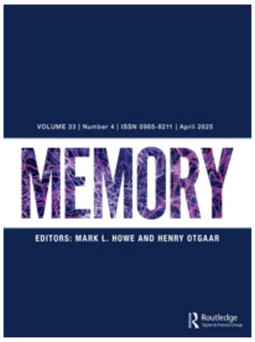

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Prediction of information value influences memory: the effect of predicted and assigned value on memory

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ABSTRACT
We tend to prioritise more valuable information at the expense of less valuable information to optimise the use of our limited memory capacity. Participants better remember information that they judge to be valuable and that they are told is valuable. Using a recognition paradigm, we sought to examine whether predicting the value of art pieces before learning the experimenter assigned value would influence memory and the quality of retrieval. In two experiments, participants made value predictions about various art pieces and then learned the assigned value. At test, participants provided old/new and remember/know judgments and were tested on the exact value. Results revealed that participants' value predictions influenced memory to a greater degree than assigned value, despite assigned value indicating the amount of reward participants would receive. We discuss these findings with regard to strategic and automatic influences of value on memory, as well as in the context of reward prediction errors (a difference in expected and actual reward).

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Value-directed remembering; recognition; reward prediction errors; metacognition

We are often exposed to substantially more information than we can remember. With our limited memory capacity, being able to prioritise which information to remember is especially important in helping us navigate our lives. For example, we may want to remember the birthdays of people we care about or which foods a child is allergic to. It is also advantageous to predict which information will be most valuable. For example, students often try to predict which information will be tested to direct cognitive resources accordingly. With these goals, we often aim to remember the most important information, including that which we predict to be important. However, our predictions are not always aligned with information's real or external value. Understanding how our predictions of value and later learned value influence memory can help illuminate how successfully we update memory for value information and how value influences memory when it aligns with expectations or does not. In the present research, we examine the influence of participants' predictions of a stimulus' value (referred to here as "predicted value") and the stimulus' experimenter-assigned value (referred to here as "assigned value") on recognition memory.

Castel (2007) proposed the value-directed remembering (VDR) framework which posits that memory is selective for information of high value. In studies of VDR, a point value or monetary reward is paired with a word or other stimulus, and participants are asked to remember the stimulus for a later test with a goal of maximising their score. Because most people cannot remember all the items presented, participants generally learn, with task experience and feedback, to remember high-value information at the expense of low-value information (Castel et al., 2002; Middlebrooks et al., 2017; Robison & Unsworth, 2017; Spaniol et al., 2014). Some work has expanded these findings to examine whether value has a similar influence on memory when it is subjectively assigned by participants (McGillivray & Castel, 2017; Murphy & Castel, 2021) and has found that participants' subjective judgments of value also drive memory, similar to experimenter assigned value.

There is evidence of both automatic and strategic influences of value on memory (see Knowlton & Castel, 2022 for a review). Value and reward are closely associated with the brain's dopaminergic pathways such that value drives both automatic and strategic memory processes. There is neuroscientific and behavioural data suggesting that reward has a more automatic influence on memory. High-value information is generally more salient and often processed more automatically with less cognitive effort (Adcock et al., 2006; Wittmann et al., 2005; Wolosin et al., 2012). Additionally, the processing of high value information tends to rely more on the hippocampus

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(Gruber et al., 2016; Moscovitch et al., 2016), and connectivity between dopaminergic and medial temporal lobe structures is predictive of enhanced episodic memory (Adcock et al., 2006; Elliott et al., 2022). In behavioural paradigms, presenting an unexpected reward has been shown to improve incidental memory for information presented close in time to the reward (Murayama & Kitagami, 2014) and source memory for items associated with reward or punishment (Shigemune et al., 2014). Additionally, when using a directed-forgetting paradigm, high-value items that were to-be-forgotten are recognised at a much greater rate than low-value to-be-forgotten items (Hennessee et al., 2019), suggesting that value or reward can enhance memory even without intention to encode information in a more automatic way.

There is also evidence that we strategically attend to and remember high-value information by engaging in encoding strategies that allow for deeper semantic processing of this information (Cohen et al., 2017). As such, we encode high-value information more effectively and retrieve it from memory more easily at the expense of lower-value information. Neural evidence supports this finding, showing differential engagement of semantic processing regions (left inferior frontal gyrus and posterior middle temporal gyrus) when high compared to low value information is presented (Cohen et al., 2014). Prior work has also shown that memory recall output tends to begin with high-value stimuli followed by low-value stimuli (Murphy et al., 2021; Murphy & Castel, 2022; Stefanidi et al., 2018), suggesting that participants are strategically prioritising high value information in memory. Taken together, value or reward can improve memory through both automatic and strategic processes, and the extent to which these processes influence memory may vary depending on task demands and participant expectations.

One methodological way to examine both strategic and more automatic effects of value on memory is by using a recognition paradigm. Studies on VDR have largely focused on memory recall (see Elliott et al., 2020; Elliott & Brewer, 2019; Hennessee et al., 2019 for exceptions), which tends to allow for more episodic and strategic retrieval of information. However, recall-based designs do not provide much insight into the quality of memory retrieval. Recognition paradigms allow us to separate fine-grained recollection processes from more familiarity-based memory (see Yonelinas, 2002; Yonelinas et al., 2010 for detailed discussion of recollection and familiarity). Recollection is facilitated by elaborative rehearsal and the episodic memory system and is typically associated with memory for contextual details (Dudukovic & Knowlton, 2006; Gardiner et al., 1994). Familiarity involves participants being fairly confident in having seen the item but unable to recall any other details associated with seeing it and is influenced by maintenance rehearsal, relying more on the semantic memory system (Gardiner, 1988).

In VDR studies using a recognition paradigm, results have shown that higher value items may be remembered largely through recollection processes (Elliott et al., 2020; Hennessee et al., 2017), and this improvement is thought to be a result of more automatic processes. However, when there is opportunity for retrieval via recall and participants receive feedback on their performance, participants tend to strategically prioritise the high value information, resulting in both greater recollection and familiarity for high value information (Cohen et al., 2017). The differences observed between recollection and familiarity suggest that when the goal is to improve score, which often involves inhibiting lower value information, more strategic processes may be at play. Thus, it is important to examine recognition across multiple study-test lists with feedback to examine how value affects recollection and familiarity when strategic processes may be at play.

Beyond effects of assigned value on memory, it is important to examine how predicted and assigned value may differentially influence memory. Specifically, making predictions about value and then learning an assigned value requires updating memory rather than simply learning an assigned value. Reward prediction errors (RPEs) refer specifically to the mismatch between predicted value and assigned value, and they can either be positive (i.e., the reward is higher than predicted) or negative (i.e., the reward is lower than predicted). With RPEs, there is an element of surprise that is thought to elicit hippocampal activity which serves to update and reconsolidate memories (Fernández et al., 2016; Haeuser & Kray, 2023; Sinclair et al., 2021; Sinclair & Barense, 2019), but the literature regarding the effect of RPEs on memory is mixed (see Ergo et al., 2020 for a review).

Specifically, some work has shown a *signed* effect of RPEs on memory, such that rewards that are higher than predicted are better remembered, while rewards that are lower than expected are remembered at lower rates (De Loof et al., 2018; Ergo et al., 2021; Jang et al., 2019). This finding is perhaps a more intuitive one, as it should be advantageous to remember information associated with higher reward (Schultz, 2017), and the increase in dopamine release from the midbrain following better-than-predicted rewards prioritises the encoding and retrieval of such information (Montague et al., 1996). However, other work has found evidence for an *unsigned* or more generalised effect of RPEs, such that rewards that are either higher or lower than expected result in better memory (Rouhani et al., 2018). As with VDR effects, the dopaminergic system is thought to play a role in a more generalised prediction error, such that this system may be sensitive to important cues (Bromberg-Martin et al., 2010; Gardner et al., 2018; Schultz, 2016). In addition, unexpected outcomes may have an element of surprise that causes them to be more memorable (Greve et al., 2017; Pearce & Hall, 1980; see Rouhani & Niv, 2021 for a discussion).

A few studies have sought to reconcile these seemingly disparate findings. Specifically, Stanek et al. (2019) show that during reward *anticipation*, greater expected value is associated with improved memory, while greater reward uncertainty experienced closer to the reward *outcome*, or when the actual reward is revealed, is related to better memory (i.e., an unsigned effect). Additionally, Rouhani and Niv (2021) showed that RPEs at reward outcome impact memory in an unsigned manner, while RPEs during reward anticipation (i.e., at cue) show a signed effect on memory. However, due to methodological differences in prior studies that highlight this difference in timing of RPEs and their subsequent effects on memory, the evidence is not entirely conclusive. Given that RPEs that occur at the reward outcome stage have been shown to elicit unsigned effects on memory, we expected to find unsigned effects on overall recognition memory in the current study. However, we were also curious about whether the valence of RPEs would be differentially related to recollection and familiarity processes, which has not been examined to our knowledge.

Current study

The purpose of this study was to investigate the unique effects of predicted value and experimenter assigned value, as well as the effect of reward prediction errors, on recognition memory, including the quality of recognition memory. In two experiments, participants viewed three lists of art and were asked to predict the value of the art before being shown the experimenter assigned value of the art pieces. Then participants were tested on their memory for the art as well as the associated values. Participants completed three study-test lists, after each of which they received feedback about the number of points they earned. This inclusion of multiple lists allowed us to assess the extent to which effects of different forms of value may change with task experience.

Consistent with the value-directed remembering framework, we predicted that the assigned value of art would have a significant effect on memory, such that higher value items would be better recognised and result in higher rates of recollective experiences than lower value items as shown in prior work (Hennessee et al., 2017). Additionally, prior work has shown that memory is improved for items judged to be of higher value by participants (Murphy et al., 2024; Murphy & Castel, 2021), so it is possible that art predicted to be of higher value results in better recognition than that predicted to be of lower value. However, in the present research, participants are rewarded for the assigned value only (i.e., regardless of their predicted value), so participants should optimally overwrite their value predictions and focus on the assigned value.

There were competing hypotheses regarding the differential influence of predicted and assigned value on recognition memory. If value is processed somewhat automatically (see Murphy et al., 2025), then the initial prediction of value may be difficult to update when learning the assigned value, leading to a stronger effect of predicted value on overall recognition. This theory would also suggest that both forms of value would show influences on recollection but not familiarity. On the other hand, if more strategic processes are at play, participants should be more likely to successfully ignore their predictions of value and prioritise items high in assigned value, and rates of both recollection and familiarity would be increased by value. Additionally, the increase of both recollection and familiarity as a function of value should become more pronounced across lists, as participants adjust their strategies to improve their point score.

