIC. We found that 19 participants were best described by the original GLAM model (GLAM_orig), 9 by the new 5-parameter GLAM model (GLAM_ρ), and 5 by the restricted GLAM model (GLAM_nobias). Notably, the difference in WAIC was small between GLAM_orig and GLAM_ρ models (difference: $M = 0.41$, $SD = 3.66$), but large between GLAM_orig and GLAM_nobias (difference: M -15.92 $SD = 15.81$) as well as between GLAM_ρ and GLAM_nobias (difference: $M = -16.33$, $SD = 14.13$). One reason why the more complex GLAM_ρ did not outperform the simpler GLAM_orig could have been the limited number of trials (i.e., remfor trials) in which the former model can actually make more accurate predictions than the latter.

With respect to WAIC-based model weights, the model classification was identical to the one based on WAIC: 19 participant are best described by the GLAM_orig, 9 by the new GLAM_ρ, and 5 by the GLAM_nobias. Fig. 7 shows the classification according to the model weights. We observed that the GLAM_ρ and the GLAM_nobias had higher weights for some participants. However, a majority of participants were best described by the GLAM_orig. When comparing the participants best described by the GLAM_ρ model to those participants best described by the GLAM_orig model, we found that the memory bias coefficient was positive for all but one participant of the former group, but there were many participants with negative coefficients in the latter group. However, this group difference did not reach significance (Mann-Whitney U test; $U(19,9) = 47$, $p = .06$; see also Fig. B1b).

In addition to assessing the quantitative model fit, we also checked whether the model variants predicted individuals' behavior qualitatively. Thereto, we compared the simulated RT and choices for each participant with the empirical data. Despite its good quantitative fit, the GLAM_orig model could not account for a presence of the memory bias (for the remfor subset of trials) on choice, in contrast to GLAM_ρ (Fig. 8). This pattern was also confirmed by testing for the memory bias in

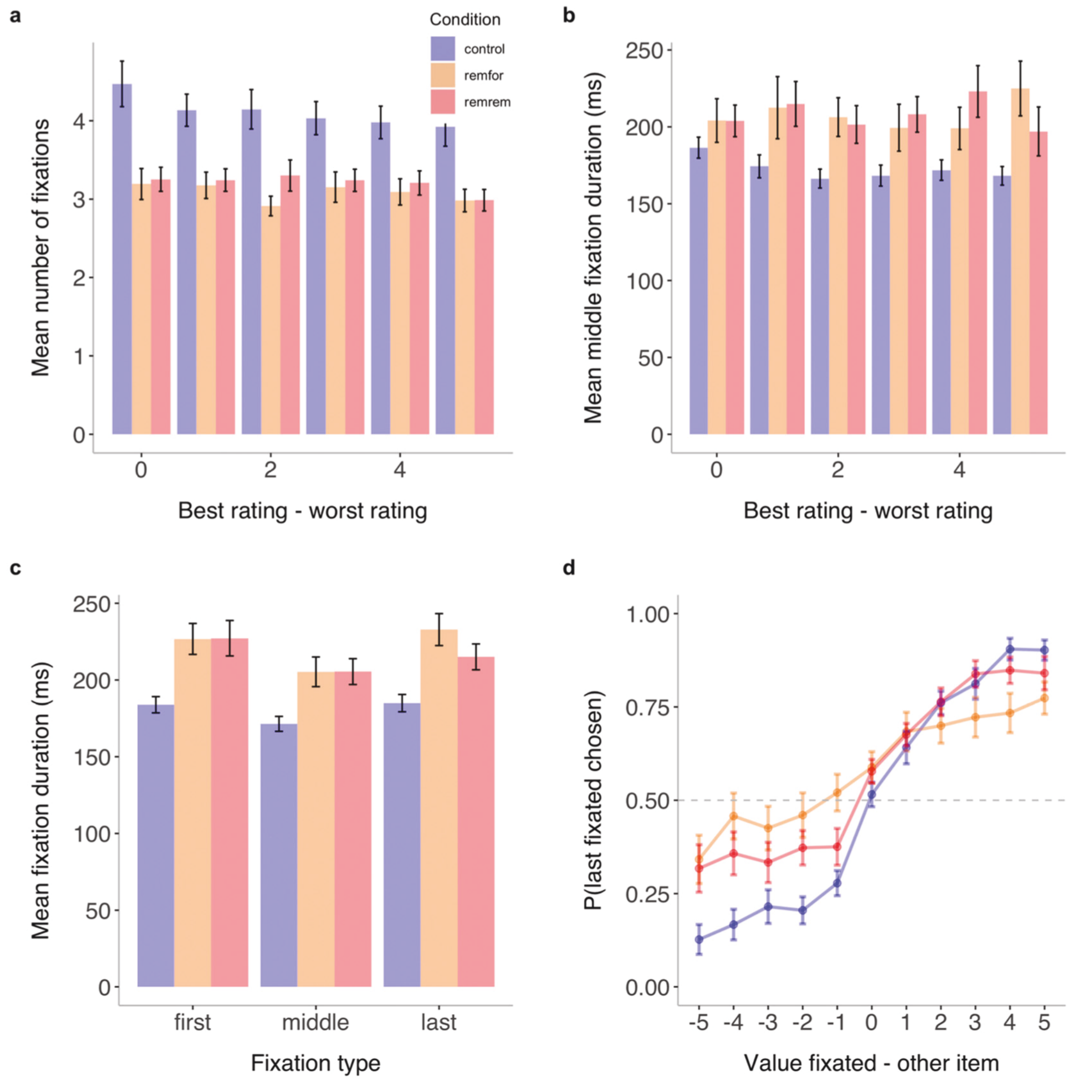

Fig. 5. Fixation properties separate per condition (control, remrem, and remfor). A) Mean number of fixations depending on the value difference bin. B) Mean middle fixation durations (i.e., all fixations that are not first or last) depending on the value difference bin. C) Overall mean fixation duration depending on the fixation type (first, middle, last). D) The probability to fixate the chosen option last, depending on the value difference between the fixated option and the other option.

simulated data. The simulated data of GLAM_ρ exhibited a significant memory bias ($t(31) = 3.60$, $p < .001$, $d = 0.63$), but not the simulated data of GLAM_orig ($t(32) = -0.14$, $p = .56$, $d = 0.03$).

Second, both the GLAM_orig model and the GLAM_ρ model could account for the stronger influence of gaze on choice in memory-based decisions (results linear mixed effects models contrast control vs. memory: GLAM_orig $t(64) = -5.79$, $p < .001$; GLAM_ρ $t(64) = -3.79$, $p < .001$). However, the GLAM_orig further predicted a difference between the remrem and remfor trials, which was not in line with the empirical data. The GLAM_ρ did not predict such a difference (results linear mixed effects models contrast remrem vs. remfor: GLAM_orig $t(64) = 2.10$, $p = .04$; GLAM_ρ $t(64) = 0.46$, $p = .65$) (Fig. 9). Note, however, that there was no significant difference when comparing these predictions of the GLAM_orig and the GLAM_ρ models directly against each other ($t(32) = -0.94$, $p = .18$, d = 0.16).

3.5.2. *Interpreting the GLAM_ρ model*

Taking both quantitative and qualitative criteria into account (Palminteri, Wyart, & Koechlin, 2017), GLAM_ρ provided a sufficient quantitative model fit and was able to predict both the memory bias on choice and the enhanced influence of attention on choice in memory-based decisions. In the following we report the parameter estimates and discuss their impact (for an overview of the GLAM_ρ model estimates, see Table 1).

The attention parameter γ determines the extent to which the accumulation of evidence for a non-fixated item is reduced. If $\gamma = 1$, there is no influence of gaze on decisions. Our individual gamma estimates ranged from -1.1 to 0.99. Importantly, the parameter estimates of γ were significantly higher for control trials compared to memory trials (γ_{memory}: $M = 0.12$, $SD = 0.46$; $\gamma_{control}$: $M = 0.42$, $SD = 0.45$, two-sided t-test: $t(32) = -3.83$, $p < .001$, $d = 0.67$), suggesting that the increased influence of gaze in memory-based decisions mapped onto a lower γ parameter. In addition, decisions in memory trials were more stochastic, meaning that decisions were less consistent with preference ratings (control: $M = 83.19\%$, $SD = 9.54\%$; remrem: $M = 76.32\%$, $SD = 10.59\%$; remfor: $M = 68.58\%$, $SD = 9.27\%$). In the GLAM, this increased stochasticity is reflected in the scaling parameter τ (which scales the difference of the relative evidence) being reduced in memory trials (τ_{memory}: $M = 0.35$, $SD = 0.24$; $\tau_{control}$: $M = 0.96$, $SD = 1.14$; two-sided t-test: $t(32) = -3.38$, $p = .002$, $d = 0.59$).

