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Reward at encoding but not retrieval modulates memory for detailed events

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ABSTRACT

Much of the evidence suggesting that rewards improve memory performance has focused on how explicit rewards facilitate encoding of simplistic stimuli. To expand beyond this focus, the current study tested how explicit rewards presented at encoding as well as retrieval facilitate memory for information contained within complex events. In a single experimental session, participants ($N = 88$) encoded videos depicting naturalistic events (e.g., getting dressed) and then completed a recognition test probing their memory for different detail types (i.e., event, perceptual, or contextual) from the video stimuli. We manipulated the explicit reward associated with each video, such that accurate memory responses for half the videos were associated with high monetary incentives and half were associated with low monetary incentives. This reward manipulation was presented at either encoding or retrieval during a recognition memory test. The reward manipulation only affected memory when presented at encoding and this effect did not depend on the type of detail probed. Drift Diffusion Modelling further revealed that presenting reward information at encoding engendered greater encoding fidelity—indexed by an increase in drift rate—but did not change response caution at the time of retrieval—indexed by response threshold. Together, our results suggest that presenting reward information when encoding but not retrieving complex events has a general facilitatory effect, likely via attentional processing, on the ability to later remember precise details from the event.

A growing body of work indicates that the presence of reward facilitates episodic memory (Miendlarzewska, Bavelier, & Schwartz, 2016; Shohamy & Adcock, 2010). However, many of the studies examining how reward and episodic memory interact have focused on the motivating effect of reward when encoding simple stimuli, such as objects or words (Adcock, Thangavel, Whitfield-Gabrieli, Knutson, & Gabrieli, 2006; Murty & Dickerson, 2016; Wolosin, Zeithamova, & Preston, 2012), leaving open questions about whether presenting incentives during retrieval equally affects performance (Halsband, Ferdinand, Bridger, & Mecklinger, 2012; Shigemune, Tsukiura, Nouchi, Kambara, & Kawashima, 2017), particularly for complex memories that contain a variety of details (e.g., event, perceptual, and contextual information; Sheldon, Amaral, & Levine, 2017). Here, we addressed both questions by examining if explicit reward incentives enhance memory for details contained within complex events, and if this reward effect depends on whether incentives are introduced during the encoding or retrieval process.

There are several lines of work demonstrating an effect of reward on memory encoding. Individuals tend to prioritize or are motivated to encode information that is explicitly associated with high reward over information associated with low reward values (Adcock et al., 2006; Ariel & Castel, 2014; Gruber & Otten, 2010; Hennessee, Patterson, Castel, & Knowlton, 2019; Kuhl, Shah, Dubrow, & Wagner, 2010; Murty & Dickerson, 2016; Shohamy & Adcock, 2010; Soderstrom & McCabe, 2011; Talmi, Kavaliauskaite, & Daw, 2021; Wolosin et al., 2012). For example, Gruber and Otten (2010) found that when words were associated with a low- versus high-reward cue during encoding, the high-value words were better remembered on a subsequent recognition memory test. However, the mechanisms underlying reward enhancements of encoding are not entirely clear. One prominent view suggests that reward signals the relative importance of information at encoding and improves memory performance by increasing motivation and leading to a greater allocation of attentional resources to rewarding material (Ariel & Castel, 2014; Gruber & Otten, 2010; Miendlarzewska et al., 2016). Evidence also suggests that reward-motivated encoding effects may be dependent on the explicit encoding strategy used (Hennessee et al., 2019). This view raises questions about whether the relative importance of information, signaled by explicit reward

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presentation, can also serve to modulate response strategies at retrieval.

In many real-life situations, the relative importance of information is only evident after encoding has taken place. For example, Dunsmoor, Murty, Davachi, and Phelps (2015) identified mechanisms by which memories related to salient future events can be enhanced after encoding. Although this finding was related to consolidation processes, recent work has identified that reward-related enhancements of episodic memory can also occur prior to consolidation, when information encoded without reward is immediately retrieved with incentives (Shigemune et al., 2017). When reward is presented at retrieval, changes to response caution may reflect strategic, top-down attempts to modulate memory performance, as this effect has also been found in a number of other cognitive domains (Green, Biele, & Heekeren, 2012; Otto & Daw, 2019). In support of this, Han et al., (2010) found that reward-motivated retrieval immediately after encoding was linked to participants' motivational state rather than their actual mnemonic performance. Whether reward-motivated retrieval can enhance memory performance for previously encoded information through short-term, putatively motivational processes such as changes to retrieval strategy, remains unclear but would shed light on a potentially adaptive method for utilizing memories post-encoding. Thus, one aim of the present study is to further understand reward-related memory enhancements: does explicit reward presented at encoding or retrieval improve episodic memory, and if so, do these effects emerge from the same mechanisms?

A second aim of our study is to move beyond prior research on reward effects on memory that have relied on simplistic stimuli (see review by Miendlarzewska et al., 2016), and to instead test rewards possible motivating effects in the context of complex event memories that better represent real-life remembering. Complex events contain varied types of information, such as event details (i.e., central plot elements), contextual details (e.g., spatial relationships), and other perceptual details (e.g., other visual information). Theories of memory have proposed distinctions between how these types of details are processed within an encoded and retrieved event (Moscovitch, Cabeza, Winocur, & Nadel, 2016; Rubin, 2006; Sekeres, Moscovitch, & Winocur, 2017). Moreover, recent empirical work highlights important behavioural differences in how these details are remembered and forgotten (Sekeres et al., 2016; Sheldon et al., 2017), lending support to the idea that certain detail types are encoded —and perhaps retrieved—differently. For example, event details may be privileged by virtue of describing the key elements of a memory (Sekeres et al., 2016). However, no study to our knowledge has investigated how these different detail types are influenced by reward—a question which may contribute significantly to our understanding of how reward enhances different aspects of complex memories.

1. Current study

We conducted two complementary experiments. In Experiment 1, we manipulated the reward value—a high value of 25-cents versus a low value of 1-cent—associated with complex event stimuli (video clips depicting everyday events, such as walking on a busy sidewalk) during encoding. The reward value indicated the amount participants could earn in a subsequent recognition test for correctly recognizing details from that event—e.g., identifying the statement "The woman removed her jacket" as True or False. In Experiment 2, participants were only informed of the reward value (25-cents versus 1-cent) for correctly answering a question about each video during retrieval. Since our research questions were not focused on testing time-dependent consolidation mechanisms, we used an immediate retrieval paradigm in both experiments, which has previously been used to demonstrate reward effects both in reward-at-encoding (Wolosin et al., 2012) and reward-at-retrieval paradigms (Shigemune et al., 2017) using simplistic stimuli. In both experiments, we expected that accuracy on the recognition memory task would be higher for questions pertaining to high- versus low-reward videos, in accord with prior studies finding memory enhancement for information associated with high rewards (Shohamy & Adcock, 2010); however, we hypothesized that in Experiment 1, improved memory performance would be driven by stronger encoding, whereas in Experiment 2, this effect would emerge from more cautious decision-making.