In terms of prediction errors, we hypothesised that reward prediction errors (items with high predicted value and low assigned value, and items with low predicted value and high assigned value) would lead to better memory performance than when there is no prediction error (i.e., the predicted value matches the assigned value). Although conflicting results have been found regarding the effect of RPEs on memory, we predict an unsigned effect, as the prediction error should take place at the reward outcome stage, rather than the reward anticipation stage of encoding.

Experiment 1

In Experiment 1, participants viewed three lists of various art pieces, including sculptures, paintings, and photographs. After viewing each image, participants judged the value of each art piece before being shown the assigned value, which was what they were told they would earn if they correctly remembered the art piece later. During testing, participants were shown the art pieces they had studied, as well as lures they had not studied (by the same artists), and were asked to make old/new and remember/know/guess judgments. Finally, participants were given feedback about their performance. We examined their overall recognition memory, remember/know responses, memory for the price of items, and reward prediction errors. We also examined participants' confidence in their memory performance, which is reported in the Supplementary Results.

Method

Participants

A total of 110 participants took part in the research study online. We excluded 11 participants from our analysis due to the proportion of New responses being greater than 75% of all test items, which suggests that the participants were not following study instructions and/or were not fully engaged in our study as selecting "New" would allow them to complete the study faster. We also excluded four participants whose reported age was under 18 or greater than 30. Therefore, our final sample consisted of 95 participants, with 75 females, 19 males, and one participant who did not identify as either gender. The participants ranged in age from 18 to 29 years ($M = 19.96$, $SD = 1.81$). The sample consisted of University of California, Los Angeles (UCLA) undergraduate students recruited from the UCLA psychology subject pool. Participants earned coursework credit or extra credit as part of their participation. The study was approved by UCLA's Institutional Review Board (#12-000617), and informed consent was obtained. We did not have an initial sampling plan, but a post-hoc sensitivity analysis revealed that for a within-subjects ANOVA with 95 participants and power of .80, we could detect small effect sizes of Cohen's $f = 0.086$.

Materials

Stimuli consisted of 180 art pieces taken from online art marketplaces, and the art pieces included paintings, photographs, and sculptures. Art pieces were taken from 90 artists, with two art pieces per artist. One art piece from each artist was presented during the study phase and the other served as a lure during the test phase. All art pieces were presented on a blank white computer screen and were standardised in size to a height of 350 pixels, regardless of shape.

In order to determine the range for low values and high values, 47 independent participants rated values from $1000 to $950,000 as low or high. Based on these responses, we made the range for low value to be between $1000 and $25,000, and high value to be between $100,000 and $500,000. A set of 30 unique values with 15 low values and 15 high values was generated from these ranges. These unique price values were randomly paired with 30 art pieces during the study phase for each list as the experimenter assigned value. In other words, these price values were not the actual value of the art pieces, but rather, they were simply randomly assigned values that participants were led to believe were the actual value of the art pieces.

Procedure

After providing informed consent and basic demographic information, participants were given the following cover story and instructions. They were told that their client, who is an art collector, is interested in obtaining high value art pieces. Participants were instructed that they would be shown various art pieces that would differ in value, and their goal was to remember as many valuable art pieces as possible. Then, during the study phase, participants were shown an art piece for 6 s. They were asked to select whether they thought the art was low-value (between $1000 and $25,000) or high-value (between $100,000 and $500,000). After making a selection, participants were shown the art piece again, along with the experimenter assigned value of the art piece for 6 s, which was randomly selected from the set of 30 unique price values. This process was repeated for 30 items, and the order in which the art pieces were presented was random. After completing the study phase, participants were then instructed to complete simple arithmetic problems for two minutes.

Next, participants were presented with the instructions for the test phase, which gave them the definitions of the terms *old*, *new*, *remember*, *know*, and *guess*. Old responses indicated that the participant had seen the item during study, whereas new responses indicated that the participant had not seen the item during study. Additionally, if participants said the item was old, they were asked to make the Remember/Know/Guess (RKG) judgment. A remember response indicates a recollection experience; a know response indicates a familiarity experience; a guess response indicates that the participant was simply guessing (see Appendix A for the exact definitions shown to participants). Participants were then presented, in a random order, with each of the 30 items they had studied, as well as 30 lure items they had not studied. When each item was presented, participants were asked to rate the art piece as definitely old, probably old, maybe old, definitely new, probably new, or maybe new. If the art piece was rated as old, participants were then prompted to identify the basis of their recognition (remember, know, or guess), then to free recall the experimenter assigned value of the art, and then to rate their confidence in their memory of the value on a 7-point Likert scale (1 = *not at all confident*, 7 = *very confident*). If the art piece was rated as new, participants then proceeded to the next art piece without being prompted for additional information.

At the end of the test phase, participants received feedback on how much the items that they correctly remembered were worth out of the total amount possible. For example, assume that both art pieces A (worth $6000) and B (worth $100,000) were presented in the study phase. If the participant correctly recognised art piece A as old but incorrectly judged art piece B as new, then they would receive feedback that they remembered items worth $6000 out of the total $160,000 item value they could have remembered. It is important to note that while participants were only awarded points for hits but not correct rejections, we did not specify this in the task instructions to ensure that participants were not incentivized to respond "old" on all trials. Rather, participants were simply told in the instructions that they would earn the value of the art pieces if they correctly recognized the items by selecting "old" when the art pieces had truly been previously shown or by selecting "new" when the art pieces had truly not been previously shown. Following the feedback, participants repeated this process for the next list. There were three study-test lists, each with 30 art pieces presented in the study list and 60 in the test list. The order of the lists were counterbalanced for each participant. A summary of the study procedure is depicted in Figure 1.

Data analysis

Overall recognition accuracy refers to how accurate participants were at categorising the items correctly as either old or new (i.e., when they correctly identified previously

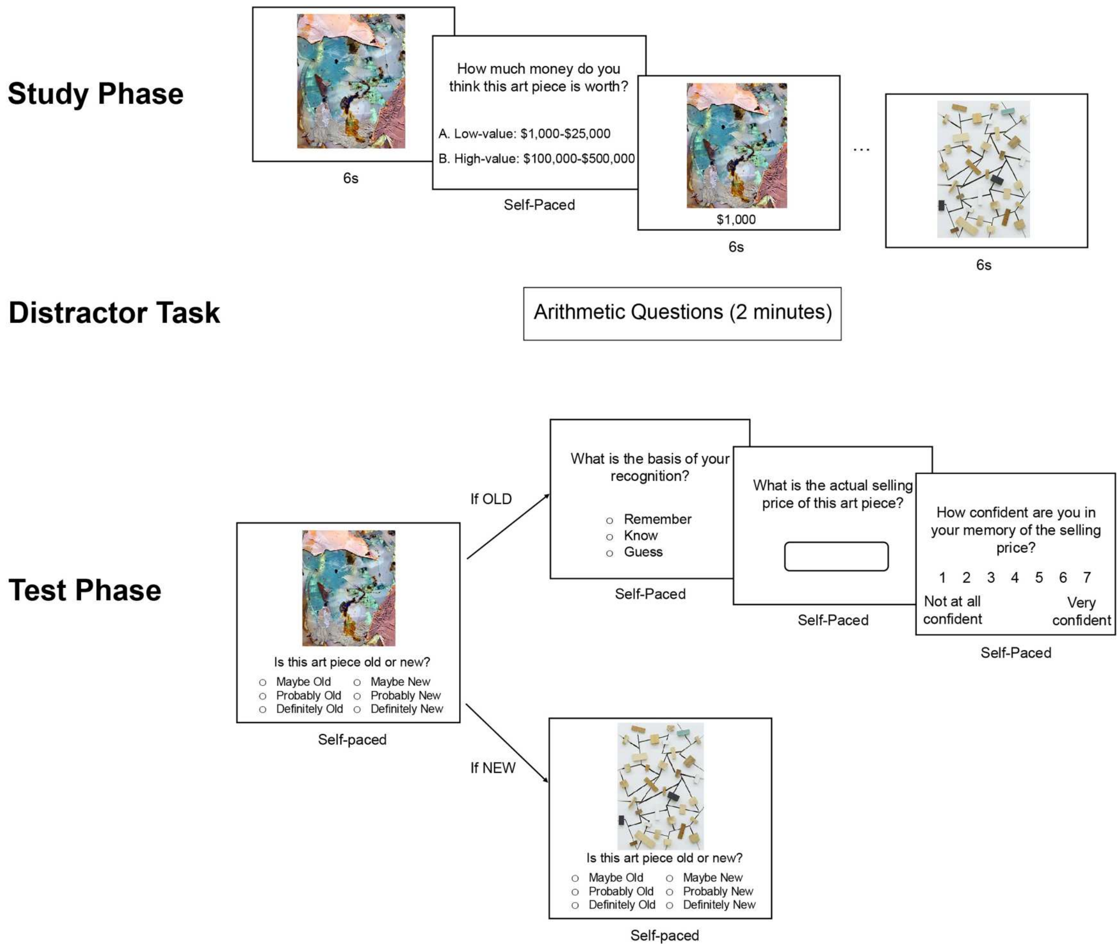

Figure 1. A summary of the study procedure in Experiment 1.

studied items as old or new items as new). As the lure/new items did not have either a predicted or assigned value, we did not include false alarms in our overall recognition calculation. Additionally, analyses regarding remember and know responses include only items that were judged as old (as participants did not make the RKG judgment for items they remembered as new) and items that were actually old (as there was no predicted or assigned value for new items). Thus, the analyses for these variables include only items that were correctly remembered as old (i.e., hits).

Memory of assigned value refers to how well participants were able to recall the experimenter assigned value. Participants correctly recalled the assigned value when participants' memory for the numeric value at test matched the correct category of assigned value (i.e., when they provided a value within the Low Value range when the assigned value was low, or when they provided a value within the High Value range when the assigned value was high). We used a categorical measure, as overall accuracy of the exact assigned value was low ($M = 0.21$).

