Testing Expectations and Retrieval Practice Modulate Repetition Learning of Visuo-Spatial Arrays

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Abstract

One of the best-known demonstrations of long-term learning through repetition is the *Hebb effect:* Immediate recall of a memory list repeated amidst non-repeated lists improves steadily with repetitions. However, previous studies often failed to observe this effect for visuo-spatial arrays. Souza and Oberauer (2022) showed that the strongest determinant for producing learning was the difficulty of the test: Learning was consistently observed when participants recalled all items of a visuo-spatial array (difficult test) but not if only one item was recalled, or recognition procedures were used (less difficult tests). This suggests that long-term learning was promoted by increased testing demands over the short term. Alternatively, it is possible that lower testing demands still lead to learning but prevented the application of what was learned. In four preregistered experiments (N = 981), we ruled out this alternative explanation: Changing the type of memory test mid-way through the experiment from less demanding (i.e., single item recall or recognition) to a more demanding test (i.e., full item recall) did not reveal hidden learning, and changing it from the more demanding to a less demanding test did not conceal learning. Mixing high and low demanding tests for non-repeated arrays, however, eventually produced Hebb learning even for the less demanding testing conditions. We propose that testing affects long-term learning in two ways: Expectations of the test difficulty influence how information is encoded into memory, and retrieval consolidates this information in memory.

Keywords: Working Memory, Long-Term Memory, Hebb Repetition Effect, Testing Effects, Testing Expectations

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A fundamental mechanism to acquire new knowledge is learning by repetition. We often need to study or look at the same content over and over again until we have acquired a stable memory representation of it. This process of repetition learning arguably involves both working memory and long-term memory. Working memory is a capacity-limited system that holds information temporally available for use in thought and action (Cowan, 2017; Oberauer, 2009). Long-term memory, on the other hand, is not limited in capacity and stores our knowledge and experiences (Tulving, 1972). When it comes to learning from repetition, both systems need to interact to form a stable, long-lasting representation of the information that is repeatedly represented in working memory.

A well-known example for studying this interaction is the *Hebb repetition paradigm* (Hebb, 1961). In this paradigm, participants are presented with several memory lists for an immediate memory test. Unbeknown to participants, one of these lists is repeated occasionally. What is typically observed is that working memory performance improves over repetitions for the repeated list but not for the non-repeated Filler lists. This result shows that repeated exposure to information in working memory can lead to the formation of new long-term memory traces.

The Hebb repetition effect has been demonstrated with a broad range of materials, including lists of digits (Hebb, 1961; Oberauer & Meyer, 2009), letters (Mızrak & Oberauer, 2022; Oberauer et al., 2015; Page et al., 2006), syllables (Norris et al., 2018;

Saint-Aubin & Guérard, 2018; Szmalec et al., 2009), words (Page et al., 2013), faces (Horton et al., 2008; Johnson & Miles, 2019) and sequences of spatial locations (Couture & Tremblay, 2006; Gagnon et al., 2005; Guérard et al., 2011; Sukegawa et al., 2019; Tremblay & Saint-Aubin, 2009). However, several studies failed to observe repetition learning effects for visual stimuli such as visuo-spatial arrays of colors or shapes, even after many repetitions (Fukuda & Vogel, 2019; Logie et al., 2009; Olson & Jiang, 2004; Shimi & Logie, 2019). This raises the question, of why visuo-spatial information is more difficult to learn and how learning could be promoted.

Souza and Oberauer (2022) compared the characteristics of studies which consistently replicated the Hebb effect for verbal lists and sequences of spatial locations to those studies failing to find this effect for visuo-spatial arrays. After ruling out several candidate factors such as presentation mode (simultaneous vs. sequential), presentation rate, and retention interval duration, they identified the testing procedure as the critical factor for promoting the learning of visuo-spatial arrays. Most of the studies which failed to replicate the Hebb effect used recognition tasks like change detection (Fukuda & Vogel, 2019; Logie et al., 2009; Olson & Jiang, 2004), which involves the test of a single element of the memory array. In contrast, Hebb studies typically use recall tasks in which all presented items are probed (Couture & Tremblay, 2006; Guérard et al., 2011; Hebb, 1961; Oberauer et al., 2015; Tremblay & Saint-Aubin, 2009). By contrasting different testing procedures for visuo-spatial arrays, Souza and Oberauer (2022) found that repetition learning effects were only consistently observed when participants were asked to recall all items of the presented arrays but not if (1) only one item of the presented arrays was recalled, or (2) different types of change detection tasks were used to test working memory (irrespective of the number of tested items).

These results show that the retrieval stage is key for establishing a robust memory representation. This is in line with previous findings from the verbal memory domain. For example, Cohen and Johansson (1967) only found learning of digit lists when lists were encoded and recalled but not if lists were only encoded. Oberauer and Meyer (2009) showed that testing working memory facilitated the Hebb effect for lists of letters. Although they still observed learning for repeated lists when they were not tested, the learning effect was larger when participants were asked to recall the lists.

Souza and Oberauer (2022) proposed that the strongest determinant for long-term learning by repetition is the difficulty of the test. Building on the assumptions of integrative models of working and long-term memory (Cowan, 1999; Oberauer, 2009), they proposed that the working memory representation of every trial will also leave a trace in episodic long-term memory. If participants are confronted with a highly demanding test at retrieval, like the recall of all presented items, the information in working memory will likely be insufficient to solve the task and participants will be forced to try to draw on other sources like episodic memory (Oberauer et al., 2017). This fosters the exchange of information between working and long-term memory and will increase the chance that participants recognize a previous encounter of the same information in long-term memory. Recognizing an existing memory trace of the same information allows the strengthening of this existing memory trace instead of simply forming new traces of every encounter, thereby enabling the formation of stable long-term memory representations. If the memory test is less demanding, like the recall of a single item, or making a recognition judgment, people might rely more on the current working memory representation, and simply form a new episodic trace of the current trial, missing the chance to strengthen the previously formed memory traces (Souza & Oberauer, 2022).

This explanation assumes that learning through repetition requires participants to recognize previous encounters of the same information while performing the working memory task (Ensor et al., 2021; Musfeld et al., 2023). An alternative account is that long-term memory traces can still accumulate over repetitions (Page & Norris, 2009), but are not retrieved during the working memory task because the task is not demanding enough to make people draw on long-term memory (Oberauer et al., 2017). This alternative account would also explain why no repetition benefit is observed in less demanding memory tests like single-item recall and change detection but would suggest a different reason: learning still occurred, it simply did not manifest during the test.

So far, existing studies were not able to distinguish between these two possible explanations or provided inconsistent results. For example, Olson and Jiang (2004) and Fukuda and Vogel (2019) showed that participants were able to recognize a repeated Hebb array at the end of a study above chance level, although their performance during the working memory change detection task did not improve over repetitions. This suggests that participants had at least some long-term memory of the repeated array, but this knowledge was not applied in the working memory test. In contrast, Goecke and Oberauer (2021) showed that participants can use long-term knowledge in a change detection task. They pre-trained participants on three specific visual arrays to a criterion. Then they randomly mixed these arrays with unique new arrays in a change detection task and found that performance for the pre-trained arrays was higher compared to new arrays. Hence, so far it remains unclear why Hebb learning is not observed with single-item recall and change detection.

The present study

The present study provided a direct test to distinguish between different explanations for why repetition learning effects for visuo-spatial arrays are observed with demanding (e.g., recall of all items), but not with less demanding memory tests (e.g., recall of single items, change detection). The first account (hereafter the *no-learning* account) is that less demanding tests do not promote the strengthening of long-term traces of the repeated array. The second account (hereafter the *not-using* account) is that long-term learning still occurs, but that the existing knowledge is not applied in the less demanding tests. Both accounts lead to the same predictions when repetition learning is solely investigated with less demanding tests. Yet, their predictions diverge when one considers a scenario in which the testing procedure is changed mid-way through the experiment. When changing from a less-demanding to a high-demanding test, the *no-learning* account predicts that learning would only start after the switch. The *not-using* account, by contrast, would predict that this switch suddenly reveals the learning that occurred during the less demanding phase. When changing from a high-demanding to a less-demanding test, the *no-learning* account predicts that learning, which was observed during the high-demanding test, remains observable during the less-demanding test. The *not-using* account, by contrast, predicts that this switch leads to the sudden disappearance of the learning effect that was observed during the high-demanding test situation.

To tease these explanations apart, we designed a set of four experiments. Experiments 1, 2, and 3 focused on the comparison between a memory test with high retrieval demands, i.e., the requirement to recall all items (referred to here as *full recall*), and a test with lower retrieval demands requiring the recall of only a single item (hereafter a *single-item recall*). Experiment 4 provided a comparison between the full recall test and a full change detection test, in which all items of the display were tested for changes. This comparison keeps the number of retrievals constant (all items are tested) while varying the difficulty of retrieval (recall is harder than recognition). To foreshadow our results, less demanding tests did not conceal learning, ruling out the *not-using* account. We also observed that less demanding tests do not entirely prevent learning. However, learning proceeds at a much slower rate in less demanding than in more demanding tests. Additionally, and different from previous studies, we show that when participants were not able to anticipate the difficulty of the test, learning effects were increased, indicating that the anticipated difficulty of the test also matters.

Experiment 1

Previous experiments observed no learning of a repeated visuospatial array with a single-item recall test (Souza & Oberauer, 2022). Experiment 1 aimed to examine why this occurs. Our goal was to distinguish between the *no-learning* account and the *not-using* account we described above. Here, we combined a single-item recall procedure with a full recall procedure in the same visuo-spatial Hebb experiment. The full recall procedure has been shown to robustly produce Hebb learning for visuo-spatial arrays (Souza & Oberauer, 2022). In the present experiment, 50% of the presented visuo-spatial arrays were tested with a full recall procedure, and the other 50% with the single-item recall procedure. Critically, across different groups of participants, the repeated Hebb array was consistently tested with either a full recall or single-item recall procedure, but this assignment could change halfway through the experiment. This led to four between-subject conditions with the following testing assignment for the repeated Hebb array: 1) single-item recall in the first and the second half of the experiment (*Rec(1) – Rec(1)* condition)[1]; 2) single-item recall in the first half, but full recall in the second half (*Rec(1) – Rec(6)* condition); 3) full recall in the first half, but single-item recall in the second half (*Rec(6) – Rec(1)* condition); and 4) full recall in the first and second half (*Rec(6) – Rec(6)* condition). Note that in the *Rec(1) – Rec(1)* and *Rec(6) – Rec(6)* conditions, no switch of the testing procedure occurred. These served as control conditions to replicate the findings of Souza and Oberauer (2022) of no learning with single-item tests but learning with full recall. The critical novel conditions were the two switch conditions (i.e., *Rec(1) – Rec(6)* and *Rec(6) – Rec(1)*), in which the testing

[1] *Rec(1) / Rec(6)* = Recall of one or Recall of six items, where six is the total number of items in the used displays.

procedure changed halfway through the experiment. For these, the proposed explanations make different predictions.