To test whether reward enhances attentional processing of to-be-encoded information manifesting as strength of evidence, or if reward shifts response strategy at retrieval via higher response caution—we used a Drift Diffusion Model (DDM; Ratcliff & Rouder, 1998). In brief, these models assume that the internal evidence (i.e., memory) used to respond to a recognition memory question builds over time until a response threshold—which controls the speed-accuracy trade-off—has been reached. These DDM parameter estimates provide unique insight into how reward information alters memory decisions (Ratcliff & McKoon, 2008). Specifically, by jointly analyzing response accuracy and response times (RTs), fitting a DDM affords additional understanding of whether the effects of reward on recognition memory accuracy are attributable to reward-induced increases in the strength of evidence accumulation (i.e., a faster drift rate; which would result in more accurate and faster responses and indicate better encoding), or by reward-induced increases in response caution (i.e., elevated response thresholds; which would result in more accurate but slower responses and indicate a shift in response strategy at retrieval). Reward incentives have been demonstrated to alter both drift rates and response thresholds across diverse task domains (Green et al., 2012; Otto & Daw, 2019). We predicted that when given reward cues at encoding, participants would show improved recognition memory performance through increased drift rates (i.e., stronger encoding), but when given reward cues only at retrieval, participants would instead adjust their response thresholds to trial-by-trial variations in available rewards.

2. Experiment 1: reward-motivated encoding

2.1. Method

2.1.1. Participants

Forty-seven undergraduate students were recruited through the McGill University participant pool and compensated with course credit. While participants were told they would receive a bonus payment based on the number of correct responses during the recognition memory task, all received $10 CAD regardless of performance. To ensure all participants were adequately engaged on the task, we assessed whether overall response accuracy (i.e., percentage of total correct) was significantly greater than chance (binomial test at the 0.05 level). One participant whose overall response accuracy (i.e., percentage of total correct) did not meet this criterion was excluded. One additional participant was also excluded, as their data did not record due to a technical error. This left us with a total of 44 participants ($\text{Mean}_{\text{age}} = 20.2$, $\text{Range}_{\text{age}} = 18$–$25$, $\text{SD}_{\text{age}} = 1.31$, 81.8% female). Participants provided informed consent, and all procedures were in accordance with the McGill University's Research Ethics Board.

2.1.2. Video stimuli

Sixteen short (range: 10 to 20 s, mean = 18.12 s, SD = 3.46 s) and silent video clips depicting naturalistic scenarios were selected from a stimulus set used previously by our group (Sheldon et al., 2017). The videos were presented in a 450- by 720-pixel window and were associated with a descriptive title (e.g. "Cleaning-up after a party", see Fig. 1). The videos were distinct from each other, and each contained a unique set of perceptual features, and portrayed naturalistic scenarios (e.g., cleaning-up; talking on the phone): eight videos contained both men and women, six videos contained only women, and two videos contained animals.

2.1.3. Recognition questions

Each of the sixteen videos was associated with nine true/false

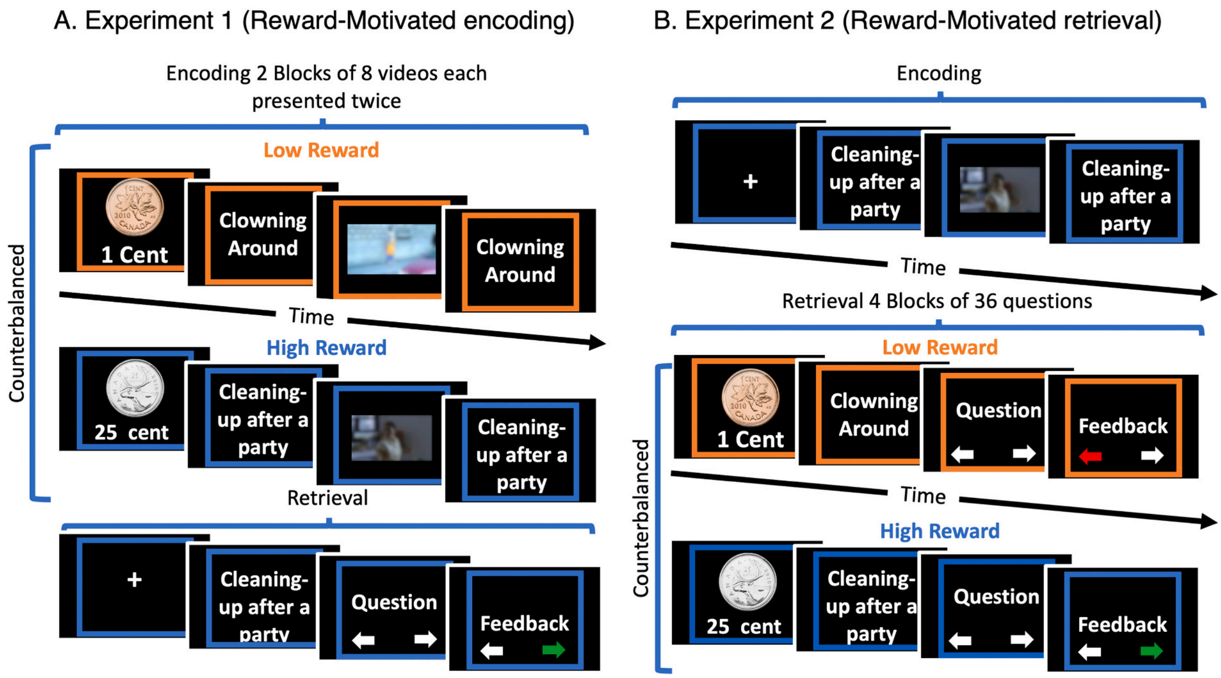

Fig. 1. Schematic Representation of the recognition memory task for both Experiments: A. First experiment with the reward manipulations at encoding and B. second experiment with the reward manipulations at retrieval. For both experiments, after the recognition memory task, participants completed a free recall of the video titles, and a memory test for the reward manipulation in that order.

statements designed to probe different types of details. For each statement, two versions were constructed, with one including true and one including false details. Three statements were previously classified as querying event details (details about events in the video, e.g., "the pedestrian's friends waited for him"), three were classified as querying perceptual details (details about the images present in the video e.g., "the clown was wearing an orange jumpsuit") and three statements queried contextual details from the videos (details about the spatial relationships in the video e.g., "the pedestrians passed behind the clown"; see Sheldon et al., 2017).