To examine overall recognition accuracy, remember and know responses, and memory of assigned value, we conducted a logistic mixed effects model with items nested within individuals. We used this analysis approach to account for variance at both the item and participant level. We included both participant and item as random intercepts. We tested the models for the inclusion of a random slope for predicted value, as this variable could vary across items, but model comparison metrics suggested the fit was not significantly improved by the inclusion of this parameter, and thus a more simple model was preferred. Because participants were able to predict the value of each item, including the item as a random intercept allows item effects to be accounted for. Predicted value (simple coded, anchored on low), assigned value (simple coded, anchored on low), list (simple coded, anchored on List 1), and their interactions served as fixed effects in the model predicting item-level outcomes, including recognition accuracy, remember responses, know responses, and memory for the value category. Random intercepts for participant and item were included to control for their individual effects, and the intraclass correlation coefficient (ICC) is reported for each model. Bonferroni corrections were used for post-hoc tests.

To test whether the types of prediction error had a different effect on memory, prediction errors were categorised into three groups: (1) when the predicted value

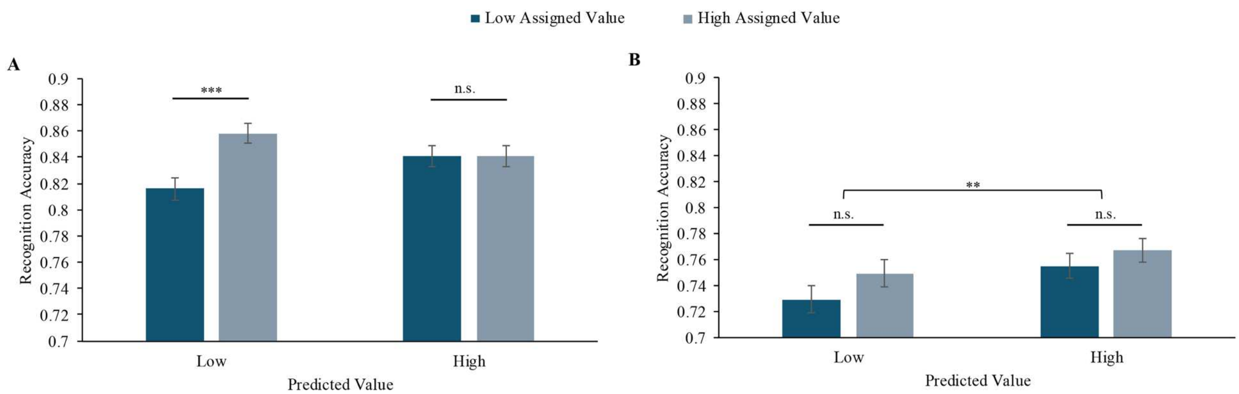

Figure 2. Recognition memory performance in Experiments 1 and 2.

Notes: Panel A shows the average recognition memory performance for each condition in Experiment 1. Panel B shows the average recognition memory performance for each condition in Experiment 2. Error bars represent ±1 standard error of the mean.

was higher than the assigned value (a negative RPE), (2) when the predicted value was lower than the assigned value (a positive RPE), and (3) when there was no prediction error (the predicted value matched the category of the assigned value; no RPE). We used a Generalized Mixed Model with binomial distribution and a log link function (logistic mixed effects regression) to examine the effects of prediction error and list on recognition accuracy. Similarly, random intercepts for participant and item effects were included to account for their variability. Bonferroni corrections were used for post-hoc tests.

Results

Overall recognition accuracy

There were 45.8% of Old responses and 54.2% of New responses collapsed across all participants and items presented. Overall recognition accuracy was 85.31%, while the false alarm rate was 7.10%. Average recognition accuracy is shown in Figure 2A, and all recognition accuracy means and standard deviations are reported in Table 1. Additionally, the proportion of items predicted to be low value was 49.42%, while 50.58% of items were predicted to be of high value. Cell sizes broken down across all variables are presented in Table 1.

Table 1. Mean (and standard deviation) of overall recognition accuracy, remember responses, and know responses.

	Experiment 1					
	Assigned Value					
	List 1		List 2		List 3	
	Low	High	Low	High	Low	High
Low Predicted						
Overall	0.86 (0.34)	0.88 (0.32)	0.81 (0.39)	0.85 (0.36)	0.77 (0.42)	0.84 (0.37)
Remember	0.69 (0.46)	0.74 (0.44)	0.76 (0.43)	0.78 (0.42)	0.76 (0.43)	0.80 (0.40)
Know	0.25 (0.44)	0.21 (0.41)	0.18 (0.38)	0.17 (0.38)	0.19 (0.40)	0.16 (0.37)
n	713	706	695	699	710	702
High Predicted						
Overall	0.88 (0.32)	0.86 (0.34)	0.82 (0.38)	0.84 (0.37)	0.82 (0.39)	0.82 (0.39)
Remember	0.69 (0.46)	0.71 (0.45)	0.76 (0.43)	0.75 (0.44)	0.76 (0.43)	0.79 (0.41)
Know	0.25 (0.43)	0.25 (0.43)	0.19 (0.40)	0.20 (0.40)	0.20 (0.40)	0.18 (0.38)
n	712	719	720	726	715	723

	Experiment 2					
	Assigned Value					
	List 1		List 2		List 3	
	Low	High	Low	High	Low	High
Low Predicted						
Overall	0.71 (0.46)	0.72 (0.45)	0.76 (0.43)	0.75 (0.43)	0.72 (0.45)	0.78 (0.42)
Remember	0.55 (0.50)	0.51 (0.50)	0.57 (0.50)	0.62 (0.49)	0.57 (0.50)	0.65 (0.48)
Know	0.25 (0.43)	0.30 (0.46)	0.25 (0.43)	0.24 (0.43)	0.25 (0.44)	0.23 (0.42)
n	583	581	592	574	557	548
High Predicted						
Overall	0.71 (0.45)	0.74 (0.44)	0.77 (0.42)	0.77 (0.42)	0.78 (0.41)	0.79 (0.41)
Remember	0.52 (0.50)	0.55 (0.50)	0.61 (0.49)	0.61 (0.49)	0.68 (0.47)	0.68 (0.47)
Know	0.31 (0.46)	0.29 (0.46)	0.25 (0.43)	0.25 (0.43)	0.21 (0.41)	0.21 (0.40)
n	687	686	678	700	704	721

Notes: "Overall" refers to overall recognition accuracy. "Remember" refers to remember responses for correctly recognised old items. "Know" refers to know responses for correctly recognised old items.

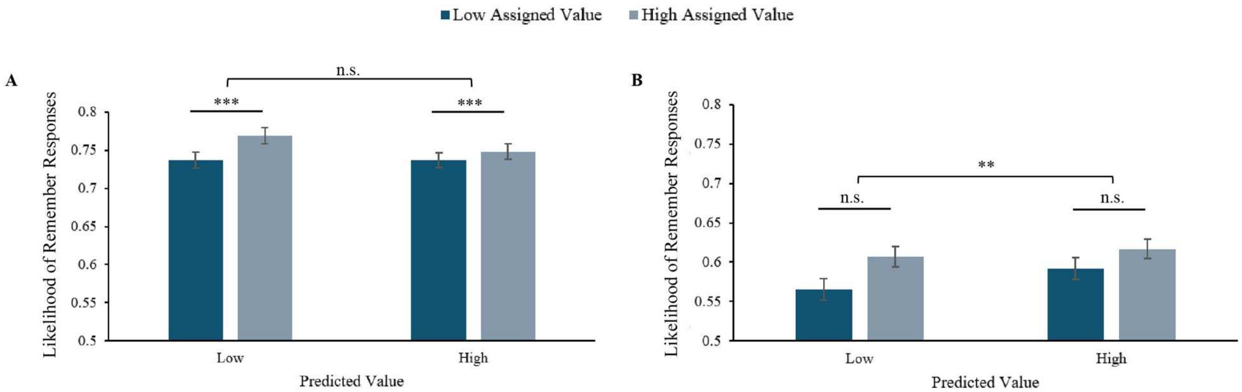

Figure 3. Likelihood of remember responses in Experiments 1 and 2.

Notes: The average likelihood of remember responses is shown for low and high predicted and assigned value in Experiment 1 (Panel A) and Experiment 2 (Panel B). Error bars represent ±1 standard error of the mean.

For overall recognition accuracy, the ICC for the participant random intercept effect was 0.38 and for the item random intercept effect was 0.17. Assigned value (*OR* = 1.24, *SE* = 0.07, 95% CI: 1.08–1.41, *z* = 3.11, *p* = .002) was a significant predictor of recognition accuracy. Items with high assigned value had greater recognition accuracy compared to items with low assigned value. Predicted value (*OR* = 1.20, *SE* = 0.07, 95% CI: 1.05–1.38, *z* = 2.58, *p* = .01) was also a significant predictor of recognition accuracy such that items with high predicted value had greater recognition accuracy compared to items with low predicted value. Furthermore, the overall effect of list, $X^2(2) = 52.60$, $p < .001$, significantly predicted recognition accuracy, such that more items were correctly remembered on List 1 than List 2 (*OR* = 1.53, *SE* = 0.13, *z* = 5.02, *p* < .001), and than items on List 3 (*OR* = 1.82, *SE* = 0.15, *z* = 7.15, *p* < .001), but recognition accuracy did not differ between List 2 and List 3 (*OR* = 1.19, *SE* = 0.09, *z* = 2.20, *p* = .08).

Additionally, there was a significant interaction between predicted value and assigned value (*OR* = 0.67, *SE* = 0.14, 95% CI: 0.51–0.87, *z* = −2.98, *p* = .003). Bonferroni-corrected post-hoc tests showed that when predicted value was low, items with high assigned value had greater recognition accuracy compared to items with low assigned value (*OR* = 0.66, *SE* = 0.06, *z* = −4.29, *p* < .001). However, when predicted value was high, there was no difference in recognition between high and low assigned value items (OR = 0.99, SE = 0.10, z = −0.09, *p* > .99). Additionally, items with higher predicted and assigned value had greater recognition accuracy compared to items with low predicted and assigned value (*OR* = 0.67, *SE* = 0.06, *z* = −4.11, *p* < .001). No other interactions were significant (all *p*s > .265).

As a sidenote, recognition confidence was not a main variable of interest in this study and thus is not reported in the paper. However, we have included the results in the Supplemental Material with means and standard deviations reported in Table S1.

