THE UNIVERSITY OF CHICAGO

INTERACTIONS BETWEEN WORKING MEMORY AND LONG-TERM MEMORY WITHIN AND ACROSS INDIVIDUALS

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ABSTRACT

In computer systems, random access memory (RAM) temporarily stores a limited amount of information for immediate use, whereas the hard disk provides larger, more durable storage. Analogously, human cognition relies on multiple memory systems, including a capacity-limited visual working memory (VWM) that maintains recently encountered information and a visual long-term memory (VLTM) system that supports the storage and retrieval of accumulated knowledge. A central question in cognitive neuroscience concerns how these systems interact within and across individuals. In this dissertation, I integrate behavioral, electroencephalography (EEG), and computational approaches to investigate the relationship between VWM and VLTM. In Chapter 1, I demonstrate that individual differences in working memory predict long-term memory performance when encoding time is sufficient, but this relationship diminishes under rapid presentation conditions (250 ms per item). This finding suggests that the correlation between VWM and VLTM is driven by a shared encoding bottleneck that constrains both systems. In Chapter 2, I characterize the neural mechanisms underlying memory retrieval, showing that both univariate activity and multivariate decoding of EEG signals reveal shared access to representations in VWM and VLTM during the test phase. In Chapter 3, I examine repeated learning and show, across a large sample of participants, that working memory capacity consistently predicts long-term memory performance across repetitions, indicating a stable role of VWM in VLTM acquisition. Finally, in Chapter 4, I investigate how neural representations differ as a function of repetition strength, comparing well-practiced and less-practiced long-term memories, and contrasting both with working memory representations at retrieval. Together, these

findings provide converging evidence that interactions between working memory and long-term memory are shaped by a shared encoding bottleneck and overlapping retrieval processes, and that these interactions remain stable across repeated learning. This work advances our understanding of how multiple memory systems coordinate to support human learning and memory.

INTRODUCTION

In computer systems, random access memory (RAM) provides fast, short-term storage for a limited amount of information, whereas the hard drive supports larger, more durable storage. A similar distinction exists in human cognition: visual working memory (VWM) maintains a small amount of recently encountered information in an active state, while visual long-term memory (VLTM) supports the storage and retrieval of vast amounts of accumulated knowledge.

A long-standing goal in cognitive psychology has been to distinguish working memory from long-term memory as separable systems. One of the earliest formalizations of this distinction comes from William James (1890), who differentiated between “primary” and “secondary” memory. Primary memory referred to information currently within conscious awareness, whereas secondary memory encompassed information that is not immediately accessible but can be retrieved. Importantly, James proposed that primary memory is inherently capacity-limited, a concept that closely anticipates modern definitions of working memory as a constrained, actively maintained store.

Building on this foundation model, Atkinson and Shiffrin (1968) introduced the *modal model* of memory, which formalized memory as a multi-stage system consisting of a sensory register, a short-term store, and a long-term store. In this framework, information is first registered through sensory input, then selectively transferred to the short-term store via attention, and ultimately consolidated into the long-term store through processes such as rehearsal. The short-term store functions as a temporary,

capacity-limited system, closely aligned with RAM-like working memory, whereas the long-term store provides a more durable and effectively unlimited repository.

These early models were largely domain-general, meaning that they were not specific to the visual domain. Extending this framework, Baddeley and Hitch (1974) proposed a multicomponent model of working memory, emphasizing its modality-specific structure. Within this account, visual and spatial information is maintained in the visuospatial sketchpad, a capacity-limited subsystem specialized for representing visual inputs. Later extensions introduced the episodic buffer (Baddeley, 2000), a mechanism that integrates information across modalities and interfaces working memory with long-term memory representations.

Collectively, these theoretical frameworks converge on the view that human memory consists of a capacity-limited working memory system alongside a high-capacity long-term memory store. However, more recent theories have challenged the necessity of strictly separate storage systems. For example, Nelson Cowan's focus of attention model conceptualizes working memory as a temporarily activated subset of long-term memory (Cowan, 1999). Within this activated pool, a small number of representations, typically around 4 items (Cowan, 2001), enter the "focus of attention", where they are directly accessible for ongoing cognitive processing. Representations outside this focus remain in a less accessible state and must be reactivated to guide behavior. In this framework, working memory reflects the portion of long-term memory that is currently activated and attended, with capacity limits arising from attentional constraints rather than from a distinct storage system.

However, while all these models provide valuable accounts of how information is represented, they offer less specificity regarding how these systems interact to support flexible behavior. For example, it is still unclear what it means, at the neural level, for a representation to be “activated,” or how such activation translates into observable behavior during memory use. More broadly, these theories do not fully specify how interactions between WM and LTM unfold in real time, how they scale across different task demands, or how they give rise to individual differences in cognitive abilities such as learning. In this dissertation, I investigate how visual working memory (VWM) and visual long-term memory (VLTM) interact both within and across individuals. To do so, I integrate behavioral measures, electroencephalography (EEG), and computational modeling, combining within-subject experimental manipulations with individual differences approaches. In Chapter 1, I show that individual differences in working memory predict long-term memory performance when encoding time is sufficient, but this relationship diminishes under rapid presentation conditions, suggesting a shared encoding bottleneck. In Chapter 2, I characterize the neural dynamics of retrieval, demonstrating that both univariate activity and multivariate decoding reveal shared access to representations in VWM and VLTM at test. In Chapter 3, I examine repeated learning and find that working memory capacity reliably predicts long-term memory performance across repetitions, indicating a stable contribution of VWM to VLTM acquisition. Finally, in Chapter 4, I investigate how neural representations evolve with repetitions, contrasting well-learned and less-learned long-term memories with working memory representations during retrieval.

Together, these findings provide converging evidence that interactions between working memory and long-term memory are shaped by shared encoding constraints and overlapping retrieval processes, and that these interactions remain stable across learning. Overall, my thesis aims to advance our understanding of how multiple memory systems coordinate to support human cognition.

CHAPTER 1.

Working Memory and Attentional Control Abilities Predict Individual Differences in Visual Long-Term Memory Tasks

Individual differences in working memory capacity are known to predict various cognitive abilities, including general intelligence (gF, Unsworth et al., 2014), reading comprehension (Turner & Engle, 1989) and complex real-world tasks (Draheim et al., 2022). One proposal for this relationship has been that working memory capacity measures appear to largely reflect variations in the efficacy of exerting attention control (Meier & Kane, 2017; Shipstead et al., 2014; Unsworth et al., 2014a). While there is still ongoing debate about whether measures of working memory capacity and measures of attention control (WMAC) reflect a single or separable factors, measurements of both are strong predictors of ability across many cognitive domains. In particular, multiple WMAC measures have been shown to be predictive of source memory performance, paired associated recall and delayed free recall performance (Unsworth et al., 2014a). One follow-up study replicated the findings that multiple working memory task measures collectively predicted variance in delayed free recall performance (Miller et al., 2019a). Moreover, pupil dilation during encoding, a measure of attention control, explained significant variance in delayed free recall performance, suggesting that successful recall of verbal materials relies on attentional control resources (Van der Wel & Van Steenbergen, 2018). These studies collectively suggest that attentional control differences have been shown to impact performance across a wide range of long-term memory tasks.

The studies above measured long-term memory abilities using either recall of verbal materials (Miller et al., 2019a), or source memory of visual images (Unsworth et al., 2014a). One common feature between these two paradigms is that the memory tests appear to be highly attention demanding, such that they exhibit higher costs under divided attention conditions as compared to recognition memory for single items. For instance, in a signature study, Craik et al. (1996) showed that when participants were asked to perform a secondary task while studying verbal materials, both recall and recognition memory were slower and less accurate compared to when participants were fully concentrating on the memory task alone. However, free recall performance showed more than twice as much accuracy cost (46%) compared to recognition memory (22%) when the divided attention task was administered during encoding. Furthermore, the response time cost was nearly five times larger for free recall (146%) than recognition task (32%) when the divided attention task was performed during retrieval. Therefore, free recall tasks appear to require more attentional control resources than recognition memory tasks during both encoding and retrieval. Similarly, Troyer et al. (1999) showed that source memory, particularly spatial location retrieval, showed a higher memory cost with divided attention than item memory. They concluded that source processing required more attentional control resources than forming item memory.

The divided attention literature raises the possibility that the robust correlations between WMAC and long-term memory may be specific to source memory and recall tasks, due to the higher level of attentional control these paradigms require. Therefore, simple recognition memory performance for items, because of its reduced reliance on attention compared to either recall or source retrieval, may not be predicted by WMAC

differences. Echoing this view, individual differences studies of item memory, source memory and recall had been shown to be better explained by a dual-factor or three-factor model than a single long-term memory factor model (Unsworth, 2019; Unsworth & Brewer, 2009). In their analyses, the recollection factor, shared by item recognition, source memory and recall, was explained by the working memory factor. By contrast, the familiarity factor, on which only item recognition loaded, did not predict the working memory factor formed with span tasks. This evidence converges with the divided-attention literature in suggesting that recognition memory for items has fewer demands for attentional or working memory resources than more effortful retrieval tasks, such as free recall or source memory tasks.

A compelling alternative hypothesis is that recognition memory, despite being less effortful to perform at a high level, still requires substantial attentional control resources for successful performance. Supporting this view, more recent literature using divided attention paradigms has suggested that performing a secondary task during encoding induces similar costs for both item and source memory. In a series of experiments, Naveh-Benjamin et al. (2003) showed that the detrimental effects of divided attention were equal for item memory and source memory between the item and its source information, such as fonts, a paired word, or a paired non-word. Moreover, they tested the participants with free recall, cued recall, and recognition memory under divided attention conditions, and found that performance under divided attention condition was equally hurt with all three test conditions. The findings suggest that the encoding of item memory may rely on similar resources to those during the encoding of source information in memory. A parallel line of research on individual differences discovered

that span task performance loaded positively on both recognition and recall factors, suggesting that attentional control might be involved in both recognition and recall (Unsworth, 2010). One potential caveat to the study, however, is that the authors included the source recognition task into the recognition factor, on which item recognition memory also loaded. As a result, the structural equation model in the paper did not separate the contribution of attentional resources to source memory from those to item recognition memory, leaving the question open for future studies.

The work reviewed above raises an important secondary question about whether individual differences in recognition and source memory form a coherent long-term memory factor. Prior studies have suggested that item recognition memory and source memory rely on distinct neural signatures. For example, when participants were instructed to encode the source of a visual item, the ERP old/new effect during the test phase was observed to be larger and earlier compared to when they were instructed to memorize the item itself without source information (Guo et al., 2006). Additionally, item memory elicited an earlier onset of visual ERP than source memory, indicating that source memory retrieval required more extensive conscious processing (Thakral & Slotnick, 2015). However, other evidence supports a more unified view, such that recognition and source memory depend upon on similar neural processes used by long-term memory. For instance, a neuroimaging study suggested that item and source memory rely on the medial temporal lobe to a similar degree (Gold et al., 2006). Furthermore, they found that hippocampal lesion participants were similarly impaired on item and source memory tasks. Together, the question of whether item and source

memory task rely on different levels of attentional resources, or instead form a single coherent long-term memory factor, remains unresolved.

In our current study, we directly tested whether working memory differences predict recognition memory performance. In each of our Experiments, subjects completed a visual working memory task, a source memory task, and a recognition memory task within a single session. In Experiment 1, we tested whether working memory abilities, measured with a change detection paradigm with visual arrays (Luck & Vogel, 1997a), predicted simple item recognition memory differences for real-world objects (Brady et al., 2008). In Experiment 2, we examined whether working memory differences continued to predict item recognition memory performance when items were presented during study at rapid rates (2 items per second) that are known to tax the temporal limits of attentional and working memory encoding (Potter, 1976). In Experiment 3, we tested whether the lack of correlation between working memory and RSVP recognition performance was due to the brief exposure duration of each image rather than the rapid rate of incoming images during the study phase. Lastly, to generalize our findings to the working memory and attentional control (WMAC) psychological factor, we administered a wide range of newly developed attentional control tasks to measure the construct (Burgoyne et al., 2023; Martin et al., 2021; Zhao et al., 2022), along with a visual working memory capacity measure. This design also allowed us to test a secondary hypothesis within each of our experiments regarding whether source memory and recognition memory were highly correlated with each other, despite the differences in retrieval demands.

Experiment 1

Humans have an exceptional ability to recognize visual objects. For example, after only a single brief presentation, we can accurately (~90%) recognize thousands of visual scenes and individually presented objects (Standing, 1973; Brady et al., 2008). This exceptional level of recognition memory ability stands in sharp contrast with other measures of long-term memory, such as free recall or source memory judgments in which accurate mnemonic performance is much more effortful and limited even for much smaller sets of stimuli. One potential explanation for the difference is that tasks such as free recall and source memory may depend more on attention-demanding processes at encoding and retrieval, as compared to less effortful recognition judgements which may rely more heavily on a general sense of familiarity. In line with this proposal, previous research has demonstrated that individual differences in WMAC measures predict source memory performance (Unsworth et al., 2014a). However, whether the easier, familiarity-driven visual recognition process also demands WMAC resources remains unresolved. To test on this question, in Experiment 1, we measured working memory, recognition memory and source memory abilities of participants. We aimed to test if 1) individual differences in working memory predicted recognition memory, 2) individual differences in familiarity-driven recognition memory predicted recollection-driven source memory, and 3) individual differences in working memory uniquely predicted familiarity-driven recognition memory even after the contribution of source memory was regressed out.

Method

Participants

For Experiment 1, 385 young residents of the United States (18-35 years old) were recruited through Prolific and received monetary compensation ($10.00/hour). All participants reported normal or corrected-to-normal vision, no color blindness, fluency in English, no history of mental illness/condition, and no cognitive impairment. All participants had successfully completed 90% or more of the studies that they had participated in previously on Prolific (filtered by approval rate >= 90%).

Materials and Procedure

For Experiment 1, all participants signed an informed consent, and completed three tasks. Each participant started with an attentional control task (**Fig. 1A**), followed by a visuo-spatial source memory task (**Fig. 1B**) and a visual recognition memory task (**Fig. 1C**).

Working Memory Task: Change Detection Paradigm

During each trial, six colored squares were displayed on the screen simultaneously for 250 milliseconds. This was followed by a blank retention interval lasting 1,000 milliseconds. Subsequently, a single-colored square appeared, and participants were required to determine whether the color of this square had changed compared to the one presented earlier in that position. Changes happened with a probability of 0.5. Participants completed a total of 140 trials for the change detection task. The dependent variable of interest was the K capacity measure (N x (hit-false alarm)) of the working memory task.

Source Memory Task: Visuo-spatial source memory

In the study phase, we presented 30 images of real-world objects. The average picture size was approximately 4.6° by 4.6° of visual angle, assuming the subject was

seated 80 cm from the screen. Each image was centered on the screen during both the study and test phases.

During the study phase, each trial started with a 500-ms fixation cross. Following that, a picture was displayed in one of the four quadrants of the screen for 2000 ms. The participants were instructed to memorize the visual appearance as well as the spatial location of the image. In the test phase, we presented each participant with the same 30 pictures one at a time, and the participants were asked to press W/E/S/D to indicate which quadrant the image was originally at (W for upper left, E for upper right, S for lower left and D for lower right). Each trial in the test phase began with a 500-ms fixation cross, followed by the presentation of the test picture at the center of the screen until the participant made a button press to record their source memory response. The stimuli were drawn from a previously published set of real-world objects (Brady et al., 2008). Both parts of the experiment were programmed using the jsPsych package (De Leeuw, 2015). The dependent variable of interest was the accuracy of the source memory task.

Recognition Memory Task

In the study phase, we presented 100 images of real-world objects. The average picture size was approximately 4.6° by 4.6° of visual angle, assuming the subject was seated 80 cm from the screen. Each image was centered on the screen during both the study and test phases.

During the study phase, each trial started with a 250-ms fixation cross. Following that, a picture was displayed at the center of the screen for 3000 ms. In the test phase,

we presented each participant with 100 pairs of pictures, two at a time, one on the left side of the screen and the other one on the right side of the screen. Among the two images on screen, one image had already been shown in the study phase and the other one was novel to the participant. The participants were asked to perform a two-alternative forced choice task to report which image was the one they had seen during the study phase. Each trial in the test phase began with a 250-ms fixation cross, followed by the presentation of the test picture at the center of the screen until the participant made a button press to record their old versus new response, along with their confidence level.

Participants used the number keys on a keyboard to indicate their confidence and which image was the one they studied earlier. Specifically, the number keys 1 and 2 indicated that the item on the left side of the screen was the studied one, with high and low confidence levels, respectively. On the other hand, the number keys 9 and 8 indicated that the item on the right side of the screen was the studied one, with high and low confidence levels, respectively. The stimuli were drawn from a previously published set of real-world objects (Brady et al., 2008). Both parts of the experiment were programmed using the jsPsych package (De Leeuw, 2015). The dependent variable of interest was the accuracy of the recognition memory task.

Sample size estimation and exclusion criterion

In Experiment 1, a stopping criterion was established when the Bayes Factor (BF) exceeded 3, indicating support for the alternative hypothesis, or fell below 0.33, indicating support for the null hypothesis. Here, without prior data on the correlation

strength between working memory and recognition memory measures, we estimated the required sample size based on a correlation of r = 0.15 and a beta of 0.2 to capture meaningful correlations between the two variables. This estimation indicated a need for 347 subjects. A multivariate exclusion criterion was applied to the behavioral data, excluding participants whose task performance fell below chance and more than 2.5 standard deviations below the mean.

Results

In Experiment 1, we first tested whether individual differences in working memory predicted source memory accuracy. We found out that working memory differences positively correlated to source memory performance differences ($r(383) = 0.30$, $p < 0.001$, **Fig. 2B**), as shown in previous studies (Unsworth et al., 2014a). More importantly, we tested whether working memory also predicted visual recognition memory, a paradigm that was presumably relying less on visual attentional resources than source memory. If the hypothesis held, then we would expect a weaker or nonsignificant correlation than that with source memory. Surprisingly, our correlation analysis revealed that working memory positively predicted recognition memory accuracies ($r(383) = 0.33$, $p < 0.001$, **Fig. 2D**), and the correlation strength was not significantly different from the correlation between working memory and source memory ($z(383) = 0.62$, $p = 0.27$). A further correlational analysis revealed that recognition and source memory strongly correlated with each other ($r(383) = 0.49$, $p < 0.001$, **Fig. 2C**), suggesting the existence of a more generalized visual long-term memory construct.

These results suggest that both source and item recognition versions of visual long-term memory tasks rely on working memory resources.

To better quantify the level of working memory resources involved in each visual long-term memory task, we performed a three-way partial regression analysis to determine the pairwise shared variance among working memory, source memory, and recognition memory tasks. Echoing our correlational results, we first found that working memory differences continued to share variance with source memory performance after recognition memory was regressed out ($r(383) = 0.16$, $p < 0.001$, BF = 15.68, **Fig. 2E**). Likewise, working memory differences also continued to explain a significant amount of variance with recognition memory even after source memory performance was regressed out ($r(383) = 0.22$, $p < 0.001$, BF > 1000, **Fig. 2E**). Additionally, recognition memory and source memory continued to share significant portions of variance even after working memory was regressed out ($r(383) = 0.44$, $p < 0.001$, BF > 1000, **Fig. 2E**). Collectively, our findings suggest that simple visual recognition memory tasks appear to rely on working memory resources just as much as source memory tasks. Moreover, visual recognition memory and source memory differences remained highly correlated with or without attention control differences in the regression model, suggesting that both may form a coherent visual long-term memory factor in explaining individual differences in human cognition.

Measure	Mean	SD	Skewness	Kurtosis	Reliability
Working Memory	2.46	1.15	0.17	-0.51	0.84
Recognition Memory	0.81	0.13	-0.51	-0.64	0.92

Source Memory	0.74	0.14	-0.56	-0.14	0.89

Table 1. *Descriptive statistics and reliability estimates for all measures in Experiment 1*

Correlation	Working Memory	Recognition Memory	Source Memory
Working Memory	--	--	--
Recognition Memory	0.33**	--	--
Source Memory	0.30**	0.49**	--

Table 2. *Correlations among all measures in Experiment 1 (** indicates p < .01 level).*

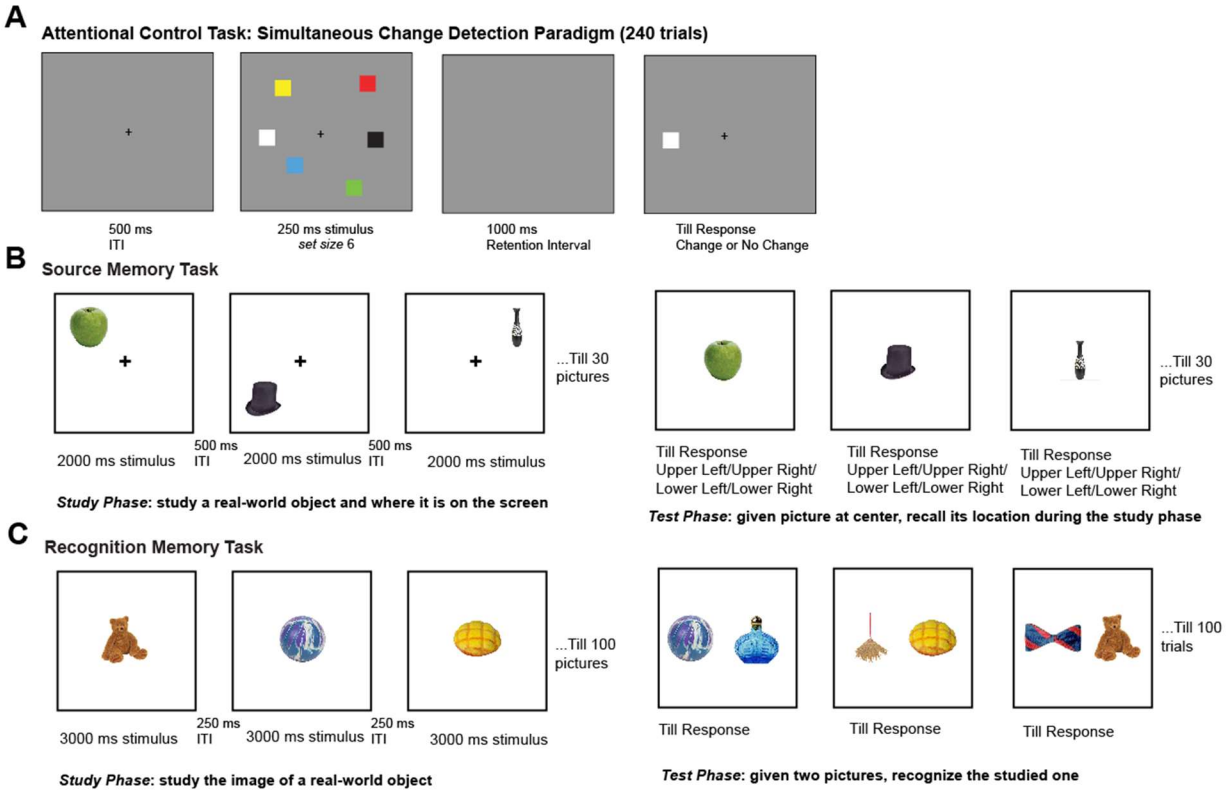


Figure 1. *Experimental Procedures for Experiment 1*
(A) Attentional Control task: simultaneous change detection paradigm. Six colored squares appeared on the screen simultaneously. At the end of the trial, participants were cued with a square at one of the six original locations, with 50% exhibited a color change and 50%
without change.
(B) Source Memory task. During each trial of the study phase, a real-world object appeared at one of the four quadrants on the screen for 2 seconds. The participants need to encode the content of the picture as well as where it was placed on the screen. We had thirty pictures in total for the study phase. During each trial of the test phase, we cued the participants with the studied object at the center of the screen, and they were asked to recall which quadrant the object was in during the study phase.
(C) A sample of the recognition memory paradigm used in Exp 1. During each trial of the study phase, a real-world object appeared at the center of the screen for 3 seconds. The participants need to encode the content of the picture. During each trial of the test phase, participants were shown two real-world images on the screen, one on the left and the other on the right. They were asked to recognize which of the image was studied. In each trial, one image was always a studied picture, and the other image was a new image that the participants had never studied in the experiment.

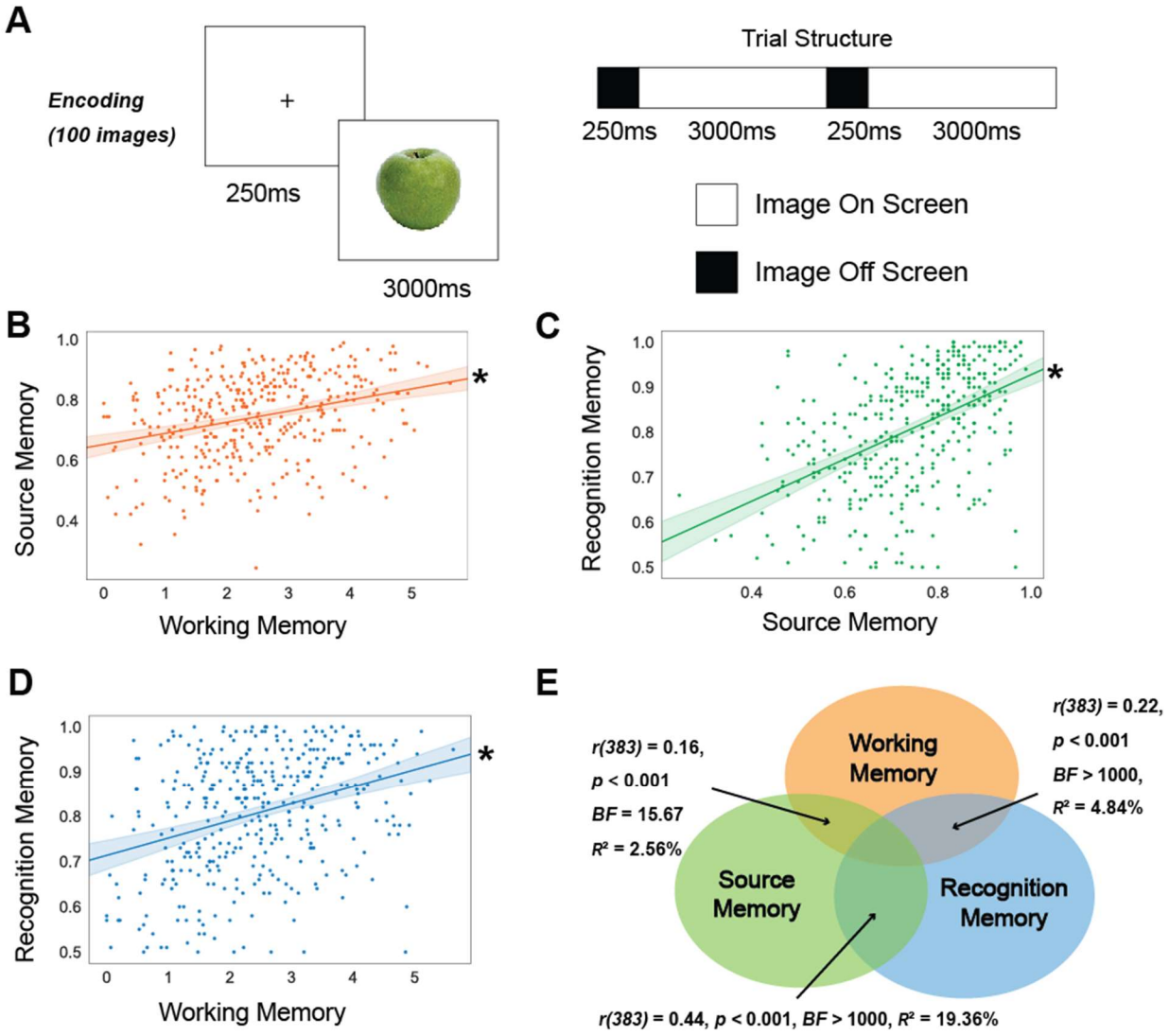


Figure 2. *Results of Experiment 1.*
(A) Schema of Recognition Memory Task in Exp 1: the images were presented on screen for 3250 ms, and 250 ms of inter-stimulus interval.
(B) Working memory differences significantly predicted source memory performances ($r(383) = 0.30$, $p < 0.001$).
(C) Source memory performances significantly predicted recognition memory accuracies ($r(383) = 0.49$, $p < 0.001$).
(D) Working memory differences significantly predicted recognition memory accuracies ($r(383) = 0.33$, $p < 0.001$).
(E) A sample Venn diagram on variance explained by working memory, source memory and recognition memory.

Experiment 2

Contrary to our predictions, in Experiment 1 we found that individual differences in working memory capacity predicted performance in a relatively easy visual recognition memory task; a relationship that was comparable to what we observed for the more effortful source memory task. One possibility for the correlation between recognition memory and working memory capacity is that the relatively slow encoding rate (3 seconds) during study provided sufficient time to rely on attentional and working memory mechanisms to bolster performance. Prior work using rapid serial visual presentation (RSVP) during the study phase of visual recognition tasks has shown that these rapid rates produce overall lower recognition performance in part because they exceed the temporal limits of an attention-demanding short-term consolidation process (e.g., Potter, 1975). However, despite the reduced recognition rate, the RSVP items appear to still receive relatively deep amounts of perceptual and semantic processing, reflected by the intact accuracy in picture and name search tasks (Potter, 1976). Considering the depth of perceptual and semantic processing, these rapidly presented items may still leave a detectable mnemonic trace. Furthermore, rapid streams of items are known to exceed the limits of working memory encoding. Participants are often unable to encode the second target into memory if it is presented too close in time following the first target (i.e., attentional blink, Shapiro et al., 1997). Similarly participants often miss the repetition of targets in rapid presentation streams (i.e., repetition blindness, Kanwisher & Potter, 1990). In Experiment 2, we directly tested whether WM differences will continue to predict recognition memory for rapid streams of images. That is, do attention control and working memory still play a role in recognition

performance for items that were presented at rates that exceed the temporal limits of attention and working memory encoding?