In total, there were 288 statements, of which half included true details, while the other half included false details. To avoid testing the same statement twice (e.g., once in the false and once in the true form), the statements were divided in two separate runs of 144 where each run contained an equal number of statements in the true or false versions (see Fig. 1). Each participant was shown these runs in a randomized order.

2.1.4. *Procedure*

Participants completed an encoding, delay, and retrieval phase in a single experimental session that lasted approximately 2 h. For each participant, eight videos were randomly assigned to the high-reward (25-cents) condition and eight videos were assigned to the low-reward (1-cent) condition. Depending on the reward condition, videos were presented either with a blue or an orange border; color was counterbalanced across participants for both experiments. Critically, participants were informed about the color-reward association at encoding and notified that they would receive the video's associated reward value for each correct response they made at retrieval. After the retrieval phase, participants were instructed to verbally recall as many of the video titles as they could, in any order. Finally, participants were asked to indicate, for each video, whether it was paired with a high-value reward or a low-value reward.

2.1.5. *Encoding phase*

Participants were first presented with an image of a 25- or 1-cent coin for one second, indicating the reward value of the following video, on a 900- by 1440-pixel screen with a black background, using PsychoPy (Peirce, 2009) The video was preceded and followed by a 5-s presentation of the video title. To maintain engagement, participants rated how entertaining they found each video (*This video was entertaining*) on a scale of 1 (*strongly disagree*) to 5 (*strongly agree*). After presenting each video once, all videos were played a second time in the same order to encourage accurate memory performance, without the entertainment rating. Following prior work in the motivated cognitive control literature (Chiew & Braver, 2014; da Silva Castanheira, LoParco, & Otto, 2021; Otto & Vassena, 2020; Parro, Dixon, & Christoff, 2018), videos were blocked to minimize carry-over effects between the high and low reward conditions (Tambini, Rimmele, Phelps, & Davachi, 2017), such that all videos assigned to the same reward condition were presented together, and the order of presentation (i.e., high-low or low-high) was counterbalanced.

2.1.6. *Retrieval phase*

After a ten-minute delay that consisted of questionnaires, participants completed a recognition memory test for details of the encoded videos. Across 144 trials, participants were first presented with a fixation cross for 1s ('+'). Following this, they were randomly presented with the title of one of the videos from the encoding phase and pressed the spacebar once they had the corresponding video in mind. A one second fixation cross followed this response, and then participants were presented with a statement about a detail contained in the video. They indicated whether the statement was true or false by pressing either the right or left arrow key on the keyboard within a 5 s time window. Keyboard response mappings were counterbalanced between participants. After responding, participants received feedback on their response: correct responses were associated with the on-screen key turning green and a one-second cash register sound ("ka-ching!"), while incorrect responses were associated with the on-screen key turning red and no sound played (see Fig. 1). No information about the previously experienced reward values was provided.

After this recognition memory test, we measured memory for the video titles by asking participants to verbally recall as many video titles as possible within 60 s. These data were not analyzed for the present paper. Finally, we measured memory for the reward associated with each video using a forced-choice task. Over a series of trials, participants saw a fixation cross for 1s, then a video title. They pressed the left or right arrow key (counterbalanced across participants) within 5 s to indicate whether they thought the video was associated with a high or low reward during the encoding task.

2.1.7. Data analysis

To examine whether reward led to an increase in recognition memory performance, we ran a Bayesian mixed-effects logistic regression, taking trial-by-trial retrieval phase accuracy as the outcome variable, and reward (low versus high), detail type (event, perceptual, and contextual) and their interaction as predictor variables. Both reward and detail type were effect-coded, where event details were chosen as the baseline (or reference)—given prior work suggesting their centrality in episodic memory (Moscovitch et al., 2016; Rubin, 2006; Sekeres et al., 2016, 2017; Sheldon et al., 2017). Thus, the main effect of reward is interpreted as the difference in log-odds of correct responding between the reward conditions across detail type, the main effects of both contextual and perceptual details reflect the change in log odds between the respective detail type compared to the global average, and their interactions reflect a change in the global effect of reward by detail type. Additionally, we estimated a separate Bayesian linear regression on participants' log-transformed response times (RTs) as a function of the same predictors.

We estimated hierarchical Bayesian regressions using the brms package (Bürkner, 2017) for R, which implements Markov Chain Monte Carlo sampling (Hoffman & Gelman, 2014). We report each effect estimate as the mean of the posterior samples and the 95% highest posterior-density (HPD) interval. Additionally, we report Bayes Factors (BFs), which reflect the relative amount of evidence favoring the alternate or the Null model: where values above 3 indicate evidence in favor of the alternate model and values below 1/3 indicate evidence in favor of the Null model (Lee & Wagenmakers, 2013). For the logistic regressions, diffuse conjugate priors were chosen for the parameters. Namely, we used a normal distribution centered at 0 with a standard deviation of 10 for the intercept, a Cauchy distribution with a location of 0 and a scale of 10 for the random effects, and a normal distribution centered at 0 with a standard deviation of 0.2 for the fixed effects which approximately corresponds to the difference between 0.50 and 0.55 in logit units. For the linear regressions examining RTs, we chose similar priors except for the regression coefficients which were given normal distributions centered at 0 with a standard deviation of 0.5. Based on visual inspection of the trace plots and the potential scale reduction factor (R-hat), which were all well below 1.1 (Brooks & Gelman, 1998), we concluded that the models converged successfully.

2.1.8. Drift-diffusion model (DDM) parameter estimation

We used hierarchical Bayesian estimation of drift diffusion model parameters to estimate the effect of reward on quality of stimulus encoding (modeled as the drift rate) and response thresholds (M. J. Frank et al., 2015). Hierarchical drift diffusion models (HDDMs) allow one to test whether trial-by-trial variations in decision-parameters (e.g. threshold and drift rate) are a function of manipulated within-subject variables (here, reward incentives). These parameters have the advantage of being fit hierarchically, both to individual subjects and constrained by the group-level parameter distribution (M. J. Frank et al., 2015; Wiecki, Sofer, & Frank, 2013). We used the DDM to jointly model responses (i.e., correct vs incorrect) and RTs produced in response to the recognition memory questions in the retrieval phase. In turn, the DDM decision parameters—the drift rate v, non-decision time t, and threshold a—were modeled using a regression and varied as a function of both reward and an intercept on each trial, where the reward level of the associated stimulus was dummy coded (low reward 0, high reward 1). When responses are accuracy-coded (as they are in the present DDM), the drift rate reflects the signal-to-noise ratio of the decision-process (here, the memory trace) whereas the threshold reflects the speed-accuracy trade-off—how much evidence is needed to make a response. Meanwhile, the non-decision time reflects the components of trial-by-trial RTs which do not factor into the decision process and thus no to directly affect accuracy (e.g., motor execution, reading the question).