Remember-know responses

The average proportion of remember responses is shown in Figure 3A, and all means and standard deviations are reported in Table 1.

For remember responses, the ICC for the participant random intercept effect was 0.51 and for the item random intercept effect was 0.12. The results showed that assigned value was a significant predictor of remember responses (*OR* = 1.27, *SE* = 0.07, 95% CI: 1.11–1.46, *z* = 3.47, *p* < .001), such that items with high assigned value had greater likelihood of receiving a remember response compared to items with low assigned value. List was also a significant predictor, $X^2(2) = 31.69$, $p < .001$. Items on List 2 (*OR* = 0.75, *SE* = 0.06, *z* = −3.48, *p* = .002) and List 3 (*OR* = 0.63, *SE* = 0.05, *z* = −5.52, *p* < .001) had greater likelihood of remember responses compared to List 1, but there were no significant differences between List 2 and List 3 (*OR* = 0.84, *SE* = 0.07, *z* = −2.04, *p* = .124). Predicted value was not a significant predictor (*OR* = 1.04, *SE* = 0.07, 95% CI: 0.90–1.20, *z* = 0.55, *p* = .584). Analyses also showed no significant interaction between predicted value and assigned value (*OR* = 0.88, *SE* = 0.14, 95% CI: 0.67–1.15, *z* = −0.92, *p* = .356). Other higher-order interactions did not yield any significant differences (all *p*s > .153).

The average proportion of know responses is shown in Figure 4A. Means and standard deviations of the proportion of know responses are included in Table 1. The proportion of remember and know responses were not perfectly proportional because of the inclusion of the "Guess" response, so we examine the two outcomes separately. The ICC for the participant random intercept effect was 0.47 and was 0.06 for the item random intercept effect. Results showed that assigned value was a significant predictor (*OR* = 0.83, *SE* = 0.07, 95% CI: 0.72–0.96, *z* = −2.61, *p* = .009), such that items with low assigned value had greater likelihood of receiving a know response compared to items with high assigned value. List was a significant predictor as well, $X^2(2) = 33.54$, $p < .001$. The likelihood of know responses were greater in List 1 than List 2

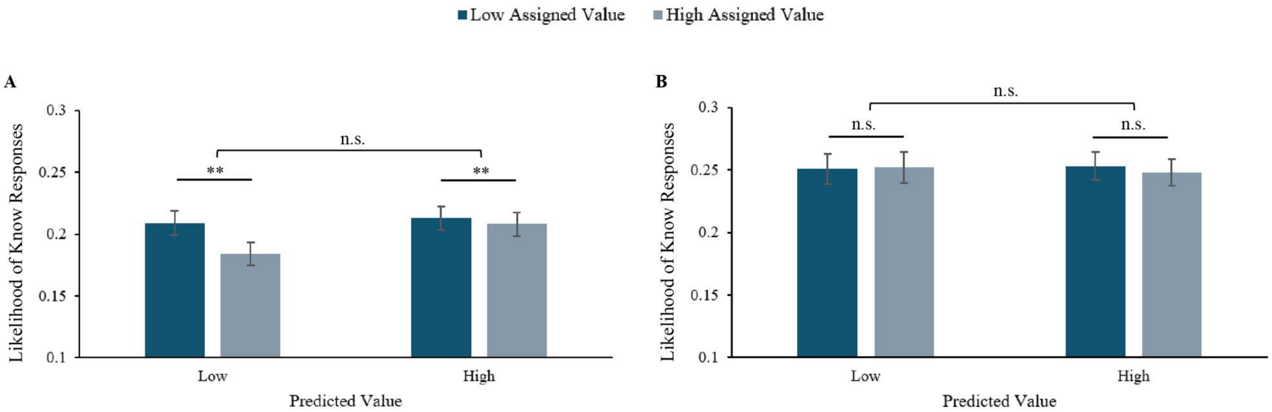

Figure 4. Likelihood of know responses in Experiments 1 and 2.

Notes: The average likelihood of know responses is shown for low and high predicted and assigned value in Experiment 1 (Panel A) and Experiment 2 (Panel B). Error bars represent ±1 standard error of the mean.

Table 2. Mean (and standard deviation) of categorical price memory.

	Experiment 1					
	Assigned Value					
	List 1		List 2		List 3	
	Low	High	Low	High	Low	High
Low Predicted	0.87 (0.34)	0.85 (0.36)	0.83 (0.37)	0.87 (0.34)	0.80 (0.40)	0.86 (0.35)
High Predicted	0.82 (0.39)	0.88 (0.33)	0.81 (0.39)	0.83 (0.37)	0.80 (0.40)	0.87 (0.33)
	Experiment 2					
	Assigned Value					
	List 1		List 2		List 3	
	Low	High	Low	High	Low	High
Low Predicted	0.68 (0.47)	0.53 (0.50)	0.65 (0.48)	0.63 (0.48)	0.67 (0.47)	0.63 (0.48)
High Predicted	0.62 (0.49)	0.66 (0.47)	0.61 (0.49)	0.68 (0.47)	0.57 (0.50)	0.72 (0.45)

($OR = 1.44$, $SE = 0.12$, $z = 4.32$, $p < .001$) and List 3 ($OR = 1.59$, $SE = 0.14$, $z = 5.36$, $p < .001$), but there was no significant difference between List 2 and List 3 ($OR = 1.10$, $SE = 0.10$, $z = 1.06$, $p = .873$). Predicted value was not a significant predictor of remember responses ($OR = 1.03$, $SE = 0.07$, 95% CI: 0.89–1.19, $z = 0.39$, $p = .698$), and no interactions in the model were significant (all $ps > .319$).

Memory of assigned value

Overall accuracy for the exact value was low ($M = 0.21$), so memory of assigned value was coded categorically as whether the recalled value was within the correct range. Means and standard deviations are reported in Table 2.

For the likelihood of correct memory of each item's assigned value, the ICC for the participant random intercept effect was 0.12 and was 0.07 for the item random intercept effect. Assigned value was a significant predictor of memory for the value category ($OR = 1.36$, $SE = 0.07$, 95% CI: 1.19–1.55, $z = 4.45$, $p < .001$), such that memory accuracy was greater for items with higher assigned value than items with lower assigned value. List was also a significant predictor, $X^2(2) = 7.41$, $p = .025$. Items on List 1 had higher memory accuracy compared to items on List 3 ($OR = 1.22$, $SE = 0.10$, $z = 2.40$, $p = .05$), but there were no differences between List 1 and List 2 ($OR = 1.22$, $SE = 0.10$, $z = 2.33$, $p = .06$), and between List 2 and List 3 ($OR = 1.01$, $SE = 0.08$, $z = 0.08$, $p > .99$). Predicted value was not a significant predictor of value memory ($OR = 0.97$, $SE = 0.07$, 95% CI: 0.84–1.12, $z = -0.43$, $p = .668$). Higher-order interactions did not yield any significant differences (all $ps > .116$).

Confidence in assigned value is not reported here as it was not a primary variable of interest, but we have included the results in the Supplemental Material with means and standard deviations reported in Table S2.

Reward prediction errors

Next, looking at the likelihood of correct recognition accuracy as a function of reward prediction error and list, the ICC for the participant random intercept effect was 0.38, and the ICC for the item random intercept effect was 0.17. The model revealed that type of prediction error, $X^2(2) = 8.99$, $p = .01$, significantly predicted recognition accuracy. Specifically, items with positive RPEs had greater recognition accuracy compared to items with no RPEs ($OR = 0.80$, $SE = 0.07$, $z = -2.65$, $p = .024$). Items with negative RPEs also had greater recognition accuracy compared to items with no RPEs, $OR = 0.84$, $SE = 0.07$, $z = 2.12$, but this

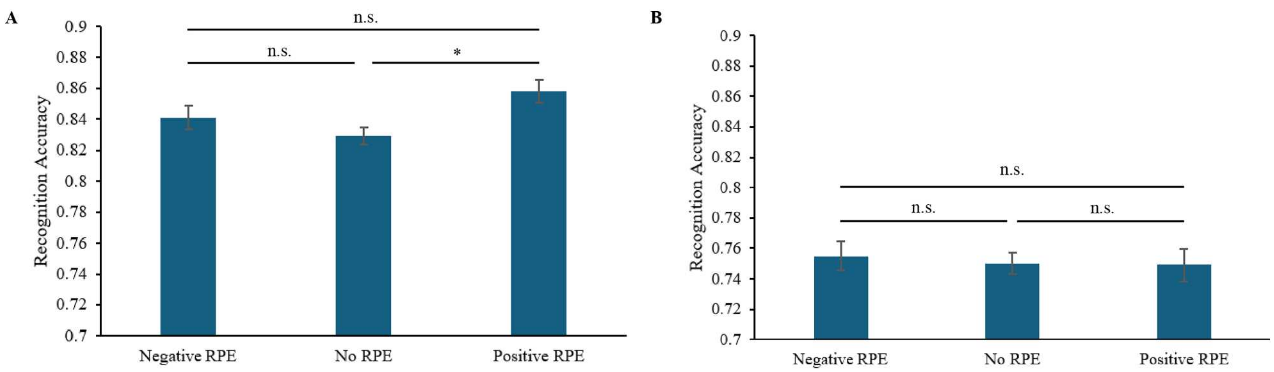

Figure 5. Recognition accuracy across different types of reward prediction error.

Notes: The recognition accuracy is shown for different types of reward prediction error (negative, none, positive) in Experiment 1 (Panel A) and Experiment 2 (Panel B). Error bars represent ±1 standard error of the mean.

finding was not significant when accounting for multiple comparisons, $p = .102$. There was no difference in recognition accuracy between items with positive RPEs and negative RPEs, $OR = 1.05$, $SE = 0.11$, $z = 0.50$, $p > .999$ (see Figure 5A).

Furthermore, list was a significant predictor of recognition accuracy, $X^2(2) = 46.33$, $p < .001$. There was greater recognition accuracy in List 1 compared to List 2 ($OR = 1.57$, $SE = 0.14$, $z = 4.98$, $p < .001$) and List 3 ($OR = 1.82$, $SE = 0.16$, $z = 6.64$, $p < .001$). Recognition accuracy did not differ between List 2 and List 3 ($OR = 1.16$, $SE = 0.10$, $z = 1.74$, $p = .245$). The interaction between list and RPE was not significant, $X^2(4) = 2.10$, $p = .718$.