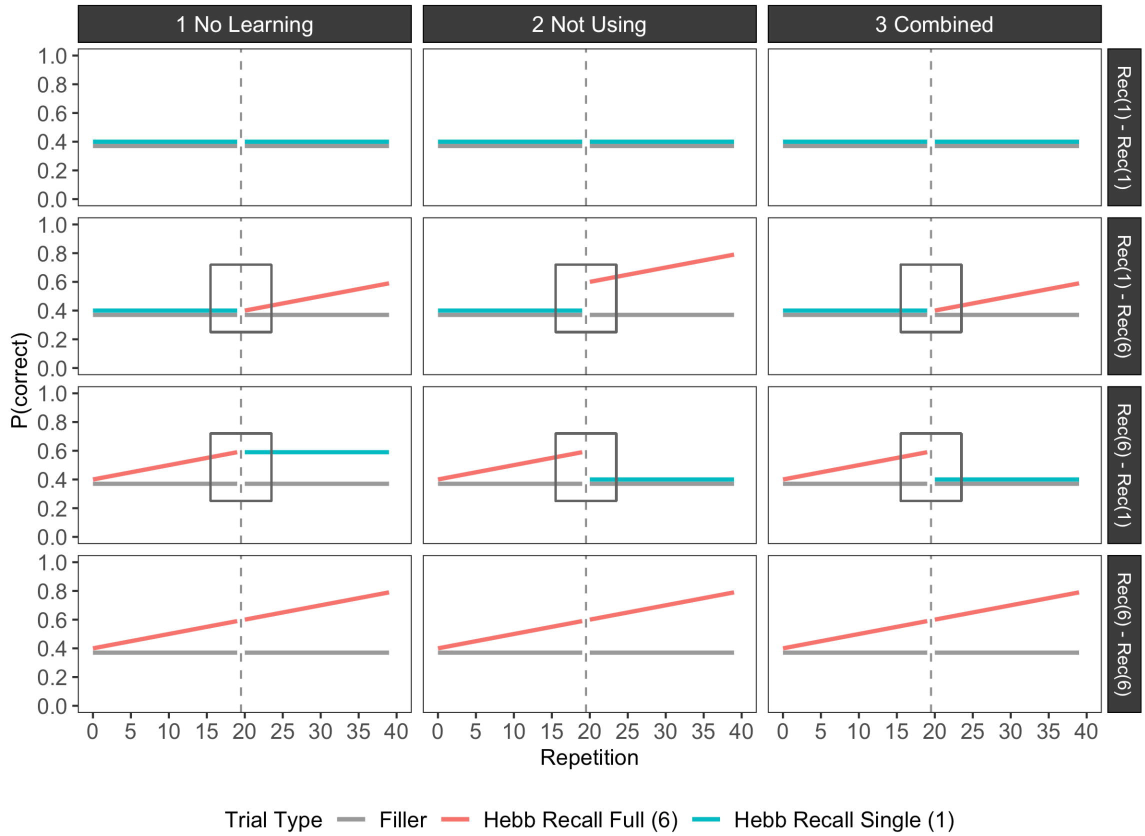
Figure 1 displays the predictions for the proposed design. According to the *no-learning* account, single-item recall does not lead to learning of the repeated array, but existing learning is not concealed by this type of memory test. Therefore, if the Hebb array is tested with single recall during the first half of the study, it would not be learned, but after switching from single-item to full recall (*Rec(1) – Rec(6)* condition) participants would begin to learn the repeated array as if this was the first exposure to the repetition. In contrast, changing from full recall to single-item recall (*Rec(6) – Rec(1)* condition), the Hebb array would have been learned in the first half of the experiment, and the learning effect would still be visible after the switch.

In contrast, the *not-using* account predicts that single-item recall leads to learning, but this learning is not used during single-item recall because this type of test conceals the learning. Consequently, under this account, we would expect a sudden revelation of previously hidden learning when switching from single to full recall (*Rec(1) – Rec(6)* condition), and a concealment of existing learning effects when switching from full to single-item recall (*Rec(6) – Rec(1)* condition).

Lastly, we also considered the possibility that learning neither happens during single-item recall nor that already existing knowledge is used. This is covered under the *combined* account in Figure 1. This account predicts no revelation of a hidden learning effect in the *Rec(1) – Rec(6)* condition and concealment of the existing learning effect in the *Rec(6) – Rec(1)* condition.

Figure 1

Predictions of the Different Hypotheses for the Experimental Design.



Note. *The rectangles mark the area of the switch point in our design where the three hypotheses differ in their predictions. We focused our hypothesis tests on this part of the data.*

Methods

Transparency and Openness

All experiments in this study were preregistered on the Open Science Framework (OSF) prior to data collection. The preregistration of Experiment 1 is available at: https://osf.io/39zrt. Experimental software, data, and analysis scripts for all experiments reported here are available in the OSF at: https://osf.io/2wdk9/ (Musfeld et al., 2022).

Not all analyses reported here were conducted as described in our preregistration because we had to adapt the analysis to some unexpected findings in the data. We have added an extra section explaining the departures from the preregistration to the method section of each experiment. Additional analyses are reported in our supplementary materials.

The study was part of a grant which received general ethics approval from the Ethics Committee of the Institute of Psychology of the University of Zurich. Specific experiments were self-approved following the ethics checklist of the Ethics Committee of the Institute of Psychology of the University of Zurich.

All experiments were conducted online via the online platform Prolific and programmed using the free and open online experiment builder *lab.js* (Henninger et al., 2022). Data analyses were conducted using *R* (R Core Team, 2022) and the R-packages *brms* (Bürkner, 2017) and *bridgesampling* (Gronau et al., 2020).

Participants

We recruited participants from Prolific between 18 and 35 years old, fluent in English, with normal or corrected to normal vision, and no color blindness. The study took approximately 40 minutes to complete, and participants were compensated with £5 for their participation.

For the data analysis, only complete data sets were considered. Additionally, participants were excluded who performed the task at a guessing level. For assessing this, we calculated participants' average recall performance separately for both halves of the experiment. For the guessing level, we considered the 99% quantile of the binomial distribution with a guessing probability of 1/9 and 280 responses as the threshold for excluding participants. This resulted in a threshold of getting at least 15.7% of the responses correct in both halves of the experiment.

Based on this criterion, we excluded four participants from the *Rec(6) – Rec(1)* condition and one participant from the *Rec(1) – Rec(6)* condition. The final sample consisted of N = 400 participants ($n_{Rec(1)\text{-}Rec(1)}$ = 102, $n_{Rec(1)\text{-}Rec(6)}$ = 98, $n_{Rec(6)\text{-}Rec(1)}$ = 101, $n_{Rec(6)\text{-}Rec(6)}$ = 99). Sample size was determined by a Bayesian stopping rule in which we aimed for Bayes Factors larger than 5 to distinguish between our hypotheses (Rouder, 2014). We started by collecting a total of 50 participants for each condition and continued data collection afterward. We extended our preregistered maximum of 80 participants per between-subject condition to 100 participants because evidence remained inconclusive with n = 80.

Design and Stimuli

Upon starting the experiment, participants were randomly assigned to one of the four between-subject conditions. For each participant, 160 unique memory arrays were created randomly anew. The memory arrays were modeled after Souza and Oberauer (2022) and consisted of six colored squares (square size corresponding to 50 x 50 viewport scaled pixels)[2], which were presented at random locations against a grey

[2] Colored squares were presented on a *lab.js* canvas screen which is scaled relative to the screen size of participants' devices. Square size was set to 50 pixels of the scaled canvas screen (800x600 pixels).

(RGB 128 128 128) background (see Figure 2 for an example). The six colors were randomly drawn from a pool of nine discrete colors (RGB): *white* (255 255 255), *black* (0 0 0), *blue* (0 0 255), *cyan* (0 255 255), *lime* (0 255 0), *yellow* (255 255 0), *orange* (255 128 0), *red* (255 0 0), and *magenta* (255 0 255). To define the possible locations of the squares on the screen, an invisible grid of 7x7 cells was created (cell size corresponding to 50 x 50 viewport scaled pixels). Each square was assigned to one randomly selected location of the grid with the constraint that all squares were separated by at least one grid cell to avoid squares touching each other. Additionally, all arrays created needed to differ from all other arrays by at least two color-location associations to guarantee that they were unique.

One array was randomly selected to be repeated throughout the experiment, referred to as the *Hebb array*. The remaining unique arrays were *Filler arrays*. The Hebb array was repeated, on average, every 4th trial. The experiment was divided into 40 mini-blocks of four trials each. Within each mini-block, the Hebb array was presented once at a random position, with the only constraint that two Hebb trials were not allowed to follow immediately after one another. Hence, the Hebb array was repeated 40 times over the experiment.

Within each mini-block, two trials were tested with single-item recall and two trials with full recall. This made sure that, overall, 50% of trials were tested with single-item and full recall, respectively. Participants were not able to anticipate which testing type to expect at the beginning of a trial. Critically, the testing procedure for the Hebb trials was fixed according to the assigned between-subject condition and could only change halfway through the experiment (in the *Rec(1) – Rec(6)* and *Rec(6) – Rec(1)* condition). The testing procedures for the Filler trials within each mini-block were assigned so that one Filler trial had the same testing procedure as the Hebb trial, and the other two Filler trials had the other testing procedure. We always compared performance of the Hebb array to that of the Filler with the same testing procedure.

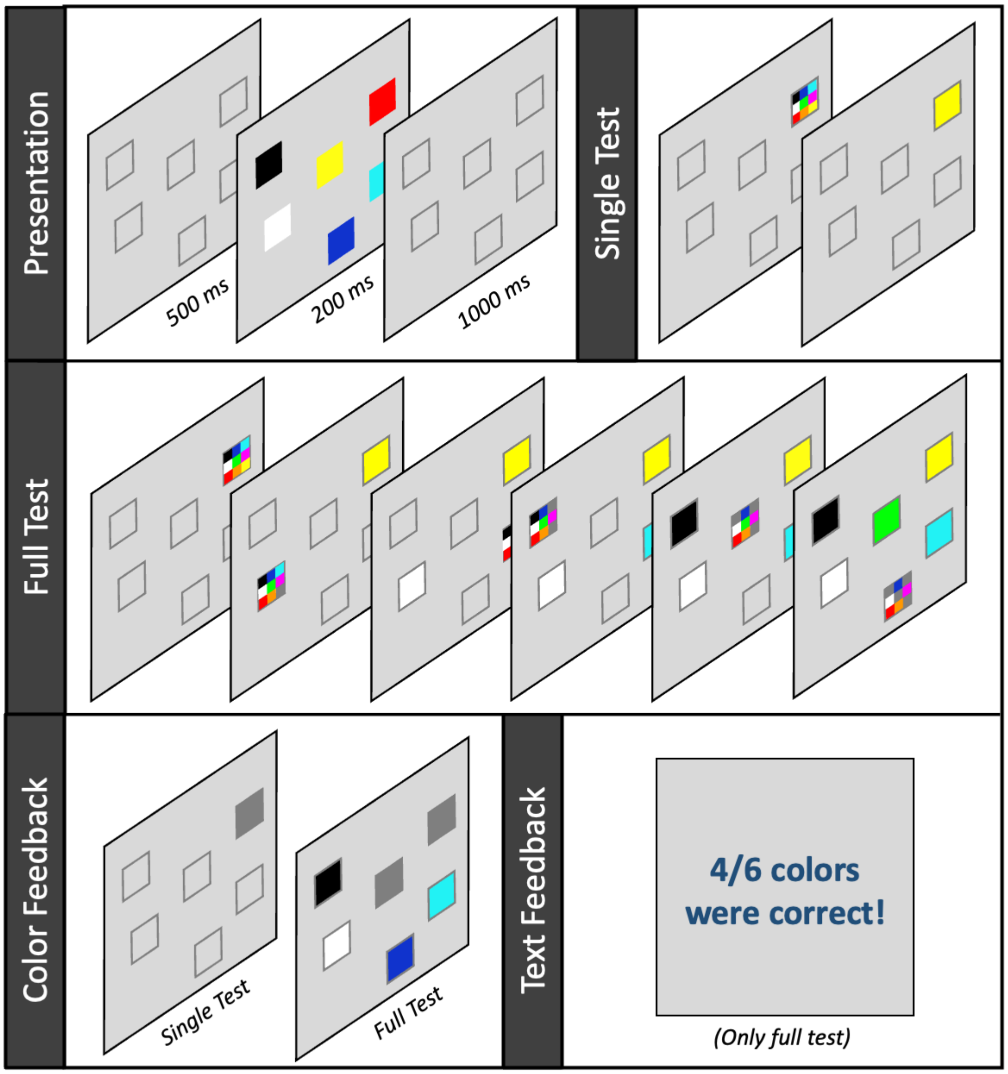
Procedure

The experiment was divided into two phases: a working memory phase and a long-term memory phase.