We estimated these parameters using the HDDM toolbox (Version 0.6.0; Wiecki et al., 2013) for Python, which uses Markov Chain Monte-Carlo techniques. Parameters were assumed to be distributed according to a normal (for real-valued parameters) or a Gamma (for positive-valued parameters) distribution and centred around the group mean with group variance for each subject. Prior distributions for each parameter were informed by several studies reporting best fitting DDM parameters recovered on a range of decision-making tasks (Wiecki et al., 2013). To estimate the HDDM parameters, 5500 samples were drawn from this model, discarding the first 500 samples for 'burn-in' and using a 'thinning' of 5, resulting in 1000 samples per chain. A total of three chains were used to estimate the degree of convergence of the model on the posterior distribution using the trace plots and the potential scale reduction factor (R-hat), which were all well below 1.1 (Brooks & Gelman, 1998). Point estimates (i.e., means) and 95% highest posterior density intervals were calculated using the aggregated posteriors of the three chains.

3. Results

3.1. Detail recognition

First, we examined whether reward improves performance on the recognition memory task. As depicted in Fig. 2A, we observed a positive effect of reward level on recognition accuracy regardless of detail type, suggesting that responses were more accurate for questions about high-reward videos ($M_{accuracy}$ = 71.9%) compared to low-reward videos ($M_{accuracy}$ = 68.6%). This effect was confirmed statistically using a hierarchical Bayesian logistic regression predicting correct responses (β = 0.142, 95% HPD = [0.026–0.256], BF = 5.446; see Table 1 for all posterior effect estimates). Next, we tested whether detail type influenced recognition memory accuracy. We found a negative effect in response accuracy for questions involving perceptual details compared to event details (β = −0.405, 95% HPD = [−0.566, −0.237], BF >100), suggesting that participants were on average less accurate at recalling perceptual details. However, no difference in response accuracy was found for questions testing contextual details compared to event details, as the 95% HPD contained zero (β = −0.045, 95% HPD = [−0.212, 0.118], BF = 0.465). Finally, reward was not found to interact with either detail type, as both 95% HPD intervals contained zero (see Table 1), suggesting reward equally affected all detail types.

Examining correct RTs in the recognition test, our analyses did not reveal any effect of reward level on RT (β = −0.005) as the 95% HPD interval crossed zero (HPDI = [−0.016, 0.027], BF = 0.025), suggesting there is likely no overall difference in correct RTs between reward levels (see Table 2). We refer the reader to the online supplemental materials for the results of the same models estimated using the frequentist framework, replicating the findings reported here.

3.2. Memory for reward incentives

We examined participants' memory of the assigned reward levels using a hierarchical logistic regression, finding that participants performed above chance ($M_{accuracy}$ = 74.3%) in reporting the reward condition assigned to a video, as indexed by the model intercept (β = 1.201, 95% HPDI = [0.940, 1.452]; see Table S1). Next, we tested whether participants were better at remembering the reward association for the high-reward videos and found that participants' memory for the reward association was not significantly different between high versus low reward videos (β = −0.111, 95% HPDI = [−0.320, 0.103], BF = 0.924; see Table S1). Additionally, we did not find that accurate memory for the

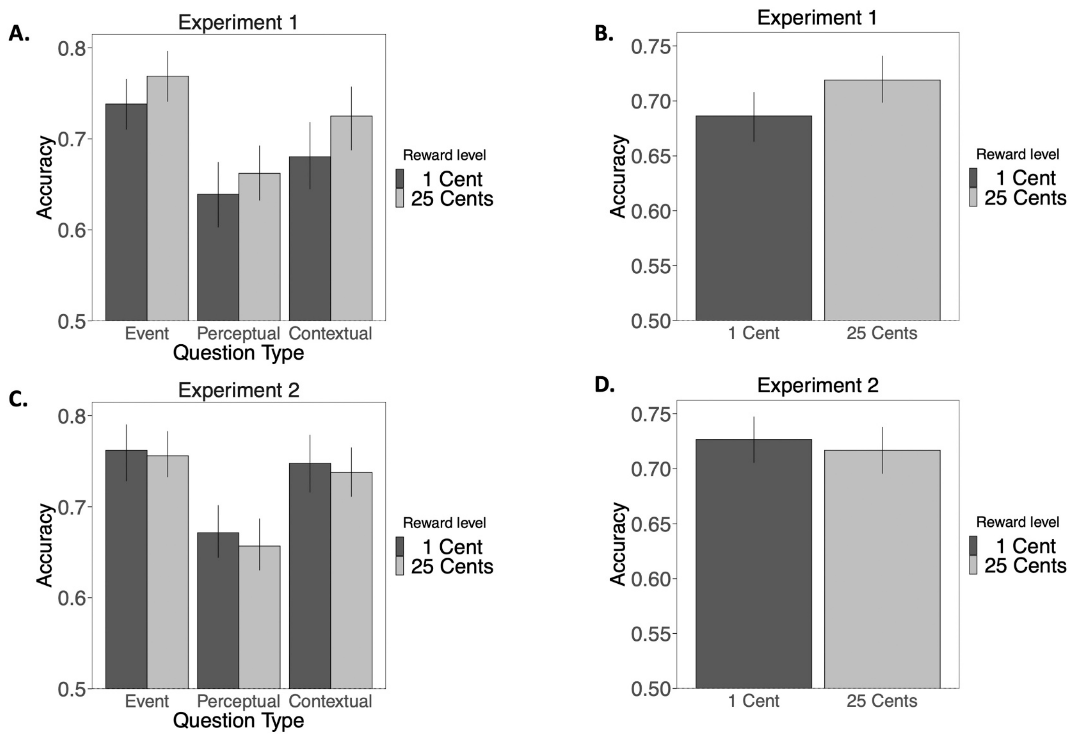

Fig. 2. The effect of reward on recognition memory. A plot of recognition accuracy for reward-motivated encoding by question type with 95% bootstrapped confidence intervals. B plot of recognition accuracy for reward-motivated encoding across question types with 95% bootstrapped confidence intervals (β = 0.142, 95% HPDI = [0.026, 0.256], BF = 5.446). C plot of recognition accuracy for reward-motivated retrieval by question type with 95% bootstrapped confidence intervals D plot of recognition accuracy for reward-motivated retrieval across question types with 95% bootstrapped confidence intervals (β = −0.046, 95% HPDI = [−0.176, 0.077], BF = 0.447).

