Journal of Experimental Psychology: General

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Online First Publication, January 27, 2025. https://dx.doi.org/10.1037/xge0001728

AMERICAN PSYCHOLOGICAL ASSOCIATION

Journal of Experimental Psychology: General

ISSN: 0096-3445

https://doi.org/10.1037/xge0001728

Individual Differences in Working Memory and Attentional Control Continue to Predict Memory Performance Despite Extensive Learning

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Individual differences in working memory predict a wide range of cognitive abilities. However, little research has been done on whether working memory continues to predict task performance after repetitive learning. Here, we tested whether working memory ability continued to predict long-term memory (LTM) performance for picture sequences even after participants showed massive learning. In Experiments 1–3, subjects performed a source memory task in which they were presented a sequence of 30 objects shown in one of four quadrants and then were tested on each item's position. We repeated this procedure for five times in Experiment 1 and 12 times in Experiments 2 and 3. Interestingly, we discovered that individual differences in working memory continually predicted LTM accuracy across all repetitions. In Experiment 4, we replicated the stable working memory demands with word pairs. In Experiment 5, we generalized the stable working memory demands model to attentional control abilities. Together, these results suggest that people, instead of relying less on working memory, optimized their working memory and attentional control throughout learning.

Public Significance Statement
Working memory ability predicts various cognitive abilities. However, whether its predictive power remains after participants repetitively study the test materials remains unknown. Here, in five experiments with visual and verbal materials, we found that individual differences in working memory and attentional control (WMAC) constantly predicted people's memory performance even after extensive training of the same materials. Our results provided a new understanding of WMAC, in that learning may better tune participants' attention and working memory toward task demands, instead of eliminating the reliance on attentional control in performing tasks.

Keywords: individual differences, attentional control, visual working memory, source memory, learning

Supplemental materials: https://doi.org/10.1037/xge0001728.supp

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 laboratory-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 (LTM) encoding (Miller et al., 2019), 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. (2014) 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

Timothy Vickery served as action editor.
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The data, stimuli, and experimental codes are posted publicly on the Open Science Framework at https://osf.io/dvumt. This study was not preregistered. The work was presented at the Psychonomic Society Annual Meeting as a poster, but the conference did not post the data and materials used in the current article. The data and idea were not shared on any online website prior to the submission of the article. The authors have no conflicts of interest to declare that are relevant to the content of this article. This research was supported by funding from the National Institute of Mental Health (Grant ROIMH087214 awarded to Edward K. Vogel), the National Institutes of Health, and the Office of Naval Research (Grant N00014-12-1-0972 awarded to Edward K. Vogel).
Chong Zhao played a lead role in conceptualization, data curation, formal analysis, investigation, methodology, writing–original draft, and writing–review and editing. Edward K. Vogel played a lead role in conceptualization, funding acquisition, resources, supervision, and writing–review and editing.
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source memory performance than those with low working memory ability ($r = 0.38$, $p < .001$). 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 × Treatment interactions," with the aptitude being the general cognitive abilities and the 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, which we later describe as the *rich-get-richer* model, suggests that the differences in skill performance between participants with high and low cognitive abilities become magnified throughout learning. This effect presents as a positive interaction between the number of learning events and general cognitive abilities, where 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 (Williams et al., 2008; B. A. Williams & Pearlberg, 2006).

Alternatively, participants with low general cognitive abilities may gradually catch up with high performers with learning. This class of models, which 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).