After reading instructions and making themselves familiar with the task in four practice trials, participants completed a total of 160 trials in the working memory phase. The general flow of a trial is shown in Figure 2. Each trial started with the presentation of six unfilled squares with a dark-grey frame (RGB 112 112 112) for 500 ms, indicating the locations of the upcoming colors (placeholders). The squares were simultaneously populated with six colors for 200 ms, followed by a retention interval of 1000 ms. Position placeholders remained onscreen throughout the trial. Immediately after, the working memory test followed. Working memory was tested by using a discrete color reproduction task (Adam & Vogel, 2017). In this task, participants were cued with a random location of the array and asked to select the color that was presented at this location from a small grid containing the nine colors of the stimulus pool from which all arrays were composed. Participants selected their responses by clicking on one of the colors inside the testing grid.

Figure 2

Illustration of the Experimental Procedure Used for all Experiments.



Note. *The color feedback was used in Experiments 1, 2, and 3, whereas the Text Feedback was only used in Experiments 3 and 4.*

Depending on the testing condition of a trial, the working memory test either followed a single-item or full recall procedure (see Figure 2). In the single-item recall, only one of the six locations was randomly selected and tested. The test ended after the response, and it was followed by immediate feedback. If the response was correct, the tested location was filled with the selected color. If the response was incorrect, the tested location was filled with dark grey. In the full recall procedure, all six locations were tested in random order by moving the recall grid to the next location after participants had selected a response. The location tested previously was filled with the responded color, and the selected response option was deactivated in the testing grid. Thus, participants were not able to respond with the same color multiple times.

Feedback was provided only after participants had given their last response: Locations with correct responses kept the selected colors, whereas locations of incorrect responses were filled with dark grey (see *Color Feedback* in Figure 2). Participants moved on to the next trial by pressing the “Space” bar. Every 40 trials, participants were informed about their progress and given the possibility to take a short break.

After completing all 160 trials of the working memory phase, a long-term memory phase followed. In the long-term memory phase, participants were first asked if they noticed anything special about the experimental design. This question was intended to examine participants’ awareness of the repeated array. Afterward, a recognition test followed. Participants were informed that one array had been presented repeatedly and asked if they were able to recognize it. For this, 12 arrays were presented one by one, and participants had to decide if the presented array was the repeated Hebb array or not. Out of the 12 arrays, five arrays were completely new arrays, which had never been presented before. Four arrays were Filler arrays which had been presented once during the experiment. The other three arrays were the original

Hebb array and two intrusion arrays, in which one and three colors of the Hebb array, respectively, had been changed.

The long-term memory phase was exploratory and not part of the main research question. Full results are presented in the supplementary materials. In summary, participants were able to correctly recognize the Hebb array and to reject new and Filler arrays above chance level in all conditions. Intrusion arrays were rejected above the chance level when three colors were changed but not when only one color was changed.

Data Analysis

All analyses in this study were conducted in a Bayesian framework. We used a parameter estimation account to estimate learning rates for the different testing procedures and Bayes Factors to distinguish between our three hypotheses. We describe the models used for both accounts below.

Parameter Estimation. To estimate the learning rate for the different testing procedures in the different experimental conditions, we fitted separate Bayesian hierarchical generalized mixed effect models to each between-subject condition and each half of the experiment. To ensure comparability between Hebb and Filler trials, only Filler trials with the same testing procedure as the Hebb trials were included in the analyses. For modeling accuracies, we used a binomial distribution (*n* out of *k* correct responses in each trial) together with a logit-link on the linear model term, following Equation 1:

$$p(correct) = \mathrm{logit}^{-1}\left(b_o + b_1 \cdot miniBlock + b_2 \cdot trialType + b_3 \cdot miniBlock \cdot trialType\right) \quad (1)$$
$$n \sim Binomial(k, p(correct))$$

The *miniBlock* variable was entered as a continuous variable into this model, starting at the value 0 for both halves of the experiment, and rescaled to a range between 0 and 1. The *trialType* variable was dummy coded with 0 = Filler Trials (baseline) and 1 = Hebb Trials. Note that for the data of the first half of the experiment, the main effect of *trialType* was omitted from the model because, at the beginning of the experiment, there was no difference between Hebb and Filler trials. In this specification of the model, the learning effect (i.e., the increase in accuracy on the Hebb array over mini-blocks) is solely reflected in the interaction term between *miniBlock * trialType*. Given the scaling of the *miniBlock* variable between 0 and 1, this parameter can be interpreted as the gain of accuracy on the Hebb trials above the Filler trials over one-half of the experiment. We used a Cauchy prior with location 0 and scale $\frac{\sqrt{2}}{4}$ on all fixed effect parameters and half-student-t priors with df = 3, mean = 0, and sd = 2 on the standard deviation parameters for the random effects. All models were run on four chains, with 1000 warmup iterations and 4000 post-warmup iterations per chain.

Hypothesis Testing. For testing the three competing hypotheses, we conducted Bayes Factor analyses on the two switching conditions (*Rec(1) – Rec(6)* and *Rec(6) – Rec(1)*), because these are the conditions for which the hypotheses made different predictions. We also only included the data directly before and after the switch point because that is where the predicted data patterns differ the most (see Figure 1). To increase power, we included the data from the four mini-blocks before the switch, and of the first four mini-blocks after it. We included four mini-blocks to increase the number of responses used to estimate parameters in the single-item recall conditions. Again, only Filler trials with the same testing procedure as the Hebb trials were included in the analysis. Accuracies were modeled by a binomial distribution (*n* out of *k* correct responses) with a logit link on the linear model term, following Equation 2:

$$p(correct) = \text{logit}^{-1}\left(b_0 + b_1 \cdot phase + b_2 \cdot trialType + b_3 \cdot phase \cdot trialType\right) \qquad (2)$$
$$n \sim Binomial(k, p(correct))$$

This time, all predictor variables were effect coded to contrast the different conditions (*trialType:* Filler trial = -0.5, Hebb trial = 0.5; *phase:* pre-switch = -0.5, post-switch = 0.5). The model was fitted to each between-subject condition separately.

Figure 1 shows the predictions for the selected part of the data, marked by rectangles. For the described model, the *no-learning* account predicts no effect in the *Rec(1) – Rec(6)* condition and only a main effect of *trialType* in the *Rec(6) – Rec(1)* condition. The *not-using* account predicts a main effect of *trialType,* a main effect of *phase,* and an interaction effect of *trialType x phase* for both, the *Rec(1) – Rec(6)* condition and the *Rec(6) – Rec(1)* condition but with the interaction effect in different directions. The *combined* account predicts no effects for the *Rec(1) – Rec(6)* condition and both main effects and the interaction effect for the *Rec(6) – Rec(1)* condition (see Table 1 for a summary of the predictions).

Table 1

Summary of Predicted Effects in the Model for each of the three Hypotheses.

Condition	Hypothesis	Effect in the Model		
		Trial Type	Phase	Trial Type x Phase
Rec(1)-Rec(6)	No learning	--	--	--
	Not using	✓	✓	✓
	Combined	--	--	--
Rec(6)-Rec(1)	No learning	✓	--	--
	Not using	✓	✓	✓
	Combined	✓	✓	✓

Note. Rec(1) / Rec(6) = Recall one or recall six items of the presented array

For testing the presence and absence of the effects in the models, we computed exclusion Bayes Factors to quantify the evidence for maintaining an effect in the model. We removed the effects one by one from the model and compared the reduced model to the full model. For the effects of interest, we used Cauchy prior with location = 0 and scale = $\frac{\sqrt{2}}{4}$, which have been proposed by Oberauer (2019) as default priors for Bayes Factor analyses with hierarchical logistic models. We report Bayes Factors in favor of the inclusion of the effect in question as BF_{10}, and Bayes Factors in favor of the null hypothesis of excluding the effect as BF_{01}, which is the inverse of BF_{10}.

For all reported Bayes Factor analyses in this paper, prior sensitivity analyses were performed with varying scale parameters of 0.2, $\frac{\sqrt{2}}{4}$, 0.5, $\frac{\sqrt{2}}{2}$ and 1, to assure robustness of the obtained results to variations of the prior within a range of reasonable default priors. All models were run on 6 chains with 1000 warmup iterations and 20000 post-warmup iterations per chain (120000 post-warmup iterations in total), to assure stable estimates of Bayes Factors with the bridgesampler.

Changes from Preregistration

Our preregistered design included another experimental between-subject condition, which is not reported in the main part of this manuscript. In this group, participants performed the same visuo-spatial Hebb experiment in which half of the trials were tested with the single-item recall procedure, and the other half were tested with the full recall procedure. Different from the other groups, a repeated Hebb array was only introduced in the second half of the experiment and subsequently tested with the full recall procedure. This condition was intended to serve as an additional control group to make sure that participants can produce a learning effect in the full recall test, even if the repeated array is introduced only during the second half of the experiment, and this was indeed the case. We did not report this condition in the main manuscript because it did not add value to our results and conclusions. The results for this condition can be found in the supplementary materials, and the data is included in the OSF.

For the data analysis, we also introduced changes to the preregistered analysis plan. The analysis plan was based on the assumption that single-item recall does not produce learning effects, as previously observed by Souza and Oberauer (2022). Therefore, we planned to only consider the data after the switch point as this would have been diagnostic to distinguish between our hypotheses. However, we did observe credible learning for the single-item recall procedure before the switch, which is why we had to adapt our analyses to consider data before and after the switch point.

Additionally, we preregistered analyses based on aggregated data, but we decided to implement all analyses at the trial level. The aggregated analyses were not included in the main manuscript because they reached the same conclusion as our trial-based hierarchical modeling approach but provided a less precise description of the data due to the aggregation. We report the results of these analyses in our supplementary materials.

Lastly, we added prior sensitivity analyses to all analyses for which we report Bayes Factors and added a new exploratory analysis to account for the effect of output interference in the full recall procedure, which is reported below.

Results

For visualization, we aggregated data from four consecutive mini-blocks into one *epoch*. This includes data from four Hebb trials and the four Filler trials with the same testing procedure as the Hebb trial. Aggregation was only used for visualization purposes. All analyses were conducted on data from individual trials. Below, we report each analysis implemented and indicate whether they match the preregistered analysis plan.