Table 1
Coefficients estimates for Bayesian Mixed-Effects Logistic Regression on response accuracy estimating the effects of Reward, detail type, and their interactions in Experiment 1 with 95% Highest Posterior Density Intervals (HPDI).

Predictors	Log-Odds	Std. Error	L-HPDI	U-HPDI	BF
Intercept	0.889	0.05	0.790	0.984	
Reward	0.148	0.06	0.022	0.256	5.588
Contextual	−0.011	0.044	−0.090	0.086	0.233
Perceptual	−0.242	0.042	−0.324	−0.157	> 1000
Trial	0	0.001	−0.001	0.001	0.003
Reward x Contextual	0.042	0.073	−0.101	0.194	0.463
Reward x Perceptual	−0.046	0.072	−0.185	0.098	0.440

Reported here are the point estimates of the posterior (mean), the standard error, the lower- and upper-highest posterior density 95% interval (L-HPDI and U-HPDI) and Bayes factor (BF). Bayes factors reflect the degree of evidence in favor of the alternate hypothesis (β ≠0). Values greater than 1 indicate evidence in favor of the alternate hypothesis, while values lower than 1 indicate evidence for the Null hypothesis (β = 0).

Table 2
Coefficients estimates for Bayesian Mixed-Effects Linear Regression on log response-times estimating the effects of Reward, detail type and their interactions in Experiment 1 with 95% Highest Posterior Density Intervals (HPDI).

Predictors	Estimates	Std. Error	L-HPDI	U-HPDI	BF
Intercept	0.789	0.023	0.742	0.830	
Reward	0.006	0.01	−0.013	0.025	0.023
Contextual	0.155	0.007	0.140	0.169	> 1000
Perceptual	−0.083	0.006	−0.095	−0.070	> 1000
Trial	−0.001	0	−0.0009	−0.0002	0.115
Reward x Contextual	0.007	0.013	−0.018	0.030	0.026
Reward x Perceptual	0.002	0.012	−0.022	0.026	0.027

reward association predicted recognition memory accuracy, nor did accurate memory for the reward association interact with the reward level (see Tables S2). Finally, we did not observe a correlation between participants' change in accuracy between reward conditions and their accuracy for recalling the reward association (r = 0.031, 95% HPDI = [−0.24, 0.29]; see supplementals for more information). These results suggest that despite having an accurate memory for the title-reward association, participants are likely not using this association to modulate their response caution on the following trial. Next, we directly test whether the reward effect reflects a modulation of participants' response caution, or whether there is a stronger correspondence of the memory trace to the stimulus using DDM analysis.

3.3. Drift diffusion model (DDM) analysis

To examine whether the observed benefits of reward upon recognition memory are explained by the increased fidelity of stimulus encoding (which would manifest as a reward-induced change in drift rate) versus a change in response strategy (manifesting as reward-induced changes in response thresholds), we jointly modeled participants' responses (i.e., correct, or incorrect) and RTs using a hierarchical DDM (Wiecki et al., 2013). Examining the posterior distributions of the DDM parameters (Fig. 3), we found that reward level significantly increased drift rates (M_{drift} = 0.064, 95% HPDI = [0.02, 0.10]; see Table 3)— suggesting that high-reward stimuli were encoded with greater fidelity compared to low-reward stimuli— but that reward level did not appear to modulate other model parameters (i.e., threshold 95%HPDI = [−0.02, 0.096]; and non-decision time 95%HPDI = [−0.035, 0.009]). Importantly, we also assessed whether the change in accuracy could be reflected as a change in participants' overall tendency to respond true/false; however, our signal-detection theory analysis suggests this is likely not the case (see supplemental materials). In other words, the DDM analysis suggests that the observed reward-induced increase in