Last, we looked at the newly added ρ parameter ($M = 3.53$, $SD = 3.42$), which replaces the value of the forgotten option in remfor trials and thus models the memory bias on choice. Although this parameter was required to reproduce the qualitative finding of a memory bias on

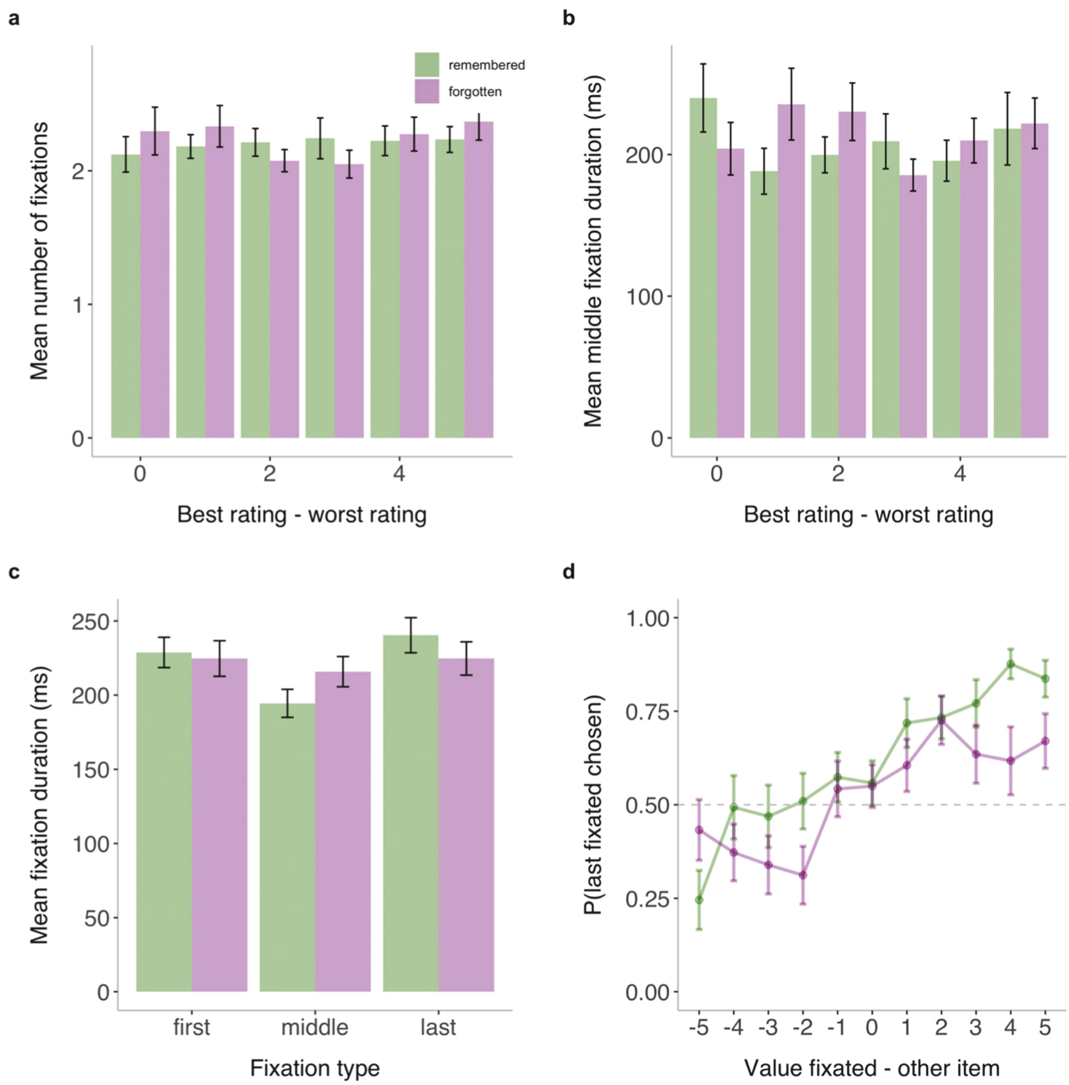

Fig. 6. Fixation properties for the remfor condition only. A) Mean number of fixations depending on the value difference bin. B) Mean middle fixation durations (i.e., all fixations that are not first or last) depending on the value difference bin. C) Overall mean fixation duration depending on the fixation type (first, middle, last). D) The probability to fixate the chosen option last, depending on the value difference between the fixated option and the other option.

choice (see Fig. 8a), it was neither significantly lower than the average value of all forgotten items ($M = 3.59$, $SD = 1.35$; one-sided t-test: $t(32) = -0.10$, $p = .54$, $d = 0.02$), nor than the average value of all used snacks ($M = 3.76$, $SD = 1.27$; one-sided t-test: $t(32) = -0.42$, $p = .66$, $d = 0.07$).

4. Discussion

This study investigated the role of attention on memory-based preferential choice and aimed to contribute to a better understanding of the underlying cognitive mechanisms. A growing body of research shows that attention plays a crucial role in decision processes (Fiedler & Glöckner, 2012; Gluth, Spektor, & Rieskamp, 2018; Krajbich, 2019; Orquin & Mueller Loose, 2013; Stewart et al., 2016; Tavares, Perona, & Rangel, 2017). Most importantly, there is strong evidence that people choose options that they have spent more time looking at. Our results indicate that the influence of gaze on preference formation is increased in memory-based as compared to non-memory-based choices. Note that the strength of the gaze influence on choice in the non-memory-based choices, which were similar in nature to regular preferential choice paradigms, was comparable to previous findings (Folke et al., 2017; Krajbich et al., 2010; Krajbich, Armel, & Rangel, 2011; Tavares et al., 2017; Thomas et al., 2019). Hence, it appears that attention indeed plays a particularly influential role in decisions that require options to be retrieved from memory. The cognitive modeling results further strengthened this notion: The GLAM parameter γ, which quantifies the influence that attention exerts on valuation and choice, was significantly different between memory-based and non-memory-based decisions. Importantly, this result rules out that the increased influence of gaze on memory-based choice is solely driven by the increased stochasticity of these decisions as compared to non-memory-based decisions (or, in other words, by the fact that memory-based decisions are less determined by subjective values). Evidently, it would be good if future research could replicate our findings that the role of attention is particularly pronounced in memory-based decisions, and that this effect can be mapped onto parameter differences in computational models describing the interplay between attention, memory and decision making.

Notably, an increased impact of attention on preference formation in memory-based decisions could be potentially relevant for studying these type of decisions in clinical populations that are known to be affected by both mnemonic and attentional deficits, such as Alzheimer's Disease (Baddeley, 2001; Calderon et al., 2001; Perry, Watson, & Hodges, 2000). A recent study investigated the impact of memory decline on choice focusing on choice inconsistencies. Older adults were less consistent according to their stated preferences but did not show more intransitive choices (Levin, Fiedler, & Weber, 2019). Interestingly, a related study,

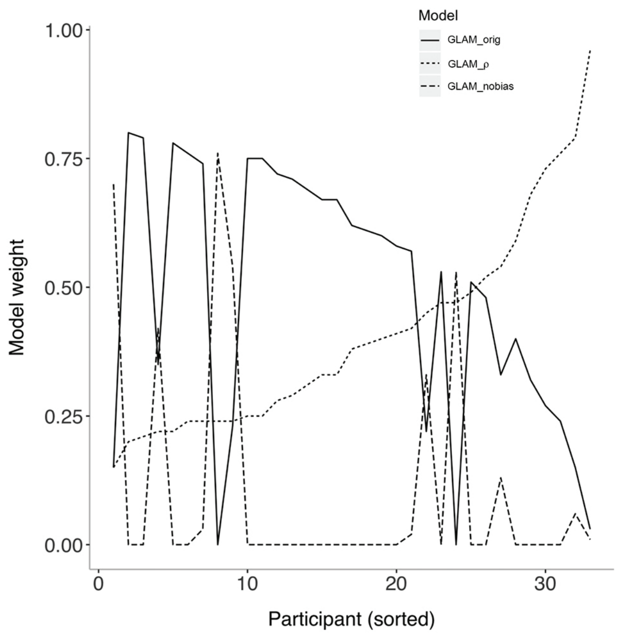

Fig. 7. Quantitative model comparison based on model weights. The model weights were calculated manually for each participant separately. Data is sorted in ascending order according to the model weights of the GLAM_ρ model.