Parameter Estimates

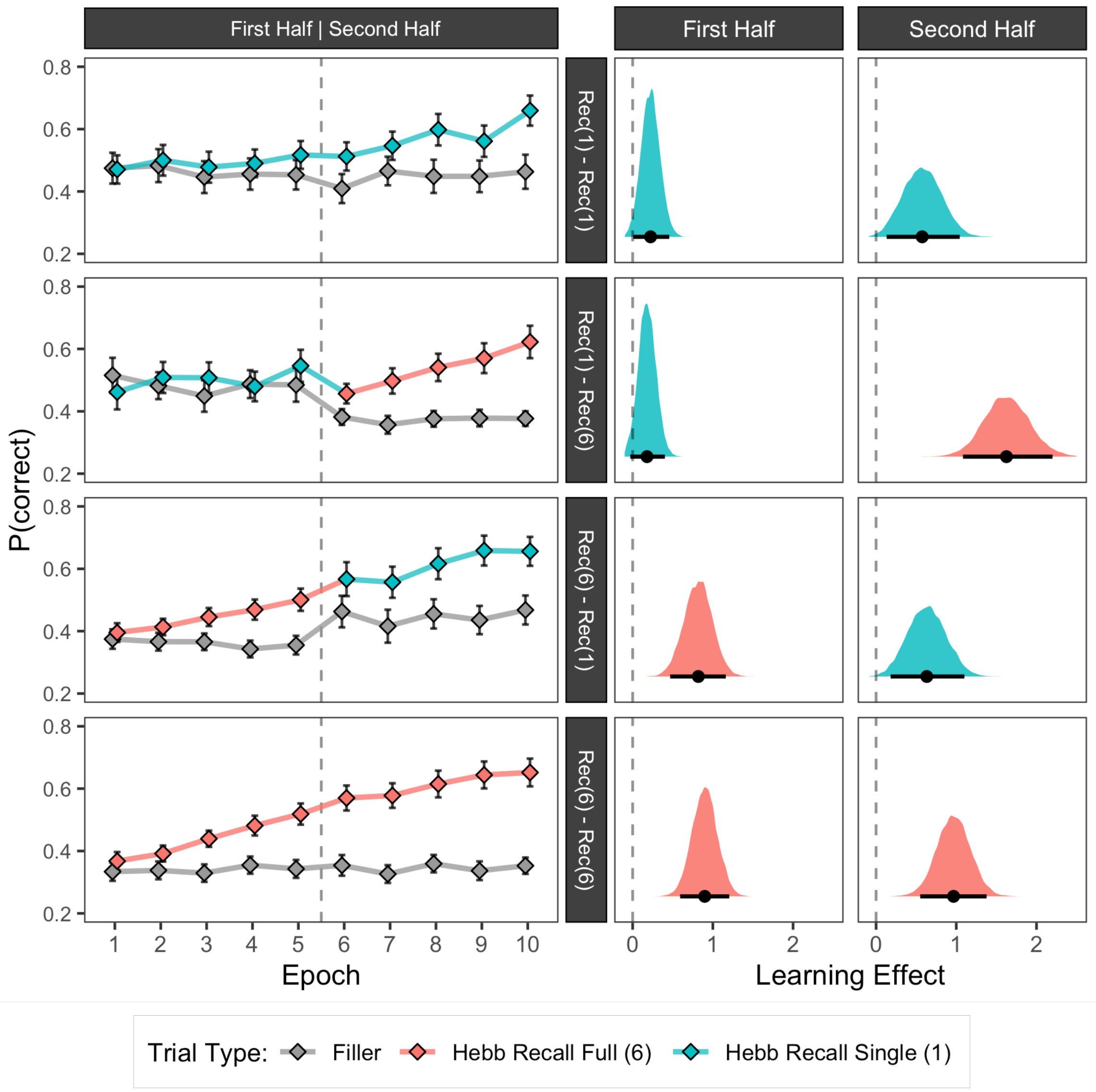
Figure 3 presents the memory performance separated by the four between-subject conditions. The left panel shows the accuracies for Hebb- and Filler-trials as a function of epochs. The right panel shows the posterior estimates of the learning effect (i.e., the performance increase in Hebb trials over Filler trials) within each half of the experiment.[3]

All conditions using the full testing procedure showed large credible learning for the repeated Hebb array in the first half of the experiment, whereas conditions with single-item recall produced small, non-credible learning in the first half of the experiment. This result replicates the findings of Souza and Oberauer (2022). Surprisingly, we observed credible learning for all conditions in the second half of the experiment irrespective of the testing procedure. This learning tended to be, however, smaller in single-item recall compared to the full recall procedure. This first analysis already allows us to rule out the *not-using* hypothesis, which predicts that single-item recall conceals learning. The learning effect observed in the full recall condition was still observed in the single-item condition after the switch, showing therefore that single-item recall does not prevent the display of learning effects. The unexpected finding in the current study was that participants learned the Hebb array eventually in the *Rec(1) – Rec(1)* condition, in which the Hebb array was always tested with the single-item recall procedure. We will consider this unexpected finding in Experiment 2.

[3] Note that the separate estimation of parameters for both halves of the experiment deviates from our preregistered plan, because we did not consider to use the data prior to the switch point in our analysis.

Figure 3

Descriptive Results and Parameter Estimates for Experiment 1.



Note. *The left panel shows working memory performance (P(correct)) for Hebb and Filler trials as a function of epochs. One epoch summarizes 8 trials, which corresponds to the presentation of 4 Hebb and 4 Filler trials. Data were aggregated by epochs for visualization purposes only. P(correct) refers to the proportion of correct responses within each epoch when considering all responses to each trial (one for single-item and six for full-item recall). Error bars represent 95% within-subject confidence intervals. The right panel shows the posterior distributions for the estimated learning rate. Points represent the median of the posterior distribution. Lines show the 95% highest density interval of the distribution.*

Our next question of interest was to determine if the switch from single to full test led to a sudden increase in performance in the Hebb trials, revealing learning during the first half of the experiment. For that, we zoomed in on the data immediately before and after the condition switch.

Hypothesis Tests

The left panel of Figure 4A presents the data from the working memory task of the two switch groups before and after the switch point. The Effects panel presents the Bayes Factors for the predictors included in the model.[4]

For both switch conditions, inconclusive but consistent evidence against the interaction effect was found ($BF_{01;\ \mathit{Rec(1)\text{-}Rec(6)}}$ = 2.86 [2.16; 6.97], $BF_{01;\ \mathit{Rec(6)\text{-}Rec(1)}}$ = 1.78 [1.47; 4.30])[5]. Overwhelming evidence for the main effect of *trialType* was found in the *Rec(6) – Rec(1)* condition (BF_{10} = 732.89 [549.44; 732.89]), whereas the evidence for a main effect of *trialType* was substantial in the *Rec(1) – Rec(6)* condition (BF_{10} = 9.08 [3.80; 9.96]). The lack of a credible interaction suggests that nothing changed when there was a switch in the test requirements: no sudden revelation of learning and no sudden concealment of learning either. The main effect of *trialType*, however, indicates that performance was higher for Hebb than Filler trials irrespective of the testing

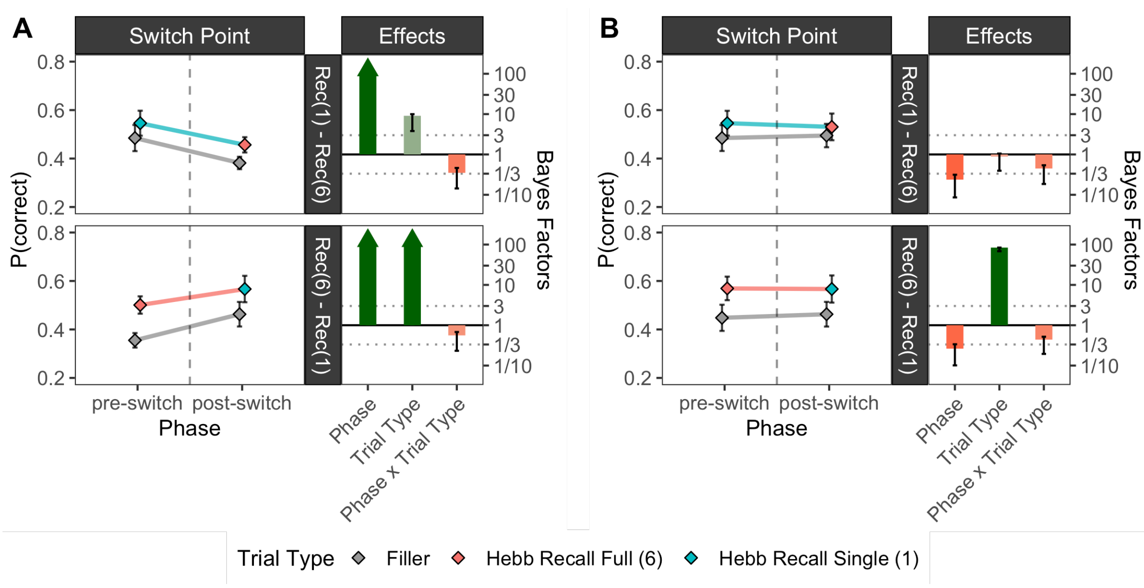
[4] Note again that this analysis deviated from our preregistered plan because we did not plan to consider the data before the switch point.

[5] The first value reports the Bayes Factor for the preregistered prior scale of $\frac{\sqrt{2}}{4}$. Values in parentheses show the range of obtained Bayes Factors in the prior sensitivity analysis.

procedure. This analysis suggests that participants were learning the repeated array in the single-item recall test.

Figure 4

Working Memory Performance and Bayes Factors for the Data at the Switch Point of Experiment 1. **A** *Includes All Responses for the Full Recall Test whereas* **B** *only Includes the First Response for the Full Recall Test.*



Note. *P(correct) shows the proportion of correct responses when considering all responses to each trial (one for single-item and six for full-item recall). Error bars for working memory performance (left) represent 95% within-subject confidence intervals. Intervals for Bayes Factors (right) indicate the variability of the Bayes Factors with regard to the prior sensitivity analysis. Arrows indicate that Bayes Factors for all prior scales were beyond 100. Note that the scaling of the y-axis for Bayes Factors was log-transformed.*

Further Exploratory Analyses

In the analysis reported above, both switching conditions showed clear evidence for the presence of a main effect of *phase* (both BFs > 100). This shows that working memory performance generally decreased when switching from single-item to full recall and increased when switching from full to single-item recall. This finding can be attributed to output interference in the full test: performance is better for the first tested item of a trial and decreases over consecutive tests in the same trial.[6] To make sure that output interference did not influence our conclusions, we repeated the analysis presented above considering only the first response in the full recall test, which is free from output interference. The results are presented in Figure 4B. The Bayes Factors now showed evidence against the effect of *phase*, suggesting that the previous effect was due to output interference in the full recall test. Both conditions also showed consistent evidence against the interaction effect, again suggesting that the switch of the testing condition did not influence recall performance. However, there was no evidence for the main effect of *trialType* in the *Rec(1) – Rec(6)* condition anymore. This is likely because of the reduced amount of data included in the analysis and suggests that learning was overall weaker with single-item recall (*Rec(1) – Rec(6)* condition) compared to full recall (*Rec(6) – Rec(1)* condition).

Discussion

The aim of Experiment 1 was to tease apart different accounts for why previous studies failed to observe repetition learning effects for visuo-spatial information with single-item tests. The *no-learning* hypothesis is that long-term representations of the Hebb array are not strengthened during this type of test. Contrary, the *not-using* hypothesis is that the long-term representation of the Hebb array is strengthened, but

[6] A visualization of this effect can be found in Figure S4 of our supplementary materials.

this knowledge is not applied in the test. The *combined* hypothesis is a combination of the two hypotheses, namely that single-item testing prevents learning and the use of existing learning.

We found that switching from single-item to full recall did not reveal hidden learning and switching from full to single-item recall did not conceal previous learning. These results show that single-item recall did not prevent the application of existing knowledge, thereby ruling out the *not-using* and the *combined* hypothesis. The data are much more consistent with the *not-learning* hypothesis. Yet, in general, we found evidence for smaller but credible learning of the Hebb array with single-item recall. Therefore, we conclude in favor of a softened version of the *not-learning h*ypothesis: Single-item testing severely reduces, but does not entirely prevent, repetition learning relative to full testing.