Method

Participants

For Experiment 2, 199 young residents of the United States (18-35 years old) were recruited through Prolific and received monetary compensation ($10.00/hour). All participants reported normal or corrected-to-normal vision, no color blindness, fluency in English, no history of mental illness/condition, and no cognitive impairment. All participants had successfully completed 90% or more of the studies that they had participated in previously on Prolific (filtered by approval rate >= 90%).

Materials and Procedure

For Experiment 2, all participants provided informed consent, and completed three tasks. Each participant started with a working memory task, followed by a visuo-spatial source memory task and a visual recognition memory task, as in Exp 1.

Working memory Task: Change Detection Paradigm

The working memory task was the same as in Exp 1.

Source Memory Task: Visuo-spatial source memory

The source memory task was the same as in Exp 1.

Recognition Memory Task: rapid presentation

The recognition memory task used the same materials and study-test procedures as in Exp 1. Different from Exp 1, during the study phase, each trial started with a 250-ms fixation cross. Following that, a picture was displayed at the center of the screen for

250 ms. Therefore, each participant was presented images at a 250-ms on and 250-ms off pace (see **Fig. 3A**). Note that this presentation rate is more than six times faster than the rate used in Exp 1.

Sample size estimation and exclusion criterion

In Experiment 2, a stopping criterion was established for when the Bayes Factor (BF) exceeded 3, indicating support for the alternative hypothesis, or fell below 0.33, indicating support for the null hypothesis. Here, with our observations from Experiment 1, we estimated the required sample size based on a correlation of r = 0.3 and a beta of 0.2 to capture meaningful correlations between the two variables. This estimation indicated a need for 85 subjects. A multivariate exclusion criterion was applied to the behavioral data, excluding participants whose task performance fell below chance and more than 2.5 standard deviations below the mean.

Results

In Experiment 2, we first tested whether individual differences in working memory predicted source memory accuracy. We replicated our findings in Experiment 1 that working memory differences positively correlated to source memory performance differences ($r(197) = 0.28$, $p < 0.001$, **Fig. 3B**). Furthermore, we tested whether working memory predicted visual recognition memory when the images were presented rapidly. If the ability to encode a rapid stream of images similarly relies on working memory resources, then we would expect a strong positive correlation between working memory and recognition memory with fast presentation rates. However, in contrast with Experiment 1 when images were presented slowly (> 3000 ms per image), our

correlation analysis revealed that working memory did not predict recognition memory accuracies with rapid presentation ($r(197) = 0.14$, $p = 0.057$, **Fig. 3D**). Moreover we found that this nonsignificant correlation with working memory was significantly weaker than the correlation between working memory and source memory ($z(197) = 1.83$, $p = 0.03$). One possibility for the lack of correlation is that recognition memory with RSVP presentation no longer relies on the common visual long-term memory factor we observed in Experiment 1. If this is the case, we would expect RSVP recognition to no longer predict Source memory performance. However, instead we found that rapid recognition and source memory were still strongly correlated with each other ($r(197) = 0.39$, $p < 0.001$, **Fig. 3C**). The robust correlation between RSVP recognition memory and the slowly-presented source memory task indicates that both forms of memory continue to form a general visual long-term memory factor, suggesting that RSVP recognition performance still utilizes the same common long term memory mechanisms as we observed in Experiment 1. Instead, the null correlation between working memory and RSVP recognition performance suggests that the reduced attentional and working memory processing for these rapidly presented items is what disconnected recognition performance from working memory capacity.

To better quantify the level of working memory resources involved in each visual long-term memory task, we performed a three-way partial regression analysis to determine the pairwise shared variances among working memory, source memory, and RSVP recognition tasks. Similar to our correlational findings, we first replicated our findings that working memory differences shared variance with source memory performance when recognition memory was regressed out ($r(197) = 0.25$, $p < 0.001$, BF

= 59.44, **Fig. 3E**). Different from Experiment 1, working memory differences stop explaining shared variances with recognition memory when images were presented rapidly ($r(197) = 0.03$, $p = 0.69$, BF = 0.096, **Fig. 3E**). However, RSVP recognition memory and source memory shared significant portions of variance after working memory was regressed out ($r(197) = 0.37$, $p < 0.001$, BF > 1000, **Fig. 3E**). Collectively, our findings reveal that visual recognition memory tasks do not rely on working memory resources if images were presented rapidly during study. Moreover, despite the severe difference between presentation rates at encoding, recognition memory and source memory individual differences remained highly correlated, suggesting that both tasks form a coherent visual long-term memory factor.

Measure	**Mean**	**SD**	**Skewness**	**Kurtosis**	**Reliability**
Working Memory	2.57	1.23	0.14	-0.38	0.73
Recognition Memory	0.69	0.12	-0.11	-0.31	0.85
Source Memory	0.73	0.15	-0.73	0.17	0.91

Table 3. *Descriptive statistics and reliability estimates for all measures in Experiment 2.*

Correlation	Working Memory	Recognition Memory	Source Memory
Working Memory	--	--	--
Recognition Memory	0.14	--	--
Source Memory	0.28**	0.39**	--

Table 4. *Correlations among all measures in Experiment 2 (** indicates p < .01 level).*

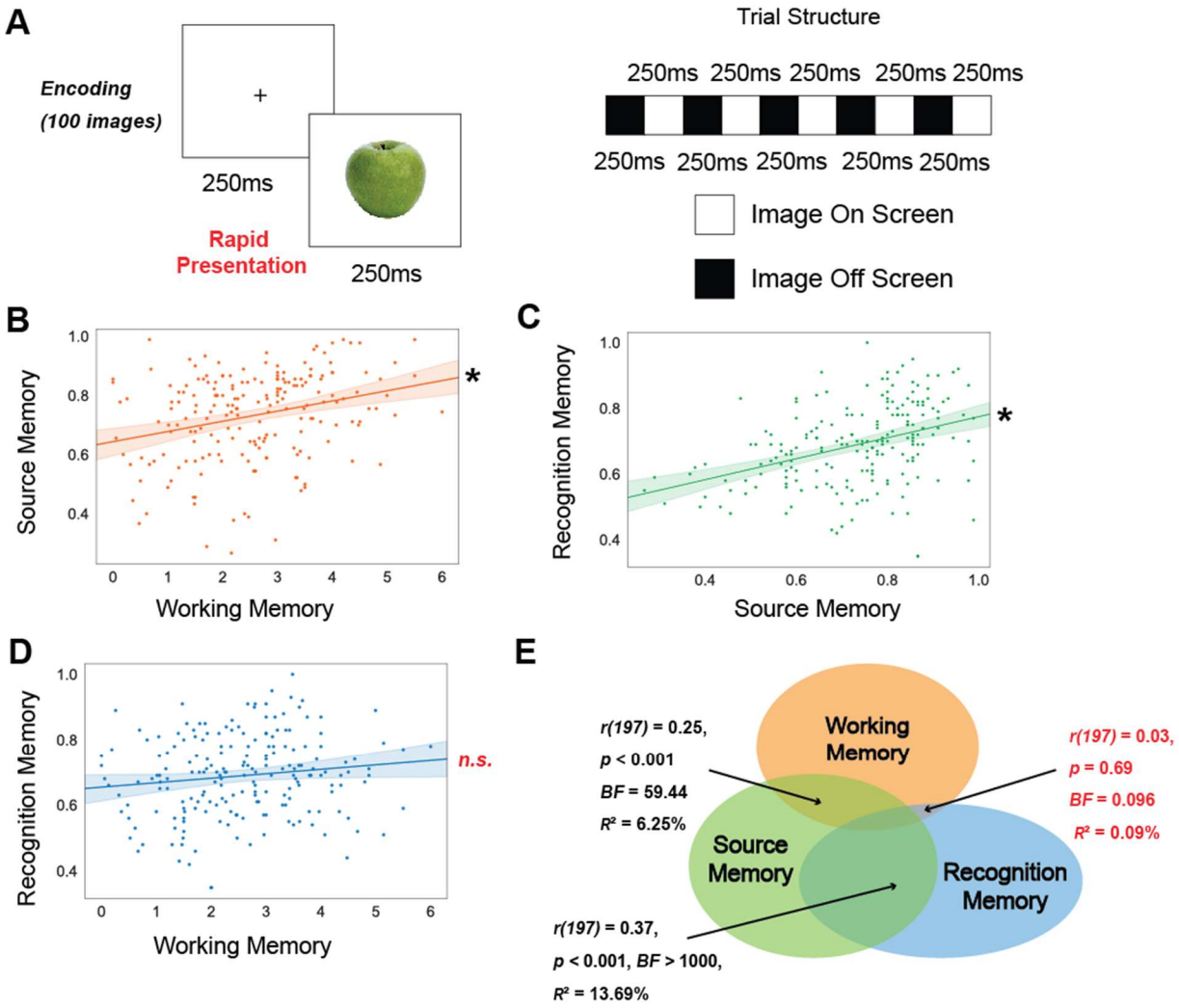


Figure 3. *Results of Experiment 2.*
(A) Schema of Recognition Memory Task in Exp 2: the images were presented on screen for 250 ms, and 250 ms of inter-stimulus interval, at a presentation rate six times faster than used in Exp 1.
(B) Working memory differences significantly predicted source memory performances ($r(197) = 0.28$, $p < 0.001$).
(C) Source memory performances significantly predicted recognition memory accuracies at a fast presentation rate ($r(197) = 0.39$, $p < 0.001$).
(D) Working memory differences did not predict recognition memory accuracies at a fast presentation rate ($r(197) = 0.14$, $p = 0.057$).
(E) A sample Venn diagram on variance explained by working memory, source memory and recognition memory.

Experiment 3

In Experiment 2, we found that working memory differences did not predict RSVP recognition memory performance. However, it is unclear whether the lack of correlation was due to the rapid rate of item presentation (2 per second) or brief stimulus exposure (250ms) of each item presented at study because these two factors were confounded. Here, we tested whether working memory differences predicted recognition memory for items with brief (250ms) exposure durations but with a slow presentation rate between items by increasing the inter-stimulus interval to 3000ms. If the null correlation between working memory and RSVP recognition was due to the rapid rate of item presentation, rather than the brief exposure duration, we would expect that the correlation will reemerge for briefly presented items that were presented at a rate that is slow enough between items to allow for full attention and working memory processing for each item.

Method

Participants

For Experiment 3, 112 young residents of the United States (18-35 years old) were recruited through Prolific and received monetary compensation ($10.00/hour). All participants reported normal or corrected-to-normal vision, no color blindness, fluency in English, no history of mental illness/condition, and no cognitive impairment. All participants had successfully completed 90% or more of the studies that they had participated in previously on Prolific (filtered by approval rate >= 90%).

Materials and Procedure

For Experiment 3, all participants provided informed consent, and completed three tasks. Each participant started with a working memory task, followed by a visuo-spatial source memory task and a visual recognition memory task, as in Exp 1.

Working memory Task: Change Detection Paradigm

The working memory task was the same as in Exp 1.

Source Memory Task: Visuo-spatial source memory

The source memory task was the same as in Exp 1.

Recognition Memory Task: long inter-stimulus interval

The recognition memory task used the same materials and study-test procedures as in Exp 1. Unlike Experiment 1, each study item was displayed at the center of the screen for 250 ms. Following that, a 3250-ms fixation cross was displayed during the blank inter-stimulus interval. Therefore, each participant saw the images at a 250-ms on and 3250-ms off pace (**Fig. 4A**), such that the exposure duration was the same as Experiment 2, but the presentation rate was the same as used in Experiment 1.

Sample size estimation and exclusion criterion

In Experiment 3, a stopping criterion was established when the Bayes Factor (BF) exceeded 3, indicating support for the alternative hypothesis, or fell below 0.33, indicating support for the null hypothesis. Here, with our observations from Experiment 1, we estimated the required sample size based on a correlation of r = 0.3 and a beta of 0.2 to capture meaningful correlations between the two variables. This estimation indicated a need for 85 subjects. A multivariate exclusion criterion was applied to the behavioral data, excluding participants whose task performance fell below chance and more than 2.5 standard deviations below the mean.

Results

In Experiment 3, we first tested whether individual differences in working memory predicted source memory accuracy. We replicated the findings from Experiment 1 and 2 that working memory differences positively correlated to source memory performance differences ($r(110) = 0.42$, $p < 0.001$, **Fig. 4B**). Furthermore, we tested whether working memory predicted visual recognition memory when the images were presented briefly, but with a slow presentation rate to allow for attention and working memory processing. Similar to Experiment 1, we found that that working memory significantly predicted recognition memory accuracy with brief exposure durations ($r(110) = 0.43$, $p < 0.001$, **Fig. 4D**), and this correlation strength was no different from the correlation we observed between working memory and source memory ($z(110) = 0.12$, $p = 0.45$). Our findings suggest that the lack of correlation between working memory abilities and RSVP recognition in Experiment 2 was not due to the brief exposure duration of the images themselves but was instead due to the high number of images presented per second. Thus, when items are presented at a rate that is sufficient for attention and working memory processing, the recognition of even briefly presented items (250ms) is well predicted by working memory ability. Moreover, we performed a correlational analysis between recognition memory with brief presentations and source memory. Similar to Experiment 1 and 2, we found that recognition and source memory remained strongly correlated with each other ($r(110) = 0.49$, $p < 0.001$, **Fig. 4C**). The robust correlation between recognition memory and source memory are consistent with our hypothesis that both forms of memory collectively form a generalized long-term memory construct.

To better quantify the level of working memory resources involved in each visual long-term memory task, we performed a three-way partial regression analysis to determine the pairwise shared variances among working memory, source memory, and brief-exposure recognition memory tasks. Similar to our correlational findings, we first replicated our findings that working memory differences shared variance with source memory performance after recognition memory was regressed out ($r(110) = 0.26$, $p < 0.001$, BF = 6.00, **Fig. 4E**). Similar to Experiment 1, working memory differences explained significant portions of shared variances with brief-exposure recognition memory ($r(110) = 0.38$, $p < 0.001$, BF = 514.05, **Fig. 4E**). Moreover, recognition memory and source memory shared significant portions of variance after working memory was regressed out ($r(110) = 0.28$, $p < 0.001$, BF = 9.87, **Fig. 4E**). Collectively, our findings demonstrate that visual recognition memory tasks rely upon working memory resources if sufficient time is provided for attention and working memory processing. Additionally, recognition memory and source memory differences remained highly correlated after working memory contributions are removed, suggesting that both tasks may form a coherent visual long-term memory factor.

Measure	**Mean**	**SD**	**Skewness**	**Kurtosis**	**Reliability**
Working Memory	2.06	1.29	-0.01	-0.56	0.76
Recognition Memory	0.71	0.14	-0.21	-1.00	0.93
Source Memory	0.70	0.15	-0.49	-0.31	0.89

Table 5. *Descriptive statistics and reliability estimates for all measures in Experiment 3.*

Correlation	Working Memory	Recognition Memory	Source Memory

Working Memory	--	--	--
Recognition Memory	0.43**	--	--
Source Memory	0.42**	0.49**	--

Table 6. *Correlations among all measures in Experiment 3 (** indicates p < .01 level).*

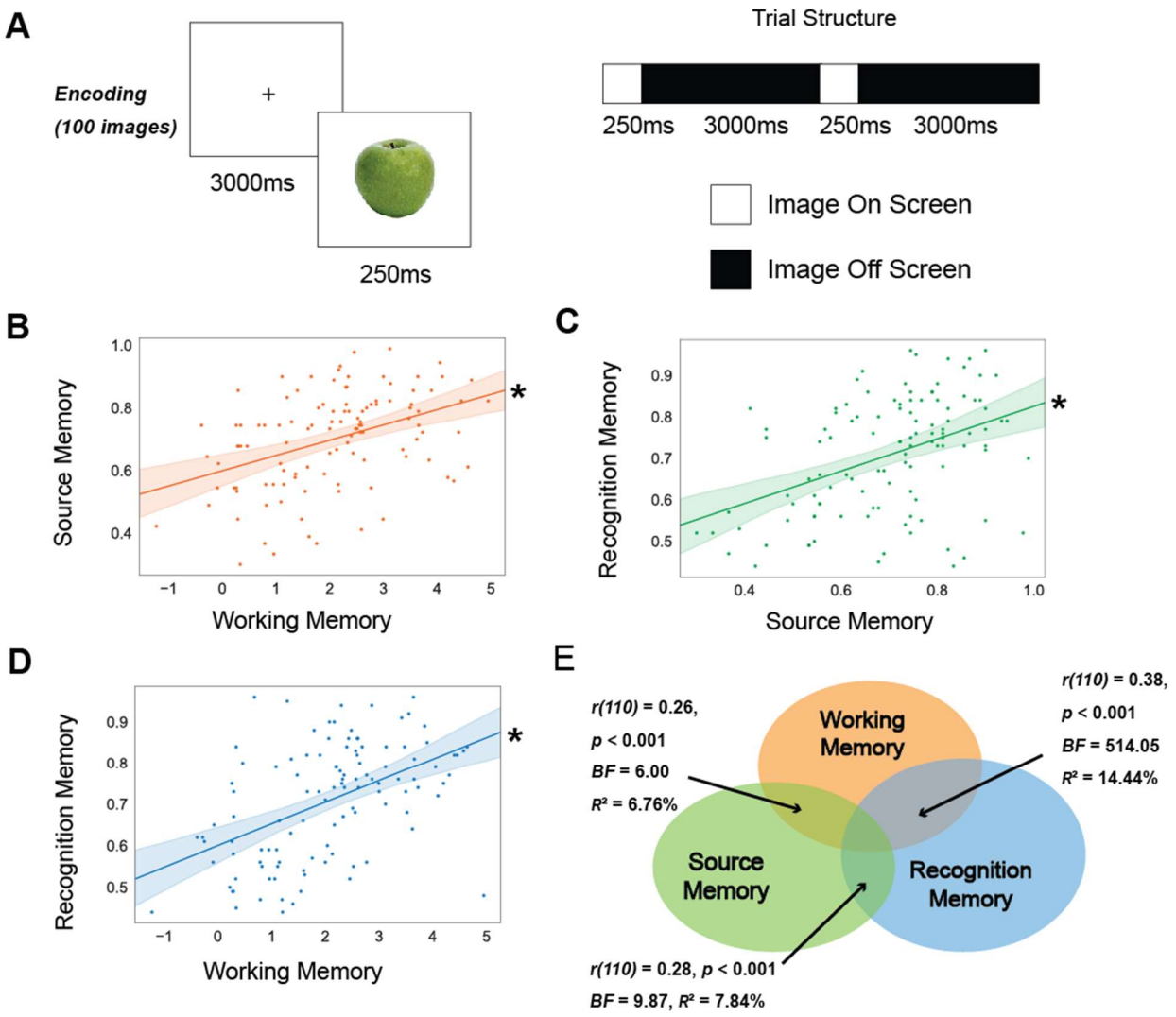


Figure 4. *Results of Experiment 3.*
(A) Schema of Recognition Memory Task in Exp 1: the images were presented on screen for 250 ms, and 3250 ms of inter-stimulus interval.
(B) Attentional control differences significantly predicted source memory performances ($r(110) = 0.42$, $p < 0.001$).
(C) Source memory performances significantly predicted recognition memory accuracies ($r(110) = 0.49$, $p < 0.001$).
(D) Attentional control differences significantly predicted recognition memory accuracies ($r(110) = 0.43$, $p < 0.001$).
(E) A sample Venn diagram on variance explained by attentional control, source memory and recognition memory.

Experiment 4

In Experiments 1-3, we found that working memory capacity was predictive of recognition memory so long as the presentation rate of items during study did not exceed attention and working memory limits. However, it is unclear whether broader measures of attentional control abilities (e.g., Kane & Engle, 2002) would also show a similar relationship with visual long-term memory performance. In Experiment 4, we administered a battery of four WMAC tasks and tested whether they revealed a relationship with recognition and source memory that was comparable to what we have observed with measures of working memory capacity.

Method

Participants

For Experiment 4, 145 young residents of the United States (18-35 years old) were recruited through Prolific and received monetary compensation ($10.00/hour). All participants reported normal or corrected-to-normal vision, no color blindness, fluency in English, no history of mental illness/condition, and no cognitive impairment. All participants had successfully completed 90% or more of the studies that they had participated in previously on Prolific (filtered by approval rate >= 90%).

Materials and Procedure

For Experiment 4, all participants provided informed consent and completed six tasks. Each participant started with four attentional control tasks (change localization paradigm, filtering change localization paradigm, Flanker square task and Simon square task, see **Fig. 5**), followed by a visuo-spatial source memory task and a visual recognition memory task, as in Experiment 1.

Working Memory and Attentional Control (WMAC) Tasks: Change localization, filtering change localization, Flanker Square, Simon square

(1) Change Localization

The Change Localization task was adopted from the color Change Localization task used in prior research (Zhao et al., 2022). During every trial, six colored squares were simultaneously displayed for a duration of 250 ms, followed by a blank retention interval lasting 1,000 ms. Subsequently, the same six squares reappeared in their original positions, but with one of the colors was changed to a hue not previously shown in that trial. Each square was assigned a digit ranging from 1 to 6, and participants were required to press the corresponding key to identify the square that changed color. The spatial arrangement of the six numbers was randomized across trials. The Change Localization measure was the capacity of the working memory, calculated from the accuracy of the task (Zhao, Vogel & Awh, 2023).

(2) Filtering Change Localization

The Filtering Change Localization task was modified from the Filtering Change Detection task (Luck & Vogel, 1997a; Martin et al., 2021). On the start of each trial, a word, either RED or BLUE, denoting the color of the items to be remembered (the selection instruction), was presented for 200 ms, followed by a 100-ms interval. Subsequently, 10 bars were displayed for 250 ms, with half of them being drawn in red and the other half in blue, which is effectively a set size 5 condition. After a 900-ms delay, only the bars corresponding to the attended color reappeared. During test phase, only one of the bars changed its orientation compared to the encoding

phase. The participants were asked to determine which one of the five bars had changed its orientation compared to the initial presentation. This Filtering Localization phase had 60 trials in total. The Filtering Localization measure was the accuracy of the localization task.

(3) Flanker Square

The Flanker Square task is a modified Flanker task (Burgoyne et al., 2023). In each trial of the Flanker Square task, participants were presented with a target stimulus alongside two possible responses. Both the target stimulus and response options consisted of sets of five arrows arranged horizontally (i.e., <<><<). Participants were instructed to choose the response option where the middle arrow aligned in direction with the outer arrows in the target stimulus. For instance, if the target stimulus displayed arrows pointing left and right (i.e., <<><<), participants would select the response option with a central arrow pointing left (i.e., >><>>). Therefore, the task required participants to focus on the outer arrows of the target stimulus and the central arrow of the response options while disregarding the central arrow of the target stimulus and the outer arrows of the response options. Each participant completed 30 seconds of practice, and 90 seconds of test phase. The Flanker Square score was calculated as the difference between number of correct and incorrect responses.

(4) Simon Square

The Simon Square task was a modified Simon task (Burgoyne et al., 2023). In each trial of the Simon Square task, participants were presented with a target stimulus and two response options. The target stimulus was represented by an arrow, and the

response options were the words "RIGHT" and "LEFT." Participants were instructed to choose the response option that corresponded to the direction indicated by the arrow in the target stimulus. For instance, if the arrow in the target stimulus pointed to the left, the participant should select the response option with the word "LEFT." Both the target stimulus arrow and the response options could appear on either side of the computer screen with equal probability. Consequently, participants had to attend to the direction indicated by the target stimulus arrow while understanding the meaning of the response options. Simultaneously, they must disregard the side of the screen where the target stimulus arrow and response options were presented. Each participant completed 30 seconds of practice, and 90 seconds of test phase. The Simon Square score was calculated as the difference between number of correct and incorrect responses.

Source Memory Task: Visuo-spatial source memory

The source memory task was the same as in Experiment 1.

Recognition Memory Task: long inter-stimulus interval

The recognition memory task was the same as in Experiment 1.

Sample size estimation and exclusion criterion

In Experiment 4, a stopping criterion was established when the Bayes Factor (BF) exceeded 3, indicating support for the alternative hypothesis, or fell below 0.33, indicating support for the null hypothesis. Here, with our observations from Experiment 1, we estimated the required sample size based on a correlation of r = 0.3 and a beta of 0.2 to capture meaningful correlations between the two variables. This estimation indicated a need for 85 subjects. A multivariate exclusion criterion was applied to the

behavioral data, excluding participants whose task performance fell below chance and more than 2.5 standard deviations below the mean.

Results

We tested whether a broad set of working memory attentional control (WMAC) measures predict visual long-term memory performance similar to what we observed with working memory capacity in our previous experiments. First, we tested if WMAC abilities, measured with four paradigms, predicted source memory performance and found that performance in all four tasks was positively corelated to source memory performance (change localization: $r(143) = 0.35$, $p < 0.001$; filtering change localization: $r(143) = 0.26$, $p = 0.002$; Flanker square : $r(143) = 0.29$, $p < 0.001$; Simon square: $r(143) = 0.26$, $p = 0.002$, see **Fig. 6 A-D**), which generalizes our findings from Experiments 1-3. Moreover, we also found that the four WMAC tasks were all predictive of simple recognition memory accuracies (change localization: $r(143) = 0.39$, $p < 0.001$; filtering change localization: $r(143) = 0.34$, $p < 0.001$; Flanker square : $r(143) = 0.32$, $p < 0.001$; Simon square: $r(143) = 0.23$, $p = 0.006$, see **Fig. 6 E-H**). These results indicate that the relationship we observed between visual long-term memory performance and working memory generalizes to other attention control and working memory measures. Furthermore, when we divide the WMAC measures into working memory and attentional control measures, visual long-term memory differences shared unique variance with both the WM and AC factors, which replicates and extends our findings with WM measures (**Fig. 7C**). Therefore, recognition memory appears to rely on similar levels of WMAC resources compared to source memory, despite prior evidence

suggesting that source memory performance is impaired more severely under split-attention tasks than recognition memory.

Lastly, we replicated our findings in Experiment 1 that source memory and recognition memory were highly correlated ($r(143) = 0.60$, $p < 0.001$, see **Fig. 7A**). To further examine if these two tasks form a coherent visual long-term memory factor, we performed an exploratory factor analysis with our four WMAC tasks and two visual long-term memory tasks. We first performed a Bartlett Sphericity test and got a significant chi square of 237.79 ($p < 0.001$), fulfilling a prerequisite to perform factor analysis. We then conducted a Kaiser-Meyer-Olkin criterion test with KMO of 0.79, indicating that our observed variables were sufficiently correlated with each other. To determine the optimal number of factors, we calculated the eigenvalues for our data. Our first two eigenvalues returned as 2.96 and 0.92, higher than the third eigenvalue 0.74 and were both close to or larger than 1.0. Therefore, we performed a two-factor factor analysis on our data (see **Fig. 7B**). We found that Flanker Square (0.52), Simon Square (0.58), Change Localization (0.67) and Filtering Localization (0.66) all significantly (> 0.3) loaded onto Factor 1, and Source Memory (0.6) and Recognition Memory (0.86) both significantly loaded onto Factor 2. The exploratory factor analysis confirmed that a common WMAC factor underlay our four tasks. More importantly, the two forms of long-term memory formed a shared visual long-term memory factor, converging with our findings in Experiments 1-3. Lastly, all six of our tasks loaded positively to both WMAC and long-term memory factors, suggesting that the predictive power between the two abilities may stem from the fact that visual long-term memory tasks generally require attentional control resources.

Measure	Mean	SD	Skewness	Kurtosis	Reliability
Change Localization	2.43	1.00	-0.11	-0.01	0.81
Filtering Localization	0.47	0.15	0.30	-0.22	0.83
Flanker Square	31.41	13.93	-0.36	-0.40	0.94
Simon Square	38.34	13.21	-0.39	0.83	0.93
Recognition Memory	0.77	0.15	-0.52	-0.60	0.93
Source Memory	0.79	0.14	-0.98	0.53	0.93

Table 7. *Descriptive statistics and reliability estimates for all measures in Experiment 4.*

Correlation	1	2	3	4	5	6
1. Change Localization	--	--	--	--	--	--
2. Filtering Localization	0.58**	--	--	--	--	--
3. Flanker Square	0.40**	0.40**	--	--	--	--
4. Simon Square	0.35**	0.32**	0.43**	--	--	--
5. Recognition Memory	0.39**	0.34**	0.32**	0.23**	--	--
6. Source Memory	0.45**	0.37**	0.36**	0.31**	0.60**	--

Table 8. *Correlations among all measures in Experiment 4 (** indicates $p < .01$ level).*

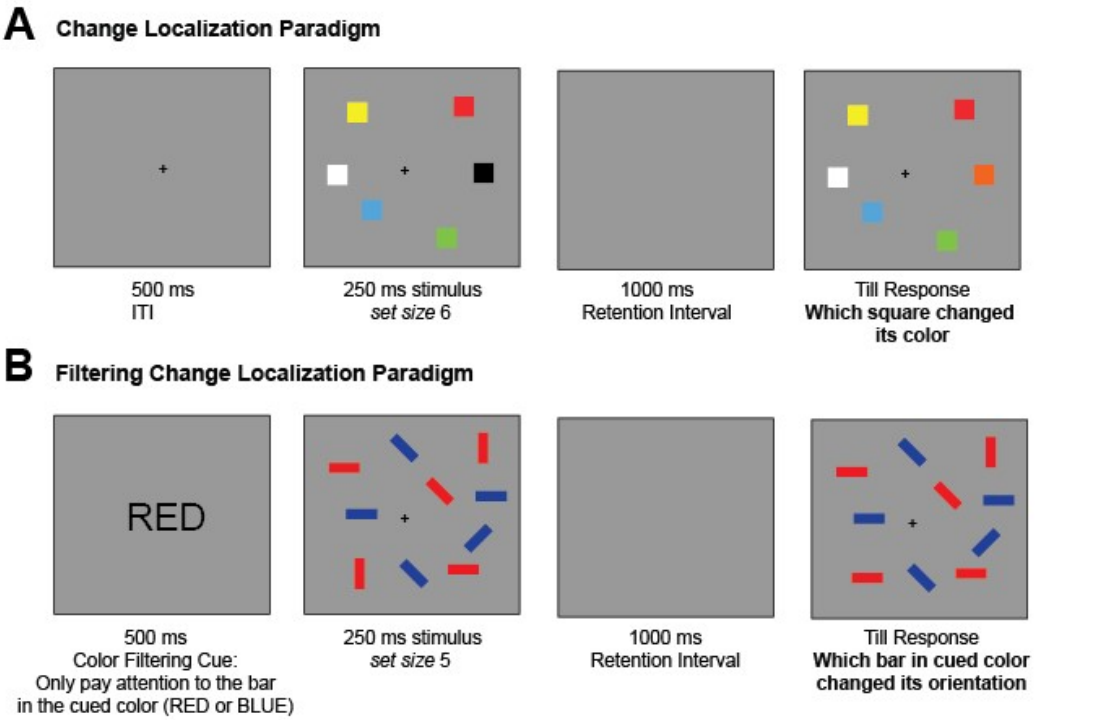


Figure 5. *Experimental Procedures for Experiment 4.*

(A) Schema of Change Localization Task.