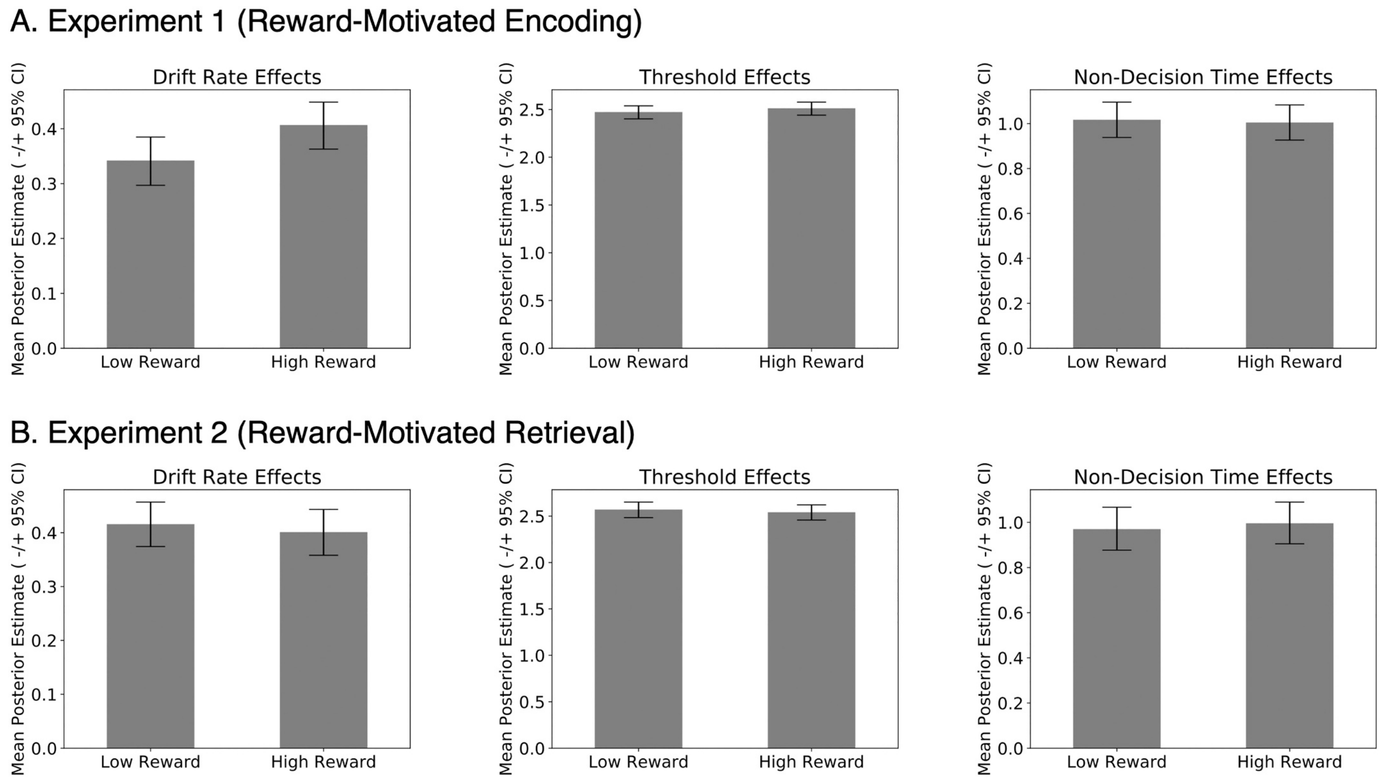

Fig. 3. Plot of posteriors of the best-fitting decision parameters for the DDM model for both A reward-motivated encoding and B for reward-motivated retrieval.

Table 3
Parameter estimates for the DDM model for reward-motivated encoding.

	Mean	Median	SD	L-HPD	U-HPD
Drift Intercept	0.341	0.341	0.022	0.295	0.383
Drift Reward	0.064	0.064	0.022	0.020	0.107
Threshold Intercept	2.468	2.467	0.034	2.399	2.534
Threshold Reward	0.038	0.039	0.031	−0.02	0.096
Non-DT Intercept	1.014	1.013	0.040	0.936	1.092
Non-DT Reward	0.012	−0.012	0.011	−0.035	0.009

recognition memory accuracy was the result of increased task-relevant processing such as strengthened stimulus encoding rather than a change in trial-by-trial retrieval strategy—in turn, corroborating the observations above that reward level affected accuracy, but did not alter RTs.

4. Experiment 2: reward-motivated retrieval

4.1. Method

4.1.1. Participants

Forty-six undergraduate students were recruited through McGill University's participant pool. Again, we excluded participants whose overall response accuracy (i.e., percentage of total correct) was not significantly greater than chance level (binomial test at the 0.05 level); two participants were excluded on this basis, resulting in 44 participants remaining in the analysis ($\text{Mean}_{\text{age}} = 20.3$, $\text{Range}_{\text{age}} = 18\text{–}22$, $\text{SD}_{\text{age}} = 0.983$, 79.5% female).

4.1.2. Encoding phase

The encoding phase was identical to Experiment 1, except for the video presentation order which was randomized and preceded only by a 1-s fixation cross (‘+’) and the video title, mirroring the retrieval phase of Experiment 1. No information about the potential to earn a reward or about the videos' associated reward value was provided at the time of encoding; reward contingencies were only present at retrieval. Again, videos were presented with a blue or orange frame, with each color associated with a reward condition—unbeknownst to the participant—and counterbalanced. Critically, both the presence of a reward manipulation and the color-reward level mapping were only revealed to participants during the instructions for the retrieval phase.

4.1.3. Retrieval phase

After a ten-minute delay period (identical to Experiment 1), participants completed 144 trials of a recognition memory test. On each trial, participants were first presented with an image of a 25-cent coin or a 1-cent coin for one second, meant to indicate the reward value of a correct response for the following statement. Next, they saw a video title, and were prompted to press the spacebar when they wished to see the recognition question. As in Experiment 1, a one second fixation cross followed this response, and then participants were presented with a statement about a detail contained in the video. Keyboard response mappings were identical to Experiment 1. Questions were presented in a blocked fashion where each block consisted of 36 questions from a single reward condition for a total of 4 blocks. The reward value alternated by block and the starting value was counterbalanced between participants. This blocking scheme was designed to parallel, as best as possible, the blocking of the reward manipulation in the encoding phase of Experiment 1. Finally, following the procedure of Experiment 1, participants completed a memory test for the titles of the videos after the retrieval phase, followed by a test of explicit memory for the reward level manipulation.

5. Results

5.1. Detail recognition

Again, we probed whether reward, now presented at retrieval, imparted any effect on recognition memory using hierarchical Bayesian logistic regression. As depicted in Fig. 2C, the reward manipulation during retrieval did not change overall response accuracy between high- ($M_{accuracy} = 72.7\%$) and low-reward ($M_{accuracy} = 71.7\%$) trials, nor did it depend on detail type. Unlike in Experiment 1, we found little evidence for an effect of reward on correct responding at the time of retrieval ($\beta = -0.046$, 95% HPDI = [−0.176, 0.077], BF = 0.447; see Table 4 for all posterior effect estimates). As with the previous experiment, we found that participants were less accurate on questions probing perceptual details ($\beta = -0.482$, 95% HPDI = [−0.636, −0.340], BF >100) compared to event details. Additionally, we did not observe any robust effects of the reward manipulation on RTs (see Fig. 2D; reward effect $\beta = -0.002$, 95% HPDI = [−0.024, 0.023], BF = 0.024; see Table 5).

5.2. Memory for reward incentives

As with Experiment 1, we found that participants' explicit memory for the reward level associated with each video ($M_{accuracy} = 74.3\%$) was better than chance ($\beta = 1.148$, 95% HPDI = [0.863, 1.454]; see Table S3). Further, participants' memory for the associated reward level was not different for the high- and low-reward videos ($\beta = 0.081$, 95% HPDI = [−0.123, 0.291], BF =0.701; see Table S3). Following Experiment 1, we failed to observe a significant correlation between reward association accuracy and the effect of reward on recognition memory ($r = 0.186$, 95% HPDI = [−0.09, 0.44]; see Supplemental Materials).

5.3. DDM analysis

In Experiment 2, we tested whether presenting varying reward incentive cues at retrieval would increase accuracy via slower, more cautious responding (i.e., increasing response thresholds). Following Experiment 1, we fit a model where DDM parameters were allowed to vary by trial-level reward values but failed to find an effect of rewards on threshold as the highest posterior density interval included zero (Fig. 3B, see Table 6). Unexpectedly, we found a modest effect of reward on non-decision-time: based on the best fitting model, the 95% HPD interval of the difference between high- and low-reward non-decision time fell between 0.001 and 0.051—suggesting that participants spent more time on presumed non-retrieval-related processes (i.e., unrelated to response accuracy) on high-reward trials. In the DDM, non-decision-time reflects the component of RTs which is independent of response accuracy (e.g., motor or other nonspecific processes). At the same time, as noted above, we failed to find a corresponding change in RTs between reward conditions.