Why did we find evidence for some repetition learning with single-item recall whereas Souza and Oberauer (2022) did not? Two differences between the two studies could be responsible. An obvious one is the number of repetitions, which was larger in our study (40) than in the earlier one (24). Another potentially relevant difference between our study and the study by Souza and Oberauer (2022) is that single and full recall testing conditions were intermixed. This made it impossible for participants to anticipate which testing procedure to expect at the beginning of a trial. In contrast, the study by Souza and Oberauer (2022) compared single and full testing in a blocked design so that either all trials were tested with the single or the full recall procedure, and participants knew which testing procedure to expect. Therefore, one possible explanation is that full recall not only facilitates learning by the increased retrieval practice during the test itself but also by the way representations are formed in working memory in expectation of the retrieval demands. Previous literature shows that different testing expectations can influence how information is encoded into memory (Carey & Lockhart, 1973; Cohen-Dallal et al., 2023; Duncan & Murdock, 2000; Schmidt, 1983; Thiede, 1996). When participants are not able to anticipate the testing procedure, they might tend to prepare for the more difficult test, which then facilitates learning even for single-item recall.

Experiment 2

The aim of Experiment 2 was to examine which factors could explain the small but credible learning observed for the single-item recall test in Experiment 1. Two factors may explain this learning: (1) more array repetitions, and (2) test expectancy. To test the contribution of each of these factors, we ran another visual Hebb experiment with 40 repetitions of the repeated array, but this time, included only single-item recall on every trial for all arrays. This condition is equal to the *Rec(1) – Rec(1)* condition of Experiment 1, but now participants were able to anticipate the test type on every trial. If the learning effect in the *Rec(1) – Rec(1)* condition of Experiment 1 was due to the higher number of repetitions, we expected to see a comparable learning effect in Experiment 2. In contrast, if the expectation of a full item test contributes to this effect, we expected an absent or smaller learning effect in Experiment 2 compared to Experiment 1.

To evaluate differences in the learning effect, we compared the data from Experiment 2 with the data from the *Rec(1) – Rec(1)* condition of Experiment 1. This allowed us to examine to what extent the learning effect was influenced by the expectation of the task demands. In addition, we compared both data sets to the data from the *Rec(6) – Rec(6)* condition of Experiment 1. In that way, we were able to tease apart to what extent learning was influenced by the expectations of the task demands and to what extent it was additionally influenced by the actual retrieval demands for the Hebb array.

Method

Participants, Design, and Procedure

We collected a new sample of *N* = 101 participants to reach a comparable sample size to Experiment 1. Data was again collected via the online participant platform Prolific, using the same filter and exclusion criteria as for Experiment 1. Additionally, participants who had taken part in Experiment 1 were not eligible to participate.

The rest of the Experiment followed the same procedure as for Experiment 1: Participants completed a total of 160 trials of the visual array task shown in Figure 2, including 40 repetitions of the Hebb array. The only difference to Experiment 1 was that this time, all trials consisted of single-item recall. As a result, the total time for the experiment was reduced to approximately 30 minutes and participants were compensated with £4.

The preregistration of Experiment 2 is available at: https://osf.io/d53tn.

Data Analysis

For analyzing the data, we combined the data for Experiment 2 (here referred to as the *Rec(1) blocked* condition) with the *Rec(1) – Rec(1)* and the *Rec(6) – Rec(6)* condition from Experiment 1 (here referred to as conditions *Rec(1) mixed* and *Rec(6) mixed*). To account for the effect of output interference, which was observed in Experiment 1, we only considered the first response of each trial in the *Rec(6) mixed* condition. This made sure that performance in the three conditions was comparable.

Akin to Experiment 1, Bayesian hierarchical generalized mixed effect models were used to estimate and compare the learning rates in the three different conditions. The model specification used for all conducted analyses is specified in Equation 3:

$$p(correct) = \text{logit}^{-1}\begin{pmatrix} b_0 + b_1 \cdot miniBlock + b_2 \cdot condition + b_3 \cdot miniBlock \cdot trialType \\ + b_4 \cdot miniBlock \cdot condition + b_5 \cdot miniBlock \cdot trialType \cdot condition \end{pmatrix} \quad (3)$$
$$n \sim Binomial(k, p(correct))$$

In this specification of the model, the difference in the learning rates between the three conditions is reflected in the three-way interaction between *miniBlock, trialType,* and *condition*. We extracted posterior estimates of the actual learning rates by conditioning the model on each of the three between-subject groups. To quantify the evidence for differences in the learning rate between the three conditions, we fitted an alternative model omitting the three-way interaction from the model and computed the exclusion Bayes Factor between the two models.

To further contrast the learning rates between the three conditions, we conducted pairwise comparisons by fitting the same models again to each pair of conditions, always excluding one of the three conditions. We again computed the exclusion Bayes Factor between the model including and excluding the three-way interaction.

Similar to Experiment 1, *miniBlock* was entered as a numerical predictor to the model, starting at 0 and scaled into the range between 0 and 1. The *trialType* variable was dummy-coded with Filler-Trials = 0 and Hebb-Trials = 1. The main effect of *trialType* and the interaction effect between *trialType* and *condition* were omitted from the model to force the model to assume equal accuracies for Filler- and Hebb-Trials at the first repetition. The *condition* variable was encoded with orthonormal contrasts to ensure equal distribution of prior probability mass to the contrasts of the different conditions (Makowski et al., 2019). Priors and prior sensitivity analysis were the same as described in Experiment 1.

Changes to Preregistration

As for Experiment 1, we preregistered an additional analysis of aggregated data. This analysis is not reported here, because it provided a less precise description of the data compared to our trial-based analysis. We report the results of this analysis in our supplementary materials.

Results

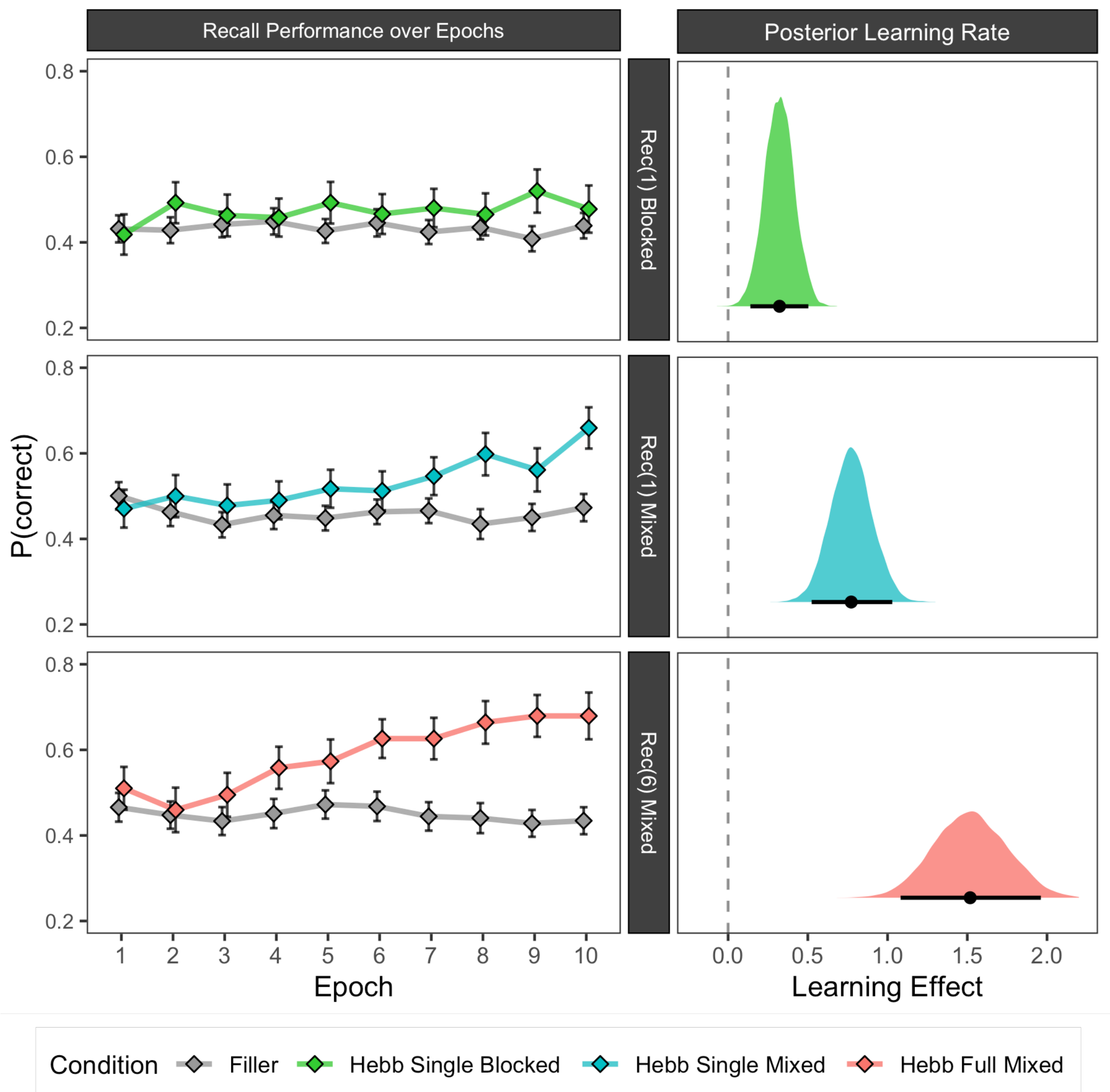
Figure 5 shows the results of Experiment 2 (top row) in relation to the results of the *Rec(1) mixed* and the *Rec(6) mixed* conditions from Experiment 1 (middle and bottom row). The left panel shows the working memory performance for Hebb and Filler trials as a function of epochs. The right panel shows the posterior distributions of the estimated learning rates for the three conditions. For the *Rec(6) mixed* condition, only the first response to each trial was considered, which is why the results look slightly different from the ones presented in Figure 3.

All conditions differed with regard to the estimated learning rate, with the *Rec(1) blocked* condition showing the smallest learning rate and the *Rec(6) mixed* condition showing the highest learning rate. Although the *Rec(1) blocked* condition showed the smallest learning rate, the estimated effect was still credibly larger than zero.

Bayes Factor analyses confirmed that there was an overall difference in learning rates between the three conditions (BF_{10} = 5.08 x 10^4 [3.79 x 10^4; 1.44 x 10^5]). Computing pairwise contrasts between all three conditions showed, that there was a credible difference between the *Rec(1) blocked* and the *Rec(1) mixed* condition (BF_{10} = 7.57 [4.87, 7.57]), between the *Rec(1) blocked* and the *Rec(6) mixed* condition (BF_{10} = 7.48 x 10^4 [4.98 x 10^4; 2.22 x 10^5]) and between the *Rec(1) mixed* and the *Rec(6) mixed* condition (BF_{10} = 44.4 [33.68; 46.95]). The credible difference between the *Rec(1) blocked* and the *Rec(1) mixed* condition confirmed that learning was facilitated by mixing single and full recall randomly in a series of trials.

Figure 5

Descriptive Results and Parameter Estimates for Experiment 2 (top row) in Comparison to the Rec(1) Mixed and the Rec(6) Mixed Condition from Experiment 1 (middle and bottom row).