(B) Schema of the Filtering Change Localization Task.

(C) Schema of the Flanker Square Task.

(D) Schema of the Simon Square Task.

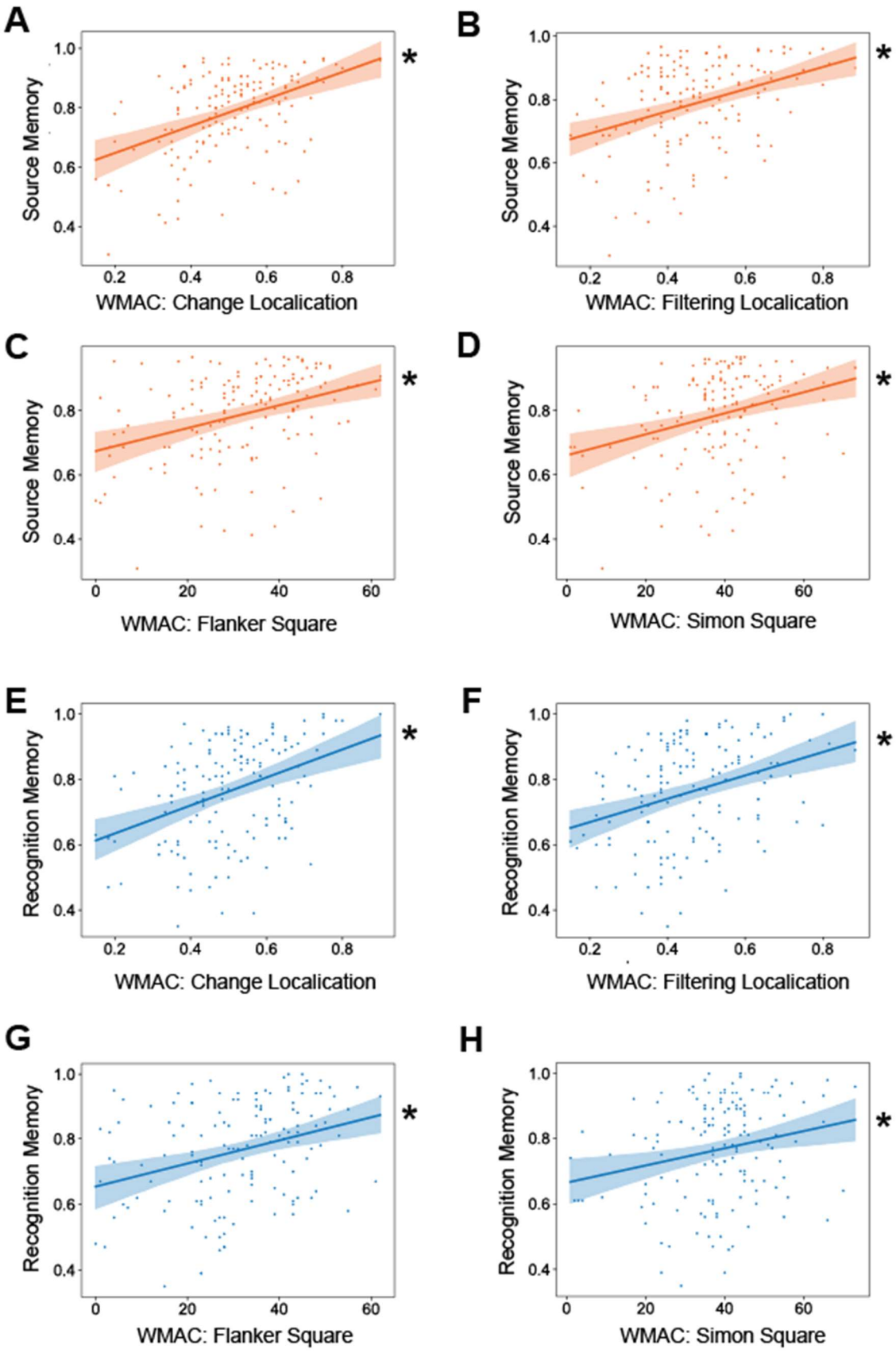

A
Source Memory
1.0
0.8
0.6
0.4
0.2
0.4
0.6
0.8
WMAC: Change Localication
*
B
Source Memory
1.0
0.8
0.6
0.4
0.2
0.4
0.6
0.8
WMAC: Filtering Localication
*
C
Source Memory
0.8
0.6
0.4
0
20
40
60
WMAC: Flanker Square
*
D
Source Memory
0.8
0.6
0.4
0
20
40
60
WMAC: Simon Square
*
E
Recognition Memory
1.0
0.8
0.6
0.4
0.2
0.4
0.6
0.8
WMAC: Change Localication
*
F
Recognition Memory
1.0
0.8
0.6
0.4
0.2
0.4
0.6
0.8
WMAC: Filtering Localication
*
G
Recognition Memory
1.0
0.8
0.6
0.4
0
20
40
60
WMAC: Flanker Square
*
H
Recognition Memory
1.0
0.8
0.6
0.4
0
20
40
60
WMAC: Simon Square
*

Figure 6. *Results of Experiment 4.*
(A-D) Working Memory Attentional Control (WMAC) differences significantly predicted source memory performances (*ps* < 0.001).
(E-H) Working Memory Attentional Control (WMAC) differences significantly predicted recognition memory performances (*ps* < 0.001).

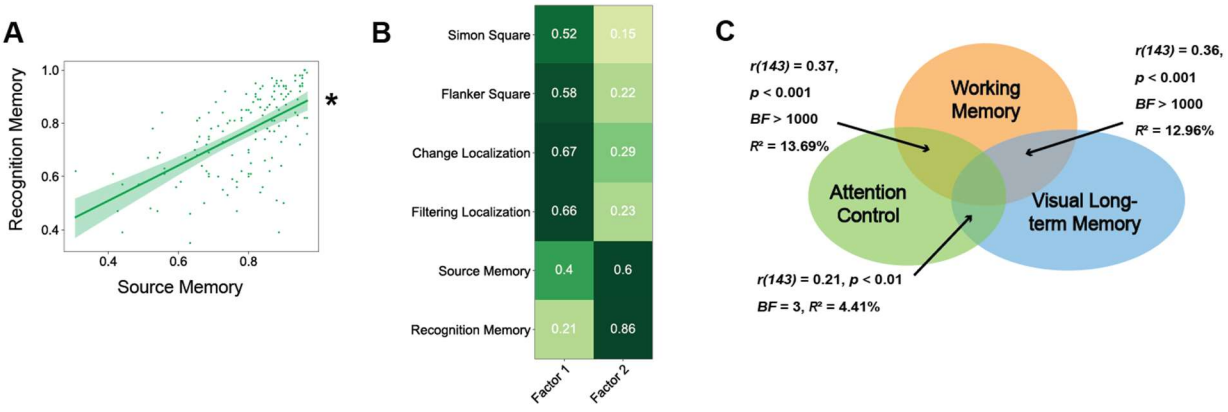


Figure 7. *Results of Experiment 4.*
(A) Source Memory differences significantly predicted recognition memory performances (*r*(143) = 0.60, *ps* < 0.001).
(B) Exploratory factor analysis results for Experiment 4. A darker green suggested a higher loading of the task on the latent factor. We observed that Flanker Square, Simon Square, Change Localization and Filtering Change Localization loaded significantly onto Factor 1. Furthermore, Recognition and Source Memory significantly loaded onto Factor 2, suggesting the existence of a long-term memory factor.
(C) A sample Venn diagram on variance explained by attentional control, working memory and visual long-term memory.

Discussion

In our study, we examined the relationship between individual differences in working memory, attentional control, source memory and recognition memory. First, we replicated previous findings that working memory and attentional control abilities predict source memory performance. Surprisingly, recognition memory performance, a paradigm that has been presumed to be less attention demanding than source memory, was also robustly predicted by working memory and attentional control abilities (Experiments 1, 3 and 4). The only exception that we observed to this relationship was when the study items were presented rapidly (2 per second), at which point, working memory no longer predicted recognition memory (Experiment 2). In addition, we found that irrespective of differences in presentation rate and exposure duration of items during study, recognition memory performance remained highly correlated with source memory performance in all four Experiments. An exploratory factor analysis confirmed our correlational results and suggests that both tasks load onto a common latent factor (Experiment 4), and that each of the WMAC tasks coherently loaded onto a separate latent factor.

Our study suggests that under most circumstances, an individual's overall recognition memory performance has significant contributions from his or her working memory and attentional control abilities. All five metrics of working memory and attentional control tasks, change detection in Experiments 1 and 3, change localization, filtering localization, Flanker square and Simon square in Experiment 4 significantly predicted recognition memory performance. A potential challenge to this robust relationship would be that although certain levels of working memory and attentional

control are necessary for recognition memory, source memory may require much higher contributions of working memory and attentional control resources than simple recognition. If this hypothesis was correct, then the remaining shared variance between WMAC measures and recognition would be expected to be close to zero once contributions from source memory were regressed out. Contrary to such prediction, we found that the shared variance between recognition memory and WMAC measures remained significant even after regressing source memory performance in Experiments 1, 3 and 4. Therefore, simple item recognition memory appears to require extensive attentional control resources, and this reliance is partially independent from the attentional control resources that source memory requires.

The one exception to this robust correlation that we observed was that when the sequence of 100 images was presented at a rapid presentation rate during study, working memory abilities no longer predicted recognition memory performance. Storage of items in working memory is known to depend upon a somewhat slow, attention-demanding consolidation process (Potter, 1976; Vogel et al., 2006) that can take several hundred milliseconds per item (Jolicøeur & Dell'Acqua, 1998). Our RSVP presentation rate of 2 items per second likely exceeded the temporal limits of this consolidation process, which would explain why RSVP recognition performance no longer depended on working memory ability. This implies that recognition performance for rapidly presented items reflects learning that occurred in the absence of significant contributions from attention and working memory resources.

Our findings may be consistent with prior reports that individual differences in working memory capacity (as measured by OSPAN) predict the magnitude of the

attentional blink (Dale et al., 2013; Willems & Martens, 2016). While Attentional Blink paradigms use similar rapid stimulus presentation procedures to what we used in our RSVP recognition task, they differ substantially in the working memory storage demands they require. In Attentional blink tasks, subjects must selectively consolidate and store just two predetermined targets from the stream into working memory. By contrast, our RSVP recognition task requires the consolidation and storage of ALL of the items in the stream. It is plausible that when attempting to store just a few items from a rapid stream (as in Attentional Blink tasks), individuals with high WMAC ability have an advantage over those with low ability because the task may rely heavily on successfully selecting just the targets for storage and filtering out the remaining distractors: an ability that is well known to be reduced in individuals with low working memory capacity (K. Adam et al., 2015; Fukuda & Vogel, 2011; Vogel et al., 2005). By contrast, the RSVP recognition task we used in Experiment 2 had no distractor filtering demands during encoding because all items were to be remembered. Here, we presume RSVP recognition performance does not correlate with working memory ability because the heavy storage demands exceed even the highest capacity individual's ability to attend and store each item in the rapid sequence into working memory.

Our findings suggest that the process of consolidating items into working memory may play a key role in explaining the correlation between WMAC and long-term memory. This process is thought to reflect the binding of item information to its spatial and temporal context (Karlsen et al., 2010). Computational models have long proposed similar binding mechanisms as a key component of working memory (Oberauer, 2019), plausibly binding an item to both the location and time it was encountered (Thyer et al.,

2022). Supporting this hypothesis, individual differences in working memory, as typically measured using simultaneous change detection (i.e., entire set of to-be-remembered objects presented together during encoding), are highly predictive of change detection measured with sequential presentations (i.e., one item presented at a time, Zhao & Vogel, 2023). Therefore, visual array tasks, or WMAC tasks in general, may engage the participants' ability to bind multiple items to different positions in displays with items presented together in time, as well as the ability to temporally bind multiple items to the same location when presented at different times within the sequence. In our visuo-spatial source memory task, working memory uniquely predicted spatial binding ability, which was not utilized in the recognition memory task. Conversely, in the recognition memory task, temporal binding appeared to play a more significant role in recognition memory formation, given that a temporal structure is often present for recognition memory even when order was is not being tested (Schwartz et al., 2005). Supporting this hypothesis, we argue that the rapid stream of images in Experiment 2 prevented the formation of sufficient temporal binding in recognition memory. Consequently, working memory performance no longer predicted recognition memory performance when items were presented rapidly.

We consistently found that recognition memory and source memory for real-world images remained correlated regardless of the presentation rate and exposure duration of the images in all four of our Experiments. Moreover, the shared variance between source and recognition memory remained significant even after attentional control abilities were regressed out. Therefore, we believe that individual differences in visual long-term memory form a construct that is somewhat correlated with, yet distinct

from, the known attentional control factor established in previous research (Kane et al., 2004; Kane & Engle, 2002). Evidence from Experiment 4 shows that both source memory and recognition memory exhibit significantly positive loadings for the same underlying factor, and that this factor is not the same as the attentional control factor from the exploratory factor analysis. Therefore, our results suggest that there is a generalized visual long-term memory factor, as suggested by a recent theoretical review (Unsworth, 2019). Future studies on this long-term memory factor are necessary to better explore the correlational and mediational relationship between this factor and other established factors such as attentional control (Engle et al., 1999), fluid intelligence (Unsworth et al., 2014a), and false memory (Roediger, III & Mcdermott, 1995), to name a few.

The current study examined the relationships amongst performance measures from several attention, working memory and visual long term memory tasks. However, because there are other general ability measures such as fluid intelligence and processing speed that are known to correlate with WMAC measures (Kail & Salthouse, 1994; Unsworth et al., 2014a), there are always lingering concerns that these untested measures may be contributing to the correlational structure we are observing between these constructs. For example, one possibility is that long-term memory tasks require certain aspects of overall general ability such as fluid intelligence (gF) instead of attention control per se. Previous research has suggested that measures of working memory capacity, attentional control, and secondary memory all mediate the relationship between working memory storage and gF (Unsworth et al., 2014). Given the positive correlations among gF, WMAC, and long-term memory, it remains unclear

whether gF and WMAC explain distinct variance in long-term memory. Likewise, declines in processing speed have been shown to impact working memory declines associated with aging (Salthouse, 1991, 1996, 2000). Thus, it is also plausible that the common resources that we observed between visual long-term memory tasks and WMAC measures may be impacted by the individual's processing speed. That said, the results of Experiment 2 cast some doubt on whether these alternative general ability constructs are sufficient to explain our current findings. For example, our RSVP recognition study was considerably more difficult than our slow recognition memory procedure as evidenced by the large difference in average recognition accuracy (i.e., 69% vs 81%), yet it is only the more challenging RSVP recognition task that is not correlated with working memory capacity. Individuals with high fluid intelligence are generally better at just about all novel task environments (Kyllonen & Kell, 2017; Tschentscher et al., 2017; Zook et al., 2004) and it's not obvious why this general ability wouldn't have also given these individuals an advantage in the challenging RSVP recognition task. Relatedly, if processing speed differences were what was producing the relationship between WMAC measures and visual long-term memory one would expect that such a relationship would continue (if not become stronger) when we increased the encoding speed demands of the stimulus presentation in Experiment 2. Instead, we found that this seemingly more processing speed-dependent task condition no longer correlated with working memory. These arguments notwithstanding, without measuring these other constructs there will always be remaining uncertainty about the role of these general factor constructs in the relationship between WMAC measures and visual long-term memory. Future work should measure these constructs directly to

better reveal the relationships between working memory, attention control and visual long-term memory.

CHAPTER 2.

Shared Neural Access to Working and Long-Term Memory During Retrieval

Imagine preparing a grocery list in your mind: the items you are actively holding and manipulating (“milk, eggs, apples”) occupy your immediate awareness, while memories of past shopping trips may also come to mind when trying to recall which brand or store you used previously. To distinguish these two types of experiences, William James (1890) introduced the concepts of primary memory and secondary memory. Primary memory refers to information actively held in consciousness, whereas secondary memory involves information that must be retrieved into consciousness for use. Building on this distinction, the classic modal model of memory (Atkinson & Shiffrin, 1968) proposed that information first enters a short-term store (i.e., primary memory) and, through processes such as rehearsal, may subsequently be encoded into a long-term store (i.e., secondary memory).

To capture how the short-term store is used in real-world cognition, the term working memory (WM) is now used to describe the capacity-limited system that supports the maintenance and manipulation of information over brief intervals. Notably, this capacity has been estimated at approximately four items (Cowan, 2001), a limit that is reflected in neural markers of visual working memory (VWM) load, which tend to plateau around this number (Vogel & Machizawa, 2004a). When the number of items exceeds WM capacity, it is assumed that excess items may be offloaded into visual long-term memory (LTM), which is thought to have a virtually unlimited capacity. Indeed, empirical studies have demonstrated that individuals can store thousands of unique

objects in visual LTM (Brady et al., 2008; Lionel, 1973), and do so with remarkable spatiotemporal precision (Wolfe et al., 2023).

Despite the stark contrast in capacity limits between WM and LTM, individual differences in these systems are often moderately correlated. For example, Unsworth et al. (2014) found that although VWM and LTM performance loaded onto distinct latent factors, the two were moderately correlated across individuals, an effect that has been replicated with both item and source memory judgments (Zhao & Vogel, 2025a, 2025b). One hypothesis for this relationship is that WM and LTM share a common encoding bottleneck, such that limitations in initial encoding processes constrain both systems. Supporting this view, Fukuda and Vogel (2019) demonstrated that VWM capacity predicted subsequent LTM performance when participants encoded supracapacity arrays (e.g., 4 or 6 objects) in a VWM task, with LTM tested after a delay. Moreover, encoding bottlenecks in both memory systems may be shaped by attentional control, as individuals with fewer attentional lapses show better VWM capacity (K. C. Adam et al., 2015) as well as improved LTM performance (Zhao & Vogel, 2025b).

Thus, WM and LTM may share common encoding constraints despite their vastly different capacity limits. However, an important and relatively unanswered question concerns the retrieval stage: do WM and LTM also rely on a shared access mechanism at test? Most electrophysiological studies of memory have focused on the test phase of LTM, examining well-established event-related potential (ERP) signatures such as the frontal and parietal old/new effects (Rugg & Curran, 2007). These effects are typically measured when items are retrieved from long-term memory and have rarely been studied within the limits of WM, or systematically compared across multiple set sizes. As

a result, it remains unclear whether the neural mechanisms that distinguish old from new items in LTM are also engaged when memory search occurs within WM, and whether these mechanisms generalize across varying memory loads.

To address this question, we first examined two well-established univariate EEG signatures: the parietal and frontal old/new effects, defined as amplitude differences between old and new trials over parietal and frontal electrodes, respectively, with larger amplitudes reflecting stronger memory-related activation. We then applied multivariate decoding to test whether WM- and LTM-dominant conditions share common neural representations. A classifier was trained on the set size 4 condition, approximating the upper limit of WM capacity, to learn patterns that discriminate old from new items. If WM and LTM rely on a shared access mechanism, this decision boundary should generalize across set sizes, indicating a common neural code for memory retrieval. Failure to generalize to larger set sizes (e.g., set size 32) would instead suggest distinct access processes for WM and LTM.

Method

Participants

One hundred and eleven participants took part in the study (mean age = 25.1 years). Sample size was determined using G*Power, aiming to achieve 80% power to detect a small effect size (r = 0.3) at the conventional alpha level of .05. All participants reported normal or corrected-to-normal vision and normal color perception, and no history of neurological disorder. Study procedures were approved by the relevant University of Chicago Institutional Review Board and participants were compensated for their participation.

Stimuli and Procedure

Images were selected from the THINGS dataset (Hebart et al., 2023), a database with 1854 unique concepts and 26107 images. One exemplar was selected from each concept so that no repeated concept was used throughout each session (i.e., apple versus avocado). The recognition memory procedure for all set sizes (1, 2, 4, 8, 16, 32 and 128) followed established protocols in the literature and consisted of separate study and test phases (Fukuda & Woodman, 2015; Zhao & Woodman, 2020). The experiment included set sizes of 1, 2, 4, 8, 16, 32, and 128. Each encoding condition consisted of a total of 128 trials. This was achieved by varying the number of blocks across set sizes, such that participants completed 128 blocks in the set size 1 condition, with progressively fewer blocks as set size increased, down to a single block in the set size 128 condition (see **Fig. 8**).

In the set size 1 condition, participants viewed a single image presented at the center of the screen for 800 ms during the encoding phase. Stimuli were displayed against a gray background (90.0 cd/m²), and a white fixation cross was superimposed on the image to encourage central fixation and discourage eye movements. The interstimulus interval was randomly jittered between 250 and 400 ms.

Following the encoding phase, participants completed a recognition test trial in which a single image was displayed at the center of the screen for 800 ms with a central white fixation cross. To minimize motor and ocular artifacts, participants were instructed to remain still while the fixation cross was visible. After 800 ms, the fixation cross disappeared and the image remained on screen until a response was made. Half of the

test images had been presented during the encoding phase (old), and the remaining half were novel (new). The order of old and new images was randomized across trials. Participants indicated whether each image was “old” or “new” using designated keyboard keys (“z” for old; “/” for new).

All other set size conditions followed the same general structure, differing only in the number of images presented during the encoding phase and the corresponding number of test trials. Block order was randomized across participants.

Preprocessing and artifact rejection of EEG signals

Participants were positioned in an electrically isolated booth, with their heads stabilized using a cushioned chinrest placed 74 cm from the display screen. Electroencephalographic (EEG) signals were recorded via 30 active silver/silver chloride (Ag/AgCl) electrodes integrated into a stretchable cap (actiCHamp system, Brain Products, Munich, Germany), arranged according to the international 10-20 placement standard (electrode sites: Fp1, Fp2, F7, F8, F3, F4, Fz, FC5, FC6, FC1, FC2, C3, C4, Cz, CP5, CP6, CP1, CP2, P7, P8, P3, P4, Pz, PO7, PO8, PO3, PO4, O1, O2, Oz). Additional electrodes were adhered to the left and right mastoids using adhesive stickers, and a ground electrode was integrated at the Fpz site within the cap. EEG signals were initially referenced to the right mastoid and subsequently re-referenced offline to the average of both mastoids. The signal was bandpass filtered (0.01–80 Hz) with a 12 dB/octave roll-off and digitized at a sampling rate of 500 Hz. All electrode impedances were maintained below 10 kΩ.

To track ocular activity such as blinks and saccades, both electrooculographic (EOG) and eye-tracking data were recorded. EOG was captured using five passive

Ag/AgCl electrodes: two for vertical EOG (above and below the right eye), two for horizontal EOG (approximately 1 cm lateral to each eye), and one ground electrode on the left cheek. Eye position was also monitored with a desktop-mounted EyeLink 1000 Plus system (SR Research, Ontario, Canada), operating at a sampling rate of 1,000 Hz.

Artifact Rejection

For horizontal eye movements, we employed a sliding-window algorithm to identify horizontal eye movements using both horizontal electrooculogram (HEOG) signals and eye-tracking gaze data. For the HEOG-based detection, a split-half sliding-window method was applied with a 100 ms window moving in 10 ms increments. An eye movement was flagged if the voltage difference between the two halves of the window exceeded 20 μV. This HEOG-based artifact detection was used only in trials where eye-tracking data were unreliable or unavailable. In parallel, eye-tracking rejection was carried out by analyzing horizontal (x-axis) and vertical (y-axis) gaze positions using the same 100 ms window and 10 ms step size. A trial was excluded if eye position shifted more than 0.5° of visual angle within any given window.

To detect blinks, we applied a sliding-window analysis to the vertical EOG signal using an 80 ms window and a 10 ms step size. A blink was marked when the voltage change across the window exceeded 30 μV. Complementarily, we identified blink periods in the eye-tracking data by locating segments where positional data were missing, indicating that the eyes were closed.

Parietal and Frontal Old/New Effect Analysis

To calculate the parietal and frontal old/new effects, we first identified sets of

electrodes associated with each region. Based on prior literature, for the parietal old/new effect, we included electrodes PO3, PO4, PO7, PO8, P3, P4, P7, P8, and Pz. For the frontal old/new effect, we used electrodes F3, F4, F7, F8, and Fz. For each region, we computed the average event-related potential (ERP) time series across the selected electrodes to obtain a representative waveform. We then focused on correct trials within each set size and repetition condition and categorized them into two trial types: old (images that participants had previously studied) and new (novel images that had never been studied). We computed the average ERP for each trial type separately. The old/new effect was then derived by subtracting the ERP waveform for new trials from that for old trials, calculated separately for each participant. This difference waveform, named old/new effect, reflects neural activity specific to recognition memory.

Result

To examine how people access working memory (WM) and long-term memory (LTM) contributions at test, we recorded EEG while participants performed a recognition memory task. The critical manipulation was the set size of a list: when the list length fell within visual WM capacity (~ 4 items), performance was expected to rely primarily on WM. In contrast, supra-capacity lists (i.e., 32 and 128 items) required retrieval from LTM.

A total of 110 participants encoded lists of images and subsequently judged whether each test image was old or new. Set size varied parametrically (1, 2, 4, 8, 16, 32, or 128 items; **Fig. 8**). At test, half of the trials were previously encoded images and half were novel foils. To equate trial numbers across conditions, participants completed 128 blocks of set size 1, 64 blocks of set size 2, and so forth, down to 1 block of set size

128, yielding 128 encoding trials and 256 test trials per condition. Block order was randomized, and set size was not disclosed until completion of encoding. Our primary question was whether the neural dynamics underlying memory-based decisions differ when recognition is supported primarily by visual WM versus LTM retrieval.

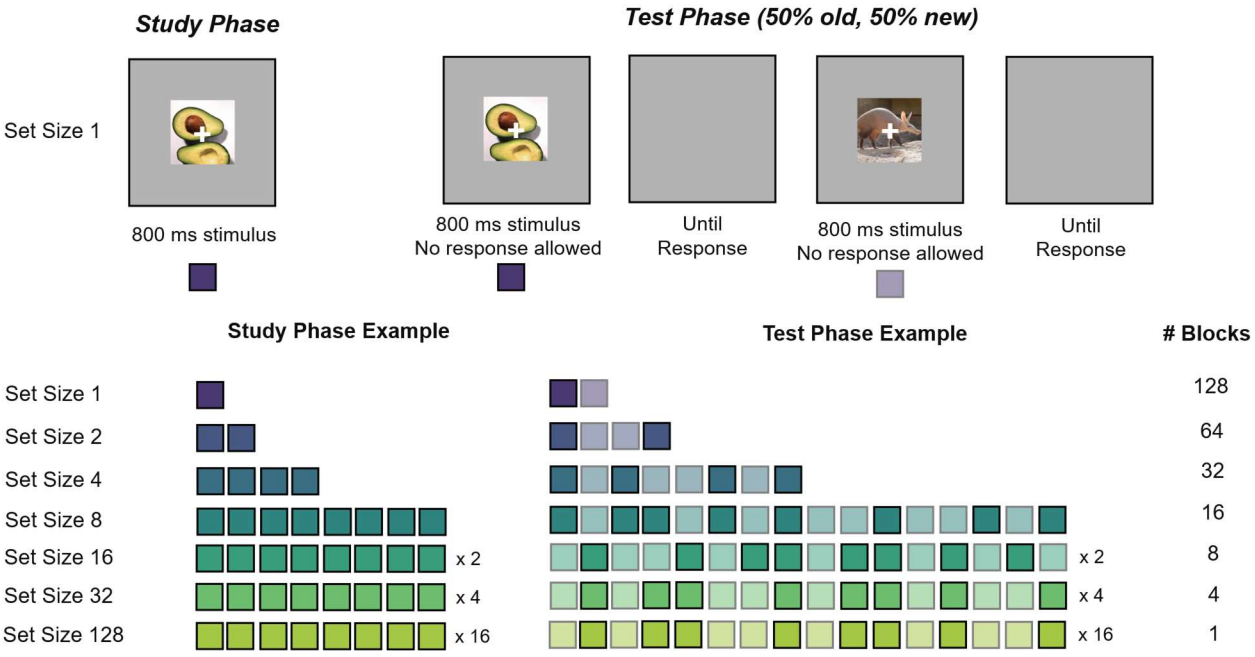


Fig 8. Visual Recognition Memory Paradigm with set size 1, 2, 4, 8, 16, 32 and 128.

Univariate Parietal old/new effect revealed shared access to working and long-term memory during retrieval

Given that WM and LTM have vastly different properties with respect to capacity limits, activation levels, and even brain areas related to storage, we asked whether working memory (WM) and long-term memory (LTM) rely on distinct access mechanisms during retrieval, or whether they share a common neural process during memory-based decision-making. A key operation in such decisions is recollection, the

recovery of an item together with details of its prior occurrence. Recollection has been studied extensively in the LTM literature (Rugg & Curran, 2007), but it remains unclear whether the same neural process supports retrieval when items fall within the limited capacity of WM. One possibility is a separate-access account, in which recollection in WM is supported by a mechanism distinct from that used for LTM, due to their differences in activation level and storage capacity. An alternative shared-access account proposes that, despite these differences, both WM and LTM are searched for using a common neural access point.