RPEs and remember and know responses

We next examined remember and know responses as a function of RPEs and List, and the ICC for the remember analysis was 0.51 for the participant random intercept effect and was 0.11 for the item random intercept effect. The results of the model showed a significant effect of list on remember responses, $X^2(2) = 29.37$, $p < .001$, which matched the effect of list on remember responses reported earlier. The effect of prediction error was marginally significant, $X^2(2) = 5.28$, $p = .071$, such that positive prediction errors resulted in slightly greater likelihood of remember responses than no PE ($OR = 1.18$, $SE = 0.09$, $z = 1.95$, $p = .051$), while there was no difference between negative PEs and no PEs ($OR = 0.95$, $SE = 0.08$, $z = -0.55$, $p = .583$).

Looking next at know responses, the ICC for the participant random intercept effect was 0.47, while for the item random intercept effect, it was 0.06. The results showed a significant effect of list on know responses, $X^2(2) = 29.22$, $p < .001$, matching that described earlier. The effect of prediction error was marginally significant, $X^2(2) = 4.97$, $p = .083$. Positive PEs resulted in somewhat fewer know responses ($OR = 0.86$, $SE = 0.09$, $z = -1.34$, $p = .082$), while there was no difference in negative PEs and no PE ($OR = 1.07$, $SE = 0.09$, $z = 0.78$, $p = .438$). The interaction between list and RPE was not significant, $X^2(4) = 3.18$, $p = .529$.

Discussion

In Experiment 1, we found that recognition memory was higher for items that participants predicted to be of high value, and that participants did not "overcome" this initial value judgment to successfully update their memory with the assigned value unless the predicted value was initially low. In other words, the results suggest that either form of value (predicted or assigned) being high resulted in better recognition memory. Further, we found evidence that high assigned value led to more recollection experiences and fewer familiarity experiences.

Experiment 1 also revealed that the type of prediction error may influence recognition memory. Specifically, participants showed better recognition memory for prediction errors that were positive (i.e., had a higher assigned value than the initial predicted value) and negative (i.e., had a lower assigned value than the initial predicted value) compared to when there was no prediction error, however the latter did not reach statistical significance when accounting for multiple comparisons. This finding suggests that any difference between expected and assigned value may improve memory performance, possibly through more surprise mechanisms than a focus on the ultimate achieved value.

However, in Experiment 1, recognition rates were overall fairly high and rates of false alarms were low. Therefore, some of our effects (or lack of effects) may have been influenced by a possible ceiling effect. Thus, in Experiment 2, we sought to address the rates of recognition and false alarms.

Experiment 2

In Experiment 2, we sought to replicate our findings from Experiment 1 and to lower the overall recognition rate, as it was fairly high in Experiment 1. One possibility for why recognition rates were high in Experiment 1 was that the stimuli were highly diverse and unique, which could have reduced pressure to prioritise some information in memory and made recollection rates higher. In order to address this issue, we decided to use the stimuli from Kornell and Bjork (2008), which showed participants landscape paintings from 12 artists. Because these works are more similar overall (i.e., all being paintings and depicting landscapes) and there were multiple examples from each artist, which should introduce more potential interference, we expected recognition rates and recollection rates to be reduced. The procedure was otherwise the same as Experiment 1, and we again examined overall recognition accuracy, remember/know responses, memory for the value, and reward prediction errors as a function of participants' value predictions, assigned value, and list. We also examined confidence ratings, which are included in the Supplementary Materials.

Method

Participants

Following Experiment 1, we conducted an *a priori* power analysis for Experiment 2 using the effect size for the interaction between predicted and assigned value. The power analysis, using G*Power (Faul et al., 2007), for a within-subjects ANOVA with effect size, *f*, of 0.14 showed that we needed a sample size of 109. Because of the number of exclusions in Experiment 1, we overrecruited. A total of 138 undergraduate students recruited from the UCLA psychology subject pool took part in Experiment 2, with 86 females, 22 males, and one participant who did not identify as either gender. Of these 138, six were excluded for not being within the 18–30 year age range, and three were excluded for responding "new" during the recognition test more than 75% of the time or less than 25% of the time. The final sample thus consisted of 129 participants. Participants ranged in age from 18 to 30 years ($M = 20.19$, $SD = 1.52$). Participants earned coursework credit or extra credit as part of their participation. This study was approved by the IRB, and informed consent was obtained.

Materials

Stimuli consisted of 120 landscape and skyscape paintings, with 10 paintings from each of the following 12 artists: Georges Braque, Henri-Edmond Cross, Judy Hawkins, Philip Juras, Ryan Lewis, Marilyn Mylrea, Bruno Pessani, Ron Schlorff, Georges Seurat, Ciprian Stratulat, George Wexler, and YieMei. These stimuli were taken from Kornell and Bjork (2008) and have been shown to elicit reasonable recognition rates. In our study, five paintings from each artist were presented during the study phase, and the other five served as lures during the test phase, and the set of five paintings that was presented during the study phase versus the test phase was counterbalanced across participants. As in Experiment 1, all paintings were presented on a blank white computer screen and were standardised in size to a height of 350 pixels, regardless of shape. The price range for low art values and high art values were also similar to that of Experiment 1. Two paintings were excluded from analysis due to experimenter error, as one was mistakenly presented twice and the other not presented at all.

Procedure

Study procedures were similar to that of Experiment 1 except for the following changes. First, there were 60 paintings presented in the study phase and 120 paintings (60 previously studied items and 60 lure items) in the test phase. This was due to prior studies only having 120 stimuli available (Kornell & Bjork, 2008). Additionally, after participants made a selection on whether they think the painting was of low-value or high-value during the study phase, rather than showing the painting again along with the true selling price, participants were only shown the true selling price. This change was made to reduce recognition compared to Experiment 1. Lastly, after rating paintings as new during the test phase, rather than proceeding to the next painting, participants were prompted for their rating of how much they liked the painting and for the value they thought the painting would be worth. This change was made to disincentivize participants from selecting "New" more often to complete the study faster. As in Experiment 1, participants completed an informed consent form by checking a box indicating their agreement to participate. Participants then reported demographic information before receiving the same instructions as in Experiment 1. Next, participants completed three study phases, each followed by a 5-min simple arithmetic distraction phase and a test phase. Finally, participants reported whether they had completed the study or a similar study before, whether they were doing anything else during the study, and whether they had experienced any disruptions to the study (e.g., having to reload a page or having to restart the study).

Data analysis

Consistent with Experiment 1, we examined overall recognition accuracy, remember and know responses, participants' memory of assigned value, and the influence of reward prediction errors on recognition accuracy using a similar logisitc mixed effects model as described in Experiment 1 with Bonferroni corrections used for post-hoc tests.

Results

Overall recognition accuracy

As in Experiment 1, recognition accuracy was calculated as the average number of correct old/new responses (i.e., including hits and correct rejections). Across all participants and items presented, there were 51.9% of old responses and 48.1% of new responses. The overall rate of recognition accuracy was 73.45%, which was lower than that of Experiment 1, likely due to the use of different materials. The overall false alarm rate was

28.24% out of the possible false alarms. Items that appeared as lures during testing but were not shown during study did not receive value predictions and were not associated with an assigned value. Thus, in all analyses that include predicted or assigned value, only items that were shown at study are included. For only items that were shown at study (i.e., including hits and misses), the rate of recognition accuracy was 75.24%. Average recognition accuracy is shown in Figure 2B, and all means and standard deviations are included in Table 1. Additionally, participants predicted 45.13% of items to be of low value and 54.87% of items to be of high value. The cell sizes for all conditions are shown in Table 1.

For overall recognition accuracy, the ICC for the participant random intercept effect was 0.15 and for the item random intercept effect was 0.06. Predicted value (OR = 1.17, SE = 0.06, 95% CI: 1.04–1.31, p = .008) was a significant predictor of recognition accuracy. There was greater recognition accuracy for items with high assigned value than items with low assigned value. List was also a significant predictor, $X^2(2) = 21.93$, $p < .001$. Items on List 2 (OR = 0.78, SE = 0.05, z = −3.67, $p < .001$) and List 3 (OR = 0.74, SE = 0.05, z = −4.29, $p < .001$) had greater recognition accuracy compared to items on List 1. There was no significant difference in accuracy between List 2 and List 3 (OR = 0.96, SE = 0.07, z = −0.65, $p > .999$). Unlike in Experiment 1, we did not find that assigned value was a significant predictor of recognition accuracy (OR = 1.08, SE = 0.06, 95% CI: 0.97–11.21, z = 1.33, p = .183), and there was no significant interaction between predicted value and assigned value (OR = 0.97, SE = 0.11, 95% CI: 0.78–1.22, z = −0.25, p = .803). Additionally, there was no significant interaction between list and predicted value, $X^2(2) = 2.88$, p = .237, nor between list and assigned value, $X^2(2) = 2.29$, p = .319. Lastly, the three-way interaction was not significant, $X^2(2) = 1.91$, p = .386.

Results on recognition confidence can be found in the Supplemental Materials with means and standard deviations reported in Table S1.

Remember-know responses

The average proportion of remember responses is depicted in Figure 3B, and all means and standard deviations are included in Table 1. The ICC for the participant random intercept effect was 0.33 and for the item random intercept effect was 0.07 for likelihood of remember responses.

The analysis revealed that predicted value was a significant predictor (OR = 1.19, SE = 0.07, 95% CI: 1.04–1.35, z = 2.62, p = .009), such that there was greater likelihood of remember responses for items with high predicted value than items with low predicted value. List was also a significant predictor, $X^2(2) = 61.37$, $p < .001$. Assigned value was not a significant predictor of remember responses (OR = 1.13, SE = 0.06, 95% CI: 1.00–1.28, z = 1.90, p = .058). Furthermore, we found a significant interaction between predicted value and list, $X^2(2) = 6.56$, p = .038. There were no significant differences in remember responses between items with low and high predicted value on List 1 (OR = 1.06, SE = 0.11, 95% CI: 1.85–1.31, z = 0.49, p = 0.63) or on List 2 (OR = 1.06, SE = 0.11, 95% CI: 0.85–1.31, z = 0.50, p = 0.62). On List 3, participants reported higher remember responses for items with high predicted value compared to items with low predicted value (OR = 1.50, SE = 0.11, 95% CI: 1.20–1.87, z = 3.57, $p < .001$). Additionally, there was a significant three-way interaction between assigned value, predicted value, and list, $X^2(2) = 9.79$, p = .007. The interaction between assigned value and predicted value was significant in List 1, $X^2(1) = 4.24$, p = .04, but post-hoc test showed that none of the interactions were significant after correcting for multiple comparison (all Bonferroni ps > 0.50). The interaction was not significant in List 2, $X^2(1) = 1.74$, p = .19. However, the interaction was revealed to be significant in List 3, $X^2(1) = 4.52$, p = .03. Specifically, for items with low assigned value, items with high predicted value received greater remember responses than items with low predicted value (OR = 0.50, SE = 0.09, z = −4.03, $p < .001$). For items with high assigned value, there were no significant differences in remember responses (OR = 0.83, SE = 0.14, z = −1.11, $p > .99$). No other interactions in the model were significant (all ps > .260).