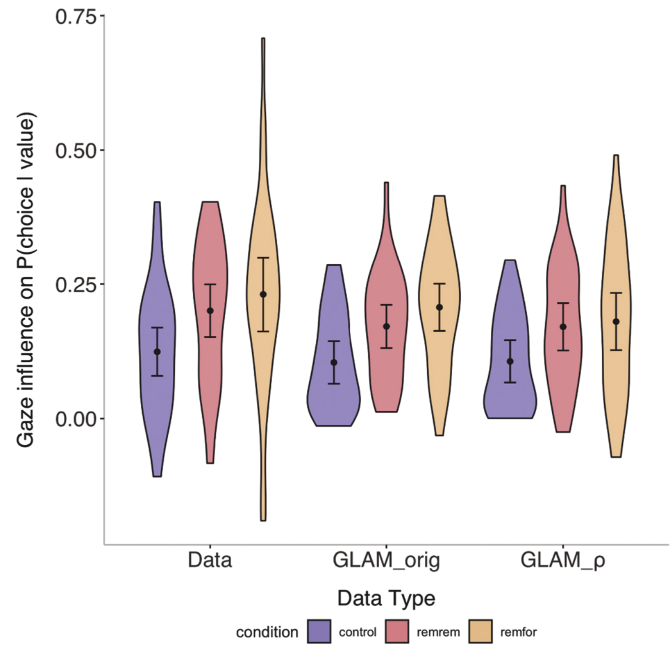

Fig. 9. The influence of gaze on choice according to simulated data from GLAM_orig and GLAM_ρ, compared to the data used for modeling. Black dots represent the mean value and the error bars the 95% confidence interval.

that used a task consisting of a learning and a decision phase (similar to our *remember-and-decide task*) found no evidence of older adults being more inaccurate (Lighthall, Huettel, & Cabeza, 2014), but they needed more time for their choices (speed-accuracy trade-off). Future studies could further address the question of how memory deficits in clinical or elderly populations affect memory-based preferential choice by including eye-tracking measures. Based on our results and previous

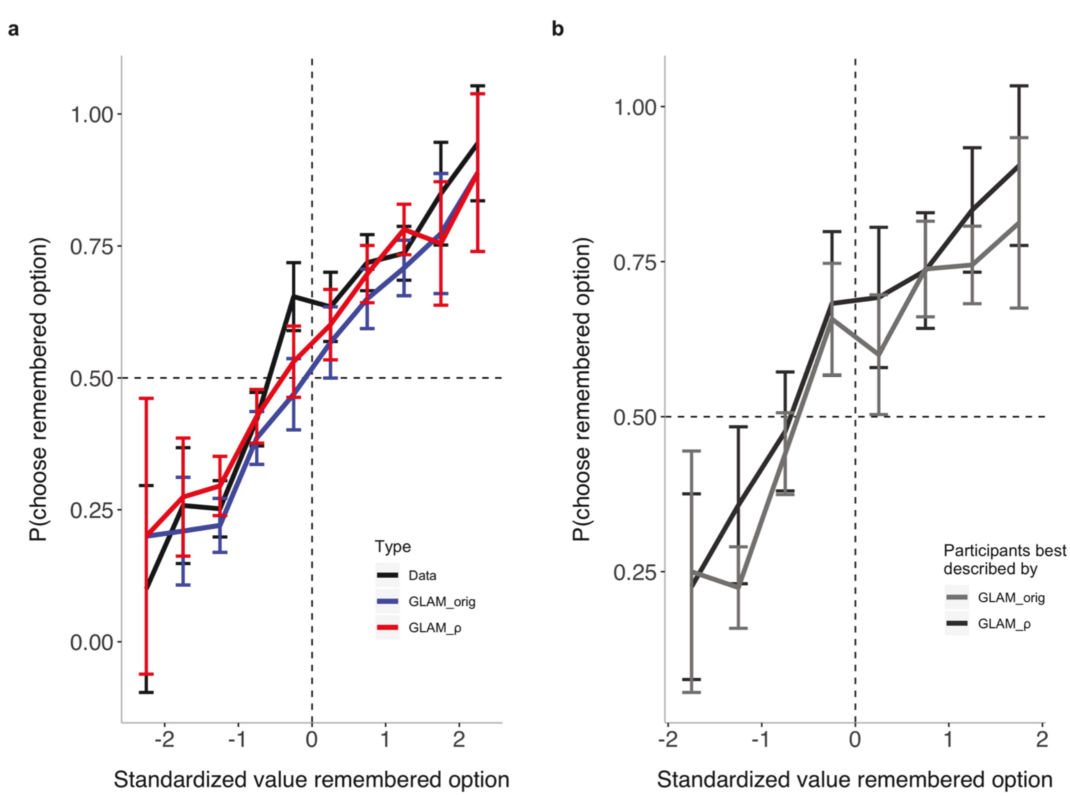

Fig. 8. a) Comparison of qualitative choice predictions of the GLAM variants without (i.e., GLAM_orig; blue line) and with the memory bias parameter (i.e., GLAM_ρ; red line). Only GLAM_ρ allows to capture the shift in the choice curve as seen in the data (black line). The data shown here refers to $n = 33$ participants for which the GLAM variants converged (in contrast to the data of $n = 39$ participants shown in Fig. 2). b) Comparison of the choice data for the subset of participants either best described by the GLAM_orig ($n = 19$; light grey line) or by the GLAM_ρ ($n = 9$; dark grey line). (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

Table 1
Summary of the parameter estimates from the GLAM_ρ model.

	Mean	sd	Median	Min	Max
γ_{memory}	0.1239	0.4602	0.1300	−1.1100	0.9500
$\gamma_{control}$	0.4179	0.4532	0.4800	−0.4700	0.9900
τ_{memory}	0.3482	0.2447	0.2700	0.0300	1.0900
$\tau_{control}$	0.9591	1.1416	0.4600	0.0900	4.7800
v	0.0001	0.0000	0.0001	0.0000	0.0002
σ	0.0097	0.0011	0.0096	0.0074	0.0126
ρ	3.5285	3.4193	3.7800	−7.9600	11.1400

findings, we would expect an even more substantial gaze influence for older adults in memory-based choice compared to younger people.

In our study, we replicated the presence of a memory bias on choice, according to which people prefer better-remembered items, even if their value is comparatively low (Gluth et al., 2015). This result confirmed our previous work (Gluth et al., 2015; Mechera-Ostrovsky & Gluth, 2018; Wagenmakers & Farrell, 2004), showing that the tendency to prefer better-remembered options is a robust and comparatively strong effect. Contrary to our prediction, however, our results suggest that attention does not mediate the memory bias. Based on previous work on the role of memory on gaze allocation (i.e., the looking-at-nothing phenomenon, Richardson & Spivey, 2000), we hypothesized that participants would pay more attention to better-remembered options during the decision phase. This increased attention could then lead to a higher choice probability, thus mediating the memory bias. Yet, remembered options did not receive more attention in our experiment. This may be because participants' tendency to look at the location of remembered options could trade off against those fixations that are made to recall the (eventually) forgotten options. Interestingly, research investigating the stability of the looking-at-nothing effect (Scholz, Mehlhorn, Bocklisch, & Krems, 2011), suggests that the effect decreases as memory uncertainty decreases, meaning that if an item is easier to recall then the effect is weaker. In our case, the recall certainty for remembered options was quite strong (i.e., people were sure about the remembered item; see additional analyses in the Appendix B), so participants might not have needed to look at their locations for long.

In previous studies, we tested two other potential mediators for the memory bias on choice. First, we showed that the memory bias is related to a person's belief that they tend to remember good options more often than bad options (Mechera-Ostrovsky & Gluth, 2018). Second, we reported evidence that the uncertainty entailed in choosing forgotten options leads people to reject these options in the gain domain but to choose them in the loss domain (Wagenmakers & Farrell, 2004). Interestingly, the present study lends further support to the view that uncertainty contributes to the memory bias on choice: We estimated an additional logistic regression to predict the choice of the remembered option in remfor trials, in which we added the (continuous) memory strength data as predictor (separately for remembered and forgotten options; see Appendix B). This analysis revealed that memory strength for the remembered option was positively associated with the probability to choose the remembered option, whereas memory strength for the forgotten option was negatively linked to it. In other words, the more certain participants were about the remembered option and the more uncertain they were about the forgotten option, the more likely they preferred the remembered option and exhibited a memory bias. Given the fact that uncertainty appears to be a critical factor, we speculate that increased gaze time could reduce this uncertainty, thereby further boosting the attractiveness of the longer fixated option, and thus causing the main finding of the current work: that the influence of gaze on choice is increased in memory-based decisions.

Acknowledgments

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Appendix A. Memory performance and its relation to encoding time, memory strength, and subjective value

A.1. Relationship between memory performance and the encoding time

During the encoding phase of our remember-and-decide task, participants saw three out of six items a second time. This additional presentation let to more accurate memory for these items. Importantly, this was only the case for memory trials (see Fig. A1). Supporting this notion, a repeated measures one-way ANOVA indicated a significant interaction between condition (memory vs. control) and encoding time (1× vs. 2×), $F(1,38) = 45.10$, $p < .001$., and post-hoc comparisons showed a significant main effect of encoding time in the memory condition $F(1,38) = 103.23$, $p < .001$, but not in the control condition $F(1,38) = 1.93$, $p = .172$.

A.2. Relationship between memory performance and memory strength

During the recall phase of the *remember-and-decide task*, participants did not only recall items but also indicated their *memory strength*, that is, how certain they were about their answer. We tested whether participants' memory strength depended on whether they recalled an item correctly or not. To compare ratings across participants, we standardized the memory strength ratings. For forgotten items, participants were confident that they did not recall the item correctly ($M = -1.47$, $SD = 0.45$; one-sided t-test if smaller than 0: $t(38) = -20.39$, $p < .001$, $d = 3.27$). Similarly, they were also confident of having indicated the correct item when they did so ($M = 0.45$, $SD = 0.19$; one-sided t-test is greater than 0: $t(38) = 15.16$, $p < .001$, $d = 2.43$). Consequently, we can conclude that participants knew fairly well whether they indicated the correct snack item or not during the recall phase (see Fig.A 2a). However, the rating distributions indicated substantial heterogeneity of memory strength for remembered and forgotten items with the distributions overlapping at least partially (see Fig. A2b for memory trials and see Fig. A2c for control trials).