We indexed recollection using the parietal old/new effect, a well-established univariate EEG signature characterized by more positive activity over parietal scalp sites for correctly recognized old items compared to new items. Under a separate-access account, this signal should be prominent when retrieval depends on LTM, but not further enhanced when decisions primarily rely on WM, which may instead be supported by a distinct mechanism based on sustained neural activity. In contrast, a shared-access account predicts that the amplitude and timing of this signal should vary systematically with memory load, forming a continuous pattern across conditions that engage WM and LTM.

Across 110 participants, we found evidence supporting the shared-access hypothesis, in that the parietal old/new effect was significant across all set sizes (1-128 items; all ps < 0.01, see **Fig. 9**). Thus, despite large differences in capacity limits and activation states, retrieval of items maintained within WM and those stored in LTM recruited the same electrophysiological signature. Moreover, the amplitude of the parietal old/new effect decreases with increasing set sizes, suggesting that the memory

strength decreases continually from WM to LTM. To further dissect this set size effect, we found that within the canonical WM capacity (1, 2, 4 items), amplitudes of parietal old/new effects did not differ from each other. Beyond capacity limits, however, the parietal old/new effect declined progressively, with marked reductions at set sizes 32 and 128. These findings suggest that the retrieval between WM and LTM shared the same neural access, with increasing set size suggesting that the memory strength was decreasing across both systems.

Another critical factor in accessing memory was how fast they successfully accessed the memory items of interest when performing a task. A classic finding in the behavioral literature is that response times are faster when people search through a small set of previously memorized items than when they search through a larger set that exceeds working memory capacity (Wolfe, 2012). If the shared-access hypothesis holds across both WM and LTM, the peak of the neural signature of recollection should mirror the response time patterns we observed with the memory search paradigms. To find when the brain accumulates peak evidence in making memory-based decisions, we quantified the temporal peak of the parietal old/new effect, namely the latency, defined as the time to reach 50% of the area under the curve (Kiesel et al., 2008). Supporting the shared-access account, we found that peak latency occurred earlier for smaller set sizes and was progressively delayed as set size increased, and latency for every set size was different from their neighboring set sizes significantly. Interestingly, this increase in neural latency followed a logarithmic rather than linear function of set size. The log shape with respect to set size suggests that, although WM and LTM recruit a common access signal, their search dynamics differ. Within the WM range, adding a

single item incurred a measurable temporal cost, consistent with more serial access. In contrast, enlarging the LTM search space (e.g., from 32 to 128 items) yielded diminishing latency costs, consistent with more parallelized retrieval. The observed logarithmic scaling mirrors prior evidence from memory search paradigms, where they specified that the response time for performing a memory search increase as a log function of memory set size. Together, the amplitude and latency profiles of the parietal old/new effect provide converging evidence for a shared neural access mechanism supporting retrieval from both WM and LTM.

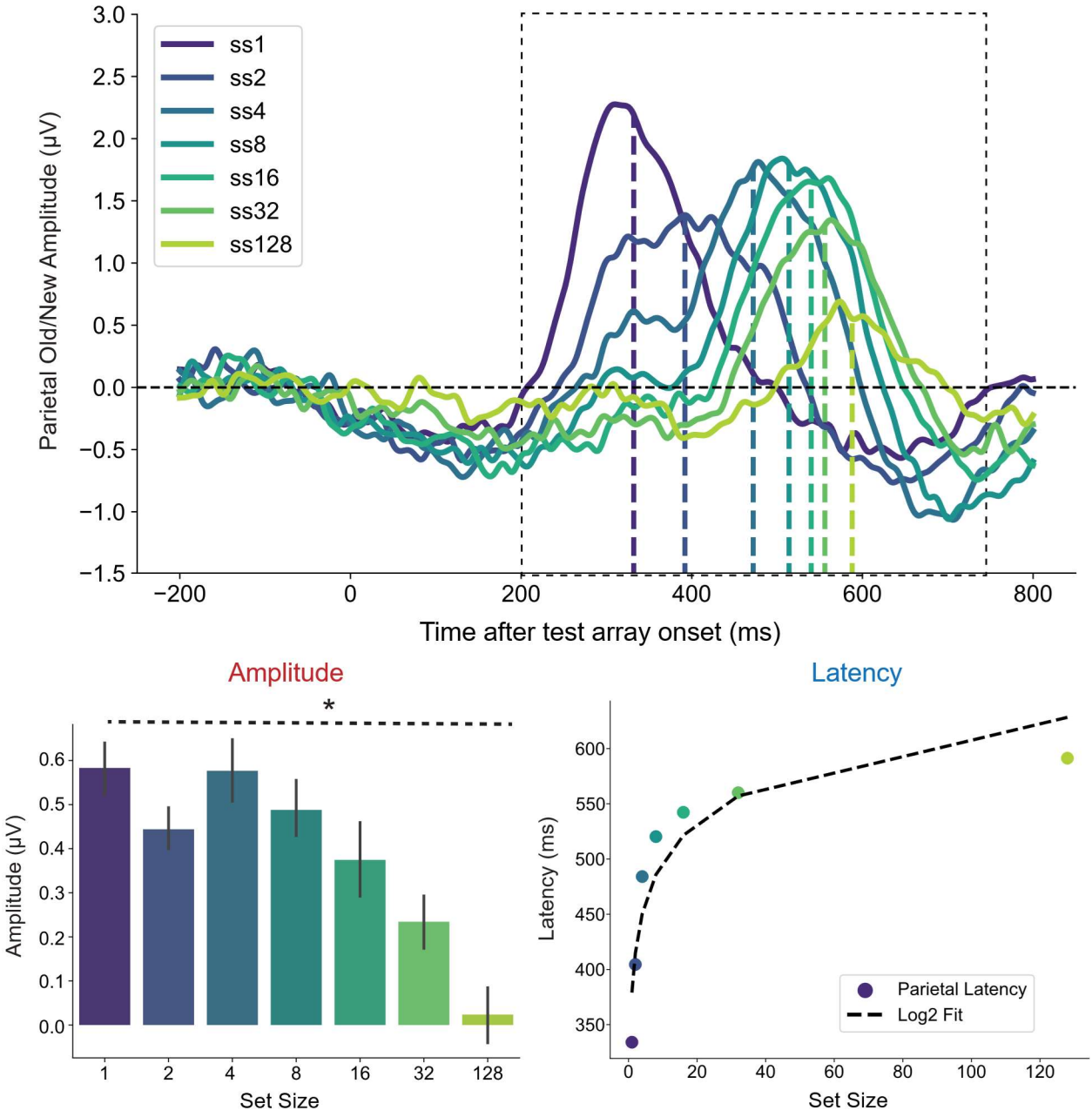


Fig 9. Amplitude and Latency of the Parietal old/new effect with set size 1, 2, 4, 8, 16, 32 and 128.

Univariate Frontal old/new effect revealed shared access to working and long-term memory during retrieval

Our results above suggest that the parietal old/new effect, a neural signature associated with recollection, emerges earlier and with greater amplitude during working memory (WM) access, but is delayed and attenuated during long-term memory (LTM) access. Despite these differences in temporal dynamics and magnitude, both forms of memory appear to rely on a common neural retrieval system at test. One plausible account is that recollection, defined as the binding of item and contextual information, constitutes a shared process across WM and LTM. In contrast, familiarity-based processes may contribute more prominently to LTM retrieval than to WM retrieval, given that shorter WM lists are more likely to rely on recollection. Under this framework, one would predict that the neural correlate of familiarity, the frontal old/new effect, would be selectively engaged during LTM retrieval and not exhibit earlier or stronger activation during WM access.

Contrary to this prediction, our findings support a shared-access account for familiarity as well. Specifically, the frontal old/new effect was significant across all set sizes (1–128 items; all *p*s < .01, see **Fig. 10**), indicating that both WM and LTM retrieval recruit a common electrophysiological signature of familiarity. Thus, despite substantial differences in capacity limits and activation states, retrieval from WM and LTM appears to engage overlapping neural mechanisms.

In addition, the amplitude of the frontal old/new effect decreased as a function of increasing set size, suggesting a continuous decline in memory strength from WM to LTM. To further characterize this effect, we examined set sizes within and beyond

canonical WM capacity. Similar to parietal old/new effect, within the WM range (1, 2, and 4 items), frontal old/new amplitudes did not significantly differ. However, beyond WM capacity limits, the amplitude declined progressively, with pronounced reductions at set sizes of 32 and 128 items. These findings further support the notion that WM and LTM retrieval rely on a shared neural access mechanism, with set size modulating the strength of the retrieved representations across both systems.

In addition to the amplitude finding, consistent with the shared-access hypothesis, peak latency occurred earlier for smaller set sizes and increased systematically with larger set sizes for frontal old/new effect. Notably, latency differences increased with set size (*p*s < .01), and this increase followed a logarithmic rather than a linear function of set size. This pattern again aligns with prior findings from memory search paradigms, which demonstrate that response time increases as a logarithmic function of memory set size.

Taken together, the findings from both the parietal and frontal old/new effects indicate that the amplitude and latency characteristics of these signals provide converging evidence for a shared neural access mechanism underlying retrieval from both WM and LTM, while also revealing systematic differences in search dynamics across memory systems.

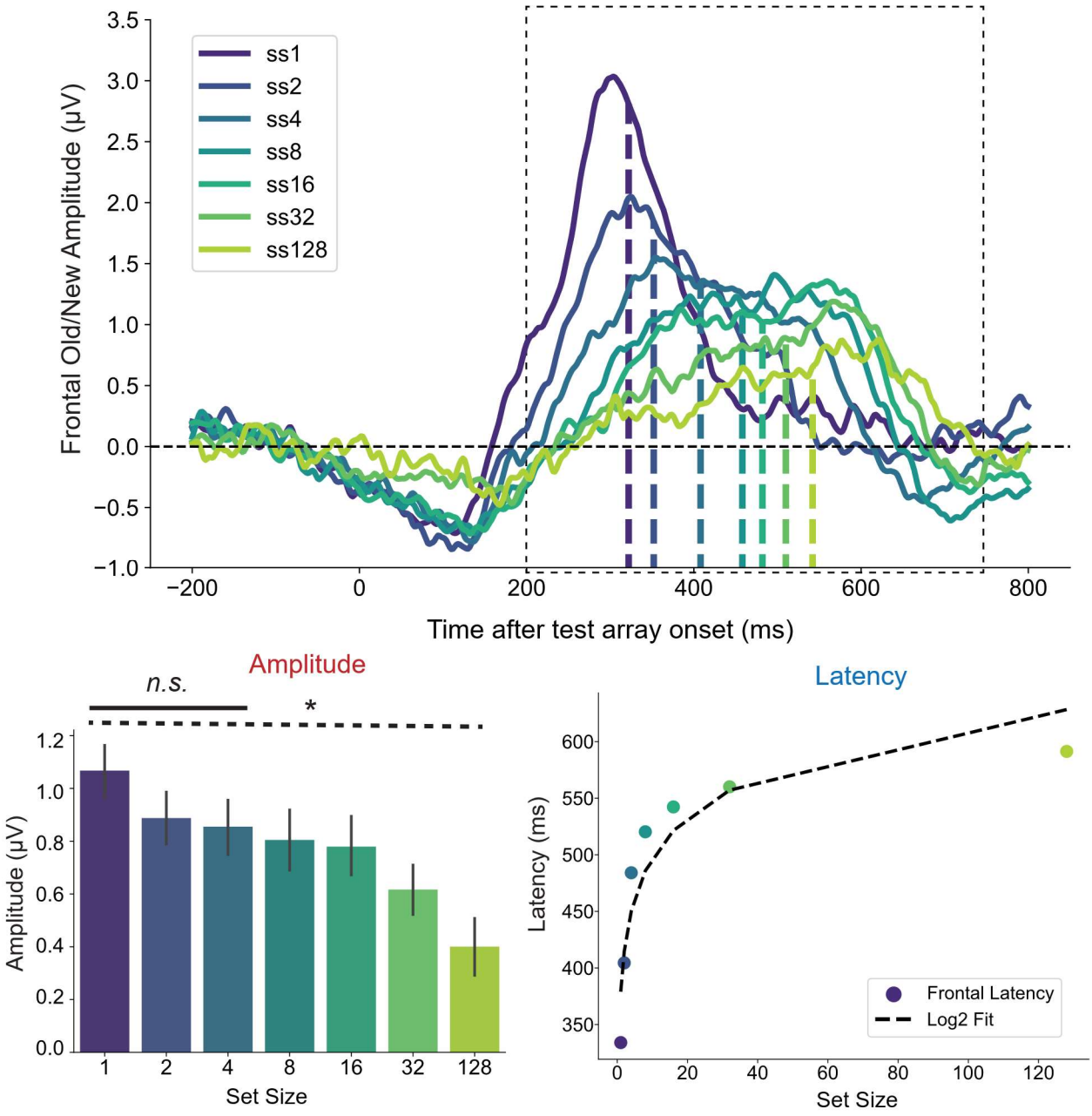


Fig 10. Amplitude and Latency of the Frontal old/new effect with set size 1, 2, 4, 8, 16, 32 and 128.

Multivariate Decoding revealed shared access to working and long-term memory during retrieval

Our univariate results collectively suggest that working memory (WM) and long-term memory (LTM) may rely on a common access mechanism in the brain. However, these univariate signatures were derived primarily from prior LTM-focused literature and may therefore be subject to bias. To more directly address this question, we implemented a multivariate classification approach to discriminate old versus new trials in the set size 4 condition, which served as a template. Set size 4 approximates the upper capacity limit of WM; thus, the classifier learns to distinguish “old” from “new” items based on distributed neural activity associated with retrieval at this capacity boundary. Critically, if this learned decision boundary reflects a general memory-access operation, rather than idiosyncratic features of the training condition, it should generalize to other set sizes. Successful generalization to both smaller and larger set sizes would therefore indicate that the neural code supporting old/new discrimination is shared across conditions, consistent with a shared-access hypothesis between WM and LTM. Conversely, failure to generalize would suggest that these memory systems rely on distinct access processes at test.

The classifier was trained on the test phase of the set size 4 condition. As shown in **Fig. 11**, multivariate decoding generalized robustly across set sizes, with significant temporal clusters indicated by the white dashed box. Notably, for set sizes 1 and 2, decoding of old versus new trials preceded that observed in the set size 4 training condition, suggesting faster signal discrimination for smaller memory loads, consistent with our univariate latency findings. In contrast, as set size increased beyond four items,

decoding latencies lagged relative to the set size 4 template, indicating slower retrieval dynamics.

Together, these findings suggest that although memory search operates via a shared mechanism across WM and LTM, retrieval speed is modulated by set size. Specifically, searching through larger memory sets is slower than accessing items actively maintained within WM. These multivariate results converge with univariate event-related potentials (ERP) findings, providing converging evidence in support of a shared-access hypothesis.

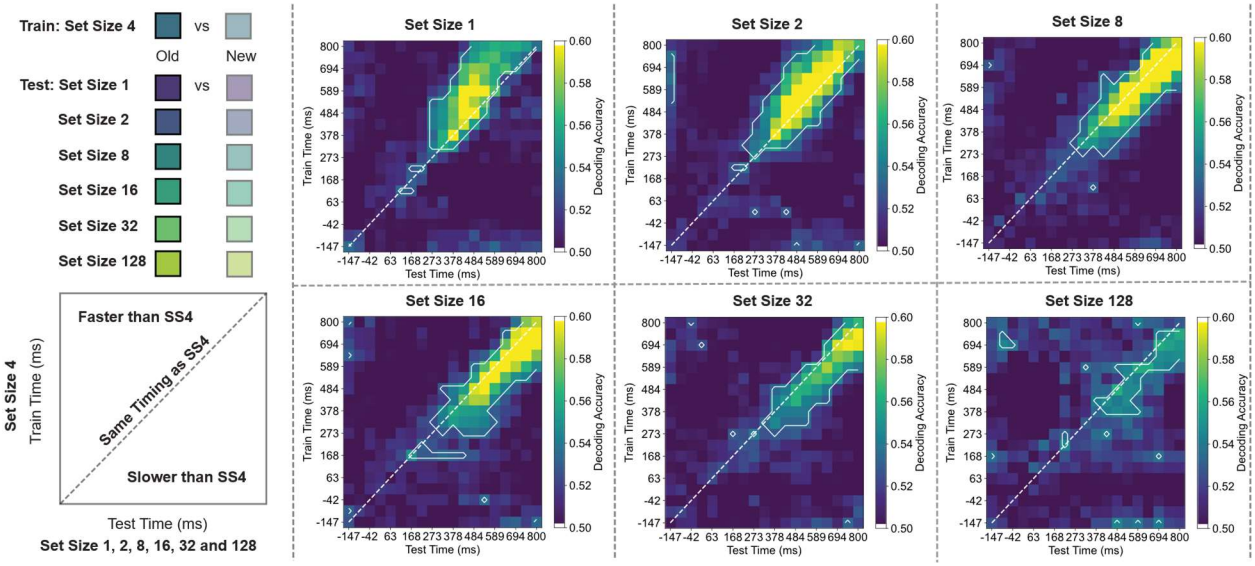


Fig 11. Multivariate Decoding of old/new items using single-trial EEG with set size 1, 2, 4, 8, 16, 32 and 128.

Individual differences in parietal old/new effect selectively predicts WM and LTM performance

So far, our analyses have focused on within-subject evidence to test whether working memory (WM) and long-term memory (LTM) share a common neural access mechanism. However, individuals vary substantially in their WM and LTM abilities, and

these capacities are often correlated. This raises a complementary question: in a well-powered sample, do neural measures of retrieval predict individual differences in memory performance?

Of the 110 participants, 82 completed an independent WM task (the change localization task), which provides a sensitive and reliable measure of WM capacity. We found that the parietal old/new effect for shorter lists significantly predicted WM performance (set sizes 1-32: rs = 0.23–0.33, FDR-corrected ps < .05; see **Fig. 12**), but not for the largest set size (set size 128; r = 0.14, p = .22). Because these correlations may partly reflect LTM contributions, we next computed partial correlations controlling for LTM performance (indexed by set size 128 accuracy). The relationship between the parietal old/new effect and WM remained significant for smaller set sizes (set sizes 1-4: rs = 0.22-0.27, ps < .05), was mixed at intermediate set sizes (set size 8: r = 0.22, p = .05; set size 16: r = 0.27, p = .01), and was no longer reliable for larger set sizes (set size 32: r = 0.17, p = .13; set size 128: r = 0.04, p = .74). Moreover, frontal old/new effect did not predict any of the WM ability measures (ps > 0.30). This pattern suggests that the parietal old/new effect for smaller set sizes primarily tracks individual differences in WM ability.

We next asked whether the same neural measure predicts LTM ability. Correlational analyses revealed that the parietal old/new effect for very small set sizes (1–2) did not predict LTM performance (set size 128 accuracy; set size 1: r = 0.05, p = .63; set size 2: r = 0.03, p = .80), whereas effects emerging at and beyond WM capacity (set sizes 4-128) were significantly associated with LTM performance (rs = 0.24-0.33, FDR-corrected ps < .05; see **Fig. 13**). After controlling for WM ability, this

relationship remained absent for small set sizes (set size 1: r = -0.03, p = .77; set size 2: r = -0.04, p = .73; set size 4: r = 0.17, p = .13), was mixed at intermediate set sizes (set size 8: r = 0.26, p = .02; set size 16: r = 0.21, p = .06; set size 32: r = 0.19, p = .09), and remained robust for the largest set size (128: r = 0.31, p < .01). Moreover, frontal old/new effect did not predict any of the LTM ability measures (ps > 0.16).

Taken together, these findings indicate that the parietal old/new effect selectively tracks individual differences in memory performance in a load-dependent manner: activity elicited by shorter lists primarily predicts WM ability, whereas activity elicited by longer lists more strongly predicts LTM ability. This pattern further supports the view that a common retrieval-related neural signal underlies both systems, while its behavioral relevance shifts as a function of memory load.

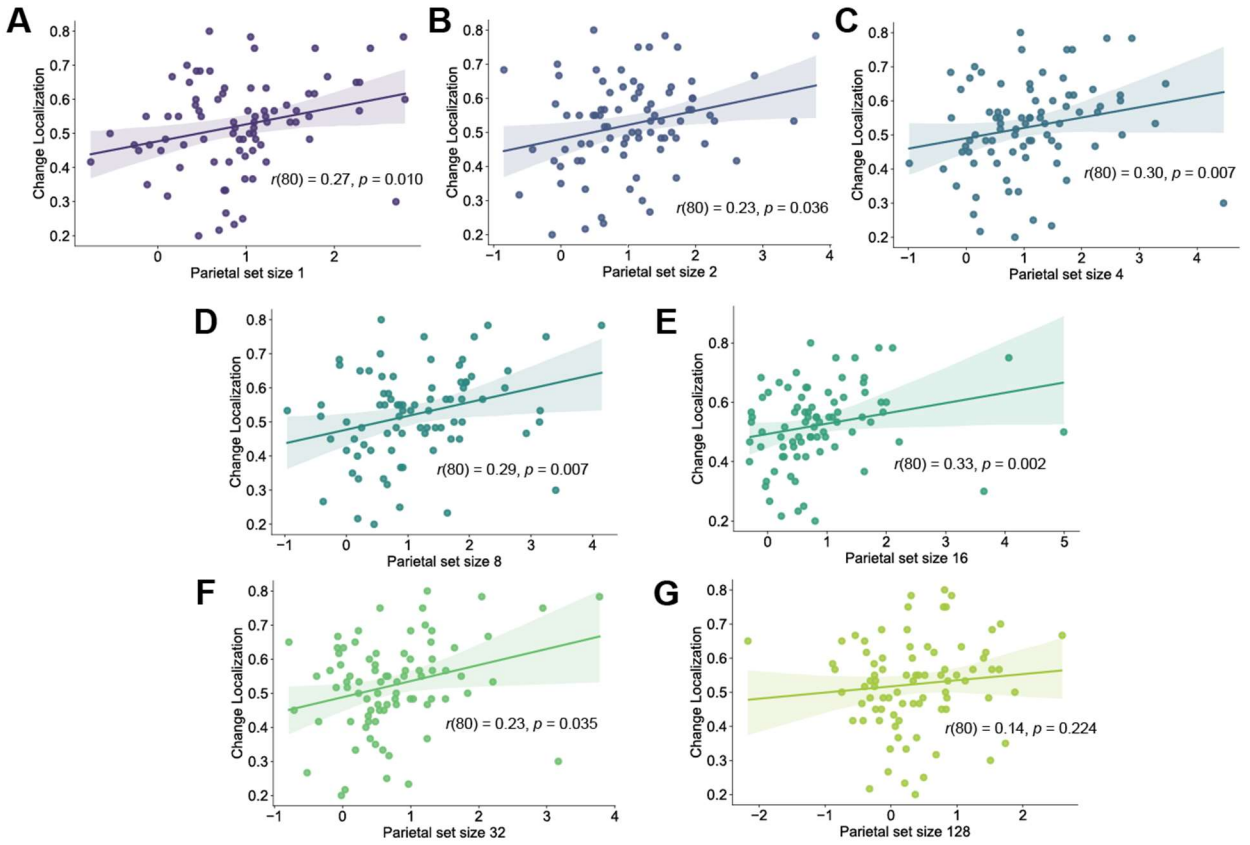


Fig 12. Parietal old/new effect for smaller set sizes selectively predict working memory performance.

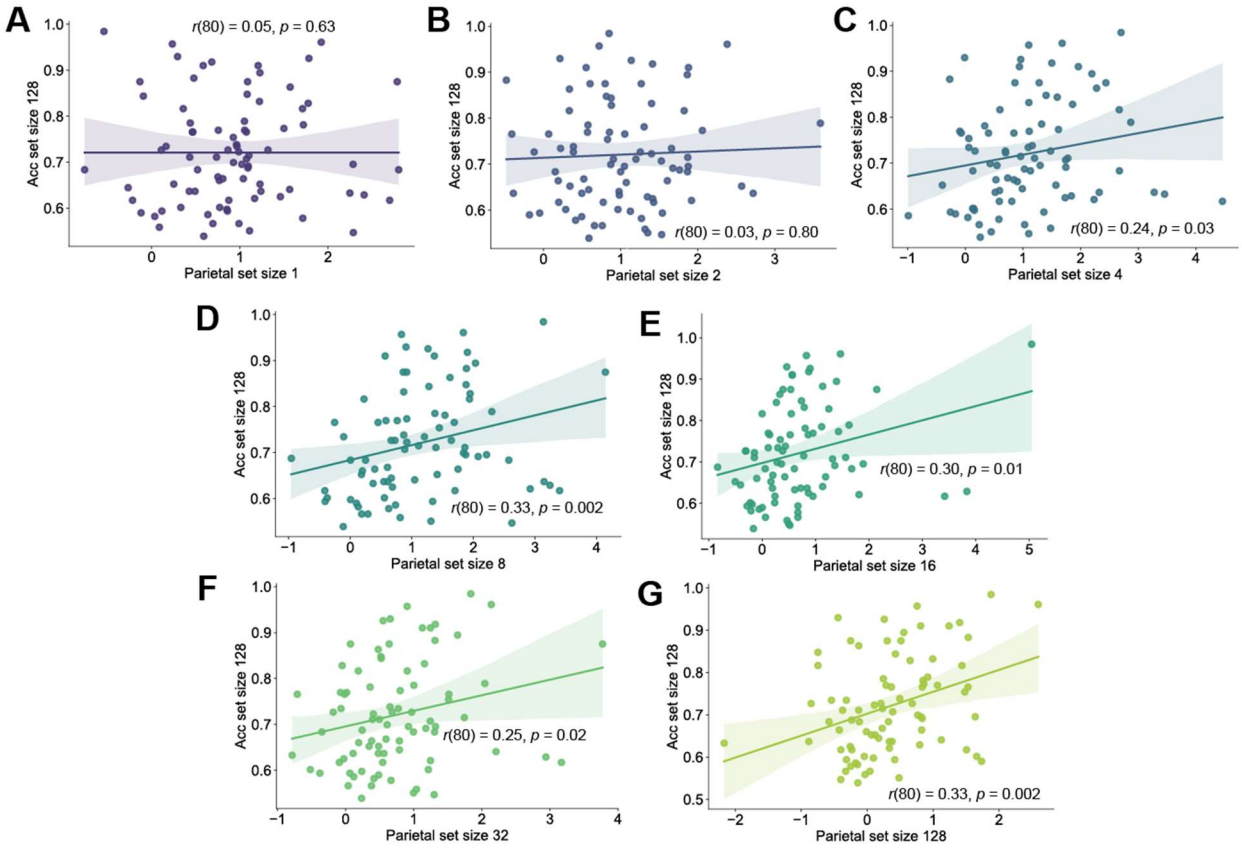


Fig 13. Parietal old/new effect for larger set sizes selectively predict long-term memory performance.

Discussion

In the current work, we tested whether working memory (WM) and long-term memory (LTM) share a common neural access mechanism at retrieval. We recorded participants' brain activity during an old/new recognition task across a wide range of set sizes (1, 2, 4, 8, 16, 32, and 128), and leveraged both univariate and multivariate neural measures to address this question. Two well-established univariate ERP markers, the parietal and frontal old/new effects, were reliably observed across both WM- and LTM-dominant conditions. Critically, the latency of these effects increased as a logarithmic function of set size, suggesting a common access process whose temporal dynamics

scale with memory load. Our neural latency pattern is consistent with a shift from relatively efficient search within WM to slower access as reliance on LTM increases in memory search literature.

Moreover, our multivariate decoding analyses similarly supported this shared access hypothesis. Classifiers trained to discriminate old versus new items generalized across set sizes, indicating a shared representational code underlying retrieval. Moreover, the temporal dynamics of decoding revealed a systematic shift: decoding in smaller set sizes (within WM capacity) preceded that of the set size 4 template, whereas decoding in larger set sizes (beyond WM capacity) lagged behind it. Together, these findings provide converging evidence that WM and LTM share a common neural access mechanism at test, with retrieval speed modulated by memory load.

Despite this shared access mechanism, we also showed that individual differences in WM and LTM were separable at the test phase. We found that the parietal old/new effect tracked behavioral performance in a load-dependent manner: activity elicited by shorter lists predicted WM ability, whereas activity elicited by longer lists predicted LTM ability. In contrast, the frontal old/new effect did not reliably predict either WM or LTM performance. This dissociation supports the idea that WM and LTM are separable cognitive constructs. Importantly, the differences in this shared decision process predicted old/new recognition performance, and this ability is more closely tied to recollection-related activity than to familiarity-based processing (Friedman & Johnson Jr, 2000; Rugg & Curran, 2007).

Importantly, the presence of a shared access mechanism does not imply that working memory (WM) and long-term memory (LTM) are functionally identical. Our

findings suggest that these systems may converge at retrieval, relying on a common neural access signal at test, while differing in how information is encoded, stored, and maintained. WM is capacity-limited and supports the active maintenance of a small number of items, whereas LTM is effectively unlimited and supports more durable, but less immediately accessible, representations. These differences likely arise from distinct encoding constraints and storage formats, even if the downstream decision process during retrieval is shared. In this view, WM and LTM may be differentiated primarily by their input and maintenance characteristics, while relying on a common mechanism to access stored information when making old/new recognition judgments.

Finally, our examination of individual differences provides an initial step toward understanding how these shared and distinct processes manifest across people. We found that recollection-related activity, indexed by the parietal old/new effect, differentially predicted WM and LTM abilities as a function of set size, suggesting that a common retrieval signal can nevertheless support distinct behavioral outcomes. Although prior work has emphasized the role of familiarity and recollection in recognition memory (Diana et al., 2006; Yonelinas, 2001), our results highlight that their contributions to individual differences, particularly across WM- and LTM-dominant conditions, remain incompletely understood. As one of the first attempts to link neural retrieval signals to both WM and LTM abilities within the same old/new recognition paradigm, our present findings underscore the need for future research to more precisely dissociate these processes and to determine how variability in their engagement shapes memory performance across individuals.