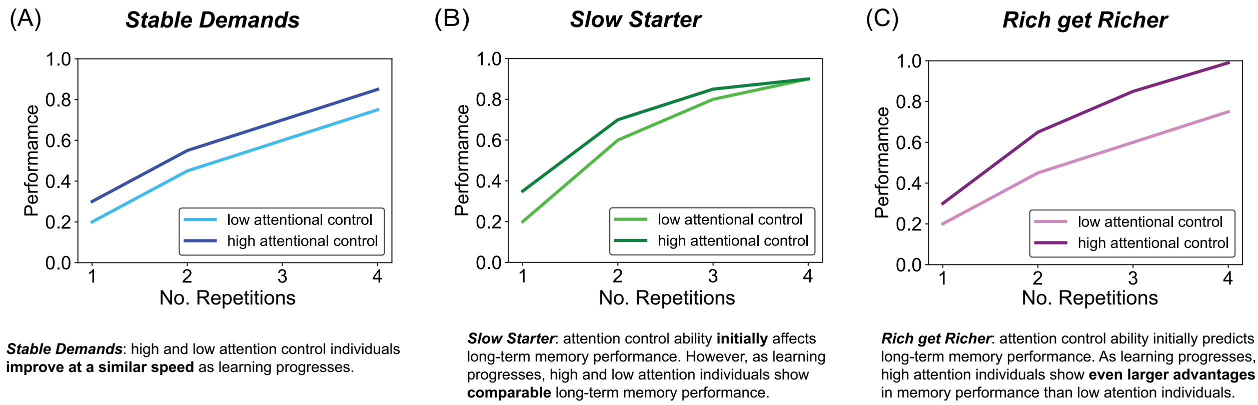
Finally, participants may continually demand similar levels of general cognitive abilities across learning. We refer to this class of hypotheses as the *stable demands* model. A prediction of this model was that participants with high and low cognitive abilities improve at a similar rate across repetitions. 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 predict the 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 the intelligence factor, *g*, continually predicted the learning performance metrics for all four repetitions, indicating that high and low performers increased at a 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 (VWM) as the measure of individual general cognitive ability. However, even the measurement of something as specific as VWM 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 VWM 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 covariance structure of performance on this task suggests that it mostly taps on to working memory abilities, and also shared variance between working memory and attentional control (WMAC), and finally attentional control the least. Alternatively, when participants performed 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 task 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 for measuring general cognitive abilities, in that the variance explained by WMAC was directly related to the level of selection that took place when performing the task.

In the present 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 Figure 1A–1C). The first one, which 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, which 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

Figure 1

A Depiction of Three Hypotheses of the Relationship Between Attention Control Ability and Memory Performance Throughout Learning Following Repeated Practice



Note. (A) Depiction of the "stable demands" hypothesis. (B) Depiction of the "slow starter" hypothesis. (C) Depiction of the "rich-get-richer" hypothesis. See the online article for the color version of this figure.

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 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 & Engle, 2002; Hambrick et al., 2014; Meinz & Hambrick, 2010). Furthermore, we aimed to test how working memory differences generalized to the learning of verbal associations in LTM, as measured by a verbal paired-associate recall task (Experiment 4). Finally, 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 the change detection task used in Experiments 1–4 (Experiment 5).