A.3. Relationship between memory performance and value

In line with our previous work (Mechera-Ostrovsky & Gluth, 2018), we found that high-value items were recalled best, low-value items were recalled second-best, and average items were recalled worst (see Fig. A3a). When regressing memory accuracy on linear and quadratic effects of subjective value, we found that the linear effect of value on memory was significant, but not the quadratic (linear effect:$t(32) = 2.38$, $p = .02$, $d = 0.41$); quadratic effect: $t(32) = 1.90$, $p = .07$, $d = 0.33$). Moreover, we correlated the GLAM parameters with the coefficients of linear value effect on memory performance. Interestingly, the only significant correlation was between the γ memory parameter and the linear effect in the GLAM_orig model ($r(31) = 0.34$, $p = .049$). Importantly, the correlation disappeared if the GLAM was estimated with our new ρ parameter ($r(31) = 0.18$, $p = .314$). The average value of the remembered options in the remrem trials ($M = 0.03$, $SD = 0.09$) was similar to the average value of the remembered option in remfor trials. Forgotten ($M = -0.1$, $SD = 0.24$) options were on average less valuable than remembered ones in remfor trials ($M = 0.06$, $SD = 0.17$).

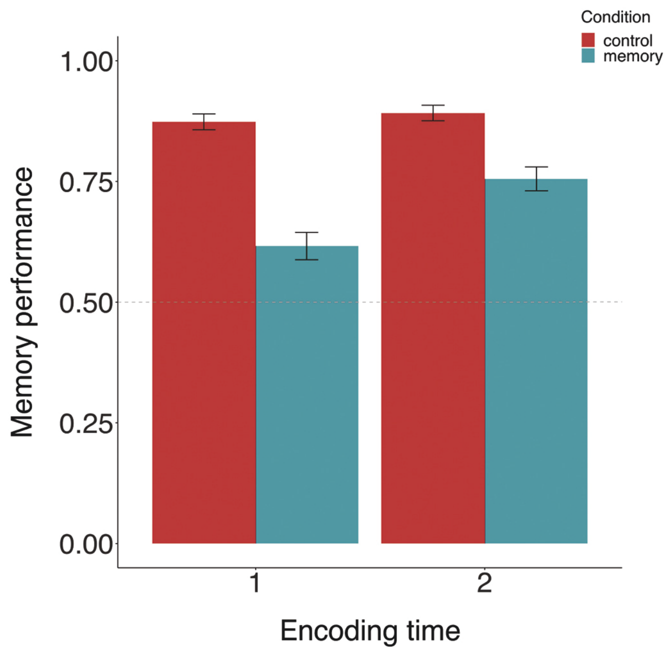

Fig. A1. Association between the memory performance (probability that an item is recalled correctly) and the encoding time (item presented once or twice during the encoding phase of the remember-and-decide task).

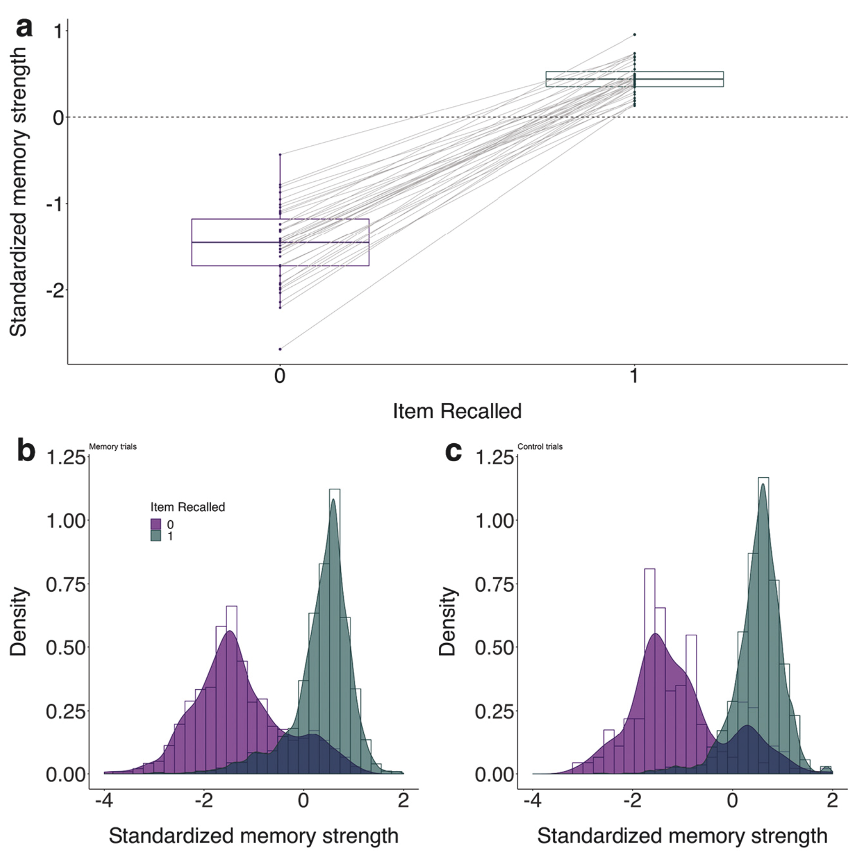

Fig. A2. (a) Association between the standardized memory strength and the actual recall (0 = item not recalled correctly, 1 = item recalled correctly). Participants appeared to be relatively confident whether they recalled an item correctly or not. (b) The distributions of memory strength for correctly and incorrectly recalled items showed at least some overlap. The left panel refers to memory-based trials, the right panel refers to non-memory-based trials.

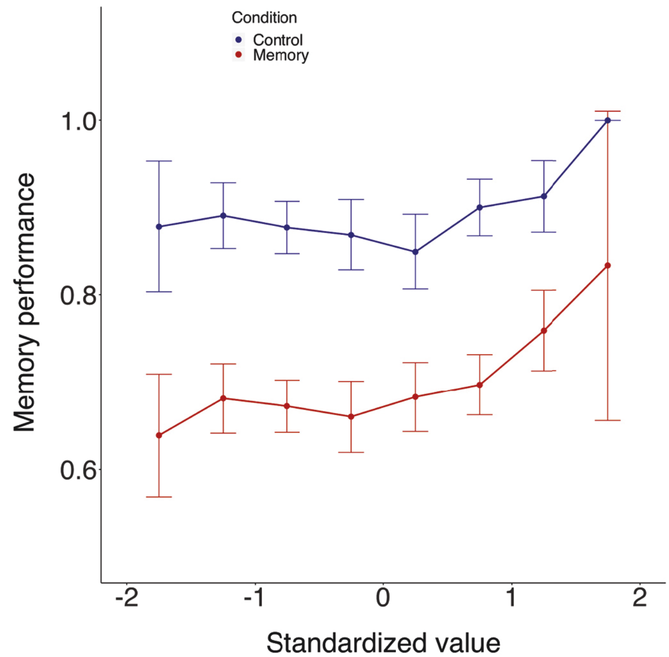

Fig. A3. Association between value and memory performance. Probability to recall an item correctly depending on the z-transformed standardized value, separately for control and memory conditions.

Appendix B. Testing individual differences and the robustness of the memory bias

B.1. Individual differences in the size of the memory bias

There were individual differences in the size of the memory bias (e.g., 11 participants showed a negative memory bias, 28 a positive memory bias). Here, we visualize this by plotting a) the memory bias for participants included in the modeling results or not, and b) for participants best described by the three model alternatives of the GLAM (GLAM_orig, GLAM_ρ, GLAM_nobias) in Fig. B1). Importantly, the size of the memory bias is not related to the number of trials ($r(37) = -0.19$, $p = .0.25$).