Note. *The left panel shows working memory performance (P(correct)) for Hebb and Filler trials as a function of epochs. One epoch summarizes 16 trials which corresponds to the presentation of 4 Hebb and 12 Filler trials. We aggregated data by epochs for visualization only. P(correct) refers to the proportion of correct responses for each epoch when only considering the first response of each trial (Rec(6) Mixed Condition). Error bars represent 95% within-subject confidence intervals. The right panel shows the posterior distributions for the estimated learning effects in the different between-subject conditions. Points represent the median of the posterior distribution. Lines show the 95% highest density interval of the distribution.*

The credible difference between the *Rec(1) mixed* and the *Rec(6) mixed* condition showed that learning was additionally facilitated by the increased retrieval demands at test.

Discussion

With only single-item recall, the learning effect was smaller than when single-item recall was mixed with full recall (i.e., the *Rec(1) – Rec(1)* condition of Experiment 1), and comparable in size to the results obtained by Souza and Oberauer (2022). Yet, there was still credible evidence for learning, different from Souza and Oberauer (2022), perhaps because the weak learning effect was better detectable in the present experiment with more repetitions and a larger sample size.

The findings from Experiment 2 suggest that testing does not only influence long-term learning by the retrieval demands at the actual test, but also by the anticipation of the retrieval demands at encoding. When participants were not able to anticipate the testing condition (as in Experiment 1), they probably prepare for the more difficult test (which is the full recall test), and thereby facilitate learning by encoding information more robustly into memory. At the same time, providing more opportunities to practice the actual retrieval by testing more items still provided an additional boost to learning, as was shown by the increased learning rate in the *full mixed* compared to the *single mixed* condition. This suggests that long-term learning is facilitated by two processes: one happening during the encoding of the information in anticipation of the retrieval demands, and the other happening during the actual retrieval. We elaborate on this in more detail in the General Discussion.

Experiment 3

One confounding factor that could have contributed to the larger learning observed for the full recall test is how feedback was provided after each trial. In Experiment 1, correctly answered items maintained their correct color on the screen, thereby allowing participants to re-study the correct array information. Given that full recall involved more responses, it also provided more array information during the feedback compared to the single-item recall. Therefore, an alternative explanation for the observed benefit of full tests could be that it was caused by having more opportunities to study the relevant array information, and not by the increased retrieval practice during the test.

We conducted Experiment 3 to address this possibility and manipulated the way feedback was provided after each trial. For one group, visual feedback was provided the same way as done in Experiment 1. For the other group, participants received text feedback, telling them how many answers they had gotten correct (e.g., *"3 / 6 answers were correct"*; see Figure 2). The text feedback did not provide any additional array information and did not inform participants about which items were answered correctly. We used the full recall procedure in both conditions. If the visual color feedback contributed to the observed learning benefit with full recall, we would expect the learning effect to be smaller in the text feedback condition. If the feedback procedure did not influence the learning effect, no differences between the color and the text feedback conditions were to be expected.

Method

Participants, Design, Procedure, and Data Analysis

We collected another two samples of participants with N_{color} = 48 and N_{text} = 53 The data collection procedure was the same as in Experiments 1 and 2. The experiment took approximately 30 minutes and participants received £4.

The general procedure and design were also similar to Experiments 1 and 2, with two differences: The full testing procedure was used on every trial, and the number of repetitions was reduced to 20. Our previous studies have shown that 20 repetitions are enough to produce a robust Hebb effect with the full testing procedure.

Participants were randomly assigned to one of the two feedback conditions. Participants in the *color feedback* condition received the same feedback after every trial as was used in Experiment 1: Correctly responded items maintained their correct color onscreen, whereas incorrectly responded items were filled with dark grey (see Figure 2). Participants in the *text feedback* condition received a short text message after each trial, stating how many items they had answered correctly (see Figure 2).

For analyzing the data, we used the same modeling approach as described in Experiment 2 (see Equation 3). The difference in the learning rate between the color and the text feedback condition was again reflected in the three-way interaction between *miniBlock, trialType,* and *condition*. We computed Bayes Factor analyses in the same way as described for Experiment 2 to evaluate this difference.

The preregistration of Experiment 3 is available at: https://osf.io/tyc3m.

Changes to Preregistration

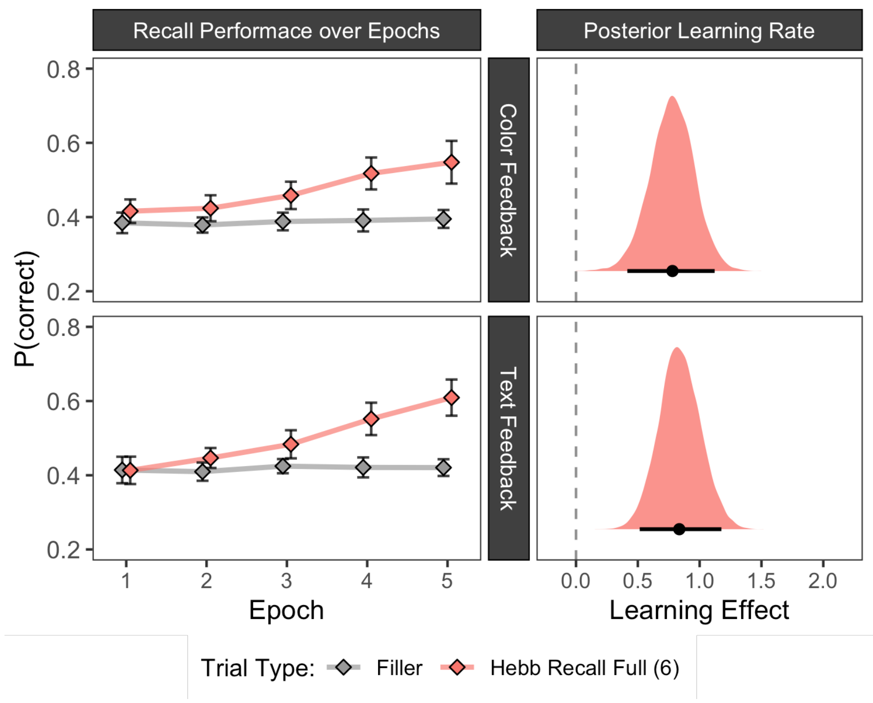
As for the previous experiments, we preregistered an additional analysis of aggregated data which is not reported here. The results of this analysis can be found in our supplementary materials.

Results and Discussion

The results of Experiment 3 are displayed in Figure 6. The right panel shows the average recall performance over epochs, and the left panel the posterior distributions of the estimated learning rates for both conditions. Both groups produced a comparable learning effect (BF_{01} = 3.61 [2.74; 6.55]). This result shows that the type of feedback is irrelevant for the learning effect in the full recall condition. It helps to rule out the hypothesis that the feedback presented at the end of the trial was critical for boosting the learning of the repeated array. Therefore, the larger learning effect of full recall compared to single-item recall should be attributed to the increased retrieval practice during the working memory test. The present result is also consistent with the observation of Souza and Oberauer (2022) that removing the feedback altogether did not prevent learning in the full recall condition.

Figure 6

Descriptive Results and Parameter Estimates for Experiment 3.



Note*. The left panel shows working memory performance (P(correct)) for Hebb and Filler trials as a function of epochs. One epoch summarizes 16 trials which corresponds to the presentation of 4 Hebb and 12 Filler trials. We aggregated data by epochs for visualization only. P(correct) refers to the proportion of correct responses within each epoch when considering all six responses of each trial. Error bars represent 95% within-subject confidence intervals. The right panel shows the posterior distributions for the estimated learning effects in the two between-subject conditions. Points represent the median of the posterior distribution. Lines show the 95% highest density interval of the distribution.*

So far, Experiments 1, 2, and 3 provided a detailed comparison between the single and full recall procedures. Our results showed that single-item recall does not prevent long-term learning from being displayed and, unlike previous studies, it also showed that learning effects can be observed with the single-item recall procedure. The difference is that these effects are just much smaller and take longer to build up, requiring therefore a large sample and more trials. This may also help explain why previous studies failed to show a credible repetition learning effect for visuo-spatial information. However, most of these studies use change detection tasks to test working memory. Therefore, we extended our comparison of testing procedures to a change detection task, to investigate if our conclusions also apply to recognition memory.

Experiment 4

Various studies investigated repetition learning in the visual domain with a change detection task and failed to observe any benefits of the repetition (Fukuda & Vogel, 2019; Logie et al., 2009; Olson & Jiang, 2004). Souza and Oberauer (2022) tested four different versions of a change detection task in a typical Hebb repetition experiment. The versions of the change detection task differed in two characteristics: 1) the number of elements presented at test (either one or the whole array), and 2) the number of tested items (either one or all elements in the array). However, none of these procedures produced a credible learning effect, even when the number of array repetitions was increased to 48. Souza and Oberauer (2022) concluded that the change detection task is not demanding enough, which makes participants mostly rely on the current working memory representation and not engage in retrieval from episodic long-term memory even with a larger number of tests. They proposed that recognition tests may also prevent participants from recognizing previous encounters of the Hebb array, and from strengthening the long-term representation of this array.

The aim of Experiment 4 was to assess if a change detection task implementing full testing hinders learning or prevents learning from being displayed, as in our original hypotheses. For this, we applied the same design as in Experiment 1 but this time, comparing the full recall test to a full recognition change detection test. The task setup was the same as in the previous experiments, with one exception. In 50% of the trials, working memory was tested by the full recall test. For the other 50% of the trials, full testing with a change detection procedure was used. We selected the single-probe full testing procedure used by Souza and Oberauer (2022), which was most similar to our full recall test. In this version, participants were also tested on every item of the array, but instead of being asked to select the color which was presented at the tested location, the tested location was filled with a specific color, and participants were asked to decide if this color was originally presented at this location (*same*) or not (*change*). In contrast to the single-item recall procedure, this equates the number of retrieved items during the test between the two procedures, while still manipulating the difficulty of retrieval.

As in Experiment 1, the repeated Hebb array was always tested with the same testing procedure, but the procedure could change halfway through the experiment. This led to the following four between-subject conditions: 1) Hebb array was tested with the change detection (CD) procedure for the whole experiment (*CD(6) – CD(6)*); 2) Hebb array was tested with change detection in the first half, but with full recall in the second half (*CD(6) – Rec(6)*); 3) Hebb array was tested with full recall in the first half but with change detection in the second half (*Rec(6) – CD(6)*); 4) Hebb array was tested with full recall for the whole experiment (*Rec(6) – Rec(6)*).

We again considered the same hypotheses as for Experiment 1: (1) the *not-learning* account, (2) the *not-using* account, and (3) the *combined* account. The predictions for Experiment 4 are the same as displayed in Figure 1, when *"Rec(1)"* is replaced by *"CD(6)".* Additionally, we considered a fourth possible outcome which was motivated by the findings of Experiment 1: If learning is not only influenced by the testing procedure itself but also by the expectation of the test, learning effects should also be observed with the change detection procedure, because participants were not able to anticipate the testing procedure of a trial. Thus, this account assumed that all conditions lead to learning and the use of this knowledge, even when the Hebb array is always tested by the change detection procedure.

Methods

Participants

Data collection and sample size determination followed the same procedure as described for the other experiments. The study took approximately 60 minutes to complete, and participants were compensated with £7.50.[7] We collected a total of 313 participants of which 33 participants were excluded due to performance at chance level (9 in *CD(6) – CD(6)*, 10 in *CD(6) – Rec(6)*, 9 in *Rec(6) – CD(6),* and 5 in *Rec(6) – Rec(6)*).

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[7] Note that different from the preregistration, we increased the study time and compensation after a test run as the experiment took longer than previously expected.