CHAPTER 3.

Individual differences in working memory and attentional control continue to predict memory performance despite extensive learning.

Working memory is the ability to maintain task-relevant information in the presence of distracting information and has been proposed to play a key role in the performance of many lab-based and real-world cognitive tasks (Draheim et al., 2022; Unsworth & Engle, 2007). Such claims are supported by the finding that individual differences in working memory predict performance on a wide range of tasks that measure many aspects of cognitive ability, such as abstract reasoning (Unsworth et al., 2014), long-term memory encoding (Miller et al., 2019b), mathematical reasoning (Raghubar et al., 2010), and even academic performance in math, science, and even some facets of literacy (Gathercole et al., 2004). For example, Unsworth et al. (Unsworth et al., 2014b) measured the relationship between working memory capacity and picture-location source memory task in which participants studied a sequence of visual objects presented sequentially in different quadrants of the screen. At test, each image was presented at the center and subjects reported which of the four quadrants it originally appeared. Individuals with high working memory showed superior source memory performance than those with low working memory ability ($r = 0.38$, $p < 0.001$). The general finding that individuals with high working memory ability have superior performance on many cognitive tasks has been observed in numerous studies over the years and has served as a key source of evidence that working memory is a critical component of the successful operation of many cognitive tasks. However, the mechanisms by which working memory abilities impact task performance are not well

understood. This is in part because most of these studies generally measure the relationship between working memory and a given cognitive ability only once - most typically during the first (and only) time the participant performed that particular cognitive task. Consequently, the reported relationship with working memory could potentially be explained by how quickly an individual initially learns to perform a new cognitive task. Relatedly, as task skill develops some have proposed that the demands for working memory become reduced (Fitts & Posner, 1967). Thus, from this perspective, the relationship between working memory and performance on a given task may be significantly altered once the individual has developed significant skill in the task.

In the skill development literature, researchers refer to these as "aptitude x treatment interactions", with the aptitude being the general cognitive abilities and treatment being the number of repeated learning events. A variety of outcomes have been observed between learning performance and general cognitive abilities. One class of hypothesis, we later describe as the "***rich get richer***" model, suggests that the differences in skill performance between participants with high and low cognitive abilities becomes magnified throughout learning. This effect presents as a positive interaction between numbers of learning events and general cognitive abilities, in that participants with higher general cognitive abilities improved more than participants with lower cognitive abilities with each repetition. An example supporting the "***rich get richer***" hypothesis was that researchers found that high-ability participants increased faster than low-ability subjects in a novel verbal sequence learning task across

repetitions, with Raven's square performance as the ability measures (B. Williams et al., 2008; B. A. Williams & Pearlberg, 2006).

Alternatively, participants with low general cognitive abilities may gradually catch up with the high performers with learning. This class of models, we refer to as the "***slow starter***" hypothesis, suggests a negative interaction between repetitions and cognitive abilities and states that cognitive abilities become less predictive of task performance as learning unfolds. For instance, when learning a new motor skill, although all participants became faster over repetitions, high performers in the initial session showed reduced advantage over low performers as learning proceeded (Ackerman, 1987). Furthermore, participants with low general intelligence abilities had a higher learning curve in motor tasks than high intelligence participants, suggested by a decrease in correlation between general abilities and task performance across repetitions (Kanfer & Ackerman, 1989).

Lastly, participants may continually demand similar levels of general cognitive abilities across learning. We refer to this class of hypotheses as the "***stable demands***" model. A prediction of this model was that participants with high and low cognitive abilities improve at a similar rate across repetitions. Therefore, the interaction between learning and general cognitive abilities would be expected to be close to null, since the number of repetitions does not change the predictive power of cognitive abilities in task performance. One example of this claim is that general abilities (verbal and visual measures) continually predicted learning of complex skills (Ackerman et al., 1995). In support of this hypothesis, evidence from paired associate learning and three-term verbal learning suggested that intelligence factor, g, continually predicted the learning

performance metrics for all four repetitions, indicating that high and low performers increased at similar speed across repetitions (Kaufman et al., 2009).

One potential challenge in interpreting these mixed results from the skill acquisition literature is that each study used a set of different cognitive ability measures, including but not limited to working memory, processing speed, fluid intelligence and attentional control measures. To test the specific relationship between aptitude and treatment interaction, we are interested in how the learning of visual items to spatial positions relates with visual working memory as the measure of individual general cognitive ability. However, even the measurement of something as specific as visual working memory has the potential of capturing other related cognitive mechanisms. Attention control mechanisms are well known to be highly related to working memory ability and have largely overlapping variance in individual ability. A common way to measure visual working memory is to ask participants to memorize an array of colors over a brief period of time, and test them on whether the color of an item of the array changed or remained the same (Martin et al., 2021). The co-variance structure of performance on this task suggests that it mostly taps on to working memory abilities, but also shared variance between working memory and attentional control, and lastly attentional control the least. Alternatively, when participants perform a variation of the task in which they were asked to selectively attend only to certain objects in the array and filter out distractors, this selective complex visual array tasks required higher levels of attentional control ability and less working memory abilities. A closer look at the covariance structure suggested that performance in a selective visual array task was explained mostly by attentional control abilities, then the shared variance between

working memory capacity and attentional control abilities and working memory abilities the least. Therefore, complex visual array tasks were well-suited in measuring general cognitive abilities, in that the variance explained by working memory and attentional control was directly related to the level of selection that took place when performing the task.

In the current study, we seek to examine the relationship between working memory, and performance on a source memory task throughout the initial stages of task learning following repeated practice. We will test three competing hypotheses that make distinct predictions about the relationship between working memory and source memory performance as task skill develops (see **Fig. 14 A-C**). The first one we label the "***stable demands***" hypothesis proposes that working memory always plays a key role in task performance regardless of the individual's level of skill in the task. This predicts that the performance advantages associated with high working memory will persist from initial learning to high levels of task performance. The other two hypotheses we will test propose that there may be significant differences in learning rate between high and low working memory individuals that may alter the relationship with attention control as skill develops. The "***slow starter***" hypothesis proposes that individuals with low attention control have poor performance on most new tasks, but that with practice and learning they can catch up to their high attention control counterparts. This predicts that there would be an initial advantage for the high working memory individuals at the beginning, but that with practice and learning these advantages would be reduced or eliminated. The "***rich get richer***" hypothesis proposes that individuals with high working memory can learn and achieve task skill more quickly than those with low working memory. This

predicts that the initial advantages of high working memory become even larger after extensive practice due to a faster learning rate for those with high ability. In addition, this procedure also allows us to test an important secondary hypothesis: do individuals with high working memory abilities learn faster than those with low working memory? By measuring individual learning rates across the repeated tests, we can test models that propose that working memory abilities determine how quickly the individual can acquire expert levels of knowledge in a task (Hambrick et al., 2014; Hambrick & Engle, 2002; Meinz & Hambrick, 2010). Furthermore, we also aimed to test how working memory differences generalized to the learning of verbal associations in long-term memory, as measured by a verbal paired-associate recall task (Exp 4). Lastly, we would like to test if our findings could be generalized from working memory to attentional control abilities, as measured with a battery of four tasks instead just of the change detection task used in Exps 1-4 (Exp 5).

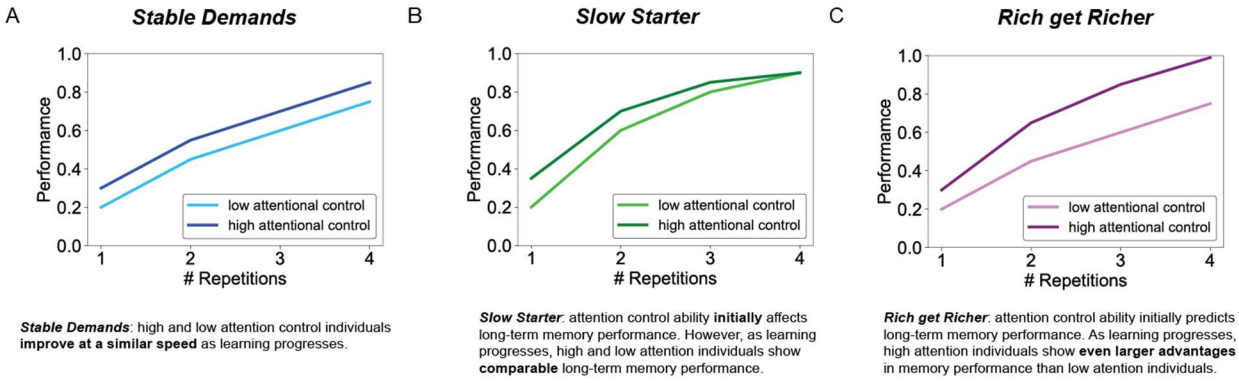


Fig. 14 A depiction of three hypotheses of the relationship between attention control ability and memory performance throughout learning following repeated practice.

Materials, Methods, and Results

Overview of Experiments

We tested our hypothesis between working memory ability and visual long-term memory in four experiments, with well-powered sample of participants recruited from Prolific online platform (n = 1250 in total), and diverse types of materials to be learned (visual in Experiment 1-3, 5 and verbal in Experiment 4, **Fig 15**). Previous research has shown that individual differences in working memory and attentional control abilities directly affected performances in visual working memory task, where participants memorized multiple visual stimuli on screen simultaneously and maintained them over a brief delay period (Martin et al., 2021). Therefore, we measured working memory abilities in our Experiments 1-4 using the change detection task, a highly reliable visual working memory task that required participants to detect the change in perceptual features between the encoding array and test probe (Luck & Vogel, 1997a; Xu et al., 2018; Zhao & Vogel, 2023). To measure the effect of learning in visual long-term memory, participants were presented with a sequence of stimuli to be repetitively learnt in every single experiments. In Experiment 1-3 and 5, subjects performed a source memory task in which they were presented a sequence of 30 objects (45 objects in Experiment 2 and 3) shown in one of four quadrants and then were tested on each item's position. We repeated this procedure for 5 times in Exp 1, and 12 times in Exp 2 and 3. In Experiment 4, we used a highly reliable foreign word paired-associate recall task (Zerr et al., 2018), which the participants were asked to learn Lithuanian-English word pairs in their initial study phase. During the test phase, they were cued with the Lithuanian word and were asked to type out its paired English word. We repeated this

study-test procedure for 4 times in Exp 4 to build up their memory on these Lithuanian-English paired associates. In Exp 5, we aimed at generalizing our findings with working memory capacity to both working memory and attentional control abilities. Therefore, we used a battery of four tasks, consisting of two working memory tasks (change localization and filtering change localization) and two attentional control tasks (Flanker Square and Simon Square tasks). All experiments were approved by University of Chicago IRB, and all participants provided informed consent online.

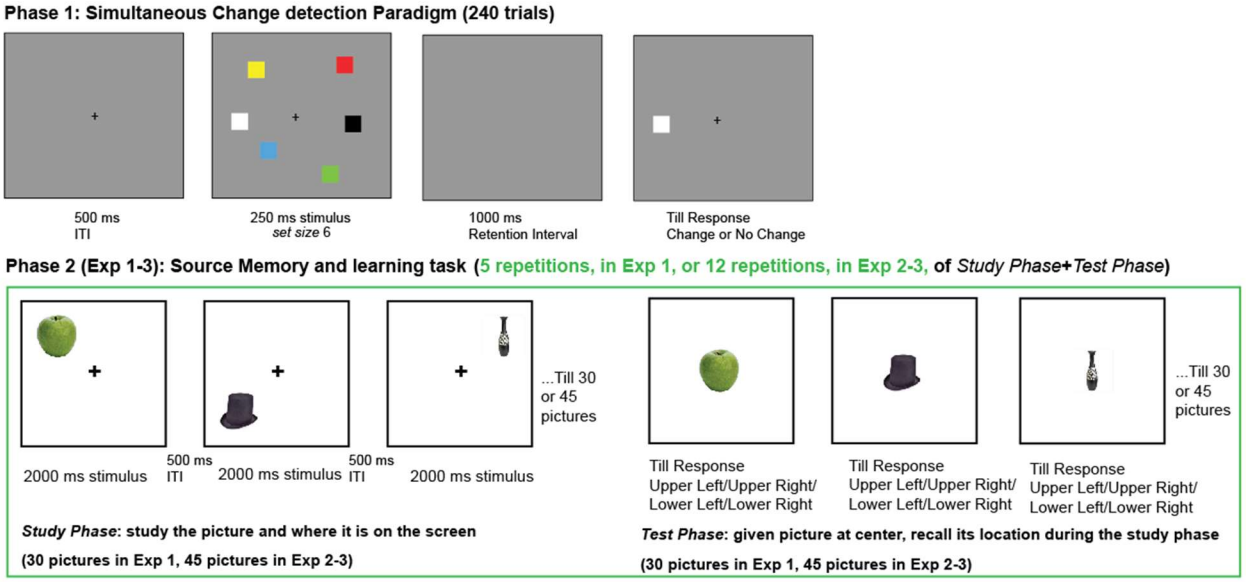
Fig. 15 *The change detection paradigm, source memory paradigm used in Exp 1-3.*

(Upper) A sample of the set size 6 simultaneous change detection paradigm. Six colored squares appeared on the screen simultaneously. At the end of the trial, participants were cued with a square at one of the six original locations, with 50% exhibited a color change and 50%

without change. (Middle) A sample of the source memory and learning paradigm used in Exp 1-3. During each trial of the study phase, a real-world object appeared at one of the four quadrants on the screen for 2 seconds. The participants need to encode the content of the

picture as well as where it was placed on the screen. We had thirty pictures in total for the study phase. During each trial of the test phase, we cued the participants with the studied object at the center of the screen, and they were asked to recall which quadrant the object was in

during the study phase. The study and the test phase were repeated for five times in Exp 1, and twelve times in Exp 2 and 3.



Transparency and Openness

This study was not preregistered before data analysis. We report how we determined all data exclusions, all manipulations, and all measures in the study. Experiments were programmed in Javascript and jspsych packages. Analyses were performed in Python 3.7, with the package matplotlib, scipy, numpy, and seaborn for plotting. Analysis scripts are publicly accessible at https://osf.io/dvumt/. Data and materials used in this study are accessible to the public in the Open Science Framework repository.

Experiment 1: Stable working memory demands despite of extensive learning of the same visual image sequence

Method

Participants Seven hundred participants were recruited at the rate of $9.50 per hour from Prolific, an online platform for participant recruitment. All participants were eighteen

to thirty-five years old, currently living in the United States, had normal or corrected-to-normal vision, and with no ongoing psychological or neurological disorders.

Stimuli In our visual working memory task, all stimuli were colored squares generated in Javascript using the jsPsych canvas keyboard interface. The colored squares were all in 40 x 40 pixels size on a 400 x 400 pixels canvas page. Color squares could appear anywhere within a circular area of the monitor within 30 to 200 pixels from the center of the canvas screen. Each square could appear in one of the nine distinct colors with no repetitions within any trial (RGB values: red = 255 0 0; green = 0 255 0; blue = 0 0 255; magenta = 255 0 255; yellow = 255 255 0; cyan = 0 255 255; orange = 255 128 0; white = 255 255 255; black = 0 0 0). Participants were instructed to fixate at a small black plus (30 px in Arial) at the center of the screen throughout the trial. In our source learning paradigm, all pictures were selected from a public picture database (Brady et al., 2008). In each picture list, we selected thirty pictures from fifteen distinct semantic categories.

Procedures In measuring visual working memory capacity, we administered a change detection task with set size 6. In each trial, six colored squares would appear onto the screen simultaneously for 250 ms, followed by 1000 ms of retention interval, when no stimuli were shown on the screen. Then, one color square would appear at one of the six previous locations the encoding array had appeared at, and the participant was asked if the color of this new square changed from the studied square that was located at the same position 1000 ms before. During half of the trials, the color of this new square would change into a new color that was not seen before. For the other half of the trials, the new square would share the same color and location as one of the six studied

squares. Each participant completed 240 trials of the change detection task in their Phase 1 (see **Fig. 15 Upper**).

After completing the visual working memory task, participants were then administered a source memory and learning task. In each trial of the study phase of the task, participants were shown a real-world object located at one of the four quadrants of the screen for 2000 ms. They were asked to remember both the content and the location of the object since both properties were relevant for their later test phase. The study phase consisted of thirty trials in total. Following the study phase, the participants were tested on the picture list they learned immediately. Each trial of the test phase started with a picture placed at the center of the screen, and participants had 5 seconds to respond to which quadrant the object was in during the study phase. The test phase maintained the same order of pictures as the study phase, and therefore also had thirty pictures in total. The study and the test phases were repeated five times in the exact same order to facilitate learning of the sequence (see **Fig. 15 Lower**).

Power Estimation A power analysis was conducted using InteractionPoweR (Baranger et al., 2023) to determine the minimum sample size required to test the study hypothesis (i.e., aptitude x treatment interaction effect). We ran 1000 simulations for each of the power estimation hyperparameters and assumed that our working memoy measures and long-term memory measures were both reliable (reliability of 0.8 and 0.9, respectively, according to Zhao & Vogel., 2024). With a small effect (interaction $r = 0.2$), to achieve 80% power with $\alpha = .05$, the estimated sample size was N = 127. Since no prior studies directly informed our design, we also ran 1000 simulations with a smaller effect size ($r = 0.1$). Results indicated the required sample size to achieve 80% power

for detecting a small effect (interaction term with outcome variable $r = 0.1$), at a significance criterion of $\alpha = .05$, was N = 556. Thus, the obtained sample size of N = 700 is adequate to test the study hypothesis, with an estimated power of 0.88.

Results

In Experiment 1, we tested if individual differences in visual working memory capacity were predictive of source memory accuracy, our memory performance measure that was expected to improve with more repetitions. We first confirmed that repeated exposure of the same image sequence resulted in improvement in source memory accuracy suggesting that participants showed significant improvement in long-term memory via learning ($F(4,694) = 291.35$, $p < 0.001$, $\eta^2 = 0.30$, **Fig. 16A**). More importantly, across 700 participants, we observed that visual working memory capacity positively correlated to the mean source memory accuracy of the five repetitions of the same picture list ($r(699) = 0.39$, $p < 0.001$, **Fig. 16B**). If the ***slow starter hypothesis*** held true for visual sequence learning, then the more participants practiced the list, the individual differences in working memory would be less predictive of performance. Therefore, this model predicts a decrease in the correlation between working memory and source memory as more repetitions of the same list were presented to the participants (see **Fig. 14B**). However, we observed sustained positive correlations between working memory and source memory accuracy for all five repetitions of the sequence ($r(699)$s > 0.26, ps < 0.001, **Fig. 16C**). That is, people with higher working memory abilities on average retained their advantage in source memory performance than those with lower working memory abilities, even as people repeatedly practice the same materials (**Fig. 16D**). Indeed, the performance advantage for the high working

memory subjects remained constant despite substantial learning across the 5 repetitions. The robust predictive power of working memory on source memory accuracy, even when participants had reached a relatively high level of recall performance, contradicts the prediction of the ***slow starter hypothesis*** and instead supports the ***stable demands hypothesis.***

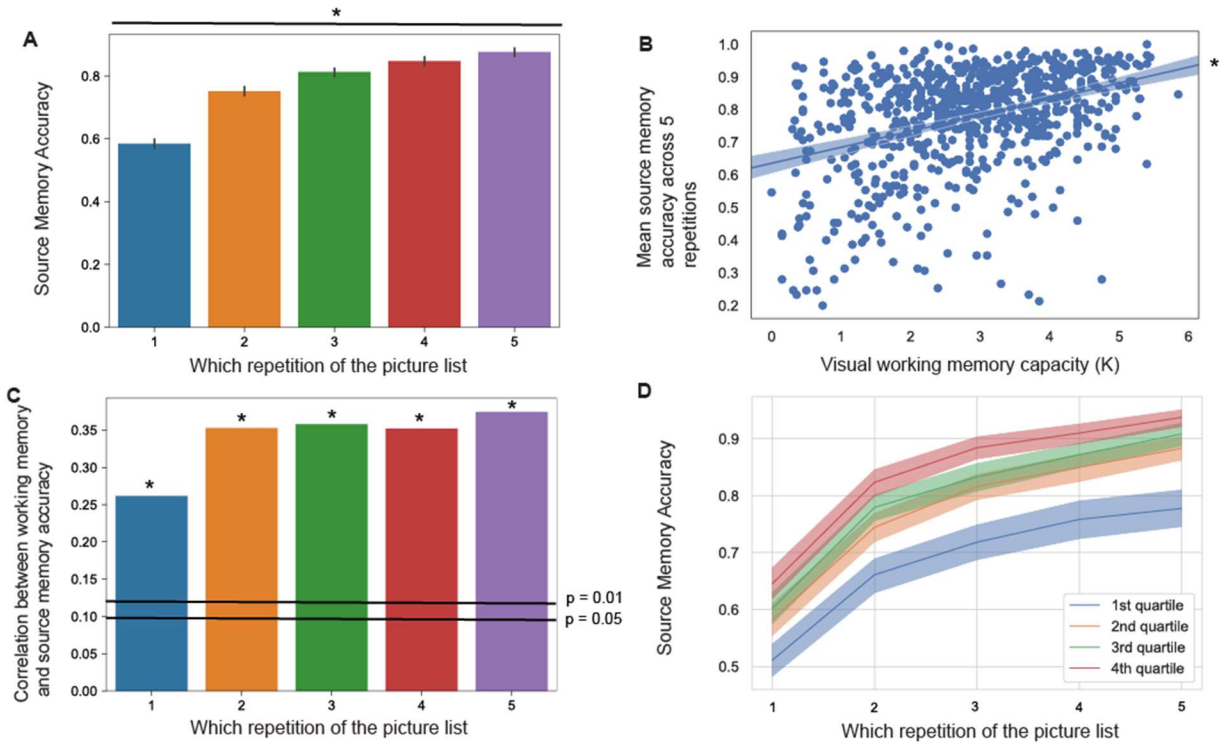


Fig. 17 *Visual working memory capacity consistently predicted source memory performance, even as people started building expertise for the source memory list.*

(A) Source memory accuracy increased as participants repeatedly learned the same

list of item-location bindings.

(B) The visual working memory capacity, estimated by change detection task of set size 6,

positively correlated to the mean accuracy of source memory task for all 5 repetitions.

(C) In each individual repetition of the picture-location list, visual working memory capacity, reflecting attentional control abilities, positively correlated to the source memory accuracy of that specific repetition, even as people already achieved expertise of the list.

(D) Source memory performance split by visual working memory quartiles. In every single repetition of the list, people with higher working memory capacity (attentional control abilities) had higher source memory performance than people with lower attentional control abilities.

Individual differences in learning rate are not related to working memory ability

As shown in **Figure 17D**, individuals with high working memory abilities had

better source memory performance than low working memory subjects beginning with

the first repetition and this advantage persisted throughout the 5 repetitions. A key implication of this pattern is that it suggests that both high and low working memory subjects improved their source memory performance by roughly **the same amounts** across the five repetitions, even though they had different starting levels of performance. This finding appears to robustly contradict the ***rich get richer hypothesis*** that proposes that high working memory subjects may learn more quickly than low working memory individuals. However, this observation of parallel learning slopes between across different quartiles of working memory ability may be too coarse to observe the relationship between working memory and individual learning slope.

To better quantify the effect of repetitions on increasing the accuracy of source memory, we first quantified each individual subject's performance with a linear model of learning, which assumed that each repetition enhanced source memory accuracy by a fixed amount of strength (**Fig. 18A**). We tested the reliability of these linear learning slopes in Exp 1 data by performing an odd-even split-half correlational analysis. The source memory trials were evenly divided into two halves, and linear slopes were calculated separately for the odd half of trials and the even half of trials. The Spearman-Brown corrected correlation between the two slope measures was 0.747, indicating that the linear slope had a high reliability (**Fig. 18B**). Alternatively, participants may learn faster in their earlier repetitions and reach a plateau during later repetitions. This form of learning could be better captured by a log-linear model, which assumes a steeper learning speed at first (**Fig. 18D**). Similarly, we then tested the reliability of the log-linear learning slopes using Exp 1 data by performing an odd-even split-half correlational analysis. The Spearman-Brown corrected correlation between the even and odd trial

slope measures was 0.750, indicating that the log slope had a high reliability (**Fig. 18E**). Different from its sustained predictive power in expertise performance, visual working memory capacity did not predict the linear learning slope ($r(699) = 0.055$, $p = 0.10$, **Fig. 18C**) or the log learning slope ($r(699) = 0.063$, $p = 0.15$, **Fig. 18F**).

To further examine the relationship between VWM capacity and learning slopes, we performed a partial correlation model to regress out the effect of mean source memory performance that may moderate the VWM-slope correlation. The partial correlation between VWM capacity and linear slope was not significant either($r(699) = 0.045$, $p = 0.23$), and the Bayes Factor strongly favored the null (BF = 10.42 favoring null). Similarly, the partial correlation between VWM capacity and log slope was also close to zero ($r(699) = 0.047$, $p = 0.21$, BF = 9.80 favoring null). In additional to directly modeling the learning slope, we also performed a linear mixed effects analysis with fixed effects for number of repetitions, working memory ability and their interaction, with random slopes and intercepts by participant. If the ***stable demands hypothesis*** held, we would expect a non-significant interaction between working memory ability and number of repetitions. Alternatively, the ***rich get richer*** hypothesis would result in a significant interaction with a positive coefficient, and the ***slow starter*** hypothesis would produce a significantly negative coefficient on the interaction term. With a well-powered sample (n = 700), we discovered that the interaction between working memory ability and number of repetitions remained not significant (β = 0.002, 95% CI: [-0.001, 0.004], $p = 0.07$). Together, these results suggest that VWM capacity does not predict the rate of learning via repetitions, supporting the ***stable demands hypothesis***.

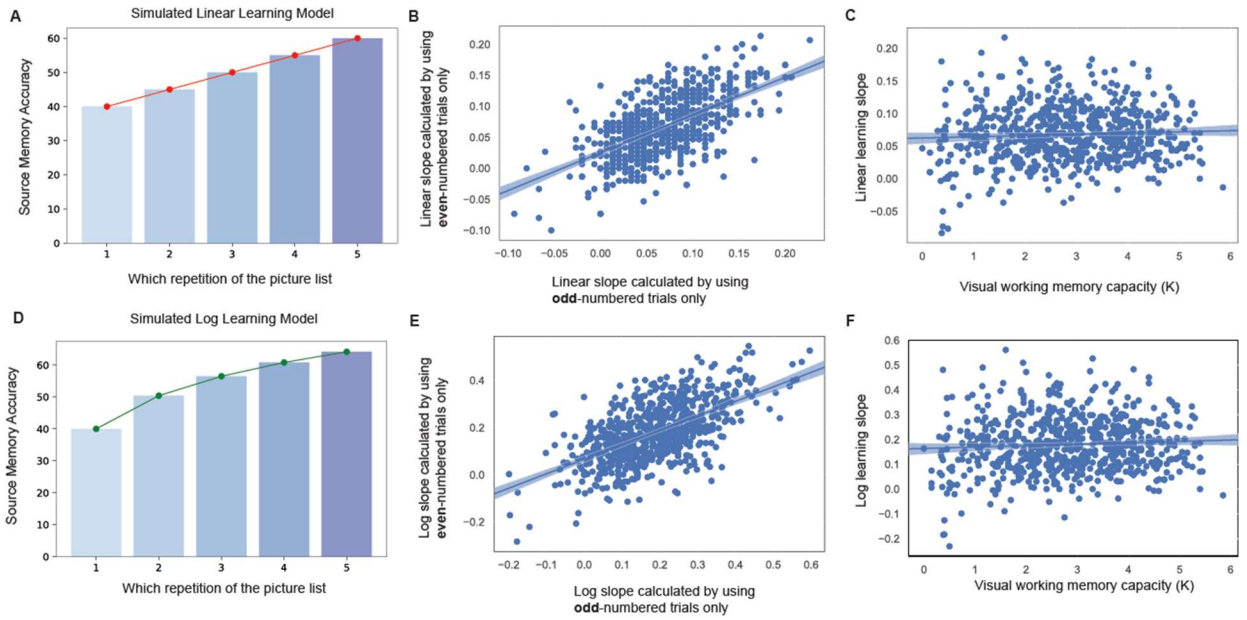


Fig. 18 *Visual working memory capacity predicted neither linear or log learning slope.*

(A) Simulated linear learning model. This model assumed that learning emerged linearly across repetitions.

(B) The linear learning model was highly reliable when applied to Exp 1 data. The odd-even split-half Spearman-Brown corrected correlation was 0.747 for the linear

model.

(C) Visual working memory capacity did not predict learning slope under the linear assumption. (D) Simulated log learning model. This model assumed that learning emerged faster during earlier repetitions than later repetitions.

(E) The log learning model was also highly reliable when applied to Exp 1 data. The odd-even split-half Spearman-Brown corrected correlation was 0.750 for the log model.

(F) Visual working memory capacity did not predict learning slope under the log assumption.

Experiment 2: Stable working memory demands when memory performance approaches ceiling

Method

Participants One hundred participants were recruited at the rate of $9.50 per hour from Prolific, an online platform for participant recruitment. All participants were eighteen to thirty-five years old, currently living in the United States, had normal or corrected-to-normal vision, and with no ongoing psychological or neurological disorders.

Stimuli The stimuli used were the same as in Exp 1.

Procedures The visual working memory task was the same as in Exp 1. After completing the visual working memory task, participants were then administered a source memory and learning task. The procedures remained the same as in Exp 1, except that the study and the test phases were repeated twelve times in the exact same order to facilitate learning of the sequence in Exp 2.

Power Estimation From our Experiment 1 data, we simulated sample sizes that were enough to observe small effect using the correlations we observed in Experiment 1. The median estimated power for our sample size (N = 95) in Exp 2 was 0.802 (100 iterations of 1000-time simulation). We plotted our power simulations with N = 100, 150, 200, 250, 300 and 700 in our **Supplemental Material**.