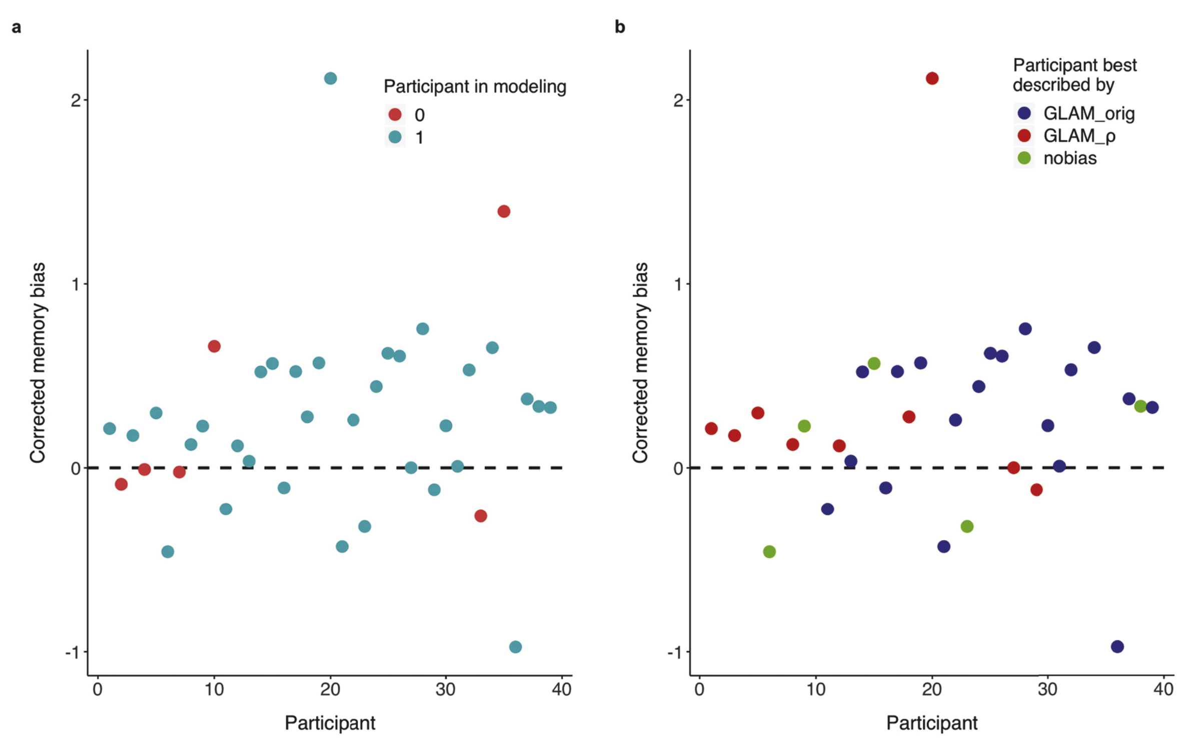

Fig. B1. Size of the memory bias separate for each participant: a) separately for participants included in the modeling results (light blue) or not (light red), b) separately for participants best described by each of the three model alternatives (blue: GLAM$_o$*rig*, *red*: GLAM_ρ, green: GLAM_nobias).

B.2. Assessing the memory bias using a hierarchical bayesian estimation method

To assess the robustness of the memory bias to variations in statistical testing, we also estimated the memory bias using a hierarchical Bayesian logistic regression, similar to our most recent work (Wagenmakers & Farrell, 2004). Note that the hierarchical Bayesian framework is especially recommended when the number of observations varies across participants, which is the case for our remfor trials (McNeish, 2016). Hierarchical priors for the two regression coefficients in the model (β_0 and β_1; see Eq. (1) in Section 2.5.1) and hyper priors were specified as follows:

$$\begin{aligned} &\mu_\beta \sim N(0,1)\\ &\sigma_\beta \sim \text{HalfCauchy}(5)\\ &\beta \sim N(\mu_\beta, \sigma_\beta) \end{aligned} \tag{12}$$

For each coefficient (intercept and slope) the mean μ_β was drawn from a normal distribution, and the standard deviation σ_β was drawn from a Half-Cauchy distribution. We specified the prior distributions based on the developers' recommendations of the used estimation package. The statistical test for an influence of memory on choice was based on the group posterior samples of the intercept parameter β_0. If the 95% HDI of the distribution did not overlap with 0, we inferred a credible memory bias.

Results of this hierarchical Bayesian logistic regression indicated the presence of a memory bias on choice, as the group posterior for the intercept was credibly larger than 0 ($M = 0.21$, $SD = 0.06$, 95% HDI = [0.09,0.33]). Also the group posterior for the slope parameter was credibly larger than 0 ($M = 0.77$, $SD = 0.09$, 95% HDI = [0.60,0.94]). In addition, we checked that the value of the forgotten option did not influence decisions in remfor trials by adding it as a second predictor in the regression model. The memory bias still persisted when including this second predictor, which itself was not credibly different from 0 ($M = -0.11$, $SD = 0.06$, 95% HDI = [−0.23,0.02]). Note, however, that a model comparison between the regression models without and with the value of the forgotten option as second predictor favored the latter ($\text{WAIC}_{\text{without}}$: 3159.33, $\text{weight}_{\text{without}}$: 0.36; $\text{WAIC}_{\text{with}}$: 3154.22, $\text{weight}_{\text{with}}$: 0.64).

B.3. The influence of memory strength on the memory bias

In light of the finding of considerable heterogeneity of subjective memory strength for successfully remembered as well as forgotten options (see Fig. A 2), we tested whether this heterogeneity influences the analysis of the memory bias. Thereto, we ran an additional hierarchical logistic regression taking memory strength into account. We included two predictors, one for the remembered and one for the forgotten option (because of the clearly distinct distributions of memory strengths for remembered/forgotten options; see Fig. A 2). Results indicated that the memory bias persisted, as the intercept was credibly higher than 0 ($M = 0.28$, $SD = 0.07$, 95% HDI = [0.15,0.41]). Moreover, the slope parameters for the value stayed similar as in the previous model ($\text{slope}_{\text{remembered}}$: $M = 0.80$, $SD = 0.09$, 95% HDI = [0.62,0.97]); $\text{slope}_{\text{forgotten}}$:$M = -0.10$, $SD = 0.06$, 95% HDI = [−0.23,0.2). Importantly, the predictor for the memory strength of the forgotten option was credibly smaller than 0 ($M = -0.12$, $SD = 0.05$, 95% HDI = [−0.23,-0.02]), and the predictor for the memory strength of the remembered option was credibly larger than 0 ($M = 0.10$, $SD = 0.04$, 95% HDI = [0.01,0.18]). This suggests that people were more likely to choose the remembered options (i.e., to exhibit a memory bias) when they were particularly uncertain about the forgotten option and particularly certain about the remembered option. Additionally, a model comparison between the classical memory bias model with this alternative model with the memory strength (certainty) as additional predictors favored the latter ($\text{WAIC}_{\text{normal}}$: 3159.33, $\text{weight}_{\text{normal}}$: 0.31; $\text{WAIC}_{\text{certainty}}$: 3145.38, $\text{weight}_{\text{certainty}}$: 0.69).

B.4. Dependency of the memory bias on the number of encoding trials

We also checked whether encoding an option once or twice affected the memory bias. Thereto, we re-run the logistic regression with the respective additional predictor. Results indicate that the memory bias was weakened slightly, as the 95% HDI included 0 (M = 0.28, $SD = 0.14$, HDI = [−0.02,0.55]; with still a 97.00% chance that the intercept was greater than 0). The slope for the encoding time of the remembered option was not credibly different from 0 (M = 0.0, $SD = 0.09$, HDI = [−0.17,0.19]). A model comparison between the model without and with this additional predictor favored the latter ($\text{WAIC}_{\text{normal}}$: 3159.33, $\text{weight}_{\text{normal}}$: 0.43; $\text{WAIC}_{\text{encoding}}$: 3158.19, $\text{weight}_{\text{encoding}}$: 0.57).

Table B1
Comparison of estimates fitted via a frequentist vs. a hierarchical Bayesian logistic regression.

	Estimation method	
Parameter	Frequentist (individual)	Bayesian (hierarchical)
Intercept	0.26 (0.52)	0.21 (0.06)
Slope	0.88 (0.58)	0.77 (0.09)

Note. The values correspond to the means, with the standard deviation in parentheses. For the individual frequentist analysis, all parameters are averaged across participants. For the hierarchical Bayesian analysis, the group posterior estimates are reported.

Appendix C. Computational modeling: GLAM

C.1. GLAM_ρ parameter recovery

We performed a parameter recovery analysis for our adapted GLAM_ρ model in the context of our study design. Parameter estimates from the individual fits were used to generate one predicted data set. This data set was then used to fit the model again. We checked whether the generating and recovered parameter estimates showed sufficiently high correlations. We only included the 33 subjects, for which the model converged (see main text). We found very high correlations for all parameters. All correlations are significant: ($r[v](31) = 0.99$, $p < .001$, $r[\gamma_{control}](31) = 0.88$, $p < .001$, $r[\gamma_{memory}](31) = 0.89$, $p < .001$, $r[s](31) = 0.91$, $p < .001$, $r[\tau_{control}](31) = 0.71$, $p < .001$, $r[\tau_{memory}](31) = 0.92$, $p < .001$, $r[\rho](31) = 0.75$, $p < .001$). Even though the correlations are lowest for the newly added ρ parameter and the scaling parameter τcontrol, they are still sufficiently high (see Fig.C 1).

C.2. Correlations between empirical data and model predictions

Finally, we assessed the correlations between the empirical data and the models' qualitative predictions concerning four measures: mean RTs, choice accuracy, gaze influence and memory bias (see Fig. C 2).

C.3. GLAM parameter correlations

We looked to what extent the parameters correlated with each other, as potential trade-offs between parameters can limit the informative value of computational models. As expected, the same parameters across different conditions such as (γ_{memory} and $\gamma_{control}$ as well as τ_{memory} and $\tau_{control}$) were correlated to a substantial degree ($r_\gamma = 0.53$; $r_\tau = 0.52$). Moreover, both τ parameters correlated substantially with the velocity parameter v ($r = -0.43$ and $r = -0.6$ respectively). All other correlation were smaller than ± 0.35 (see Fig.C 3).