6. General discussion

Although reward is known to enhance episodic memory, and in turn, guide future behaviour (Shohamy & Adcock, 2010), the nature of these enhancements is yet unclear. The present study assessed the effects of reward on memory at both encoding and retrieval and determined whether reward targets certain aspects of complex, detailed memories. We used a novel experimental paradigm in which participants viewed video stimuli depicting complex events and completed a recognition memory test for different detail types (i.e., event, contextual, and perceptual) from the videos. In Experiment 1, reward information was presented immediately prior to encoding the videos, and we found a reliable difference in recognition memory accuracy for all detail types between high- versus low-value videos, providing evidence for a reward-motivated encoding effect on memory (Adcock et al., 2006; Murty & Dickerson, 2016; Wolosin et al., 2012). In Experiment 2, reward information was presented immediately prior to the recognition memory questions, and we failed to find a reliable difference in recognition memory accuracy for details from high- versus low-value videos. Using DDM analyses, we found evidence that the corresponding change in accuracy observed when reward was presented at encoding reflected an increase in the fidelity of the memory trace rather than a change in explicit retrieval strategy.

The reward-motivated encoding effect observed in our study fits with previous work identifying an episodic memory benefit for highly rewarded information over low or unrewarded information using simpler laboratory-based stimuli (Castel, Murayama, Friedman, McGillivray, & Link, 2013; Miendlarzewska et al., 2016; Murty & Dickerson, 2016; Murty, Tompary, Adcock, & Davachi, 2017; Talmi, Kavaliauskaite, & Daw, 2021; Wolosin et al., 2012). We build upon this work by showing that reward-motivated encoding enhanced the ability to recognize all detail types from complex events. Prior work has demonstrated that different detail types are remembered in different ways (Moscovitch et al., 2016; Rubin, 2006; Sekeres et al., 2016, 2017; Sheldon et al., 2017), with a notable memory benefit for event details over perceptual details (Sekeres et al., 2016). Thus, our results suggest that when reward is explicitly presented at encoding, memory processes are equally oriented toward all three of these detail types.

Unlike some work identifying that reward enhancements at encoding stem from the presence of prediction errors (Frank, Kafkas, & Montaldi, 2021; Jang, Nassar, Dillon, & Frank, 2019; Rouhani, Norman, & Niv, 2018; Rouhani, Norman, Niv, & Bornstein, 2020), our study presented reward in a blocked fashion at encoding, such that there was no inherent element of surprise or 'error' in the presence of reward. We further found that the enhanced recognition accuracy for details from events encoded with high reward (Experiment 1) could not be explained by participant's explicit memory for the reward manipulation itself, implying that the participants had better memory for high-value event details without recalling that the video in question was highly rewarded. This suggests that participants are not explicitly recollecting the reward associated with each video upon retrieval—although our results do not exclude the

Table 4
Coefficients estimates for Bayesian Mixed-Effects Logistic Regression on response accuracy estimating the effects of Reward, detail type, and their interactions in Experiment 2 with 95% Highest Posterior Density Intervals (HPDI).

Predictors	Log-Odds	Std. Error	L-HPDI	U-HPDI	BF
Intercept	0.976	0.04	0.901	1.066	
Reward	−0.043	0.064	−0.167	0.084	0.386
Contextual	0.089	0.045	0.004	0.174	1.465
Perceptual	−0.273	0.041	−0.348	−0.191	> 1000
Trial	0	0.001	−0.001	0.001	0.003
Reward x Contextual	−0.004	0.078	−0.152	0.135	0.385
Reward x Perceptual	−0.016	0.073	−0.146	0.134	0.440

Table 5
Coefficients estimates for Bayesian Mixed-Effects Linear Regression on log response-times estimating the effects of Reward, detail type, and their interactions in Experiment 2 with 95% Highest Posterior Density Intervals (HPDI).

Predictors	Estimates	Std. Error	L-HPDI	U-HPDI	BF
Intercept	0.796	0.023	0.752	0.841	
Reward	−0.009	0.01	−0.030	0.011	0.029
Contextual	0.161	0.007	0.148	0.173	> 1000
Perceptual	−0.098	0.007	−0.111	−0.085	> 1000
Trial	−0.001	0	−0.0008	−0.0002	0.084
Reward x Contextual	0.005	0.012	−0.019	0.028	0.026
Reward x Perceptual	−0.005	0.012	−0.029	0.017	0.026

Table 6
Parameter estimates for the DDM model for reward-motivated retrieval.

	Mean	Median	SD	L-HPD	U-HPD
Drift Intercept	0.414	0.415	0.021	0.374	0.456
Drift Reward	−0.014	−0.015	0.021	−0.056	0.027
Threshold Intercept	2.564	2.564	0.042	2.484	2.651
Threshold Reward	−0.028	−0.029	0.034	−0.093	0.038
Non-DT Intercept	0.968	0.967	0.048	0.872	1.059
Non-DT Reward	0.026	0.026	0.013	0.002	0.052

possibility that implicit reward-related neural reactivation is enhancing memory performance (Wimmer & Büchel, 2016). While previous work suggests that participants can form detailed, explicit memories of reward-item associations, which in turn influence their decision-making (Murty, FeldmanHall, Hunter, Phelps, & Davachi, 2016), our study provides evidence that this may not be the case for more complex, naturalistic event memories.

To explain the global effect of high reward at encoding on complex event memories, we consider that the reward-motivated encoding effect reported here is attentional in nature. Work by Aly and Turk-Browne (2016) has found that the hippocampus, a region of the brain crucial for encoding episodic memories, is modulated by attention, and allows a person to focus on information that is relevant to behavioural goals during learning. Thus, we suggest that the participants in Experiment 1 were either automatically or strategically allocating their attentional resources toward details within the high-value videos to maximize later memory performance, and consequently rewards (Hennessee et al., 2019). This interpretation is further buttressed by the lack of relationship observed between participants' ability to remember the reward-stimulus association and the relative benefits incurred by the reward manipulation; thus, the observed reward-induced changes in performance were not driven by retrieval strategy. While we did not directly measure any markers of overt attention at encoding, we further corroborated this account by using DDM to jointly model responses and RTs.