Results

In Experiment 1, participants eventually reached an average accuracy of 87.62% by their fifth repetition, which was still significantly higher than the accuracy for fourth repetition (M = 84.72%, $t(699) = 8.42$, $p < 0.001$). That is, despite an over 25% improvement in memory accuracy from the first repetition to the fifth, subjects may not yet have reached performance asymptote. This raises the possibility that contributions from the individual's working memory ability would only diminish once near-perfect task

performance has been achieved. To address this question, we designed a 45-picture source memory task in Experiment 2 (n = 95) and asked a new set of participants to repeat the study-test procedure for 12 times instead of 5 times as in Experiment 1. As we expected, participants showed a significant learning effect across repetitions as in Experiment 1 ($F(11,82) = 60.74$, $p < 0.001$, $\eta^2 = 0.42$, **Fig. 19A**). Examining the accuracy for each individual repetition, we discovered that participants on average stopped improving in their source recall accuracy starting by the seventh repetition of the sequence (under Bonferroni correction, ps > 0.0045 starting seventh repetition). Under the ***slower starter hypothesis***, individual differences in working memory abilities should be no longer predictive of source memory performance as expertise was fully developed, especially following the seventh repetition in Experiment 2. However, we did observe sustained predictive power of working memory on source memory accuracy at the seventh repetition ($r(94) = 0.24$, $p = 0.02$). It is difficult to accurately measure correlations when performance on one task is at or near ceiling because there is a restriction of range. After performing range restriction correction to mitigate the ceiling effects of source memory accuracy for later repetitions (Sackett & Yang, 2000), we found that working memory abilities consistently positively correlated to source memory accuracy until tenth repetition of the list (corrected $r(94) = 0.35$, 0.39, 0.43 and 0.28 for 7^{th}, 8^{th}, 9^{th} and 10^{th} repetitions, respectively, $ps < 0.01$, **Fig. 19B,** ps > 0.05 for the 11^{th} and 12^{th} repetitions because the range restriction correction method was insufficient to handle the most extreme ceiling effects). To further investigate the interactions between working memory and learning, we performed a linear mixed effects analysis with fixed effects for number of repetitions, working memory ability and their interaction, with

random slopes and intercepts by participant. If the ***stable demands hypothesis*** held, we would expect a non-significant interaction between working memory ability and number of repetitions. Alternatively, the ***rich get richer*** hypothesis would result in a significant interaction with a positive coefficient, and the ***slow starter*** hypothesis would produce a significantly negative coefficient on the interaction term. Echoing our previous findings, we discovered that the interaction between working memory ability and number of repetitions remained not significant ($\beta = 0.004$, 95% CI: [-0.007, 0.014], $p = 0.49$). Furthermore, although response time decreased as more repetitions of task were shown, it reached asymptote at the 7th repetition and did not reliably correlate with working memory abilities (**Supp. Fig. 1, A & B**). Therefore, we concluded that gaining asymptotic levels of memory performance for a visual sequence did not eliminate the differences in performance between high and low working memory participants, supporting the ***stable demands hypothesis***.

Experiment 3: Stable working memory demands even when test utilized a different serial order from the encoding list

Method

Participants One hundred and one participants were recruited at the rate of $9.50 per hour from Prolific, an online platform for participant recruitment. All participants were eighteen to thirty-five years old, currently lived in the United States, had normal or corrected-to-normal vision, and with no ongoing psychological or neurological disorders.

Stimuli The stimuli used were the same as in Exp 1 and 2.

Procedures The visual working memory task was the same as in Exp 1 and 2. After completing the visual working memory task, participants were then administered a source memory and learning task. The procedures remained the same as in Exp 2, except that the items in the study and the test phases were repeated twelve times, but in randomized order instead of the fixed order used in Exp 1 and 2.

Power Estimation From our Exp 1 data, we simulated sample sizes that were enough to observe small effect using the correlations we observed in Experiment 1. The median estimated power for our sample size (N= 101) in Exp 3 was 0.823 (100 iterations of 1000-time simulation). We plotted our power simulations with N = 100, 150, 200, 250, 300 and 700 in our **Supplemental Material**.

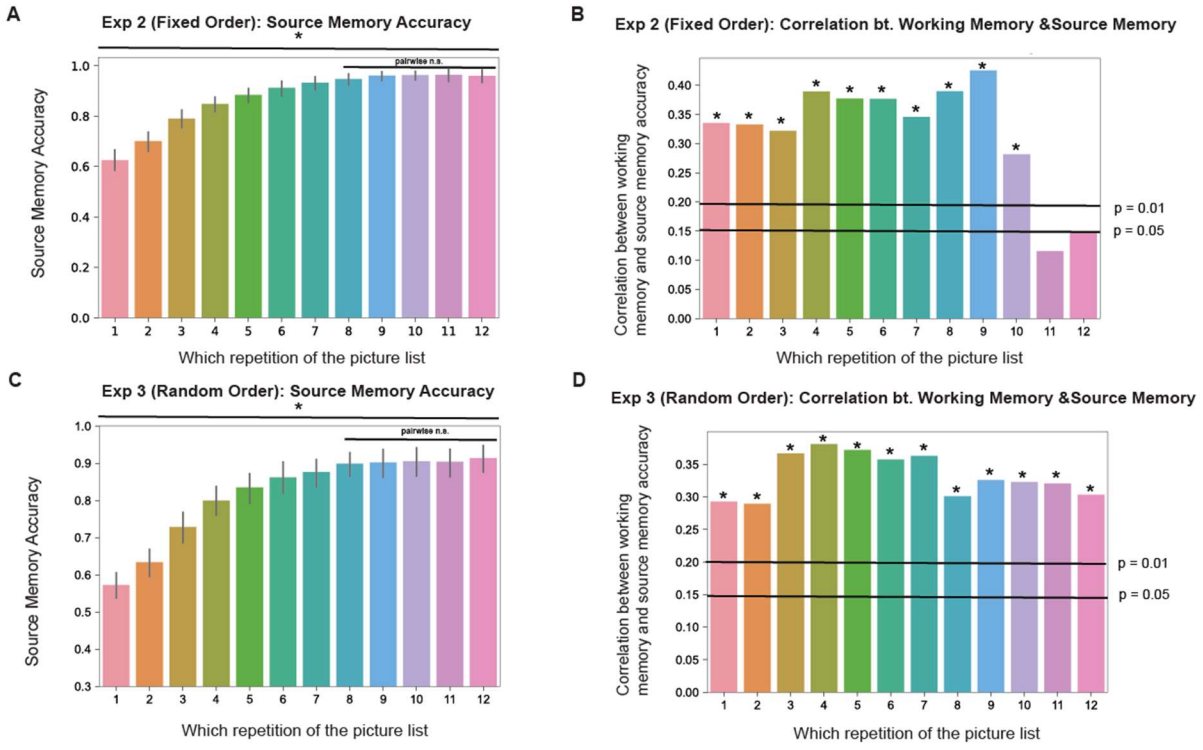


Fig. 19 *Visual working memory capacity predicted the accuracy in each repetition of source memory list in Exp 2 and Exp 3.*

(A) Source memory accuracy increased as participants repeatedly learned the same list of item-location bindings for 12 times in Exp 2.

(B) Visual working memory capacity, reflecting attentional control abilities, positively correlated to the mean accuracy of source memory task performance up to 10th repetition after correction of range restriction.

(C) Source memory accuracy increased as participants learned the same list of item-location bindings, but presented in randomized order for each iteration, for 12 times in Exp 3.

(D) Visual working memory capacity, reflecting attentional control abilities, positively correlated to the mean accuracy of source memory task performance for all 12 iterations of learning.

Results

To facilitate learning of the visual bindings, we tested the image-location bindings in the same exact sequence order as the order during the encoding phase in Experiment 1 and 2. In a more realistic scenario, however, one would expect that participants, with enough practice, should be able to utilize the learned memory associations flexibly even without the contextual benefits that result from using the same order for study and test. Therefore, in Experiment 3, we used the same study-test procedures as in Experiment 2, but with a completely randomized order of items for each repetition of the 45-item visual sequence (n = 101). With this slight change in our experimental design, we were able to directly acquire a purer metric of source memory knowledge for each individual image-location binding, eliminating a potential confound brought by retrieving temporally neighboring items during test. Similar to the previous experiments, participants showed significant learning effects for the locations of items across repetitions ($F(11,88) = 30.07$, $p < 0.001$, $\eta^2 = 0.38$, **Fig. 19C**). Examining the accuracy for each individual repetition, we discovered that participants on average

stopped improving in their source recall accuracy starting at their seventh list (under Bonferroni correction, *p*s > 0.0045 starting seventh list, except from eighth list). Replicating Exp 1 and 2, we observed sustained positive correlations between visual working memory capacity and source memory accuracy (raw Pearson *r*(100)s >= 0.29, *ps* < 0.001, **Fig. 19D**). To further investigate the interactions between working memory and learning, we performed a linear mixed effects analysis with fixed effects for number of repetitions, working memory ability and their interaction, with random slopes and intercepts by participant. If the ***stable demands hypothesis*** held, we would expect a non-significant interaction between working memory ability and number of repetitions. Alternatively, the ***rich get richer*** hypothesis would result in a significant interaction with a positive coefficient, and the ***slow starter*** hypothesis would produce a significantly negative coefficient on the interaction term. Echoing our previous findings, we discovered that the interaction between working memory ability and number of repetitions remained not significant (β = -0.001, 95% CI: [-0.015, 0.013], *p* = 0.90). Furthermore, although response time decreased as more repetitions of task were shown, it reached asymptote at the 6th repetition and did not consistently correlate with working memory abilities (**Supp. Fig. 1, C & D**). In conclusion, we successfully validated our findings in Exp 1 and Exp 2 that individual differences in working memory abilities predicted task performance even after participants acquired extensive performance expertise for the images in the list, again supporting the ***stable demands hypothesis***.

Experiment 4: Stable working memory demands generalize to verbal associative memory

Method

Participants Two hundred participants were recruited at the rate of $9.50 per hour from Prolific, an online platform for participant recruitment. All participants were eighteen to thirty-five years old, currently living in the United States, had normal or corrected-to-normal vision, and with no ongoing psychological or neurological disorders.

Stimuli The stimuli used in the working memory task were the same as in Exps 1-3. The word stimuli used in the Lithuanian-English word pairs were used in previous research (Zerr et al., 2018), and were selected such that the length of the pairs were similar and within reasonable range. All word pairs were displayed in all capital letters on a white background in black with a 48-point Arial font.

Procedures The visual working memory task was the same as in Exp 1. After completing the visual working memory task, participants were then administered a verbal source memory and learning task. Participants studied 45 Lithuanian-English word pairs presented sequentially, and the order of presentation was randomized across participants. Each pair was presented one at a time for 4 s each and were separated by a 1-s interstimulus interval. Participants were instructed to learn the word pairs for a later cued-recall test. During the test-relearn phase of the task, participants were provided with a Lithuanian word as retrieval cue and were asked to recall the English word that was paired with the cue during study phase. Immediately after the

participants finished responding to the cue, the studied Lithuanian-English pair was presented to them for them to restudy the pair. After all 45 pairs were tested and restudied, participants were instructed to proceed to another test-relearn phase. The test-relearn phase of the task was repeated four times for each participant (see **Fig. 20A**).

Power Estimation From our Experiment 1 data, we simulated sample sizes that were enough to observe small effect using the correlations we observed in Experiment 1. The median estimated power for our sample size (N= 188) in Exp 4 was 0.954 (100 iterations of 1000-time simulation). We plotted our power simulations with N = 100, 150, 200, 250, 300 and 700 in our **Supplemental Material**.

Results

Our results from all three experiments above collectively suggest the importance of working memory in expert performance even after extensive learning of image-location bindings. One remaining question is whether individual differences in working memory play a similar role for the development of expertise for other materials in long-term memory, such as memory for verbal paired associates. In Exp 4, we examined the relationship between working memory and verbal long-term memory using a paired associate task developed by Zerr et al. (2018). Participants were shown 45 Lithuanian-English word pairs during encoding. Following the study phase, they were cued with Lithuanian words and were asked to type out the associated English word during test (see **Fig. 20A**). Each participant repeated the test procedures for 4 times and finished a change detection task to test their working memory abilities as in all previous experiments. Across four iterations of learning and testing, participants showed

significant learning effect for the English words paired with the Lithuanian cues ($F(3,185) = 124.83$, $p < 0.001$, $\eta^2 = 0.40$, **Fig. 20B**). Right after the first exposure of the paired associates, working memory abilities were not predictive of their verbal long-term memory performance ($r(186) = 0.14$, $p = 0.058$). However, as participants started building expertise on the English-Lithuanian pairs, their working memory abilities started to positively correlate to their verbal long-term memory accuracy (2nd repetition: $r(186) = 0.21$, $p = 0.004$; 3nd repetition: $r(186) = 0.25$, $p < 0.001$; 4th repetition: $r(186) = 0.29$, $p < 0.001$, **Fig. 20C**). If the ***slow starter hypothesis*** held, we would expect that working memory abilities predicted verbal long-term memory the best when participants were inexperienced with the pair associates. Contrary to this prediction, we instead observed that working memory played a constant role in verbal memory performance as participants built up their expertise with these paired associates, supporting our ***stable demands hypothesis***. Therefore, we generalized our conclusion from Exp 1-3, suggesting that individual differences in visual working memory abilities remained predictive of expertise performance with both visual and verbal materials.

To further examine the relationship between VWM capacity and learning slopes, we performed a partial correlation model to regress out the effect of mean source memory performance that may moderate the VWM-slope correlation. The partial correlation between VWM capacity and linear slope was not significant ($r(186) = 0.14$, $p = 0.06$, 95% CI = [-0.00, 0.28]), and the Bayes Factor slightly favored the null (BF = 0.56 favoring null). Additionally, we performed a linear mixed effects analysis with fixed effects for number of repetitions, working memory ability and their interaction, with random slopes and intercepts by participant. If the ***stable demands hypothesis*** held,

we would expect a non-significant interaction between working memory ability and number of repetitions. Alternatively, the ***rich get richer*** hypothesis would result in a significant interaction with a positive coefficient, and the ***slow starter*** hypothesis would produce a significantly negative coefficient on the interaction term. Echoing our previous findings, we discovered that the interaction between working memory ability and number of repetitions remained insignificant (β = 0.012, 95% CI: [-0.001, 0.025], *p* = 0.07). Together, these results suggest that VWM capacity does not predict the rate of learning via repetitions, thus supporting the ***stable demands hypothesis***.

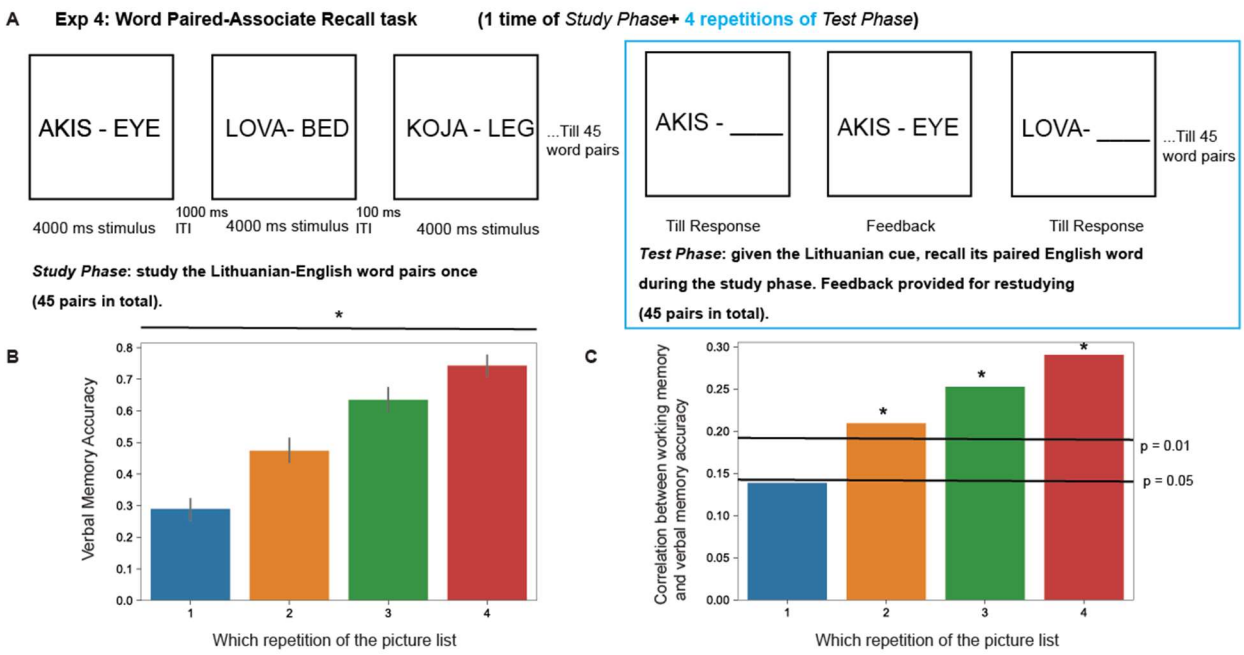


Fig. 20 *Visual working memory capacity predicted the accuracy in each repetition of verbal associative memory list in Exp 4.*

(A) A sample of the word paired-associate recall task used in Exp 4. The participants were asked to learn Lithuanian-English word pairs in their initial study phase. During the test phase, they were cued with the Lithuanian word and were asked to type out its paired English word. The correct answer would be presented as feedback after every test trial, and participants were expected to learn from this immediate feedback. The test phase was repeated 4 times to facilitate learning of verbal paired associates.

(B) Source memory accuracy increased as participants repeatedly learned the same list of verbal associative memory for 4 times in Exp 4.

(C) Visual working memory capacity positively correlated to the mean accuracy of source memory task across 2-4 repetitions.

Experiment 5: Stable attentional control demands following repetitive learning

In Exp 5, we examined the relationship between working memory and attentional control abilities, and its relationship with source memory across learning. Our main goal here was to generalize our findings from a single working memory measure to multiple tasks that had been shown to load heavily onto both working memory and attentional control abilities. If the slow starter hypothesis held true for visual sequence learning, then the more participants practiced the list, the individual differences in attentional control and working memory tasks would be less predictive of performance. Therefore, this model predicts a decrease in the correlation between attentional control and source memory as more repetitions of the same list were presented to the participants.

Method

Participants For Experiment 5, 145 young residents of the United States (18-35 years old) were recruited through Prolific and received monetary compensation ($10.00/hour). All participants reported normal or corrected-to-normal vision, no color blindness, fluency in English, no history of mental illness/condition, and no cognitive impairment. All participants had successfully completed 90% or more of the studies that they had participated in previously on Prolific (filtered by approval rate >= 90%).

Materials and Procedure For Experiment 5, all participants signed an informed consent, and completed five tasks. Each participant started with four attentional control tasks (change localization paradigm, filtering change localization paradigm, Flanker square task and Simon square task, see **Fig. 21**), followed by a visuo-spatial source memory and learning task, as in Experiment 1.

Working Memory and Attentional Control (WMAC) Tasks: Change localization, filtering change localization, Flanker Square, Simon square

(1) Change Localization

The Change Localization task was adopted from the color Change Localization task used in prior research (Zhao et al., 2022). During every trial, six colored squares were simultaneously displayed for a duration of 250 ms, succeeded by a blank retention interval lasting 1,000 ms. Subsequently, the same six squares reappeared in their original positions, but with one of the colors altered to a hue not previously shown in that trial. Each square was assigned a digit ranging from 1 to 6, and participants were required to press the corresponding key to identify the square that

underwent a color change. The spatial arrangement of the six numbers was randomized across trials.

(2) Filtering Change Localization

The Filtering Change Localization task was modified from the Filtering Change Detection task (Luck & Vogel, 1997a; Martin et al., 2021; Zhao & Vogel, 2024). In each trial, a word, either RED or BLUE, denoting the color of the items to be attended (the selection instruction), was presented for 200 ms, followed by a 100-ms interval. Subsequently, 10 bars were displayed for 250 ms, with half of them being printed in the color designated for attention, effectively a set size 5 condition. After a 900-ms delay, only the bars corresponding to the attended color reappeared. During the test phase, only one of the bars changed its orientation compared to the encoding phase. The participants were asked to determine which one of the five bars had changed its orientation compared to the initial presentation. This Filtering Localization phase had 60 trials in total.

(3) Flanker Square

The Flanker Square task was one of the tasks modified from the Flanker task (Burgoyne et al., 2023). In each trial of the Flanker Square task, participants were presented with a target stimulus alongside two possible responses. Both the target stimulus and response options consist of sets of five arrows arranged horizontally (i.e., <<><<). Participants were instructed to choose the response option where the middle arrow aligned in direction with the outer arrows in the target stimulus. For instance, if the target stimulus displayed arrows pointing left and right (i.e., <<><<),

participants should select the response option with a central arrow pointing left (i.e., >><>>). Therefore, the task required participants to focus on the outer arrows of the target stimulus and the central arrow of the response options while disregarding the central arrow of the target stimulus and the outer arrows of the response options. Each participant completed 30 seconds of practice, and 90 seconds of test phase. The Flanker Square score was calculated as the difference between the number of correct and incorrect responses.

(4) Simon Square

The Simon Square task was one of the tasks modified from the Simon task (Burgoyne et al., 2023). In each trial of the Simon Square task, participants were presented with a target stimulus and two response options. The target stimulus was represented by an arrow, and the response options were the words "RIGHT" and "LEFT." Participants were instructed to choose the response option that corresponded to the direction indicated by the arrow in the target stimulus. For instance, if the arrow in the target stimulus pointed to the left, the participant should select the response option with the word "LEFT." Both the target stimulus arrow and the response options could appear on either side of the computer screen with equal

probability. Consequently, participants had to attend to the direction indicated by the

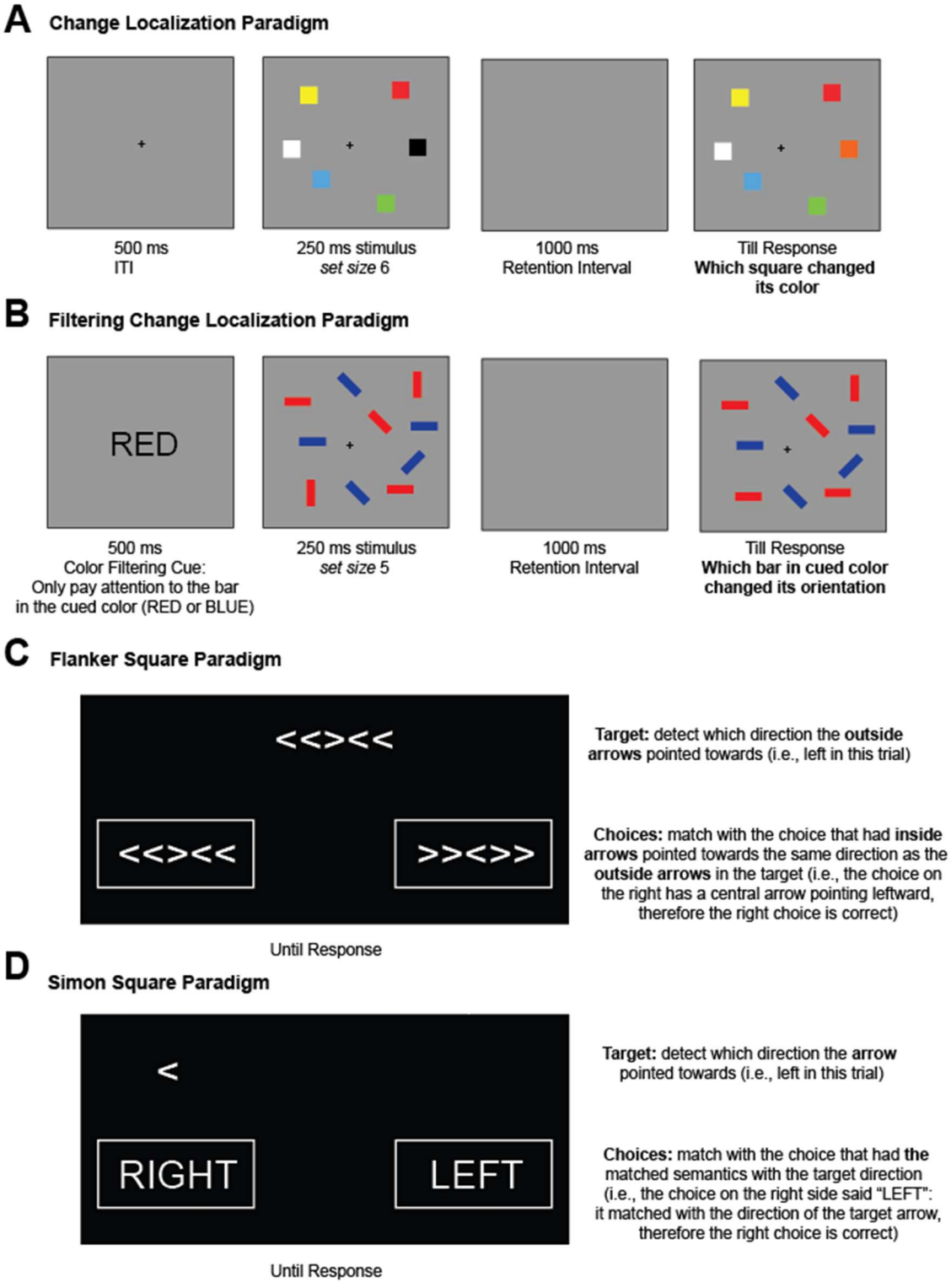


Fig 21. *Experimental Procedures for Experiment 4.*

(A) Schema of Change Localization Task.

(B) Schema of the Filtering Change Localization Task.

(C) Schema of the Flanker Square Task.

(D) Schema of the Simon Square Task.

target stimulus arrow while understanding the meaning of the response options. Simultaneously, they must disregard the side of the screen where the target stimulus arrow and response options were presented. Each participant completed 30 seconds of practice, and 90 seconds of test phase. The Simon Square score was calculated as the difference between the number of correct and incorrect responses.

Source Memory and Learning Task: Visuo-spatial source memory

The source memory and learning task was the same as in Exp 1.

Power Estimation From our Experiment 1 data, we simulated sample sizes that were enough to observe small effect using the correlations we observed in Experiment 1. The median estimated power for our sample size (N= 145) in Exp 5 was 0.880 (100 iterations of 1000-time simulation). We plotted our power simulations with N = 100, 150, 200, 250, 300 and 700 in our **Supplemental Material**.

Results

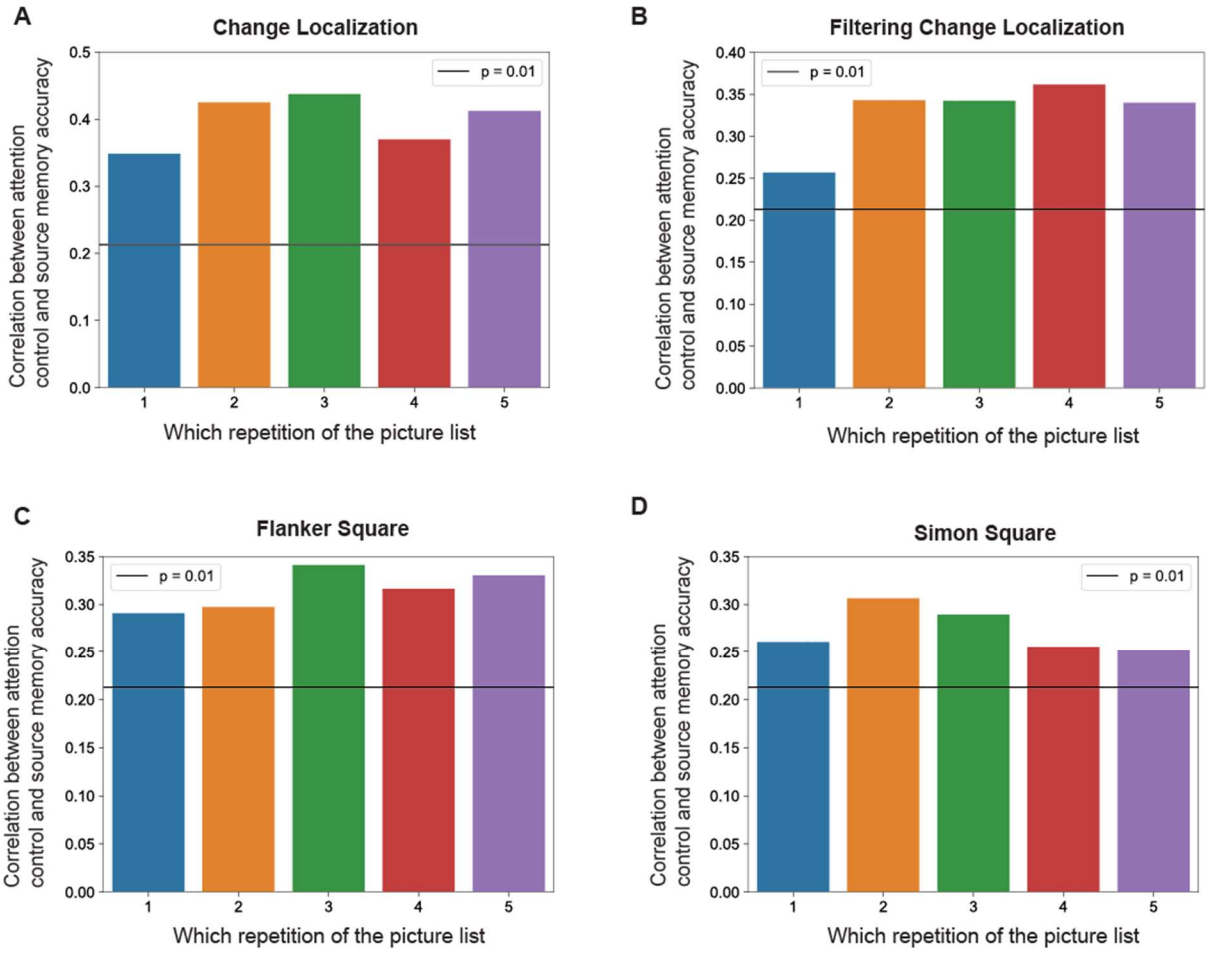


Fig. 22 *Working memory and attentional control abilities predicted the accuracy in each repetition of verbal associative memory list in Exp 5.*

(A) Visual working memory capacity, measured by change localization task, positively correlated to the mean accuracy of source memory task performance for all 5 repetitions.