We also examined participants' "Know" or K responses. Again, the proportion of R responses and K responses were not perfectly proportional because of the inclusion of the "Guess" response. Therefore, we examine the two outcomes separately. The means and standard deviations of the proportion of know responses are included in Table 1. The average proportion of know responses is depicted in Figure 4B. We conducted a similar Generalized Linear Model as the previous with the outcome being likelihood of responding "know" for each item. The ICC for the participant random intercept effect was 0.24, while for the item random intercept effect, it was 0.01. The analysis revealed that list was a significant predictor of know responses, $X^2(2) = 25.83$, $p < .001$. There was a greater likelihood of know responses on List 1 compared to List 2 (OR = 1.31, SE = 0.11, z = 3.36, p = .002) and List 3 (OR = 1.51, SE = 0.12, z = 4.96, $p < .001$), but there was no difference between List 2 and List 3 (OR = 1.15, SE = 0.09, z = 1.66, p = .289). Assigned value (OR = 0.96, SE = 0.06, 95% CI: 0.84–1.10, z = −0.59, p = .56) and predicted value (OR = 0.98, SE = 0.07, 95% CI: 0.86–1.12, z = −0.34, p = .736) were not significant predictors of know responses. No interactions in the model were significant (all ps > .071).

Memory for assigned value

As in Experiment 1, memory for the exact price of each item was overall fairly low (M = 0.08), so we examined memory for price in a categorical way, as measured by whether participants' memory for the price fell into the "low value" or "high value" category. On this categorical measure, responses were scored as correct if their memory for the price was within the correct value category (i.e., "low value" = less than or equal to $25,000; "high value" = greater than or equal to \$100,000). Means and standard deviations for this measure are shown in Table 2.

The analysis predicting the likelihood of correctly remembering each item's value category as a function of predicted value, assigned value, and list had an ICC of 0.06 for the participant random intercept effect, and an ICC of 0.01 for the item random intercept effect. The analysis revealed that neither predicted value ($OR = 1.04$, $SE = 0.05$, 95% CI: 0.94–1.16, $z = 0.80$, $p = .423$) nor assigned value ($OR = 1.06$, $SE = 0.05$, 95% CI: 0.95–1.17, $z = 1.05$, $p = .294$), were significant predictors. There was, however, a significant interaction between predicted and assigned value ($OR = 2.16$, $SE = 0.11$, 95% CI: 1.76–2.66, $z = 7.27$, $p < .001$), such that for items with low assigned value, categorical value memory was higher for items with low predicted value than items with high predicted value ($OR = 1.41$, $SE = 0.11$, $z = 4.51$, $p < .001$). For items with high assigned value, categorical value memory was higher for items with low predicted value than items with high predicted value ($OR = 0.65$, $SE = 0.05$, $z = -5.69$, $p < .001$). In other words, when the assigned value of items was high, memory for the value was improved only if participants had predicted the value to be high.

List was not a significant predictor, $X^2(2) = 3.31$, $p = .192$. However, the interaction between assigned value and list was significant, $X^2(2) = 16.95$, $p < .001$. No other interactions in the model were significant (all ps $> .132$).

Results on confidence in assigned value memory can be found in the Supplemental Materials with means and standard deviations reported in Table S2.

Reward prediction errors

To examine the effect of RPEs on recognition memory, we conducted a logistic mixed effects model as described earlier. The ICC for the participant random intercept effect was 0.15 and for the item random intercept effect was 0.07. Recognition accuracy across different types of prediction error is depicted in Figure 5B. Prediction error was not a significant predictor of recognition accuracy, $X^2(2) = 0.80$, $p = .671$. However, list was a significant predictor, $X^2(2) = 23.28$, $p < .001$, which aligned with the GLM on overall recognition accuracy reported above. Lastly, the interaction between prediction errors and list was not significant, $X^2(4) = 2.23$, $p = .694$. Thus, in Experiment 2, we did not find differences in recognition accuracy as a function of participants' prediction errors.

RPEs and remember and know responses

Next, we analysed the likelihood of remember and know responses as a function of RPEs and List, as described in the analysis plan above. For remember responses, the ICC for the participant random intercept effect was 0.34 and for the item random intercept effect was 0.07. The model revealed no significant effect of prediction error, $X^2(2) = 0.23$, $p = .889$. There was a significant effect of list, $X^2(2) = 73.53$, $p < .001$, which aligned with the results of the previously reported analysis. Lastly, there was a significant interaction between list and prediction errors, $X^2(4) = 11.35$, $p = .023$, such that, examining simple effects, the likelihood of remember responses was higher on List 1 when there was no prediction error than when there was a positive prediction error ($OR = 0.74$, $SE = 0.14$, $z = -2.13$, $p = .033$), but not when there was a negative prediction error ($OR = 0.80$, $SE = 0.13$, $z = -1.66$, $p = .097$). On List 2, neither positive ($OR = 1.20$, $SE = 0.14$, $z = 1.33$, $p = .184$) nor negative ($OR = 1.03$, $SE = 0.13$, $z = 0.26$, $p = .799$) prediction errors resulted in different recognition accuracy from no prediction error. On List 3, positive prediction errors did not differ from no prediction error ($OR = 1.07$, $SE = 0.14$, $z = 0.50$, $p = 618$), but negative prediction errors resulted in more remember responses than no prediction error ($OR = 1.31$, $SE = 0.13$, $z = 2.05$, $p = .040$). Taken together, no RPE resulted in greater likelihood of remember responses on List 1, and by List 3, negative prediction errors were more predictive of remember responses, though these effects were small.

Next, looking at know responses, the ICC for the participant random intercept effect was 0.24, while for the item random intercept effect, it was 0.01. The model revealed no significant effect of prediction error on know responses, $X^2(2) = 0.05$, $p = .976$, but there was a significant effect of list, $X^2(2) = 32.61$, $p < .001$, which aligned with previous results on know responses. The interaction between list and prediction error was not significant, $X^2(4) = 5.20$, $p = .267$.

Discussion

In Experiment 2, we replicated the finding that predicted value was a significant influence on overall recognition accuracy. While we did not find an interaction between predicted and assigned value, the results showed that predicted value was a stronger influence on memory than assigned value, suggesting that participants may have focused more on predicted value or that it was difficult to overwrite the predicted value once learned. This general pattern is consistent with the results of Experiment 1.

Additionally, we found evidence that the likelihood of remember responses was higher for high predicted value items than low predicted value items. This finding replicates prior work (Hennessee et al., 2017) and was likely detectable in Experiment 2 because of the reduced overall recognition rate. It also extends prior work by showing that making a prediction of an item can further influence the quality of memory processes, either at encoding or retrieval. Specifically, predicting an item to be of high value may lead to similar processes as simply learning that an item is worth a high value. This presents an important direction for future work on value-directed remembering. However, the finding that items with high assigned value had greater proportion of remember responses was not replicated. Furthermore, results showed that the main effect of predicted value and the interaction effect between predicted value and assigned value was only significant in List 3, suggesting that it may take more experience with the task for participants' recollection performance to be sensitive to value.

Lastly, we did not replicate the finding that prediction errors led to improvements in memory. It is possible that this finding is simply not as reliable or that some aspect of the materials (e.g., greater interference) could influence the extent to which prediction errors influence memory performance.

General discussion

The present study aimed to examine the effects of predicted value and experimenter-assigned assigned value, as well as the effects of reward prediction errors, on recognition memory. We utilised a more naturalistic value-directed remembering paradigm using art pieces, which have varying values, to explore our research questions. Participants were tested on their recognition of the art pieces over multiple study-tests lists, which allowed us to assess differences in recollection and familiarity, as well as changes in these processes with task experience. In Experiment 1, participants studied various art pieces, including sculptures, paintings, and mixed media art, whereas in Experiment 2, participants studied landscape paintings from Kornell and Bjork (2008). We found evidence across both experiments that recognition memory was better for items predicted to be of high value than for items predicted to be of low value. This finding extends those from prior VDR studies, which have found memory selectivity for information judged to be more valuable (McGillivray & Castel, 2017; Murphy & Castel, 2021) and that we are told is more valuable (Castel et al., 2002; Middlebrooks et al., 2017; Robison & Unsworth, 2017; Spaniol et al., 2014).

In terms of memory updating, our findings suggested that initial value information may be difficult to overwrite. In Experiment 1, we found that when initial value judgments were low, assigned value was prioritised, whereas when initial value judgments were high, assigned value did not significantly influence recognition memory. However, in Experiment 2, we did not find this pattern. Rather, only high predicted value items were prioritised in memory. The study, by design, incentivized participants to update their memory of predicted value with the assigned value to accumulate points, as this is how they were to earn their point reward. We can only speculate about reasons why memory updating was less successful in Experiment 2, but it is possible that there was greater interference, given that the stimuli were more homogeneous (a choice made to reduce recognition rates). Taken together, the findings from both experiments suggest that, in this experimental design, making a value judgment may have influenced the ability to update memory when learning assigned value later. This lends some support for the idea that an initial value judgment may be processed somewhat automatically, reducing the ability to update memory, similar to that of a directed forgetting paradigm (see Hennessee et al., 2019). Future work will be required to make stronger claims concerning the automatic influence of predicted value on memory.