C.4. GLAM qualitative model fit

Here, we use Bayesian mixed-effects models to test whether the different GLAM variants reproduce the gaze influence on choice, the memory bias, and overall choice accuracy (defined as the consistency of decisions with preference ratings) and RT effects on a qualitative level. The models were implemented and estimated using the code made available from Thomas et al. (2019). Accordingly, we used the Python library bambi, sampled two chains with 20,000 samples each and used the NUTS sampler. As for the GLAM estimation, the convergence was tested with the Gelman-Rubin statistic ($\widehat{R} < 1.05$). Fixed effects were statistically meaningful when the 95% HDI excludes zero. The predictor was a binary variable, indicating whether the dataset represents empirical data (predicted = 0) or simulated data based on model estimates (predicted = 1). We performed a mixed-effects regression for each behavioral measure: mean response times (RTs), choice accuracy, gaze influence and memory bias. As random effect we included the condition (control, remrem, remfor).

Overall, the predicted data accurately replicated the empirical choice and RT patterns for all three model variants. However, the GLAM_nobias model version (γ parameter fixed to 1), could not predict the influence of gaze on the choice probability (depending on value). In addition, the GLAM_orig model could not predict the memory bias on choice (see details in Table C1 1).

C.5. Relationship between the ρ parameter and the behavioral data

In addition to our qualitative predictions reported in the main text, we checked if the estimated memory bias parameter ρ is also associated with the behaviorally estimated memory bias as well as its relation to the mean of all forgotten values (the reference value used in the GLAM_orig model for the forgotten item in remfor trials). In general, there is a significant negative association between the estimated ρ parameter and the memory bias as well as between the mean of all forgotten items and the memory bias (see Fig.C 4). Interestingly, there is no significant association between the estimated ρ parameter from the GLAM_ρ model and the average value of all forgotten items (the reference value used, if no ρ parameter is estimated).

It could be that, as the model aims to find the parameters best describing the data overall, the smaller number of remfor trials were less influential. However, the number of trials per condition were not different across participants described best by one of the three model alternatives (number of trials: $M_{\text{GLAM\_orig}} = 65.42$, $SD_{\text{GLAM\_orig}} = 20.37$; $M_{\text{GLAM}\_\rho} = 66.78$, $SD_{\text{GLAM}\_\rho} = 16.80$; $M_{\text{GLAM\_nobias}} = 73.00$, $SD_{\text{GLAM\_nobias}} = 25.54$). Accordingly, a one-way analysis of variance (ANOVA) did not yield a significant result ($F(2,3) = 0.28$, $p = .76$).

C.6. Other GLAM alternatives

C.6.1. Taking into account the memory strength

Besides testing the influence of memory strength by including it as predictor in our logistic regression analysis (see Appendix B above), we also included the memory strength (*certainty$_i$*) in our GLAM model. Thereto, we adapted the absolute evidence signal A_i, to:

$$A_i = gaze_i{*}(value_i{*}certainty_i + \rho{*}(1 - certainty_i)) + (1 - gaze_i){*}\gamma{*}(value_i{*}certainty_i + \rho{*}(1 - certainty_i)) \tag{13}$$

The memory strength was linearly transformed to range between 0 and 1 in the memory trials, while in the control trials it was fixed to 1. Thus, the memory strength was only influential in memory trials but the model could be estimated for all trials types simultaneously.

Results indicated that this model was not able to predict our data better than the model without the uncertainty information. Moreover, similar to the model reported in the main text, quantitatively more participants were best described by the GLAM_orig model with $n = 19$ participants, followed by $n = 11$ participants best described by the GLAM_ρ, and $n = 3$ by the nobias model (classification by model weights: 19 by GLAM_orig, 10 by GLAM_ρ, 4 by GLAM_nobias). Most importantly, the model failed to predict the data in remfor trials on a qualitative level (see Fig. C5).

C.6.2. Varying the ρ parameter as a function of value

Additionally, we adapted our GLAM_ρ model to estimate an intercept for ρ and a slope for ρ that is multiplied with the options' value. If the options' value is not important, we expect the slope to be close to 0. The absolute evidence signal A_i becomes:

$$\begin{gathered} A_i = gaze_i{*}value_i{*}remembered_i + \\ gaze_i{*}\left(\rho\_intercept + \rho\_slope{*}value_i\right){*}(1 - remembered_i) + \\ (1 - gaze_i){*}\gamma{*}value_i{*}remembered_i + \\ (1 - gaze_i){*}\gamma{*}\left(\rho\_intercept + \rho\_slope{*}value_i\right){*}(1 - remembered_i) \end{gathered} \tag{14}$$

Results indicated that this model is similar to our GLAM_ρ with respect to quantitative and qualitative model fits. In terms of WAIC, 22 participants are best described by the GLAM_orig, 6 by the GLAM_ρ, and 5 by the GLAM_nobias (classification by model weights: 23 by GLAM_orig, 4 by GLAM_ρ, 6 by GLAM_nobias). Qualitatively, the model predicts a memory bias, but makes less accurate predictions for the gaze influence (see Fig. C6).

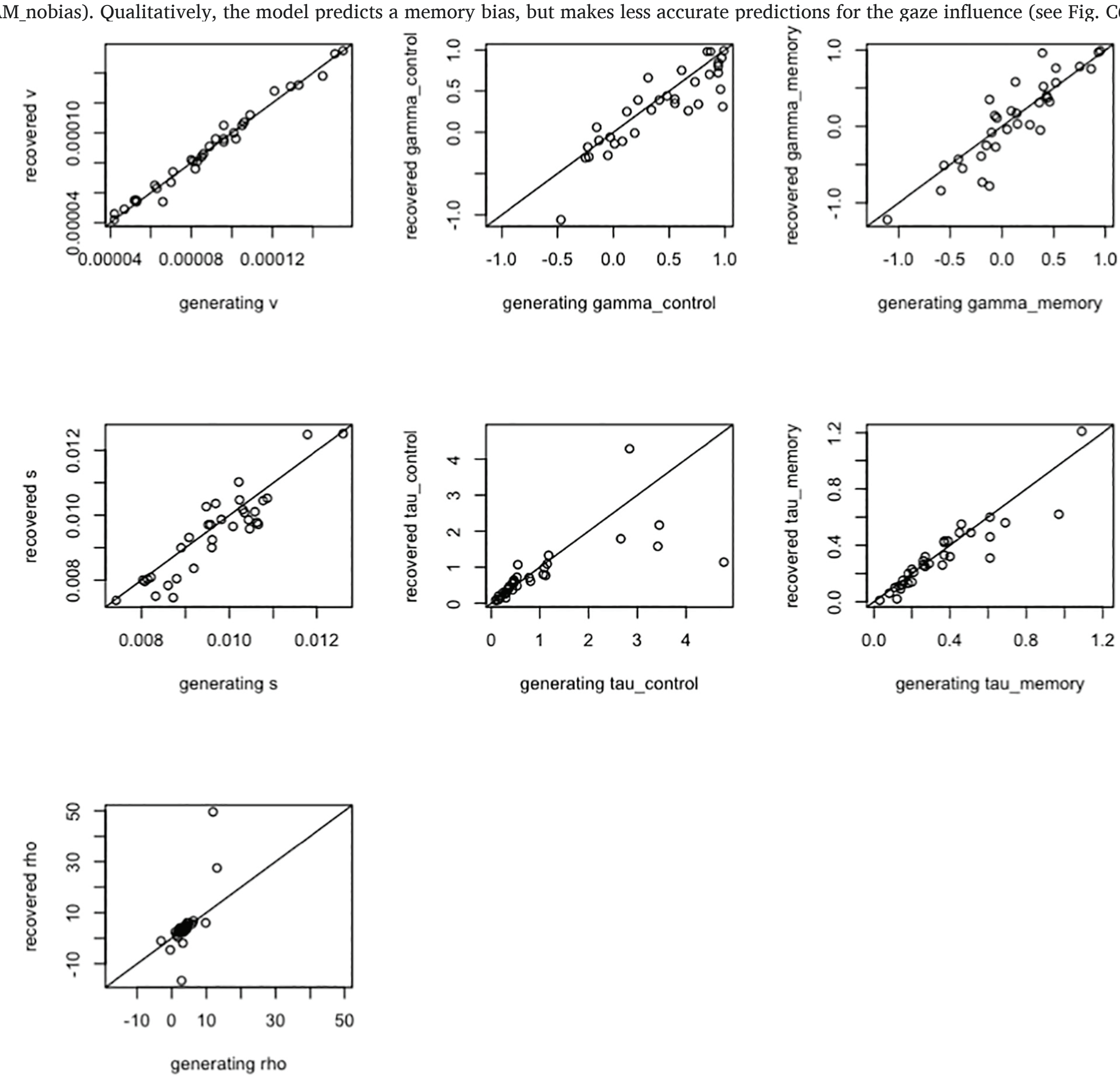

Fig. C1. Parameter correlations between the generating and the recovered estimates.