(B) Working memory and attentional control abilities, measured by filtering change localization task, positively correlated to the mean accuracy of source memory task performance for all 5 repetitions.

(C) Attentional control abilities, measured by Flanker Square task, positively correlated to the mean accuracy of source memory task performance for all 5 repetitions.

(D Attentional control abilities, measured by Simon Square task, positively correlated to the mean accuracy of source memory task performance for all 5 repetitions.

Across five iterations of learning and testing, participants showed significant learning effect for the item-location bindings, replicating our results from Exp 1-3 ($F(4,139) = 105.11$, $p < 0.001$, $\eta^2 = 0.43$). However, across all four attentional control and working memory tasks used in our experiment, we observed sustained positive correlations between attentional control and source memory accuracy for all five repetitions of the sequence (change localization: $r(143)s > 0.35$, $ps < 0.001$; filtering change localization: $r(143)s > 0.27$, $ps < 0.002$; Flanker square: $r(143)s > 0.29$, $ps < 0.001$; Simon square: $r(143)s > 0.25$, $ps < 0.002$; **Fig. 22**). To further investigate the interactions between attentional control and learning, we performed a linear mixed effects analysis with fixed effects for number of repetitions, attentional control ability and their interaction, with random slopes and intercepts by participant. If the ***stable demands hypothesis*** held, we would expect a non-significant interaction between attentional control ability and number of repetitions. Alternatively, the ***rich get richer*** hypothesis would result in a significant interaction with a positive coefficient, and the ***slow starter*** hypothesis would produce a significantly negative coefficient on the interaction term. Echoing our previous findings, we discovered that the interaction between all four attentional control tasks and number of repetitions remained not significant (change localization: $\beta = -0.028$, 95% CI: [-0.079, 0.023], $p = 0.28$; filtering change localization: $\beta = -0.001$, 95% CI: [-0.054, 0.051], $p = 0.97$; Flanker Square: $\beta < -0.001$, 95% CI: [-0.001, 0.000], $p = 0.31$; Simon Square: < -0.001, 95% CI: [-0.001, 0.000], $p = 0.41$). Therefore, the performance advantage for the high attention control

subjects remained constant despite substantial learning across the 5 repetitions. In conclusion, the robust predictive power of attentional control on source memory accuracy, even when participants had reached a relatively high level of recall performance, contradicted the prediction of the ***slow starter*** hypothesis or ***rich get richer*** hypothesis and instead supported the ***stable demands*** hypothesis.

Discussion

Our findings reveal that individual differences in working memory and attentional control abilities remain predictive of long-term memory task performance even after participants reached asymptote level performance for the visual sequence. Importantly, individual differences in visual working memory abilities affected long-term memory performance in a source memory task when the visual sequence was learnt five times (Exp 1), twelve times (Exp 2) or twelve times with different orders of encoding (Exp 3). Moreover, we generalized our findings into the domain of verbal long-term memory, arguing that differential working memory abilities consistently resulted in differences in retrieval accuracy of verbal paired associates throughout repetitive learning (Exp 4). Lastly, we also showed that working memory and attentional control abilities, measured with four highly reliable tasks, continued to be predictive of performance throughout learning (Exp 5). Our results from all five experiments reject the ***slow starter hypothesis***, in that we did not observe a decrease in working memory and attentional control requirement as expertise built up. Instead, we observed sustained (Exp 1, 2, 3 and 5), or even slightly increasing (Exp 4), involvement of working memory and attentional control as people repeatedly learned the test materials. Our findings instead mostly supported an alternative hypothesis, the ***stable demands hypothesis***, that

domain-general attentional control abilities may affect domain-specific long-term memory performance even after repetitive learning.

One potential explanation of why performing a well-trained task may feel less attention demanding is that training may allow one to more efficiently deploy attention in a task-effective manner as compared to novices. Instead of no longer relying on attentional control abilities, trained participants may develop certain strategies that allow them to focus their visual attention more efficiently on task-relevant contents. For instance, expert athletes have shown to have better domain-general lab-monitored attentional task performance (Voss et al., 2007). The transfer of domain-specific expertise to domain-general advantages in attentional abilities supported our ***stable demands*** view of learning in that trained participants practiced to better utilize attentional resources, not getting less reliance on visual attention. One result of the ***stable demands*** hypothesis was a more compressed way to encode and decode visual information as participants learnt the materials repetitively. For instance, a study that compared eye scan path between experienced and novice drivers suggested that experienced drivers had a way higher variance in eye fixations than novice drivers during complex road situation, suggesting that they allocated their attention more efficiently than novices (Underwood, 2007). Additionally, another large-scale study used a mobile application game that trained participants to search for hazards from mock airport scans (Ericson et al., 2017). In their dataset, thousands of participants were trained over extended period of time, and they were awarded one of the three achievement levels, pro, elite or expert, depending on their reaction time in this game. With massive number of trials and participants, they showed that people's first trial

reaction time could predict their eventual achievement level. Since attentional control affected both first and eventual performance, our ***stable demands hypothesis*** suggested that the predictive power of first trial reaction time may result from the stable demands of attentional control even when players repeatedly practiced. Thus, empirical evidence with real-world expertise supports our ***stable demands hypothesis***.

While domain-general working memory and attentional control abilities predict source memory performance during learning, they surprisingly did not predict learning rate. This general finding contradicts models that propose that high attention control abilities can acquire task performance at a faster rate than those with low attention control, namely the ***rich get richer hypothesis*** (Hambrick & Engle, 2002; Meinz & Hambrick, 2010). As depicted in **Fig. 4**, we modeled the learning slopes of 700 participants across the 5 repetitions in Experiment 1. We revealed that there were substantial individual differences in learning slopes and that these slope estimates were highly reliable. However, despite these necessary psychometric properties, we saw no relationship between an individual's learning slope and his or her attention control ability. That is, we observed that the learning slopes for the high and low attention control groups are essentially parallel to each other across learning, suggesting that people with higher attentional control abilities did not learn faster than those with worse attentional control, despite starting at a higher level of performance. The differential effect of attentional control on increasing long-term memory accuracy but not learning speed appears to suggest that learning rate may be independent from attention control. However, future studies will be needed to investigate whether individual differences in learning rates reflect a general psychological construct (Zerr et al., 2018).

Our support for the stable demands hypothesis aligns with prior work examining aptitude x treatment interactions (e.g., Kaufman et al., 2009) but diverges with the conclusions of other work in that area (Williams & Pearlberg, 2006; Ackerman, 1987). Perhaps a potential reason for the discrepancy may lie in the types of learning tasks used in each of these studies. In a sequence learning task, such as three-term contingency tasks, aptitude plays an increasing role across learning, thereby supporting the ***rich-get-richer*** hypothesis (Williams & Pearlberg, 2006). By contrast, in simple motor tasks that use reaction time as a performance metric, the aptitude × treatment interaction aligns with the ***slow starter*** hypothesis, where lower intelligence subjects catch up with more repetitions (Ackerman, 1987). Finally, our ***stable demands*** hypothesis is supported by prior findings from associative learning tasks (Kaufman et al., 2009). In the present work, our visual and verbal learning tasks are arguably most comparable to the paired-associate learning task used in Kaufman et al 2009, and our results similarly align with their conclusion supporting a ***stable demands*** hypothesis. However, considering that in each of these studies there was no single task battery that included sequence learning, motor learning, and paired-associate learning, future research is needed to determine whether the type of learning influences aptitude-treatment interactions. In addition to the types of learning, the measures of aptitude in the skill learning literature were mixed, while our focus of cognitive abilities was on attentional control and working memory. For example, Ackerman (1987) used initial task performance as a proxy for general cognitive abilities, but the high autocorrelation between performance in early and later stages of skill learning likely confounded these aptitude measures more than our attentional control metrics. Therefore, the variety of

the general cognitive ability measures used in the literature may result in mixed results on the relationship between aptitude and treatment (i.e., learning). Lastly, even in studies with aptitude measures more closely aligned to attentional control and working memory, smaller sample sizes increase vulnerability to outliers. For instance, in Williams and Pearlberg (2006), sample sizes of 98 and 60 across their two experiments left their Raven × treatment interactions positioned ambiguously between predictions of the ***rich get richer*** and ***stable demands*** hypotheses. In measuring the domain-general attentional control and working memory abilities, we used the change detection task in Exps 1-4 and a battery of four working memory and attentional control tasks in Exp 5. We showed that working memory abilities constantly predicted performance across repetitions (Exp s 1-4), and attentional control task also similarly constantly predicted performance with learning (Exp 5). A related ongoing debate in the field questions whether attentional control abilities form a unitary construct (Kane et al., 2004), or instead reflects distinct underlying constructs. One example of the distinct process model, the model of executive function, proposes that three different components, inhibition, updating, and switching, account for individual differences in complex “frontal lobe” tasks (Miyake et al., 2000). Alternatively, a dual mechanism view of cognitive control suggests that participants may use either proactive or retroactive attention in performing task (Braver, 2012). Additionally, one multi-dimensional model of working memory subdivided the process of working memory into the binding, updating, and removal of information from the focus of attention (Oberauer, 2019). In our study, we found that the ***stable demands*** hypothesis generalized from working memory to measures of attentional control abilities, which suggests that these differences may be

drawn from mechanisms that are in common between these two constructs. Although it is beyond the scope of the current work to discern whether attentional control abilities are better explained by a unitary or multi-faceted construct of attention control, future studies will be needed to examine the finer relationship between attentional control and learning with more tasks that selectively tap onto each process defined by these distinct models.

In conclusion, we did not observe a decrease in attentional control requirements as participants repeatedly practiced visual and visual materials. Instead, we observed sustained or even increasing involvement of attentional control as people repeatedly learned the test materials, supporting the ***stable demands hypothesis***. Our data support the hypothesis that domain-general cognitive abilities do impact the development of domain-specific performance. Furthermore, our ***stable demands*** of attention view of expertise suggest that well-trained individuals may not rely less on attention control abilities but rather develop strategies that allow them to deploy attention more efficiently to task-relevant information. While domain-general attention control ability predicts source memory throughout learning, they surprisingly did not predict learning rate. This finding suggests that learning rate may be independent of attention control ability. Lastly, our work hinted that attentional control abilities may play a role in expertise development. Although we made attempt to train participants with in-lab tasks to an asymptote performance, we did not train our participants with complex tasks over extended period of times. Future studies should be directed at examining whether individual differences in attentional control abilities predict expertise performance in various domains with real-world tasks (Ericson et al., 2017).

Furthermore, while the goal of our work was to examine initial phases of learning, our result may have implications for the development of expertise. Prior expertise studies in real-world settings often involve months to years of training eventually leading to ***automatized*** performance, with a common assumption being that general cognitive ability no longer predicts performance once the individual has reached an expert level (Ericsson et al., 1993). However, recent findings have challenged this assumption and instead proposed that innate cognitive abilities, including attentional control, continue to explain significant variance in expert performance even when the effect of deliberate practice was controlled for (Hambrick et al., 2014; Hambrick & Engle, 2002; Meinz & Hambrick, 2010). While beyond the scope of our current study, further research is needed to determine whether attentional control and working memory abilities continue to play a role once task performance becomes more automatized. Overall, our results help demonstrate the persisting role of individual differences in working memory and attentional control in contributing to domain-specific learning.

CHAPTER 4.

Neural Dynamics Underlying Repeated Learning of Visual Image Sequences

Humans possess a remarkable capacity for recognition memory, storing visual objects with high fidelity and even spatio-temporal precision (Brady et al., 2008; Lionel, 1973; Wolfe et al., 2023). This ability prompts important questions about the cognitive and neural mechanisms that support such detailed memory. To investigate how the brain distinguishes previously encountered objects from novel ones, researchers have frequently turned to event-related potentials (ERPs) to examine the temporal dynamics of memory retrieval. ERP studies have offered valuable insights into the neural correlates of recognition memory, particularly by focusing on the differential brain responses elicited by old versus new items, commonly referred to as “old/new effects” (Kwon et al., 2023; Rugg & Curran, 2007).

The first identified old/new ERP effect is the parietal old/new effect, typically observed between 500–800 ms after stimulus onset and maximal over left parietal scalp regions. This effect is strongly associated with recollection, as it reflects greater positivity for items that are recognized with contextual detail or source memory. It is most often elicited in "remember" responses—those accompanied by high confidence and retrieval of specific episodic details—rather than in "know" responses, which reflect familiarity-based recognition with lower confidence (Friedman & Johnson Jr, 2000; Wilding & Rugg, 1996). The parietal old/new effect is consistently enhanced when participants are required to retrieve contextual features such as the source or spatial location of previously studied items (Mecklinger, 2000; Vilberg & Rugg, 2008). Neuroimaging studies have implicated the left lateral parietal cortex, particularly the

angular gyrus, in the generation of this effect, suggesting its involvement in the integration and conscious experience of source information (Cabeza et al., 2008; Wagner et al., 2005). Together, these findings provide strong evidence that the parietal old/new effect serves as a neural marker of memory retrieval during recognition memory tests.

Complementing the parietal old/new effect, researchers have also identified a frontal old/new effect, which emerges earlier, typically between 300-500 ms post-stimulus, and is most prominent at mid-frontal scalp sites, and is widely associated with successful recognition. This ERP component is characterized by a more positive-going waveform for correctly recognized old items compared to new ones, particularly in conditions that emphasize familiarity. It is reliably elicited in remember/know paradigms when participants classify items as “known” rather than “remembered”, indicating a familiarity-driven process (Curran, 2000, 2004; Rugg & Curran, 2007). The amplitude of this effect is modulated by factors that influence the strength of familiarity signals, such as conceptual fluency, and priming strength (Leynes, 2012; Paller et al., 2007). Neuroimaging evidence points to regions of the anterior prefrontal cortex as potential sources of the frontal old/new effect, implicating this area in strategic monitoring and decision-making based on familiarity (Duarte et al., 2006; Yonelinas et al., 2005). Collectively, these findings support the interpretation of the frontal old/new effect as a neural correlate of successful memory retrieval during the test phase of recognition tasks.

Despite extensive research on the frontal and parietal old/new ERP effects, there remain ongoing debates about whether these two components reflect distinct neural

processes or overlapping memory retrieval mechanisms. Several lines of research suggest that the two effects reflect distinct neural processes, as they respond differently to experimental manipulations and show unique temporal and topographical profiles (Curran & Cleary, 2003; Woodruff et al., 2006). For example, the frontal effect has been shown to remain intact in individuals with hippocampal damage, whereas the parietal effect appears more sensitive to tasks involving relational encoding or source retrieval (Addante et al., 2012; Opitz & Cornell, 2006). Meta-analytic findings further support this distinction, highlighting reliable differences in the timing and scalp distribution of the two effects across studies (Kwon et al., 2023). However, other work suggests that these ERP components may reflect graded or interactive processes, with overlapping contributions to recognition, particularly under conditions that vary in memory strength or decision confidence (Squire et al., 2007; Wixted, 2007). Moreover, studies combining ERP with source localization and multivariate analysis have shown both distinct and partially overlapping neural generators, indicating that the two effects may not be entirely independent (Hoppstädter et al., 2015; Rugg & Vilberg, 2013). Overall, prior studies support a functional separation between the frontal and parietal old/new effects. However, all of these studies have examined episodic memory following only a single exposure. As a result, it remains unclear how repeated learning modulates these neural signatures of successful memory retrieval.

In the present study, we addressed this question using a recognition memory learning paradigm. Our primary aim was to determine which neural signatures, the frontal or parietal old/new effects, are modulated by learning. Participants repeatedly studied a fixed set of 32 real-world images across up to five study-test cycles. This

design allowed us to track how electrophysiological markers of memory change as representations become more robust through repeated exposure. We also included a portion of trials with only 1 item in the list. Because the memory load for these trials is low and the interval between study and test is uninterrupted and short, subjects likely use working memory to aid the recognition process. Considering this, we expect that the ERP old/new effects (in both frontal and parietal electrodes) from 1-item lists would be earlier than that from 32-item lists because the memorandum is already active in working memory when the test is presented and does not require the additional time-consuming process of retrieval from long-term memory. In the current study, we sought to use these trials as a comparison point for evaluating the learning effects for the 32-item lists. This would allow us to test whether repetitive learning of a 32-item list produced ERP old/new effects that begin to approximate those observed when they are supported by working memory.

Method

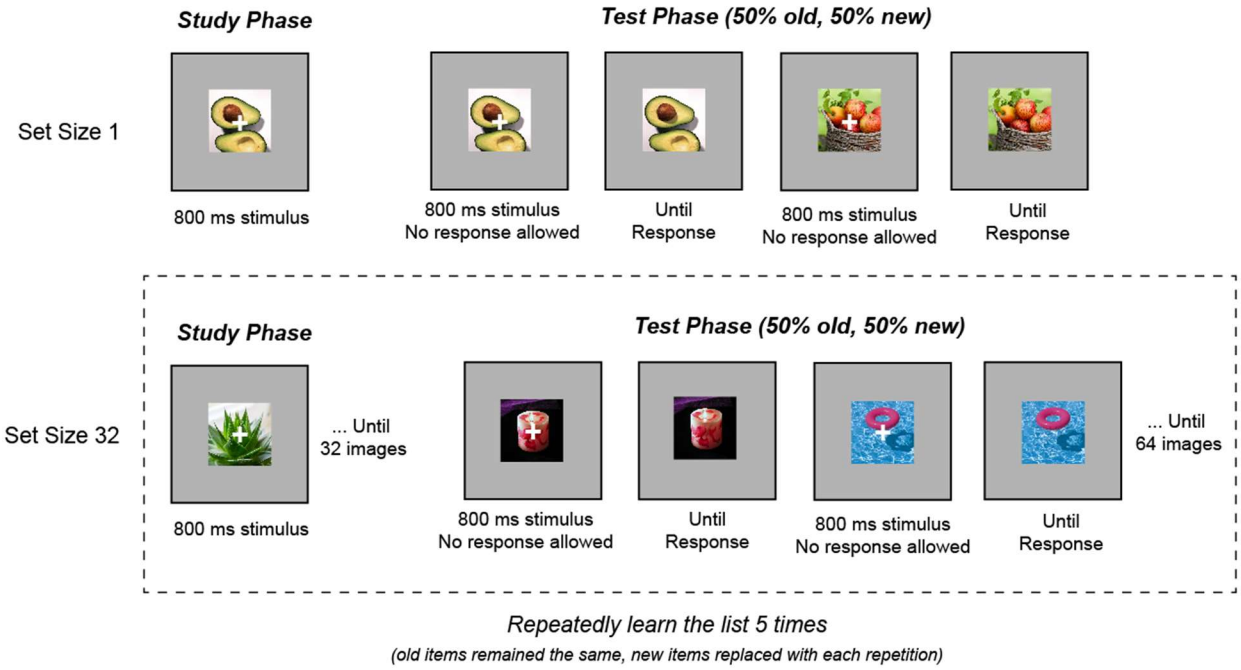


Fig 23. *Recognition Memory and Learning Paradigm.*

In the *set size 1* condition, each trial began with a single centrally presented image (5° × 5°) shown for 800 ms with a white fixation cross. Participants encoded the image into memory while maintaining fixation. A self-paced blank screen followed, after which participants completed two recognition trials. Each test image appeared at the center for 800 ms with a fixation cross, followed by a response window where the image remained on screen until a response was made. One image was old (from the encoding phase), and the other was new; their order was randomized. Participants responded using keyboard keys ("z" = old, "/" = new).

In the *set size 32* condition, participants viewed a stream of 32 images, each presented for 800 ms with a superimposed fixation cross. Interstimulus intervals were jittered between 250–400 ms. After the stream, participants completed a series of recognition test trials following the same timing and response procedure as in the set size 1 condition. To examine repetition-based learning, the study-test cycle was **repeated five times**. The same 32 images were used as old items across repetitions, while new images were replaced on each test phase to prevent familiarity confounds.

Participants

The experimental procedures were approved by the Institutional Review Board at The University of Chicago. All participants provided informed consent and were compensated with a cash payment of $20 per hour. They reported having normal color vision and normal or corrected-to-normal visual acuity. Participants were recruited from The University of Chicago and the surrounding community.

A priori power analysis was conducted to determine the required sample size to detect a repetition effect of 0.5 μV with a standard deviation of 0.5 μV, using a two-tailed paired-sample t-test. With an alpha level (α) of 0.05 and desired power (1 − β) of 0.90, the analysis indicated that a minimum of 15 subjects is required to detect the expected effect. A total of 25 subjects were recruited, and 1 subject was rejected due to excessive eye movement.

Stimuli and Procedure

Images were selected from the THINGS dataset (Hebart et al., 2023). One exemplar was selected from each category so that no repeated category was used throughout each session. The recognition memory procedure followed established protocols in the literature and consisted of separate study and test phases (Fukuda & Woodman, 2015; Zhao, Fukuda, et al., 2025; Zhao & Woodman, 2020). In the set size 1 condition, each trial began with the presentation of a single image (5° × 5°) centered on the screen, accompanied by a white fixation cross. The image was displayed for 800 ms, during which participants were instructed to encode it into memory. Afterward, a self-paced blank interval followed, allowing participants to initiate the test phase at their own pace. Each test phase consisted of two recognition trials. On each test trial, an image appeared at the center of the screen for 800 ms along with a white fixation cross.

To minimize motor and ocular artifacts, participants were instructed to avoid any movements while the fixation cross was present. After 800 ms, the fixation cross disappeared, and the image remained on screen until a response was made. One of the two test images matched the image from the encoding phase (old), while the other was a novel image that had not been seen before (new). The order of the old and new images was randomized across blocks. Participants were asked to indicate whether the image was “old” (previously studied) or “new” (not previously seen) using designated keyboard keys (“z” for old, “/” for new).

In the set size 32 condition, participants viewed a stream of 32 images, each presented sequentially at the center of the screen for 800 ms. A white fixation cross was superimposed on each image to help maintain central fixation and discourage eye movements. The interstimulus interval (ISI) between images was randomly jittered between 250 and 400 ms to reduce anticipatory responses. Following the encoding phase, participants completed a series of recognition test trials. On each test trial, a single image was displayed at the center of the screen for 800 ms, again with a central white fixation cross. To minimize motor and ocular artifacts, participants were instructed to remain still and refrain from any movements while the fixation cross was visible. After 800 ms, the fixation cross disappeared, and the image remained on screen until a response was made. Half of the test images had been shown during the preceding study phase (old), while the other half were entirely new (new). The order of old and new images was randomized across trials. Participants indicated whether each image was old or new using the same response keys as in the set size 1 condition (“z” for old, “/” for new).

To investigate the effect of repetition-based learning, the study and test phases of the set size 32 condition were repeated five times with pseudorandomized sequence without any constraint in shuffling old and new images. Across these five repetitions, the old images remained the same, allowing participants to learn them across repeated exposures, while new images were replaced with novel ones on each test phase to avoid familiarity confounds (see **Fig. 23**). For recognition memory, we use accuracy (%) as our primary behavioral measure.

Preprocessing and artifact rejection of EEG signals

Participants were positioned in an electrically isolated booth, with their heads stabilized using a cushioned chinrest placed 74 cm from the display screen. Electroencephalographic (EEG) signals were recorded via 30 active silver/silver chloride (Ag/AgCl) electrodes integrated into a stretchable cap (actiCHamp system, Brain Products, Munich, Germany), arranged according to the international 10-20 placement standard (electrode sites: Fp1, Fp2, F7, F8, F3, F4, Fz, FC5, FC6, FC1, FC2, C3, C4, Cz, CP5, CP6, CP1, CP2, P7, P8, P3, P4, Pz, PO7, PO8, PO3, PO4, O1, O2, Oz). Additional electrodes were adhered to the left and right mastoids using adhesive stickers, and a ground electrode was integrated at the Fpz site within the cap. EEG signals were initially referenced to the right mastoid and subsequently re-referenced offline to the average of both mastoids. The signal was bandpass filtered (0.01–80 Hz) with a 12 dB/octave roll-off and digitized at a sampling rate of 500 Hz. All electrode impedances were maintained below 10 kΩ.

To track ocular activity such as blinks and saccades, both electrooculographic (EOG) and eye-tracking data were recorded. EOG was captured using five passive

Ag/AgCl electrodes: two for vertical EOG (above and below the right eye), two for horizontal EOG (approximately 1 cm lateral to each eye), and one ground electrode on the left cheek. Eye position was also monitored with a desktop-mounted EyeLink 1000 Plus system (SR Research, Ontario, Canada), operating at a sampling rate of 1,000 Hz.

Artifact Rejection

For horizontal eye movements, we employed a sliding-window algorithm to identify horizontal eye movements using both horizontal electrooculogram (HEOG) signals and eye-tracking gaze data. For the HEOG-based detection, a split-half sliding-window method was applied with a 100 ms window moving in 10 ms increments. An eye movement was flagged if the voltage difference between the two halves of the window exceeded 20 μV. This HEOG-based artifact detection was used only in trials where eye-tracking data were unreliable or unavailable. In parallel, eye-tracking rejection was carried out by analyzing horizontal (x-axis) and vertical (y-axis) gaze positions using the same 100 ms window and 10 ms step size. A trial was excluded if eye position shifted more than 0.5° of visual angle within any given window.

To detect blinks, we applied a sliding-window analysis to the vertical EOG signal using an 80 ms window and a 10 ms step size. A blink was marked when the voltage change across the window exceeded 30 μV. Complementarily, we identified blink periods in the eye-tracking data by locating segments where positional data were missing, indicating that the eyes were closed.

Frontal and Parietal Old/New Effect Analysis

To calculate the parietal and frontal old/new effects, we first identified sets of electrodes associated with each region. Based on prior literature, for the parietal

old/new effect, we included electrodes PO3, PO4, PO7, PO8, P3, P4, P7, P8, and Pz. For the frontal old/new effect, we used electrodes F3, F4, F7, F8, and Fz. For each region, we computed the average event-related potential (ERP) time series across the selected electrodes to obtain a representative waveform. We then focused on correct trials within each set size and repetition condition and categorized them into two trial types: old (images that participants had previously studied) and new (novel images that had never been studied). We computed the average ERP for each trial type separately. The old/new effect was then derived by subtracting the ERP waveform for new trials from that for old trials, calculated separately for each participant. This difference waveform, named old/new effect, reflects neural activity specific to recognition memory.

Result

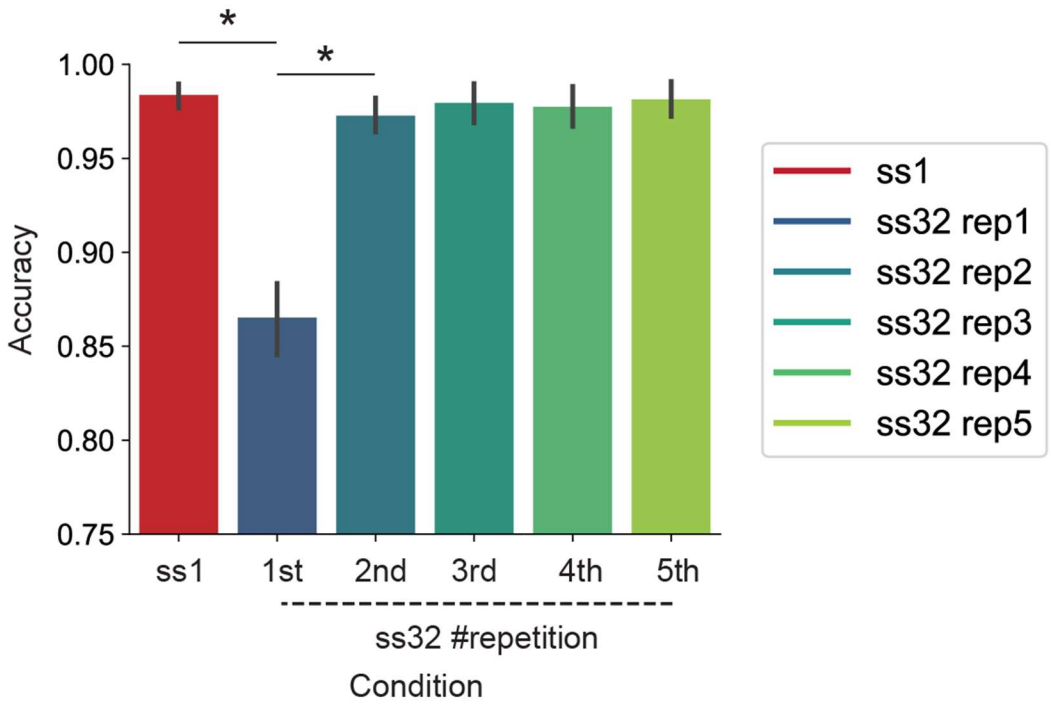


Fig 24. *Recognition Memory and Learning Behavioral Accuracy.*

Participants showed improved accuracy from repetition 1 to 2 in the set size 32 condition, and accuracy in later repetitions did not differ significantly from that of the set size 1 condition.

Our primary goal was to examine how repetition influences the neural signatures of memory. To do so, we first needed to confirm that participants were indeed learning the images through repeated exposure. Before looking at the learning effect, we first verified the well-established list length effect using two baseline conditions, set size 1 and set size 32, with no repetitions. Participants showed significantly lower recognition accuracy when encoding 32 images compared to just 1 ($t(23) = 6.80$, $p < .001$, **Fig. 24**). Next, we examined whether participants' accuracy improved with repeated exposure to the 32-image set, which would indicate learning across repetitions. As predicted, accuracy significantly increased over the five study-test cycles ($F(4, 18) = 16.78$, $p < .001$). Post-hoc t-tests revealed that accuracy improved substantially from the first to the second repetition ($t(23) = 6.80$, $p < .001$), with a modest but statistically marginal gain from the second to the third repetition ($t(23) = 2.04$, $p = .05$). No further significant improvements were observed between the third, fourth, and fifth repetitions (all ps $> .30$).