There are a few potential explanations for the finding that predicted value was a more reliable predictor of recognition memory than experimenter assigned value. First, it could reflect that our own predictions may be deemed more important or motivating than an arbitrary assigned value. Research shows that when participants make judgments of importance for to-be-learned information, they tend to remember the higher importance items at a higher rate (Murphy & Castel, 2021). In the present study, our design lends itself to participants making an evaluative judgment about the value of different art, which could act as a subjective rating of importance or value metric that is especially motivating. Alternatively, it could suggest that the processing of the initial value information is difficult to overwrite. More specifically, past work has found that when participants are asked to forget items of either high or low value, those with high value are remembered at a higher rate than those with low value on a later recognition test (Hennessee et al., 2019). This work suggests that processing high value items (regardless of where the value information is from) may lead to persistent memory that is not easily forgotten, providing further support for value (even in predicted form) having more automatic effects on memory. However, it is important to note that in our study, there is no condition in which the assigned value is shown before participants make their own value judgment (as this would likely influence their judgments). Therefore, we cannot disentangle the influence of value more broadly (i.e., which value does a participant learn first?) from that of the source of the value (i.e., participants' judgments vs. experimenter assigned).

One goal of the current research was also to determine how predicted and assigned value would influence the quality of memory. In terms of recollection and familiarity processes as a function of predicted and assigned value, Experiment 1 showed that higher assigned value was associated with more recollection and fewer familiarity responses, and in Experiment 2, assigned value had a marginal effect on recollective processes, while higher predicted value was associated with more recollection. However, value did not predict familiarity responses in Experiment 2. These findings show that value, either predicted or assigned value, may have a more automatic influence on memory, as value is thought to improve detailed episodic memory more automatically (Elliott et al., 2020; Hennessee et al., 2017). Specifically, dopaminergic processes are thought to drive these more automatic influences of value on memory (Elliott et al., 2022; Shigemune et al., 2014; Wittmann et al., 2005; Wolosin et al., 2012), and our results lend support for this hypothesis. It is also worth noting that we predicted that the inclusion of multiple study-test lists with feedback may encourage more strategic processing of value (and thus greater influence of value on familiarity as well as recollection) across lists. In Experiment 1, we did not find interactions with the list variable, but in Experiment 2, the three-way interaction between assigned value, predicted value, and list was significant. This interaction, though difficult to interpret, suggested that early in the task, alignment of predicted and assigned value resulted in more recollective experiences. However, later in the task, recollective responses were greatest when either form of value was high. Thus, participants may have shifted their strategy throughout the task, prioritising the goals of the task and overriding some automatic influences on recollection.

Another goal of the research was to examine how reward prediction errors play a role in recognition. Results from Experiment 1 revealed that positive reward prediction errors led to better recognition than no prediction error, while negative reward prediction errors also led to numerically higher recognition rates, but did not reach statistical significance while accounting for multiple comparisons. This result is in line with some prior work (Rouhani et al., 2018, 2020) and supports the idea that RPEs present at reward outcome may have an unsigned effect on memory (Rouhani & Niv, 2021; Stanek et al., 2019), though future work will need to confirm these effects. We did not find an effect of RPEs on memory in Experiment 2. While it is not entirely clear why participants in Experiment 2 could be struggling to update their memory with the assigned value, again there could be differences due to the materials, in that stimuli in Experiment 1 were more diverse, whereas in Experiment 2, stimuli were more similar. We did find that participants predicted a greater proportion of items to be of high value in Experiment 2, whereas value predictions were more balanced in Experiment 1, which could have impacted the ability to detect differences.

We also examined the extent to which RPEs influence the quality and depth of memory by examining differences in remember and know responses. In Experiment 1, the effects of prediction errors on remember and know responses did not reach statistical significance, but analyses of the marginal effects suggested that positive prediction errors may result in more recollective experiences and fewer familiarity experiences. These potential effects suggest that positive prediction errors may have resulted in more automatic processing of value, with specific benefits for recollection at the expense of familiarity. However, in Experiment 2, we found that the effect of RPEs on recollective experiences changed across lists, with lack of prediction errors leading to the most remember responses on List 1 and negative prediction errors being more influential on List 3. The effects in Experiment 2 suggest that participants may have adjusted their strategy throughout the task, leading to inconsistencies in which type of prediction error influences recollection. Taken together, RPEs likely do influence recollection and familiarity processes, but future research will need to confirm the nature of these effects.

Our study has provided several important insights into how value influences memory. However, there are several limitations that are important to discuss. One limitation is our measurement of recognition performance in our study, where we were only able to measure how well participants identified art pieces that they previously studied as old. We were unable to consider false alarms as a function of our variables, because we did not collect participants' predicted value for these art pieces, and they had no assigned value. Therefore, we were unable to calculate recognition performance using the signal detection theory framework that is more common in other literature on recognition memory. However, our approach was in line with other work (e.g., Rouhani et al., 2018), and false alarms were overall fairly low ($M_{Exp1} = .07$; $M_{Exp2} = .28$). Another limitation is that our RPE measure was categorical. Predicted value was measured as a categorical variable in our study. As a result, we were unable to examine and conclude how the magnitude of prediction error (i.e., how far off the participants' predictions were from the assigned value) impacts memory performance. Future studies could seek to examine this by measuring predicted value as a numeric variable.

Overall, the current study has contributed to research on value-directed remembering. It reveals that when making a prediction about the value of to-be-learned information, memory selectivity is driven by these predictions. Furthermore, it may be difficult to update memory when learning an assigned or assigned value after making a prediction. Future studies are needed to replicate this finding and clarify the specific mechanisms underlying this phenomenon. This study also contributes to the literature on VDR, examining the influence of value on the type and depth of encoding and retrieval processes to show that we engage in deeper encoding processes for high-value stimuli compared to low-value stimuli, regardless of whether the value is participant assigned or experimenter assigned. Taken together, these findings suggest that evaluative judgments of value may influence the way we remember information and its assigned value, which has implications for theory on value-directed remembering and also everyday settings in which remembering value is important to our goals.

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References

Adcock, R. A., Thangavel, A., Whitfield-Gabrieli, S., Knutson, B., & Gabrieli, J. D. E. (2006). Reward-motivated learning: Mesolimbic activation precedes memory formation. *Neuron*, *50*(3), 507–517. https://doi.org/10.1016/j.neuron.2006.03.036

Bromberg-Martin, E. S., Matsumoto, M., & Hikosaka, O. (2010). Dopamine in motivational control: Rewarding, aversive, and alerting. *Neuron*, *68*(5), 815–834. https://doi.org/10.1016/j.neuron.2010.11.022

Castel, A. D. (2007). The adaptive and strategic use of memory by older adults: Evaluative processing and value-directed remembering. In A. S. Benjamin & B. H. Ross (Eds.), *Psychology of learning and motivation* (Vol. 48, pp. 225–270). Academic Press. https://doi.org/10.1016/S0079-7421(07)48006-9

Castel, A. D., Benjamin, A. S., Craik, F. I. M., & Watkins, M. J. (2002). The effects of aging on selectivity and control in short-term recall. *Memory & Cognition*, *30*(7), 1078–1085. https://doi.org/10.3758/BF03194325

Cohen, M. S., Rissman, J., Hovhannisyan, M., Castel, A. D., & Knowlton, B. J. (2017). Free recall test experience potentiates strategy-driven effects of value on memory. *Journal of Experimental Psychology. Learning, Memory, and Cognition*, *43*(10), 1581–1601. https://doi.org/10.1037/xlm0000395

Cohen, M. S., Rissman, J., Suthana, N. A., Castel, A. D., & Knowlton, B. J. (2014). Value-based modulation of memory encoding involves strategic engagement of fronto-temporal semantic processing regions. *Cognitive, Affective & Behavioral Neuroscience*, *14*(2), 578–592. https://doi.org/10.3758/s13415-014-0275-x

De Loof, E., Ergo, K., Naert, L., Janssens, C., Talsma, D., Van Opstal, F., & Verguts, T. (2018). Signed reward prediction errors drive declarative learning. *PLoS One*, *13*(1), e0189212. https://doi.org/10.1371/journal.pone.0189212

Dudukovic, N. M., & Knowlton, B. J. (2006). Remember–know judgments and retrieval of contextual details. *Acta Psychologica*, *122*(2), 160–173. https://doi.org/10.1016/j.actpsy.2005.11.002

Elliott, B. L., Blais, C., McClure, S. M., & Brewer, G. A. (2020). Neural correlates underlying the effect of reward value on recognition memory. *NeuroImage*, *206*, 116296. https://doi.org/10.1016/j.neuroimage.2019.116296

Elliott, B. L., & Brewer, G. A. (2019). Divided attention selectively impairs value-directed encoding. *Collabra: Psychology*, *5*(1), 4. https://doi.org/10.1525/collabra.156

Elliott, B. L., D'Ardenne, K., Murty, V. P., Brewer, G. A., & McClure, S. M. (2022). Midbrain-hippocampus structural connectivity selectively predicts motivated memory encoding. *The Journal of Neuroscience: The Official Journal of the Society for Neuroscience*, *42*(50), 9426–9434. https://doi.org/10.1523/JNEUROSCI.0945-22.2022

Ergo, K., De Loof, E., & Verguts, T. (2020). Reward prediction error and declarative memory. *Trends in Cognitive Sciences*, *24*(5), 388–397. https://doi.org/10.1016/j.tics.2020.02.009

Ergo, K., De Vilder, L., De Loof, E., & Verguts, T. (2021). Reward prediction errors drive declarative learning irrespective of agency. *Psychonomic Bulletin & Review*, *28*(6), 2045–2056. https://doi.org/10.3758/s13423-021-01952-7

Faul, F., Erdfelder, E., Lang, A.-G., & Buchner, A. (2007). G*Power 3: A flexible statistical power analysis program for the social, behavioral, and biomedical sciences. *Behavior Research Methods*, *39*(2), 175–191. https://doi.org/10.3758/BF03193146

Fernández, R. S., Boccia, M. M., & Pedreira, M. E. (2016). The fate of memory: Reconsolidation and the case of prediction error. *Neuroscience & Biobehavioral Reviews*, *68*, 423–441. https://doi.org/10.1016/j.neubiorev.2016.06.004

Gardiner, J. M. (1988). Functional aspects of recollective experience. *Memory & Cognition*, *16*(4), 309–313. https://doi.org/10.3758/BF03197041

Gardiner, J. M., Gawlik, B., & Richardson-Klavehn, A. (1994). Maintenance rehearsal affects knowing, not remembering; elaborative rehearsal affects remembering, not knowing. *Psychonomic Bulletin & Review*, *1*(1), 107–110. https://doi.org/10.3758/BF03200764