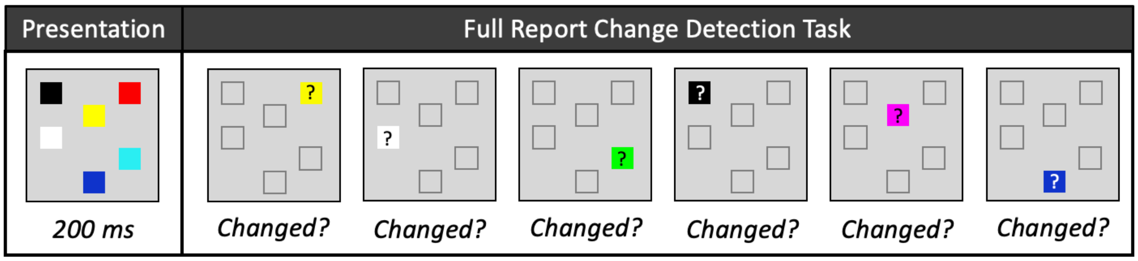
This resulted in a final sample of N = 280 ($n_{CD(6)\text{-}CD(6)}$ = 71; $n_{CD(6)\text{-}Rec(6)}$ = 69; $n_{Rec(6)\text{-}CD(6)}$ = 72; $n_{Rec(6)\text{-}Rec(6)}$ = 68).

Design, Procedure, and Data Analysis

The logic for the design was the same as in Experiment 1. Upon starting the study, participants were randomly assigned to one of the four between-subject conditions. In all conditions, participants performed a total of 160 trials, of which 50% were tested with full recall and 50% with the full-testing change detection task. The conditions only differed in how the testing procedures were assigned to the repeated Hebb array in the two halves of the experiment. The full recall test followed the same procedure as described previously. The procedure of the change detection task was similar but based on recognition memory: After the presentation of the array, participants were presented with a probe at a random memory location. The probe was filled with a color and a question mark. Participants were asked to make a *same / change* judgment to the probe (see Figure 7 for an example). Participants gave their responses by clicking on buttons for “same” or “different” which appeared underneath the probed location. Overall, there was a 50% chance that the probe color was the same as originally presented in this location and a 50% chance that the color was changed. If the cued color was a change, it was either a new color that had not been presented in the current array (external change, 25% chance) or it was a color that had been presented at a different location of the current array (internal change, 25% chance). New colors were selected from the three colors which were not part of the current array. Because we did not allow for color repetitions during the test, the number of external changes within each trial was limited to three.

Figure 7

Illustration of the Change Detection Procedure used in Experiment 4.



Note. *Participants responded by pressing a button for "same" or "different" which were presented underneath the probed location. Buttons are not shown in the Figure for visibility reasons.*

Due to a programming error, we did not control for the possibility that in a trial in which five tested colors had been selected to match the originally presented colors (*same*), the sixth color must be an external change. An internal change was not possible due to the restriction that probe color repetitions were not allowed. When this scenario happened in the experiment, it had the effect that the probed location was not filled with any color. This only applied to 0.08% of the trials, which were excluded from the analysis. The rest of the Experiment followed the same procedure as in Experiment 1 with the only difference that the text feedback condition from Experiment 3 was used and not the color feedback (see Figure 2). Data was analyzed in the same way as described in Experiment 1.

The preregistration of Experiment 4 is available at: https://osf.io/jf6be.

Changes to Preregistration

As for the previous experiments, preregistered analyses based on the aggregated data can be found in our supplementary materials. Additionally, the switch point analysis (see Experiment 1) was not part of our preregistered analysis plan.

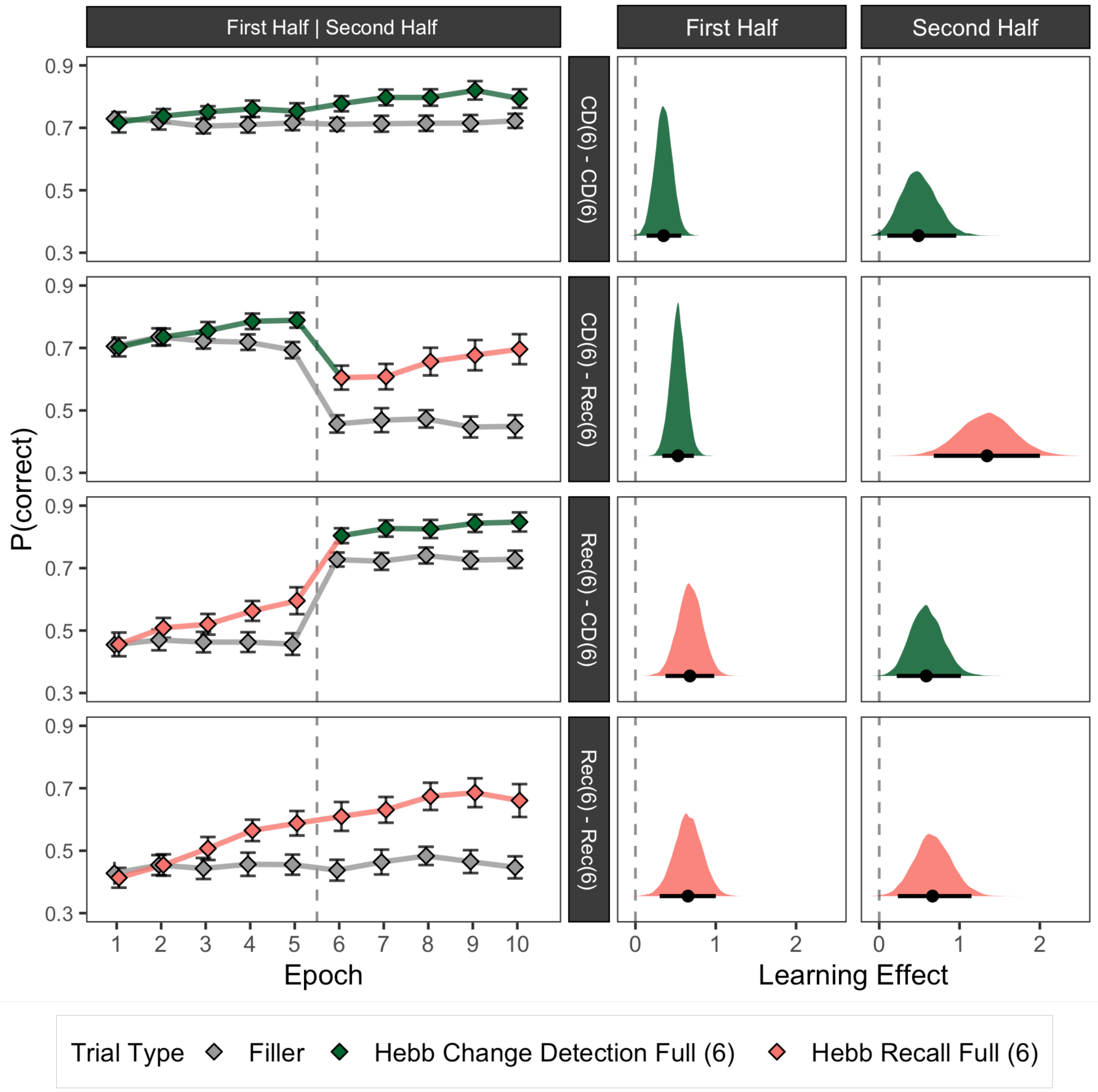
Results

Figure 8 presents the working memory performance for Hebb and Filler trials as a function of epoch for the four between-subject conditions, together with the posterior estimates of the learning rates. Credible learning effects were observed for all experimental conditions, even if the repeated array was always tested by the change detection procedure (*CD(6) – CD(6)* condition). This closely resembled the pattern observed in Experiment 1. Computing Bayes Factors for the learning rate in the *CD(6) – CD(6) condition* for both halves of the experiment together showed overwhelming evidence for the presence of a learning effect (BF = 8.97×10^3 [6.82×10^3; 1.25×10^4]).

Figure 9 shows the data from the working memory task zoomed into the area before and after the switch point, together with the Bayes Factors for the effects of the predictor variables. Again, we found consistent evidence for a main effect of *trialType* and against the interaction between *trialType* and *phase* in both switch point conditions. This shows that learning effects were present regardless of the testing procedure and that learning was neither revealed nor hidden by switching the testing procedure halfway through the experiment. This is consistent with our findings from Experiment 1 and reiterates the idea that learning is also influenced by the expectations of the test.

Figure 8

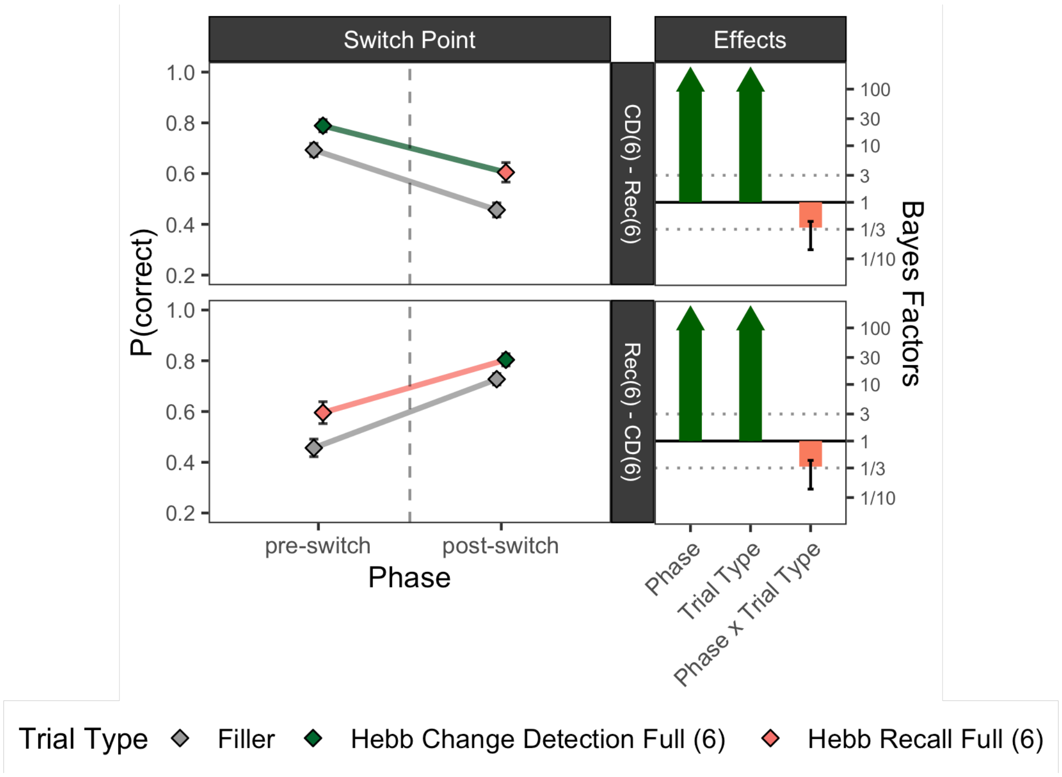
Descriptive Results and Parameter Estimates for Experiment 4.



Note. *The left panel shows working memory performance for Hebb and Filler trials as a function of epochs. One epoch summarizes 8 trials, which corresponds to the presentation of 4 Hebb and 4 Filler trials. We aggregated data by epochs for visualization only. P(correct) refers to the proportion of correct responses within each epoch when considering all six responses of each trial. Error bars represent 95% within-subject confidence intervals. The right panel shows the posterior distributions for the estimated learning effects in the different conditions separated for the two halves of the experiment. Points represent the median of the posterior distribution. Lines show the 95% highest density interval of the distribution. Note that baseline performance in the change detection and the recall task is different due to different chance levels of the task (1/2 for the change detection task and 1/9 for the recall task).*

Figure 9

Working Memory Performance (left) and Bayes Factors (right) for the Data at the Switch Point of Experiment 4.