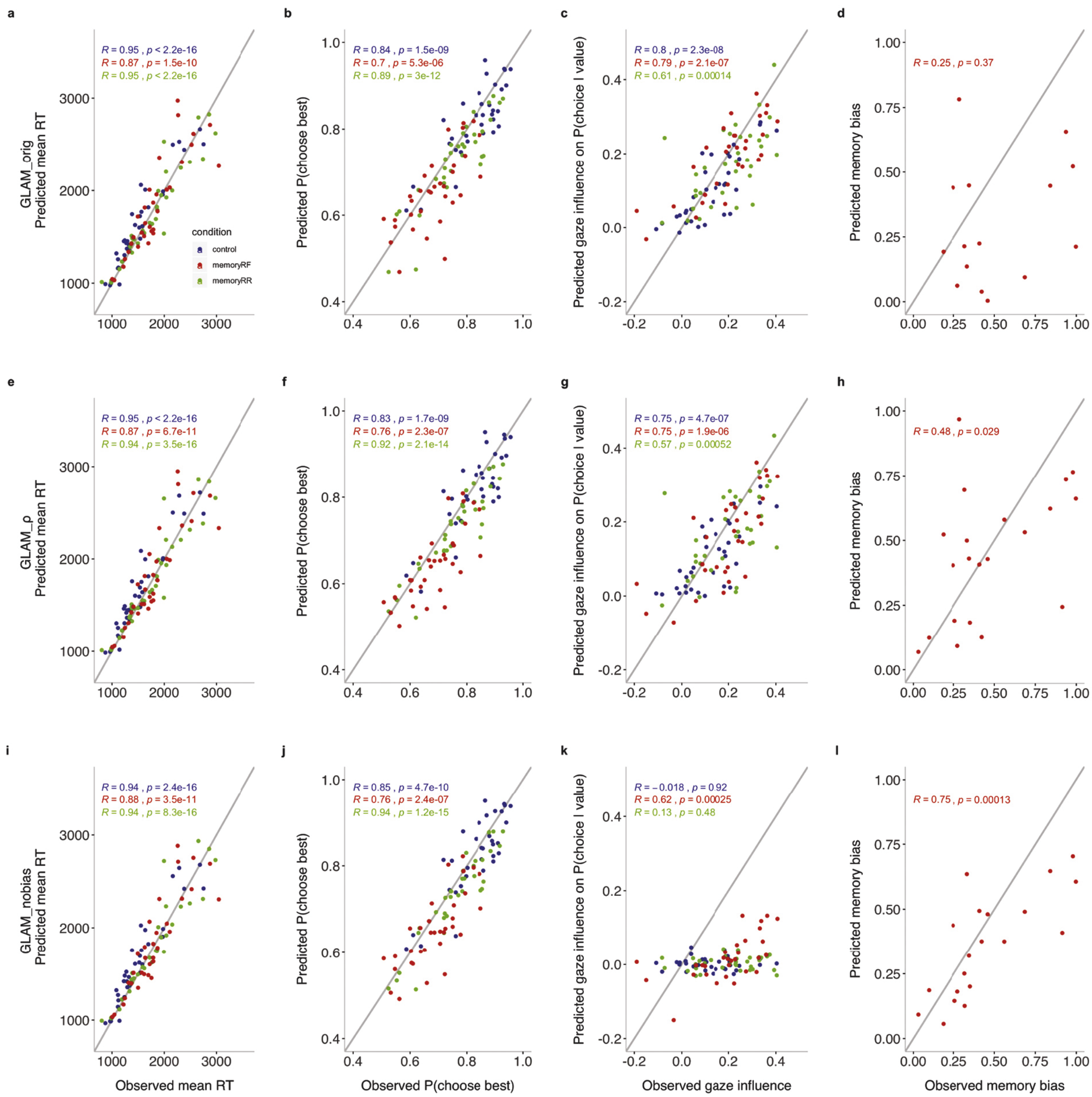

Fig. C2. Correlations between the observed data and model predictions. Each of the three rows depict a model variant (upper row = GLAM_orig, middle row = GLAM_ρ, lower row = GLAM_nobias). All model variants predict the mean RT and choice proportions similarly well. However, GLAM_nobias fails to predict the gaze influence on choice, and GLAM_orig does not predict the presence of a memory bias.

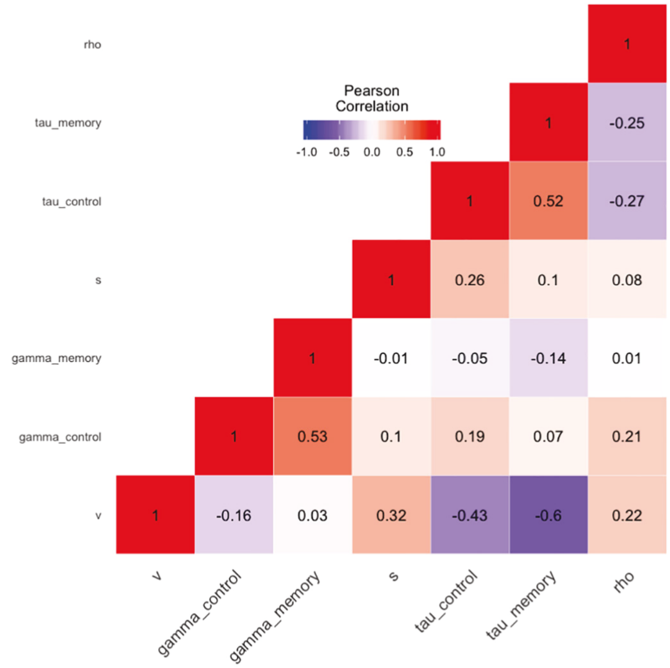

Fig. C3. Parameter correlations across all parameters in the GLAM_ρ.

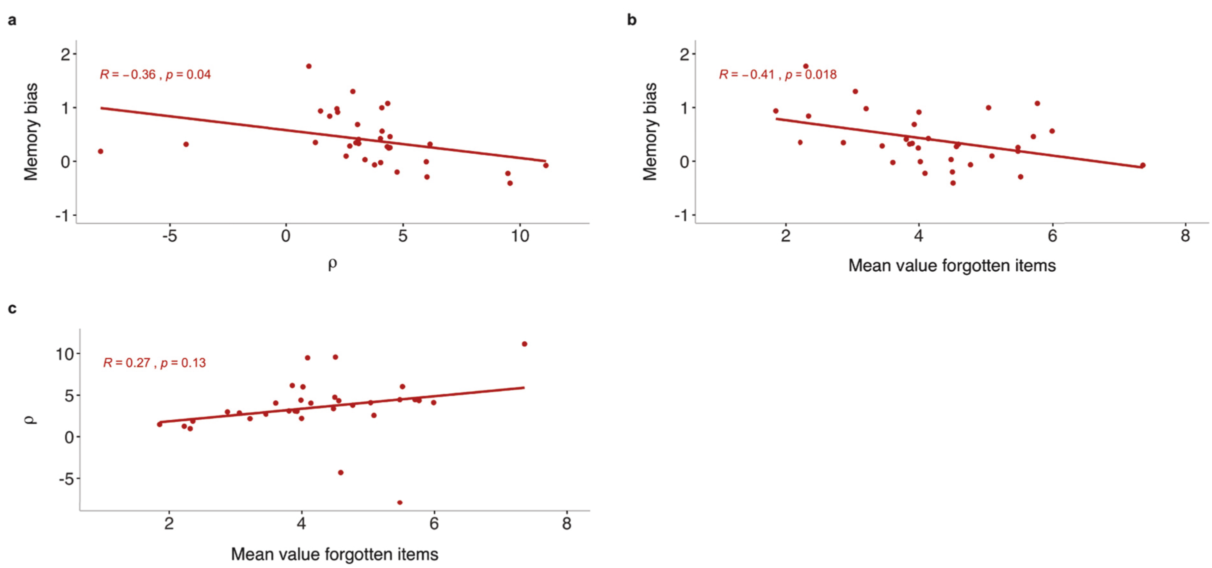

Fig. C4. Correlations between the behaviorally estimated memory bias and the model estimates of the *rho* parameter (a), the mean value of all forgotten items (b), and the estimated ρ parameter and the mean value of all forgotten items (c).