Overall, the behavioral results indicate that although participants had a lower accuracy with larger memory loads (set size 32 versus set size 1), they showed clear evidence of learning, as accuracy improved with repeated exposure to the set size 32 list. After confirming that participants were indeed learning the image list, we turned to the EEG data to examine which of the neural signatures of memory were modulated by this learning. Our first focus was the parietal old/new effect, a well-established ERP

component associated with recognition memory (see **Fig. 25**). According to prior research, a greater positivity in the ERP signal for correctly recognized old items (compared to new ones) reflects stronger memory (scalp topography shown in **Fig. 27**). To quantify this, we measured the mean amplitude of the parietal old/new effect within a 200–600 ms window following test stimulus onset. We found that this neural signature increased with repetition ($F(4, 18) = 4.24$, $p = .003$, BF10 = 24.83). Specifically, the effect grew significantly from the first to the third repetition ($t(23) = 2.27$, $p = .03$, BF10 = 1.81), and again from the third to the fourth ($t(23) = 2.36$, $p = .03$, BF10 = 2.12). However, no further increase was observed between the fourth and fifth repetitions ($t(23) = 0.23$, $p = .82$, BF10 = 0.22). These findings suggest that repeated study of the same image list leads to a strengthening of the parietal old/new effect. Additionally, we showed that the parietal old/new effect for set size 1 was similarly high as set size 32 repeated 4 or 5 times (set size 1 vs. set size 32 repeated 4 times: $t(23) = -1.24$, $p = 0.23$; size 1 vs. set size 32 repeated 5 times: $t(23) = -0.88$, $p = 0.39$), suggesting that repetition strengthened well-trained long-term memory recollection to a similar level as working memory.

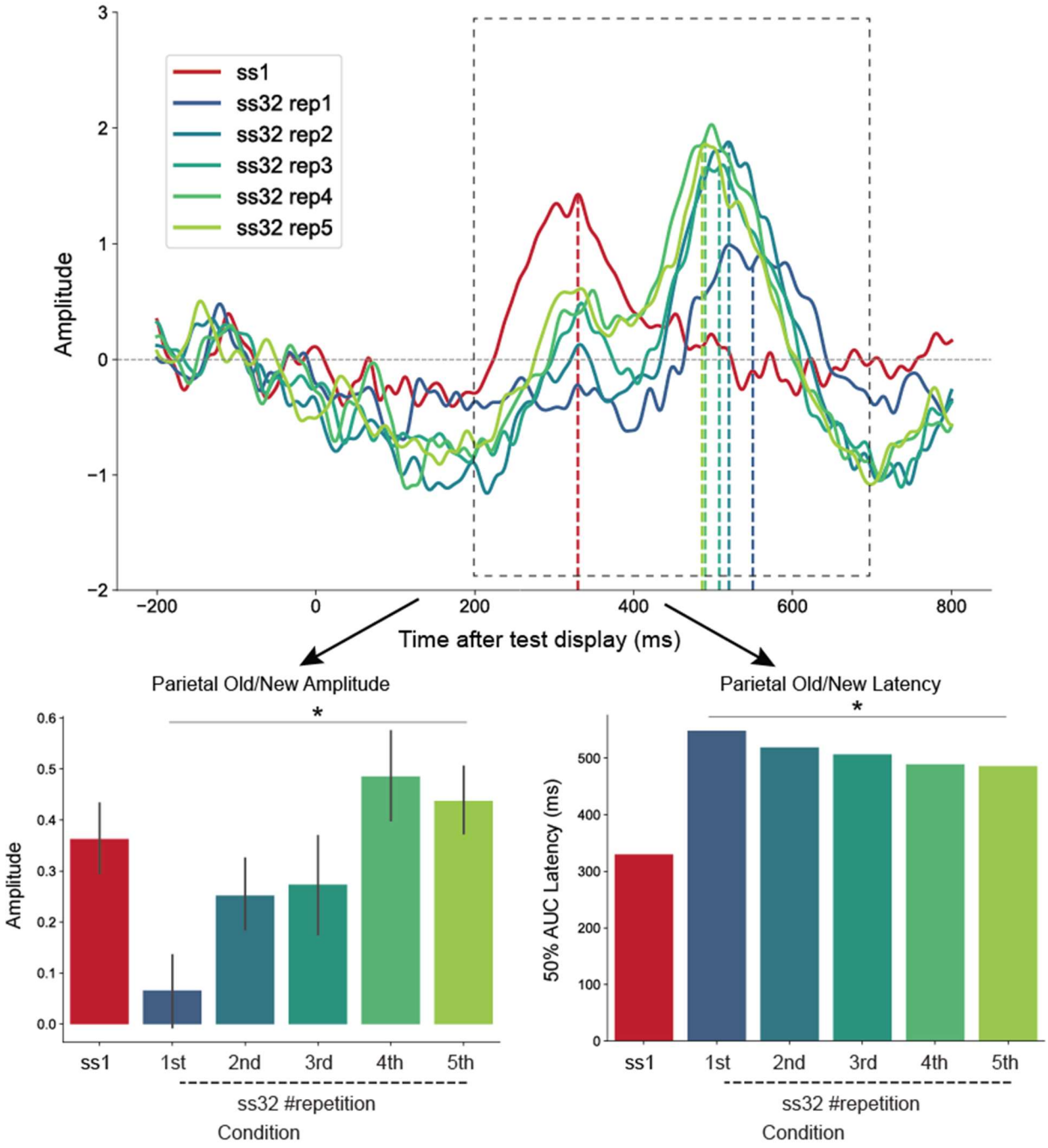

ss1
ss32 rep1
ss32 rep2
ss32 rep3
ss32 rep4
ss32 rep5
Amplitude
Time after test display (ms)
Parietal Old/New Amplitude
Parietal Old/New Latency
50% AUC Latency (ms)
ss1
1st
2nd
3rd
4th
5th
ss32 #repetition
Condition

Fig 25. *Amplitude and Latency of Parietal Old/New Effect.*

A higher amplitude and earlier latency of the parietal old/new effect were observed with increased repetitions. However, despite the latency in the set size 32 condition becoming earlier across repetitions, it remained significantly later than in the set size 1 condition.

In addition to increasing amplitude, previous research has shown that earlier latency of the parietal old/new effect is associated with faster memory-based decision-making during the test phase. To examine this, we conducted a 50% area-under-the-curve (AUC) analysis (Kiesel et al., 2008), identifying the time point at which half of the total ERP area was reached within the relevant time window. To maximize reliability, we employed a jackknife approach for latency estimation, using a leave-one-out method across 24 participant subgroups. We calculated the latency for each subgroup and then averaged these values to obtain a robust estimate of the component's latency. In line with our findings on amplitude, we observed that repetition significantly reduced the latency of the parietal old/new effect. Specifically, latency decreased with each successive repetition ($F(4, 18) = 10.57$, BF10 = $1.69 * 10^4$, $p < 0.001$): from 549.68 ms on the first exposure to 519.44 ms on the second, 506.96 ms on the third, 488.88 ms on the fourth, and 485.44 ms on the fifth (all *p*s < .001). These results indicate that repetition not only strengthens the amplitude of the parietal old/new effect but also accelerates its onset, reflecting more efficient memory retrieval with repeated exposure.

Another well-established neural marker of successful memory is the frontal old/new effect, whose amplitude has been linked to increasing memory strength, explicit memory retrieval, and even priming (scalp topography shown in **Fig. 27**). Because prior research suggests that this component becomes more positive with stronger memory

signals, we examined whether repeated learning would enhance the frontal old/new effect in a manner similar to the parietal old/new effect. Contrary to our expectations, we found no evidence that repetition increased the amplitude of the frontal old/new effect ($F(4, 18) = 0.58$, $p = .68$, BF10 = 0.036, see **Fig. 26**). Paired t-tests comparing all consecutive repetitions also showed no significant changes in amplitude across repetitions (all ps > .60). Additionally, the frontal old/new effect observed in the set size 1 condition did not differ significantly from any repetition of the set size 32 condition (all ps > .24). When replicating our finding with non-parametric tests (Sawaki, Geng, & Luck, 2012; Maris & Oostenveld, 2007; Sawaki & Luck, 2013), we again found that all set size 32 repetitions and set size 1 frontal old/new effect amplitude were mostly the same (set size 1 not different from set size 32 repetition #1,2,4 and 5; only higher than repetition #3, corrected $p = 0.03$), despite its high peak and very steep rise-to-peak compared to set size 32 conditions. These findings suggest that, unlike the parietal old/new effect, the frontal old/new effect is not modulated by repeated exposure to the same stimuli, indicating that repetition does not strengthen this particular neural signature of memory.

In addition to examining the amplitude of the frontal component, we also analyzed the latency of the frontal old/new effect during the test phase. Using the same method applied to the parietal old/new latencies, we conducted a 50% area-under-the-curve (AUC) analysis to identify the time point at which half of the total ERP area was reached within the relevant time window. To ensure robust latency estimates, we employed a jackknife approach with a leave-one-out method across 24 participant subgroups, calculating and then averaging the latency for each subgroup.

In contrast to the parietal old/new effect, the latency of the frontal old/new effect did not show a reliable change across repetitions ($F(4, 18) = 0.64$, BF10 = 0.042, $p = .63$). Although there was an initial reduction in latency, from 533.04 ms on the first exposure to 506.08 ms on the second, and 487.28 ms on the third, this trend did not continue. Instead, latency plateaued at 446.84 ms on the fourth repetition and slightly increased to 495.04 ms on the fifth. This non-monotonic pattern suggests that the frontal old/new effect is unlikely to be the primary mechanism driving the benefits of repetition during learning. Rather, the absence of a consistent latency reduction implies that other neural processes may be more directly responsible for the observed improvements in memory retrieval efficiency. Furthermore, all of these latencies were significantly slower than that observed for the frontal old/new effect at set size 1 (308.88 ms), indicating that while this component is generally sensitive to memory access time, it does not exhibit the same orderly change with repetition as the parietal old/new effect.

Lastly, we asked whether recency in a working-memory list reflects a stronger recollective experience, indexed by the parietal old/new effect, or instead a familiarity boost, indexed by the frontal old/new effect. To test this, we split the set-size-1 trials into two types: (1) “old-first” trials, where the old image was presented first at test immediately after encoding, and (2) “new-first” trials, where the new image was presented first and the old image came second. We found a stronger parietal old/new effect for old-first set-size-1 trials ($t(23) = 2.09$, $p = 0.047$), but no corresponding frontal old/new effect ($t(23) = 0.64$, $p = 0.53$), relative to new-first trials (**Fig. 28**). This suggests that the recency of an experience, when no interfering distractor (i.e., new image in our task) intervenes, can significantly enhance recollection, but not familiarity, for a working-

memory representation.

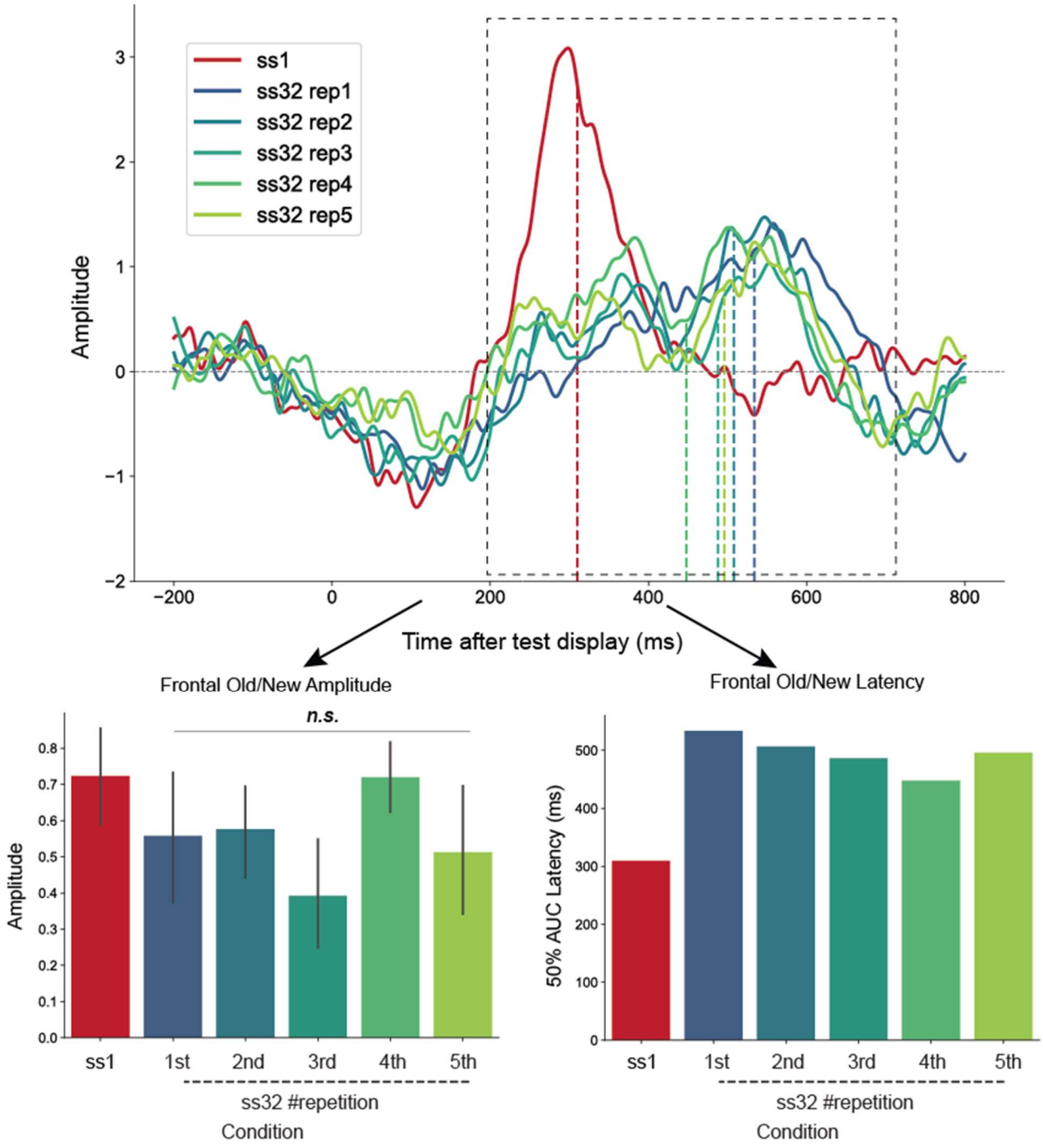


Fig 26. *Amplitude and Latency of Frontal Old/New Effect.*

In contrast to the parietal old/new effect, the amplitude and latency of the frontal old/new effect did not change significantly across repetitions. However, despite the latency in the set size 32 condition becoming earlier across repetitions, it remained significantly later than in the set size 1 condition.

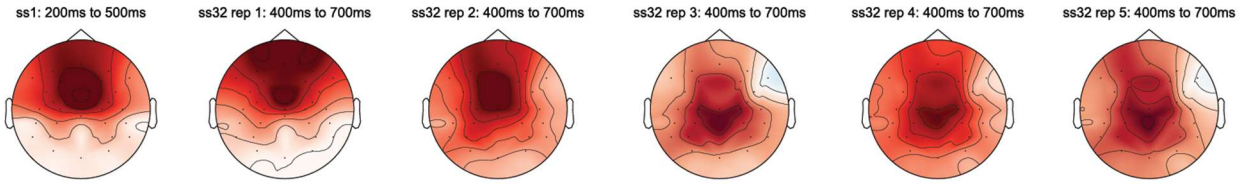


Fig 27. Scalp Topography of set size 1, and set size 32 repetition 1 to 5 conditions.

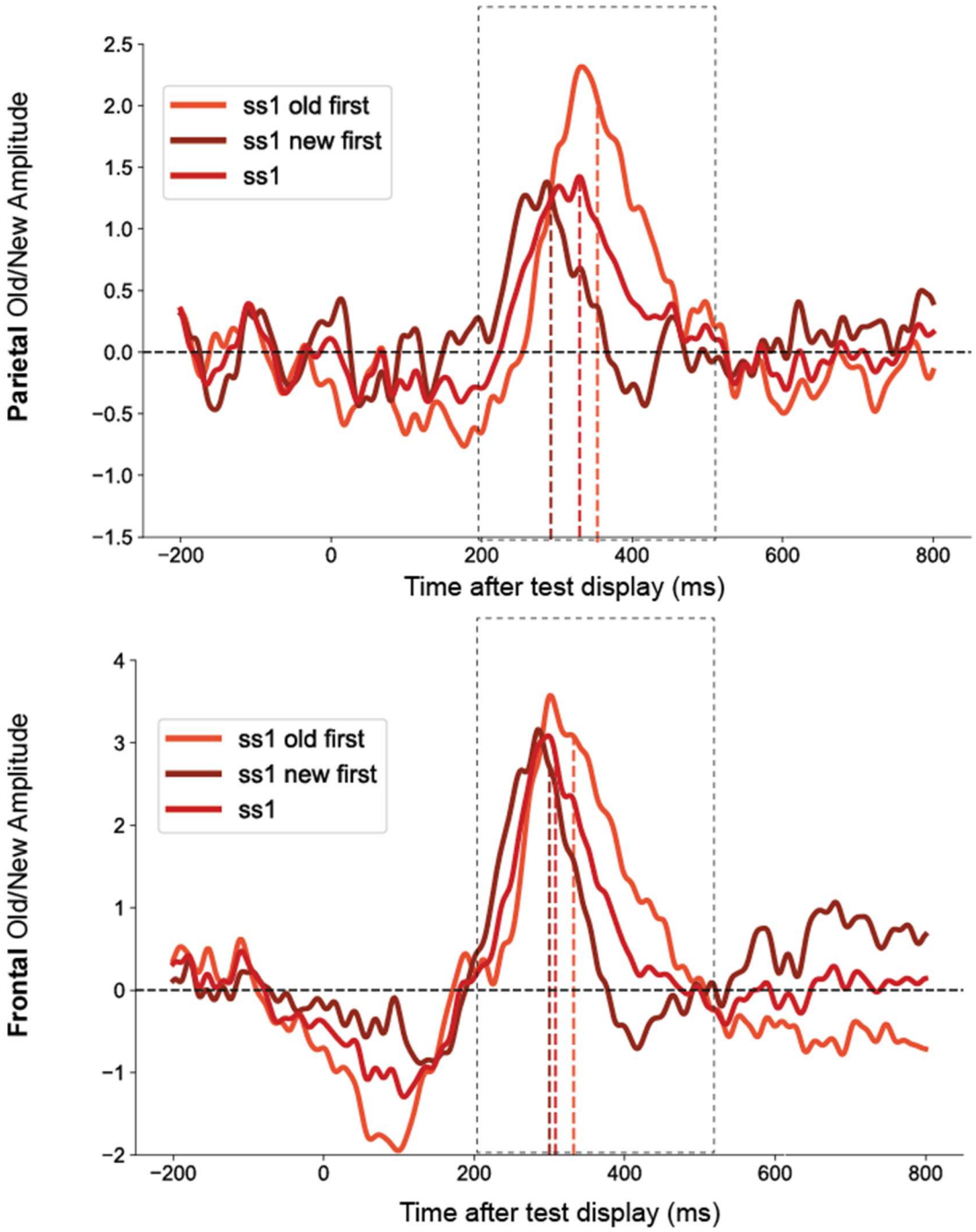


Fig 28. *Parietal and Frontal Old/New Effect for set size 1: serial position effect.*

Within set size 1 condition, set size 1 old first trials (encoding and test had 0 image in between) triggered a particularly high parietal old/new effect amplitude compared to set size 1 new first trials, but showed no differences in frontal old/new amplitude.

Discussion

In our current study, we aimed at quantifying the neural correlates of repetitive learning in the human brain. We asked the participants to learn a sequence of 32 images repetitively for up to 5 times while EEG was recorded. In particular, we are interested in whether parietal old/new effect and frontal old/new effect, two ERP correlates of recognition memory test, change with repetitive learning. We found that the parietal old/new effect increased in its amplitude and the peak became earlier with more repetitions. By contrast, we found that neither the amplitude nor the latency of frontal old/new effect was impacted by number of repetitions. These results suggest a dissociation between the two old/new effects: one, the parietal old/new effect, that becomes earlier and larger through repeated learning; and another, the frontal old/new effect, that appears largely the same despite significant behavioral learning improvements through repeated practice.

Our study demonstrated that two well-established ERP components, the parietal and frontal old/new effects, exhibit distinct patterns of change as participants repeatedly study a fixed sequence of images. Prior research has consistently linked the parietal old/new effect to recollection and the frontal old/new effect to familiarity (Kwon et al., 2023; Rugg & Curran, 2007; Yonelinas, 1994). However, the functional specificity and dynamic interaction of these processes during repeated learning remain incompletely understood. Our findings suggest that study repetition provides a powerful lens through which to dissociate these memory processes. As memory representations become more robust with repeated exposure, the changing dynamics of the frontal and parietal ERP components may reflect shifts in the relative contributions of familiarity and recollection.

Importantly, the dissociation observed in our data supports the idea that these two processes follow different trajectories during sequence learning.

First, our study showed that repeating a sequence selectively increased ERP markers of recollection, but not familiarity. These neural findings align with prior behavioral evidence that, under non-speeded test conditions, item repetitions selectively increase recollection rates (Jacoby, Jones, & Dolan, 1999). Moreover, our results are consistent with empirical work showing that increasing item repetitions produces larger gains in recollection than in familiarity estimates in recognition memory tasks (Parkin & Russo, 1993; Parkin, Gardiner, & Rosser, 1995). In contrast to the parietal recollection findings, we did not observe a significant change in the frontal old/new effect with repetition. One possibility is that a single long exposure to an image is already sufficient to saturate the familiarity signal. This aligns with the picture-superiority effect observed in studies using images rather than words (Rowe & Paivio, 1971). Prior behavioral work has also shown that familiarity responses can occur even when recollective detail is not retrieved by simply accessing the picture's name (Dewhurst & Conway, 1994). Given this relatively low threshold for familiarity with images, additional repetitions may not enhance familiarity to the same extent that they enhance recollection. Future studies should continue to leverage repeated learning designs to clarify how recollection and familiarity contribute to long-term memory formation, and how these processes are reflected in neural activity over time.

Additionally, our study addressed a key secondary question: how well-learned long-term memories differ from working memory in their neural representation. To examine this, we included a block of set size 1 image recognition trials, designed to

primarily engage working memory processes, given that memory loads below three or four items typically fall within working memory capacity (Cowan, 2001; Luck & Vogel, 1997b; Vogel & Machizawa, 2004b). We focused on the timing (latencies) of ERP components associated with recognition. Notably, both the frontal and parietal old/new effects occurred significantly earlier for the set size 1 condition compared to the well-learned set size 32 sequence, even though participants exhibited near-ceiling accuracy for both conditions. This temporal dissociation suggests that robust episodic long-term memories, despite their strength, are neurally distinct from working memory representations. These findings align with prior work examining proactive interference and the separability of memory systems (e.g., Nee et al., 2008; Oberauer, 2009), and extend that literature by showing that ERP latencies can provide a sensitive neural marker for distinguishing between working memory and long-term memory. Future research should further explore this distinction by increasing the number of learning repetitions and extending the study period across multiple sessions (K. C. Adam et al., 2024; Musfeld et al., 2023). Such designs would allow investigation into the role of sleep-dependent consolidation and whether expertise-like memory representations begin to resemble working memory in either timing or topography. Notably, we also discovered that recency effect in working memory, where no new image happens between encoding and test, produced a particularly high parietal old/new effect, suggestive of a high level of recollection.

Lastly, we found that the latency of the parietal old/new (P3) effect decreased with repeated learning. This suggests that learning may allow participants to compress or restructure larger memory sets into more efficient representations. This finding aligns

with prior research in working memory, where higher set sizes are associated with delayed P3 responses due to increased decision-making demands (Hyun et al., 2009). Extending this to long-term memory, our data showed that recognition responses for set size 32 were significantly slower than for set size 1, despite comparable accuracy, indicating that retrieving from larger sets involves more prolonged or effortful processing. Critically, the reduction in P3 latency with practice highlights this component as a potential marker of retrieval efficiency. Similar to findings in working memory, where P3 latency reflects the efficient editing of relevant items (Zhao, Adekoya, et al., 2025), our results suggest that learning may involve a comparable editing process in long-term memory. Future studies should further investigate how such editing mechanisms operate across varying memory loads and timescales, and whether additional practice enables more efficient compression of larger memory sets into smaller, more manageable representations. Moreover, well-established long-term memory representations may also alter the speed of motor planning. This can be indexed by known ERP components such as the lateralized readiness potentials (Zhao, Adekoya, et al., 2025) during recognition. Future work should therefore investigate how motor planning changes as expertise develops (Ericsson et al., 1993; Ericsson & Kintsch, 1995; Zhao & Vogel, 2025a), as well as how learning shapes motor working memory.

GENERAL CONCLUSIONS

Prior theories have largely focused on distinguishing working memory (WM) and long-term memory (LTM) as separate storage systems with different functional properties. Here, we offer a more integrative perspective, suggesting that despite these differences, WM and LTM share important commonalities in their underlying mechanisms. In particular, their relationship may not be driven solely by shared encoding processes, but rather by the combined influence of encoding constraints, retrieval operations, and learning dynamics that together shape how these systems interact.

In addition, our findings provide insight into how well-practiced LTM relates to WM. We observed that WM capacity continues to predict LTM performance even after repeated learning, indicating a stable relationship between the two systems. At the neural level, well-learned LTM representations appear to become highly robust, approaching those observed in WM, yet they remain slower to access. This pattern suggests that repeated learning strengthens LTM representations without making them functionally equivalent to WM, highlighting an important distinction between representational strength and accessibility.

In Chapter 1, we first examined how WM and LTM interact with each other across individuals. Across multiple experiments, we replicated that WM and attentional control reliably predict source memory performance and, importantly, also strongly predict recognition memory, despite the latter often being considered less attentionally demanding. This relationship held across a variety of task conditions, with one key exception: when study items were presented rapidly, WM no longer predicted

recognition performance, suggesting that fast presentation disrupts WM-dependent encoding processes. Notably, recognition and source memory remained highly correlated across all conditions and loaded onto a common latent factor, indicating a shared underlying long-term memory ability that is partially independent of attentional control. Together, these findings suggest that attention-dependent consolidation and binding processes play a central role in linking WM and LTM, while also highlighting that their relationship can break down when encoding demands exceed attentional and WM limits.

To determine whether shared neural mechanisms at retrieval account for the similarity between working memory (WM) and long-term memory (LTM), we examined whether these systems rely on a common access process in Chapter 2. Specifically, we recorded brain activity during an old/new recognition task spanning a wide range of set sizes to test whether WM and LTM engage shared neural mechanisms at retrieval. Both the parietal and frontal old/new ERP effects were reliably observed across WM- and LTM-dominant conditions, with their latencies increasing as a logarithmic function of set size, suggesting a shared access process that scales with memory load. Converging evidence from multivariate decoding showed that classifiers trained at set size 4 generalized across conditions, with earlier decoding for smaller set sizes and delayed decoding for larger ones, further supporting a common retrieval code. Despite this shared mechanism, individual differences revealed a functional dissociation: the parietal old/new effect predicted WM ability at smaller set sizes and LTM ability at larger set sizes, whereas the frontal effect did not reliably predict performance. Together, these findings indicate that WM and LTM share a common retrieval process, while remaining

behaviorally and functionally distinct systems, with performance differences more closely linked to recollection-related neural activity.

Thus far, Chapters 1 and 2 have focused on single exposures to visual sequences without repetition. However, real-world learning typically involves repeated encounters with the same information (e.g., frequently visiting the same Trader Joe's in Hyde Park). To address this, we designed an experiment in which participants repeatedly studied the same set of images across multiple learning cycles, allowing us to track how memory performance (Chapter 3) and neural measures (Chapter 4) evolve with practice. Across repetitions, we found no evidence that task demands on WM diminish with learning. Instead, individual differences in WM and attentional control continued to predict memory performance (e.g., source memory) across repetitions, although they did not predict the rate of learning. This dissociation suggests that WM and attentional control supports the quality of performance rather than the speed of acquisition. More broadly, these findings imply that skilled performance may not arise from reduced reliance on attention, but rather from more efficient allocation of it.

In Chapter 4, I further examined the neural dynamics of repeated learning by recording electroencephalography (EEG) while participants repeatedly learned a sequence of 32 images. We focused on two well-established recognition-related ERP components, the parietal and frontal old/new effects, and examined how they changed with repetition. Results revealed a clear dissociation: the parietal old/new effect increased in amplitude and exhibited earlier peak latencies with repetition, whereas the frontal old/new effect remained largely unchanged. This pattern suggests that repeated learning selectively enhances recollection-related processes, while familiarity-related

signals may reach a ceiling early and show limited modulation. Additionally, by comparing well-learned long-term memory sequences with a low-load working memory condition (set size 1), we found that both ERP components occurred earlier for working memory, despite comparable accuracy, indicating that even highly practiced long-term memory representations remain neurally distinct from working memory. Finally, the reduction in parietal effect latency with repetition suggests that learning improves retrieval efficiency, potentially reflecting the compression or restructuring of memory representations over time.

Understanding how working memory (WM) and long-term memory (LTM) interact, both within and across individuals, using behavioral and neural measures has the potential to substantially advance our understanding of intelligence and other higher-level cognitive functions. Future research should extend these approaches to more naturalistic settings and broaden their scope to include related abilities such as sustained attention and mental imagery. By integrating individual differences with carefully controlled experimental designs, we can move toward a more comprehensive account of how WM and LTM support cognition in everyday life. It is hoped that this thesis contributes to the theoretical foundation for such efforts.

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