Note. *P(correct) shows the proportion of correct responses when considering all six responses to each trial. Error bars for working memory performance represent 95% within-subject confidence intervals. Intervals for Bayes Factors indicate the variability of the Bayes Factors with regard to the prior sensitivity analysis. Arrows indicate that Bayes Factors for all prior scales were beyond 100. Note that the scaling of the y-axis for Bayes Factors was log-transformed.*

Additionally, we again found a main effect of *phase* for the *CD(6) – Rec(6)* and the *Rec(6) – CD(6)* condition, showing that working memory performance was generally higher in the change detection task compared to the full recall task. However, this time, this effect was not related to output interference but to the fact that the chance of guessing the correct response is much higher for the change detection task (1/2 vs. 1/9).[8]

Discussion

Previous studies often failed to find repetition learning effects for visual stimuli when working memory was tested by a change detection task. Experiment 4 was conducted to test whether these null effects with change detection tasks were related to the fact that participants did not learn the repeated array, or if existing knowledge was not used in this kind of task.

Our results provided clear evidence that prior long-term memory can be used in the change detection task to improve working memory performance. This suggests that the failure of previous studies to observe learning effects cannot be explained by the concealment of learning. Hence it is likely that no long-term learning had taken place over the repetitions implemented in these studies, or the sample size was just not sufficient to detect learning. In our study, we observed clear learning effects even when the Hebb array was always tested by the change detection procedure. Although this is inconsistent with previous studies, the finding is in line with the results from Experiments 1 and 2. For example, differently from Souza and Oberauer (2022) who tested working memory with a change detection task on every trial, our study mixed the

[8] The decrease in memory performance over output positions did not differ between the change detection and the recall task. The results of this comparison are included in the supplementary materials and visualized in Figure S8.

change detection task with a full recall task across trials so that participants were not able to anticipate the testing procedure of the current trial. This might have led participants to orientate their expectations more towards the more difficult memory test and change the way how information was encoded into memory (Carey & Lockhart, 1973; Duncan & Murdock, 2000; Schmidt, 1983). As we have shown in Experiments 1 and 2, the expectation of a more difficult memory test can already facilitate long-term learning, even when the repeated Hebb array is always tested with a less difficult test, which previously did not facilitate learning when used solely (e.g., the single-item recall task in Souza and Oberauer, 2022). Replicating the same pattern of results for the change detection task lends credibility to the hypothesis that testing not only facilitates long-term learning by the actual retrieval demands during the test itself but also by changing how information is encoded into memory in expectation of the retrieval demands.

General Discussion

The presented study investigated how different testing procedures influence the long-term learning of repeatedly presented visual information. More specifically, we tested different explanations for why previous studies often failed to find repetition learning effects for visual materials. Test procedures that did not lead to learning in previous studies – single-item recall tests, as well as change detection tests – could have produced null effects of repetition because they prevent learning, or because they prevent the expression of what is learned. Here, we conducted four experiments to tease these possibilities apart. Experiments 1, 2, and 3 focused on the single-item recall test, whereas Experiment 4 focused on the change detection test.

The results from our four experiments can be summarized as follows: Testing all array items through recall leads to more learning than testing recall of only a single item or testing through change detection. When switching testing procedures after a period of full recall tests, in which learning effects were established, to one of the other two test procedures, the benefit of learning is still expressed in performance. Conversely, transferring from a learning period with single-item recall or change detection to full recall tests does not suddenly reveal substantial knowledge of the Hebb array that has been acquired before. This shows that long-term knowledge was used in single-item recall and change detection tests when available, but participants learned little during these types of tests.

Different from previous studies, testing the Hebb array through single-item recall or change detection over the whole experiment eventually produced learning. This was caused by two design features that distinguished our experiments from previous ones: (1) more repetitions of the Hebb array, and (2) participants not being able to anticipate if a trial was tested by single-item recall/change detection or full recall. We conclude that the beneficial effect of full recall testing on learning is caused through two routes: The expectation of a (possible) full recall test which leads participants to encode the array in a way that fosters long-term learning, and the actual retrieval demands of going through the full recall of all items, which further boosts long-term learning.

Overall, our findings provide a clear answer to our research question. We rule out the possibility that learning happened but was not used in single-item recall or change detection tests (i.e., when the test was less difficult). Rather, learning was less likely to occur, and proceeded at a much slower rate, under these testing conditions, resulting in smaller overall effects. Previous studies might not have been powered enough to detect these small effects because of smaller sample sizes and fewer repetitions of the Hebb array.

Our findings also add another puzzle piece to our understanding of the mechanisms underlying long-term learning by repetition. As we have argued in Souza and Oberauer (2022) and Musfeld et al. (2023), repetition learning is likely to depend on a two stage-process: an initial stage of recognizing the repetition and a second stage of forming a stable representation of the repeated information once the repetition was recognized. In the initial phase of a repetition learning experiment, every trial encoded during the working memory test leaves a new memory trace in episodic long-term memory (Hintzman, 1984; Jamieson et al., 2022; Logan, 2002; Shiffrin & Steyvers, 1997). With every new trial, the current representation encoded into working memory is matched against previous encounters of similar information in episodic long-term memory. When the same information is presented again, as is the case for the repeated Hebb array, two scenarios are possible: 1) a person could fail to recognize to have seen this information before. In this case, no strengthening of an existing memory trace is possible. Instead, another separate memory trace of the same information is laid down in episodic long-term memory; 2) a person recognizes a previous encounter of this same information. This triggers the retrieval of the previous memory trace and allows to integrate the existing memory trace with the newly encoded memory representation, thereby strengthening the existing memory trace.

This assumption that repetitions only strengthen existing memory traces when the repetition is recognized during encoding is based on the concept of study-phase retrieval, which assumes that repetitions only benefit memory if a previous encounter of the same information is retrieved during re-encoding (Benjamin & Tullis, 2010; Hintzman, 2004; Melton, 1967). Recent simulation work has shown that this is a necessary assumption for computational models of episodic memory like REM (Shiffrin & Steyvers, 1997), to successfully account for several memory phenomena (Ensor et al., 2021). In Musfeld et al. (2023) we have found strong empirical evidence for this hypothesis in the Hebb paradigm: Participants' performance in a visuo-spatial and a verbal repetition learning task only improved once they recognized the repeating information.

How can this process be influenced by the retrieval demands during the working memory test? Souza and Oberauer (2022) argued that when the test's retrieval demands are low, participants are less likely to engage in extensive searches for supportive information in long-term memory and are more likely to rely on the current information in working memory (Oberauer et al., 2017). This makes it less likely that previous encounters of the same information are recognized, and therefore prevents the strengthening of previously formed long-term representations. If retrieval is more demanding, however, learning is facilitated by two processes: (1) higher retrieval demands make it more likely that participants search for supporting information in episodic memory, which increases the chance of recognizing previous encounters of the same information; (2) recalling more information increases retrieval practice of that information during the test, which strengthens the previously encoded memory representation and makes it more likely to retrieve it again on the next repetition. This is consistent with another finding by Souza and Oberauer(2022), showing that the size of the learning effect increased monotonically with the number of array elements tested (one, three, or six).

One might argue that the explanation of differential engagement of long-term memory depending on the retrieval demands at test is an overcomplication for the results observed. Instead, a simpler explanation could be that some learning always occurs due to the repeated encoding of the same information. Being re-exposed to the encoded information during test then provides additional learning opportunities, with the full test allowing more learning opportunities than single-item tests. Whereas this simpler account could explain the differences observed between the full and the single-item test, it is inconsistent with the finding that learning was also reduced for the change detection task. In the change detection procedure used in this study and the study by Souza and Oberauer (2022), all array items were tested. Hence, the comparison of change detection to full-array recall equates the number of items retrieved during the test – thereby providing the same amount of additional learning opportunities – while only manipulating the difficulty of retrieval. Still, learning was weaker for the change detection compared to the recall test, rendering it unlikely that learning was driven solely by pure re-exposure to the encoded information at test. Instead, it seems more likely that it is the difficulty of retrieval which drives the difference in learning. Unlike recognition tests, recall tests provide fewer external retrieval cues, making retrieval of information from working memory harder, which may prompt the retrieval of additional information from episodic long-term memory.

Next to the actual testing effects, our findings also revealed that long-term learning was facilitated by the expectation of higher retrieval demands. Yet, it is less clear how these expectancy effects can influence the proposed mechanisms of repetition learning. One possibility is that expectations about the testing format influence how information is encoded into memory. Previous work has shown that expecting a recall test compared to a recognition test can influence memory in various ways (Carey & Lockhart, 1973; Cohen-Dallal et al., 2023; Duncan & Murdock, 2000; Schmidt, 1983; Thiede, 1996; Thiede et al., 2011). For example, Thiede (1996) has shown that participants studied longer and performed better when they were expecting a recall compared to a recognition test. Similarly, Cohen-Dallal et al. (2023) showed that working memory representations were more precise when participants expected to be tested by a delayed estimation task compared to a change detection task. Duncan and Murdock (2000) as well as Carey and Lockhart (1973) found that serial position curves were altered depending on whether or not participants expected to be tested by a recall or a recognition test. All these findings suggest that people can flexibly adapt how information is encoded and represented in working memory depending on how they expect to use this information in a later test. When multiple tests are mixed, people seem to default to anticipating the more difficult memory test (Duncan & Murdock, 2000; Schmidt, 1983; Thiede, 1996).

How can differential encoding of information into memory affect the proposed processes of repetition learning? If we assume that the quality of a memory trace which is laid down in episodic memory for each trial depends on the current representation in working memory, then this can influence the likelihood of recognizing repeating information. For example, if the expectation of a recognition test leads to a less precise representation in working memory, as has been shown by Cohen-Dallal et al. (2023), this would also lead to a less precise representation in episodic long-term memory. Consequently, this weaker memory trace would decrease the likelihood of recognizing a repeated encounter of the same information, thereby decreasing the chance of learning from repetition.

Less research has focused on how the expectations of the difficulty of different kinds of recall procedures influence the encoding of information into memory. Thiede (1996) manipulated participants' expectations about the difficulty of a later recall test (by varying the number of letters absent in a cued recall test of a letter string) but did not find any effect of expected difficulty on later memory performance. Bhatarah et al. (2008) as well as Grenfell-Essam and Ward (2012) investigated the effects of expecting a serial vs. a free recall test in an immediate memory task but also without observing any differences. Still, our findings suggest that expectations about specific retrieval demands (recalling one vs. six items) also affect the long-term learning of visual configurations. To this point, we can only speculate why this is the case. Chunharas and Brady (2023) recently showed that in typical visual working memory tasks, items are not represented independently but show strong inter-item dependencies. One possibility could be that these inter-item dependencies are strengthened in expectation of a full recall test compared to a single recall test, thereby leading to a more integrated representation of the full display. Such integrated representations would be more distinct from other representations, thereby making it more likely to recognize their repetition. Future research will need to investigate in more detail the flexibility with which people can encode new information into memory in response to different memory test demands, and the factors which determine how such encoding processes can be altered.

Taken together, our study provides clarification for existing findings in the literature: In conditions in which little or no learning is observed, this is because learning is weak, not because participants fail to use the acquired knowledge. We also provide new insights into the mechanisms of how testing influences long-term learning by repetition. We propose that the way how information is encoded into memory in anticipation of the test mainly influences the chance of recognizing the repeated information, which we have found to be necessary to initiate the learning process (Musfeld et al., 2023). Providing more opportunities to practice retrieval of the whole array during a full recall test favors the strengthening of the memory trace as a more integrated representation and thereby further boosts learning.

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