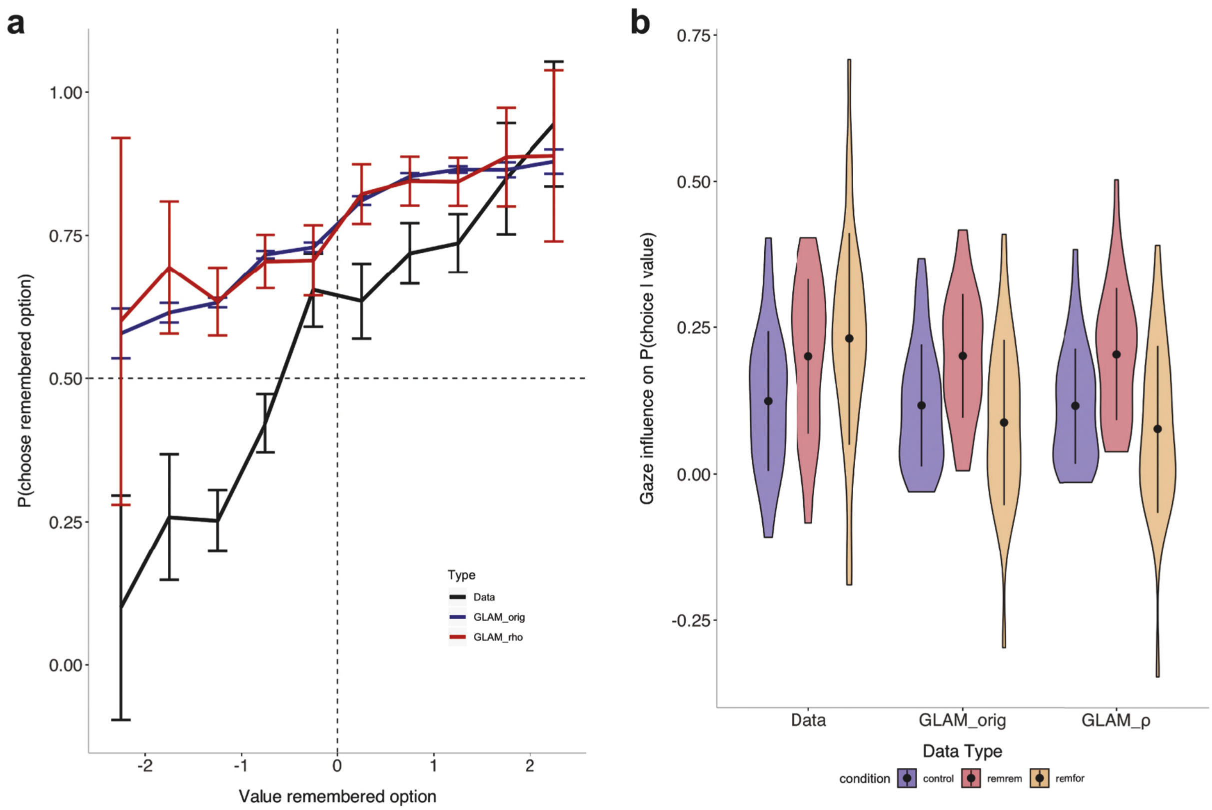

Fig. C5. Qualitative predictions from GLAM models including memory strength. The model predicts too many choices of the remembered option in remfor trials (a). Similarly, the predictions for the gaze influence on choice are inaccurate in remfor trials (b).

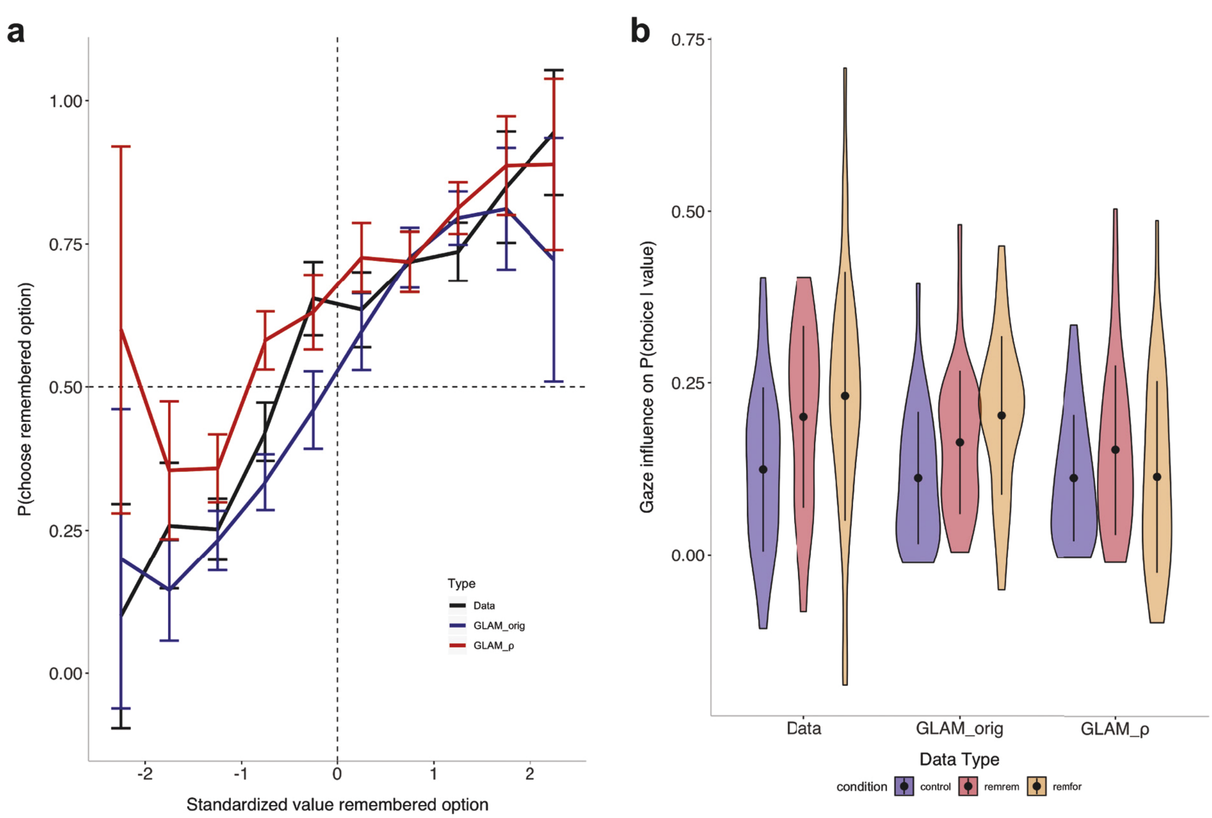

Fig. C6. Qualitative predictions from a GLAM_ρ model with two ρ: an intercept and a slope. The model is able to predict a memory bias (a), but the predictions for the gaze influence on choice are inaccurate in remfor trials (b).

Table C1
Fixed effects estimates and credible intervals for the Bayesian mixed-effects models comparing the empirical and the simulated data.

	GLAM_orig		*GLAM_nobias*		*GLAM_ρ*	
	β	95 % *HDI*	*β*	95 % *HDI*	*β*	95 % *HDI*
RTs (ms)	40.28	[−242.51,319.71]	36.93	[−235.64,333.55]	28.05	[−297.30,409.31]
CA (%)	−3.02	[−10.90,6.32]	−2.85	[−11.37,6.33]	−3.27	[−11.82,6.13]
GI (%)	−2.42	[−9.64,4.41]	−16.08	[−25.34,-3.24]	−3.20	[−10.65,4.22]
MB	−0.22	[−0.41,-0.03]	−0.05	[−0.27,0.18]	−0.08	[−0.28,0.11]

Note. RTs = reaction times; CA = choice accuracy; GI = gaze influence; MB = memory bias. Estimate β is the mean estimated difference between the empirical and the simulated data.

Appendix D. Sequential presentation session

As stated in the main article, we included a second experimental session, where the options were presented sequentially during the decision phase ($n = 40$ participants). Presentation durations were either long (1500 ms) or short (500 ms). We varied all possible combinations, resulting in four types of presentation length trials: long/long, short/short, long/short, short/long.

We hypothesized that a longer presentation of an option would increase its choice proportion, whereas a shorter presentation time would decrease its choice proportion. However, our behavioral results indicated that the presentation duration had no influence on the choice proportion. Instead, across all possible four types of presentation length trials, the choice proportion was stable. In the control trials, participants chose the first and the second option equally often (around 50% of the time), while in the memory trials there was a small preference for the last presented option. Accordingly, a repeated-measures 2 × 4 ANOVA with the factors Trial Type (memory vs. control) and Presentation Length (long/long, short/long, long/short, short/short) and the probability to choose the last presented option as dependent variable showed a significant effect of Trial Type ($F(1,301) = 27.87$, $p < .001$), but no main effect of presentation length ($F(3,301) = 1.99$, $p = .116$) nor an interaction effect ($F(3, 301) = 0.72$, $p = .542$, see Fig.D 1).

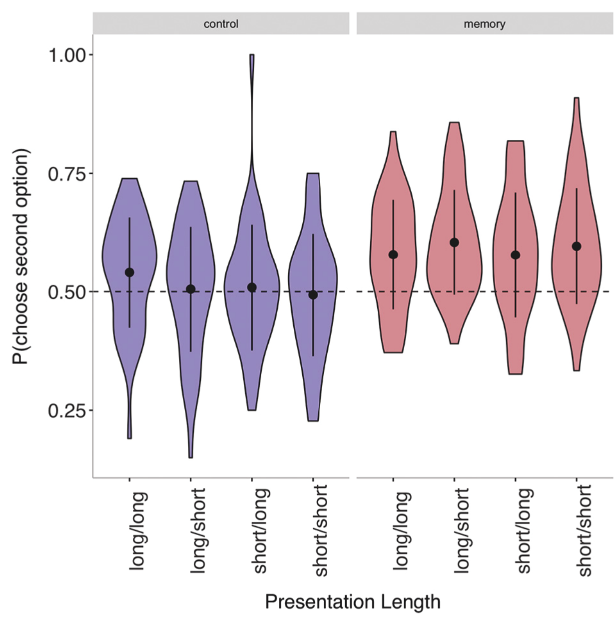

Fig. D1. Choice proportion of the item presented last in the sequential presentation session. Left the control trials are depicted, right the memory trials. Across the presentation length conditions there was no difference in the choice proportion, even though, participants tend to choose the item presented last more often in the memory trials.

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