The results of our DDM showed that the effect of reward likely operates through enhanced stimulus encoding (i.e., attention) rather than a change in response threshold taking place during the retrieval phase in response to video title cues that varied in reward. While higher drift rates can also result in faster response-times, this may depend on the other decision-parameters controlling response speed (Clithero, 2018). In previous tasks where DDMs have been used to model recognition memory data, higher drift rates are thought to represent a better match between the test stimuli and encoded memory (Ratcliff, Thapar, & McKoon, 2004). The threshold is typically used as a measure of how much evidence an individual requires in order to make a response (i.e., cautious or impulsive responses) (Ratcliff & McKoon, 2008). Indeed, some studies in the memory domain have used the DDM to model the effects of aging on recognition memory (Ratcliff et al., 2004; Ratcliff, Thapar, & McKoon, 2010), as well as decision biases in the recognition of emotional stimuli (Bowen, Spaniol, Patel, & Voss, 2016).

An implicit assumption of the DDM of a speed/accuracy trade-off may map onto dual process theories of episodic memory functioning, which frame familiarity as a fast, automatic process and recollection as a slow, constructive one (Yonelinas, 2002). It is possible that a speed/accuracy trade-off may become apparent in populations with declining recollective capacity, such as older adults, due to their increased reliance on familiar information in decision-making tasks (Amer, Giovanello, Nichol, Hasher, & Grady, 2019; Umanath & Marsh, 2014). Our findings highlight the utility of DDMs in memory research, particularly with respect to disentangling the processes underlying performance changes in response to motivational manipulations like reward.

The lack of an effect in Experiment 2, when reward was placed at retrieval, was buttressed by our Bayesian analyses that found equivocal evidence for an effect of reward (BF = 0.447). The lack of a difference in memory accuracy and RTs between the high- and low- value videos, as well as the lack of effect of reward on drift rate and threshold (as estimated by the DDM analysis) lead us to conclude that the mechanism underlying reward-induced memory enhancements likely do not occur during retrieval. This interpretation is in accord with previous neuroimaging work finding that regions of the brain associated with reward, such as the striatum, are activated when a reward is presented during retrieval due to participants' motivational goals, without influencing mnemonic performance (Han et al., 2010).

In Experiment 2, we did find a reward-induced increase in non-decision time—taken as the component of RTs independent of response accuracy—without a corresponding change in response-times. We speculate that this effect may reflect participants' increased hesitation on high reward trials and may manifest in lower feelings of subjective confidence (Murty & Dickerson, 2016) possibly stemming from an increased motivation to respond accurately on high reward trials. Again, it is worth noting that we do not attribute these results to reward prediction error effects on encoding; while some work suggests that encountering a salient event, such as a reward, during encoding can enhance memory performance, the opposite effect may emerge at retrieval (Frank et al., 2021). Our blocked design for retrieval in Experiment 2 minimized the likelihood of prediction errors, as participants were likely to learn the reward value of the block early on. Thus, the design of Experiment 2 assessed top-down motivational changes in response strategy and found no improvement in memory performance.

Our finding that reward-motivated retrieval does not affect memory performance contrasts with prior work by Shigemune et al. (2017), who had participants encode word pairs which were subsequently retrieved under high versus low reward incentive levels. We believe that the difference in our findings is due in part to the stimuli used (word pairs, in contrast to the complex video stimuli in the present work), but we also acknowledge other differences in our methodology that might have influenced this result. First, Shigemune et al., (2017) presented the high- and low-reward conditions randomly at the trial level, which likely induced prediction errors and permitted bottom-up modulation of memory that stands in contrast to our blocked design, which limited prediction errors as well as carry-over effects between the high and low reward conditions. Finally, Shigemune et al., (2017) penalized participants for incorrect memory judgments, which we did not do in the current study.

7. Limitations and future directions

Unlike rewarding good performance, avoiding punishment for poor performance may improve memory via putatively different mechanisms. Recent work has found disparate effects of punishment on performance leading to an increase in response thresholds, but leaving drift-rates unaffected (Leng et al., 2020). Indeed, some work has found that punishment may improve memory performance (Dunsmoor et al., 2015; Shigemune, Tsukiura, Kambara, & Kawashima, 2014), although with some inconsistent findings (Murty, LaBar, Hamilton, & Adcock, 2011). Relatedly, a limitation of our current experimental design is the difficulty in concluding whether the prospect of high reward enhances recognition memory performance, or whether the prospect of low rewards leads to performance decrements. This ambiguity is further complicated by the possibility that introducing neutral trials (i.e., no reward) among rewarded trials could be interpreted as a loss (Kahneman & Tversky, 1979). Although we interpret our study as evidence for reward-motivated enhancements to memory encoding, given the design of our study, we cannot rule out the possibility that the difference between high- versus low-value videos is driven by poorer memory for low-value videos. Thus, it remains unclear whether motivationally disparate stimuli can result in memory improvements via distinct mechanisms.

Another avenue for future investigation is examining the role of consolidation processes in the effects of reward on memory performance. Prior work has suggested an important role for consolidation in enhancing reward-associated memories (Braun, Wimmer, & Shohamy, 2018; Dunsmoor et al., 2015; Patil, Murty, Dunsmoor, Phelps, & Davachi, 2017; Stanek, Dickerson, Chiew, Clement, & Adcock, 2019), which was not considered in the present study. Similarly, future work could address whether the effects of reward on memory differ depending on how memory is probed. This follows work identifying that recall memory tasks tend to rely more on recollection processes than recognition memory tasks (Payne & Roediger, 1987; Tulving, 1985), and neuroimaging work suggesting that reward might have specific influences on recollection, such as enhancing details related to context (Elward, Vilberg, & Rugg, 2015). Future work might employ a similar design alongside free recall of the videos to assess whether encoding and retrieval processes are similarly modulated by reward.

8. Conclusion

In conclusion, the effect of reward on memory for complex stimuli depends on whether incentive information is presented either when encoding or retrieving memoranda, but not on the type of information being retrieved. Our DDM and behavioural analyses jointly suggest that the effect of reward on memory likely reflects changes in attentional processing at encoding rather than changes in retrieval strategy engendered by an explicit memory for the reward manipulation. Our study builds upon well-established literature in the episodic memory domain which identifies an effect of reward-motivated encoding on memory performance, as well as on the burgeoning literature on reward effects at retrieval. Bringing together this work with techniques such as the DDM, our findings contribute to our understanding of the mechanisms underlying reward's effects on episodic memory.

Data and code availability

Raw data and analysis code is available on our Open Science Framework repository (https://osf.io/8w6pt/) .

Author contributions

All authors contributed equally to the design and analysis of the experiments. KDSC, AL, KO ran the experiments. AL, KDSC, ARO, SS wrote and edited the manuscript.

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Appendix A. Supplementary data

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