Gardner, M. P. H., Schoenbaum, G., & Gershman, S. J. (2018). Rethinking dopamine as generalized prediction error. *Proceedings. Biological Sciences*, *285*(1891), 20181645. https://doi.org/10.1098/rspb.2018.1645

Greve, A., Cooper, E., Kaula, A., Anderson, M. C., & Henson, R. (2017). Does prediction error drive one-shot declarative learning? *Journal of Memory and Language*, *94*, 149–165. https://doi.org/10.1016/j.jml.2016.11.001

Gruber, M. J., Ritchey, M., Wang, S.-F., Doss, M. K., & Ranganath, C. (2016). Post-learning hippocampal dynamics promote preferential retention of rewarding events. *Neuron*, *89*(5), 1110–1120. https://doi.org/10.1016/j.neuron.2016.01.017

Haeuser, K. I., & Kray, J. (2023). Effects of prediction error on episodic memory retrieval: Evidence from sentence reading and word recognition. *Language, Cognition and Neuroscience*, *38*(4), 558–574. https://doi.org/10.1080/23273798.2021.1924387

Hennessee, J. P., Castel, A. D., & Knowlton, B. J. (2017). Recognizing what matters: Value improves recognition by selectively enhancing recollection. *Journal of Memory and Language*, *94*, 195–205. https://doi.org/10.1016/j.jml.2016.12.004

Hennessee, J. P., Patterson, T. K., Castel, A. D., & Knowlton, B. J. (2019). Forget me not: Encoding processes in value-directed remembering. *Journal of Memory and Language*, *106*, 29–39. https://doi.org/10.1016/j.jml.2019.02.001

Jang, A. I., Nassar, M. R., Dillon, D. G., & Frank, M. J. (2019). Positive reward prediction errors during decision-making strengthen memory encoding. *Nature Human Behaviour*, *3*(7), 719–732. https://doi.org/10.1038/s41562-019-0597-3

Knowlton, B. J., & Castel, A. D. (2022). Memory and reward-based learning: A value-directed remembering perspective. *Annual Review of Psychology*, *73*(1), 25–52. https://doi.org/10.1146/annurev-psych-032921-050951

Kornell, N., & Bjork, R. A. (2008). Learning concepts and categories: Is spacing the "enemy of induction"? *Psychological Science*, *19*(6), 585–592. https://doi.org/10.1111/j.1467-9280.2008.02127.x

McGillivray, S., & Castel, A. D. (2017). Older and younger adults' strategic control of metacognitive monitoring: The role of consequences, task experience and prior knowledge. *Experimental Aging Research*, *43*(3), 233–256. https://doi.org/10.1080/0361073X.2017.1298956

Middlebrooks, C. D., Kerr, T., & Castel, A. D. (2017). Selectively distracted: Divided attention and memory for important information. *Psychological Science*, *28*(8), 1103–1115. https://doi.org/10.1177/0956797617702502

Montague, P. R., Dayan, P., & Sejnowski, T. J. (1996). A framework for mesencephalic dopamine systems based on predictive Hebbian learning. *The Journal of Neuroscience: The Official Journal of the Society for Neuroscience*, *16*(5), 1936–1947. https://doi.org/10.1523/JNEUROSCI.16-05-01936.1996

Moscovitch, M., Cabeza, R., Winocur, G., & Nadel, L. (2016). Episodic memory and beyond: The hippocampus and neocortex in transformation. *Annual Review of Psychology*, *67*(1), 105–134. https://doi.org/10.1146/annurev-psych-113011-143733

Murayama, K., & Kitagami, S. (2014). Consolidation power of extrinsic rewards: Reward cues enhance long-term memory for irrelevant past events. *Journal of Experimental Psychology: General*, *143*(1), 15–20. https://doi.org/10.1037/a0031992

Murphy, D. H., Agadzhanyan, K., Whatley, M. C., & Castel, A. D. (2021). Metacognition and fluid intelligence in value-directed remembering. *Metacognition and Learning*, *16*(3), 685–709. https://doi.org/10.1007/s11409-021-09265-9

Murphy, D. H., & Castel, A. D. (2021). Metamemory that matters: Judgments of importance can engage responsible remembering. *Memory*, *29*(3), 271–283. https://doi.org/10.1080/09658211.2021.1887895

Murphy, D. H., & Castel, A. D. (2022). The role of attention and aging in the retrieval dynamics of value-directed remembering. *Quarterly Journal of Experimental Psychology (2006)*, *75*(5), 954–968. https://doi.org/10.1177/17470218211046612

Murphy, D. H., Hoover, K. M., Castel, A. D., & Knowlton, B. J. (2025). Memory and automatic processing of valuable information in younger and older adults. *Aging, Neuropsychology, and Cognition*, *32*(1), 142–168. https://doi.org/10.1080/13825585.2024.2360226

Murphy, D. H., Rhodes, M. G., & Castel, A. D. (2024). The perceived importance of words in large font guides learning and selective memory. *Memory & Cognition*, *52*(7), 1463–1476. https://doi.org/10.3758/s13421-024-01555-2

Pearce, J. M., & Hall, G. (1980). A model for Pavlovian learning: Variations in the effectiveness of conditioned but not of unconditioned stimuli. *Psychological Review*, *87*(6), 532–552. https://doi.org/10.1037/0033-295X.87.6.532

Robison, M. K., & Unsworth, N. (2017). Working memory capacity, strategic allocation of study time, and value-directed remembering. *Journal of Memory and Language*, *93*, 231–244. https://doi.org/10.1016/j.jml.2016.10.007

Rouhani, N., & Niv, Y. (2021). Signed and unsigned reward prediction errors dynamically enhance learning and memory. *eLife*, *10*, e61077. https://doi.org/10.7554/eLife.61077

Rouhani, N., Norman, K. A., & Niv, Y. (2018). Dissociable effects of surprising rewards on learning and memory. *Journal of Experimental Psychology. Learning, Memory, and Cognition*, *44*(9), 1430–1443. https://doi.org/10.1037/xlm0000518

Rouhani, N., Norman, K. A., Niv, Y., & Bornstein, A. M. (2020). Reward prediction errors create event boundaries in memory. *Cognition*, *203*, 104269. https://doi.org/10.1016/j.cognition.2020.104269

Schultz, W. (2016). Dopamine reward prediction error coding. *Dialogues in Clinical Neuroscience*, *18*(1), 23–32. https://doi.org/10.31887/DCNS.2016.18.1/wschultz

Schultz, W. (2017). Reward prediction error. *Current Biology*, *27*(10), R369–R371. https://doi.org/10.1016/j.cub.2017.02.064

Shigemune, Y., Tsukiura, T., Kambara, T., & Kawashima, R. (2014). Remembering with gains and losses: Effects of monetary reward and punishment on successful encoding activation of source memories. *Cerebral Cortex*, *24*(5), 1319–1331. https://doi.org/10.1093/cercor/bhs415

Sinclair, A. H., & Barense, M. D. (2019). Prediction error and memory reactivation: How incomplete reminders drive reconsolidation. *Trends in Neurosciences*, *42*(10), 727–739. https://doi.org/10.1016/j.tins.2019.08.007

Sinclair, A. H., Manalili, G. M., Brunec, I. K., Adcock, R. A., & Barense, M. D. (2021). Prediction errors disrupt hippocampal representations and update episodic memories. *Proceedings of the National Academy of Sciences of the United States of America*, *118*(51), e2117625118. https://doi.org/10.1073/pnas.2117625118

Spaniol, J., Schain, C., & Bowen, H. J. (2014). Reward-enhanced memory in younger and older adults. *The Journals of Gerontology. Series B, Psychological Sciences and Social Sciences*, *69*(5), 730–740. https://doi.org/10.1093/geronb/gbt044

Stanek, J. K., Dickerson, K. C., Chiew, K. S., Clement, N. J., & Adcock, R. A. (2019). Expected reward value and reward uncertainty have temporally dissociable effects on memory formation. *Journal of Cognitive Neuroscience*, *31*(10), 1443–1454. https://doi.org/10.1162/jocn_a_01411

Stefanidi, A., Ellis, D. M., & Brewer, G. A. (2018). Free recall dynamics in value-directed remembering. *Journal of Memory and Language*, *100*, 18–31. https://doi.org/10.1016/j.jml.2017.11.004

Wittmann, B. C., Schott, B. H., Guderian, S., Frey, J. U., Heinze, H.-J., & Düzel, E. (2005). Reward-related fMRI activation of dopaminergic midbrain is associated with enhanced hippocampus- dependent long-term memory formation. *Neuron*, *45*(3), 459–467. https://doi.org/10.1016/j.neuron.2005.01.010

Wolosin, S. M., Zeithamova, D., & Preston, A. R. (2012). Reward modulation of hippocampal subfield activation during successful associative encoding and retrieval. *Journal of Cognitive Neuroscience*, *24*(7), 1532–1547. https://doi.org/10.1162/jocn_a_00237

Yonelinas, A. P. (2002). The nature of recollection and familiarity: A review of 30 years of research. *Journal of Memory and Language*, *46*(3), 441–517. https://doi.org/10.1006/jmla.2002.2864

Yonelinas, A. P., Aly, M., Wang, W.-C., & Koen, J. D. (2010). Recollection and familiarity: Examining controversial assumptions and new directions. *Hippocampus*, *20*(11), 1178–1194. https://doi.org/10.1002/hipo.20864

Appendix A

Terms	Definitions provided to participants
Old	Art piece that was previously presented
New	Art piece that was not previously presented
Remember	You should choose "Remember" if you consciously recollect seeing the item in the previous list. If the art piece brings back to mind a particular association or thought that you had during the study, or something about its appearance or position (i.e., what came before or after the art piece), then you can choose "Remember". For example, if you see someone on the street, you recognise their face and remember talking to the person at the party the previous night.
Know	You should choose "Know" if you know the item was one you studied, but you cannot recollect any details associated with seeing it before. For example, if you see someone on the street, you know you recognise them because of strong feelings of familiarity, but you have no recollection of seeing this person before.
Guess	You should choose "Guess" if you think you may have seen the art in the gallery presentation but you do not remember explicitly seeing it. For example, if you see someone on the street, they may be wearing a shirt that you have seen before so you guessed that you have met them before.