Materials, Method, and Results

Overview of Experiments

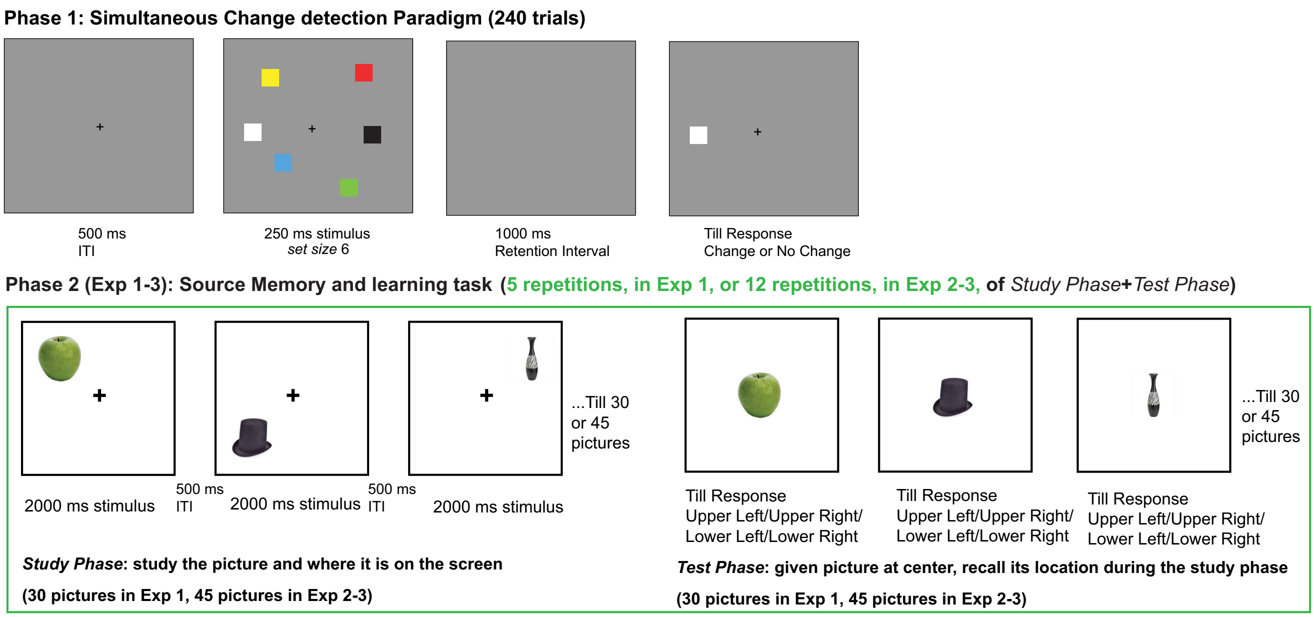
We tested our hypothesis between working memory ability and visual LTM in four experiments, with a well-powered sample of participants recruited from the Prolific online platform (n = 1,250 in total), and diverse types of materials to be learned (visual in Experiments 1–3 and 5 and verbal in Experiment 4, Figure 2). Previous research has shown that individual differences in WMAC abilities directly affected performances in VWM 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 VWM task that required participants to detect the change in perceptual features between the encoding array and the test probe (Luck & Vogel, 1997; Xu et al., 2018; Zhao & Vogel, 2023). To measure the effect of learning in visual LTM, participants were presented with a sequence of stimuli to be repetitively learned in every single experiment. In Experiments 1–3 and 5, subjects performed a source memory task in which they were presented with a sequence of 30 objects (45 objects in Experiments 2 and 3) shown in one of four quadrants and then were tested on each item's position. We repeated this procedure for five times in Experiment 1 and 12 times in Experiments 2 and 3. In Experiment 4, we used a highly reliable foreign word paired-associate recall task (Zerr et al., 2018), in which 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 asked to type out its paired English word. We repeated this study–test procedure for four times in Experiment 4 to build up their memory on these Lithuanian–English paired associates. In Experiment 5, we aimed at generalizing our findings with working memory capacity to both WMAC 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 the University of Chicago Institution Review Board, and all participants provided informed consent online.

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.

Figure 2

The Change Detection Paradigm, Source Memory Paradigm Used in Experiments 1–3



Note. (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% exhibiting a color change and 50% without change. (Middle) A sample of the source memory and learning paradigm used in Experiments 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 s. The participants need to encode the content of the picture as well as where it was placed on the screen. We had 30 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 test phases were repeated for five times in Experiment 1 and 12 times in Experiments 2 and 3. Exp = Experiment; ITI = intertrial interval. See the online article for the color version of this figure.

Experiment 1: Stable Working Memory Demands Despite of Extensive Learning of the Same Visual Image Sequence

Method

Participants

Seven hundred participants were recruited at a rate of $9.50 per hour from Prolific, an online platform for participant recruitment. All participants were 18–35 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 VWM task, all stimuli were colored squares generated in Javascript using the jsPsych canvas keyboard interface. The colored squares were all 40 × 40 pixels in size on a 400 × 400 pixels canvas page. The colored squares could appear anywhere within a circular area of the monitor within 30–200 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; and 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 30 pictures from 15 distinct semantic categories.

Procedure

In measuring VWM capacity, we administered a change detection task with Set Size 6. In each trial, six colored squares would appear simultaneously on the screen for 250 ms, followed by 1,000 ms of retention interval, when no stimuli were shown on the screen. Then, one colored square would appear at one of the six previous locations at which the encoding array had appeared, and the participant was asked if the color of this new square changed from the studied square that was located at the same position 1,000 ms before. During half of the trials, the color of this new square would change into a new color that was not seen before. In 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 Figure 2 Upper).

After completing the VWM 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 30 trials in total. Following the study phase, 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 s 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 30 pictures in total. The study and the test phases were repeated five times in the same order to facilitate the learning of the sequence (see Figure 2 Lower).

Power Estimation

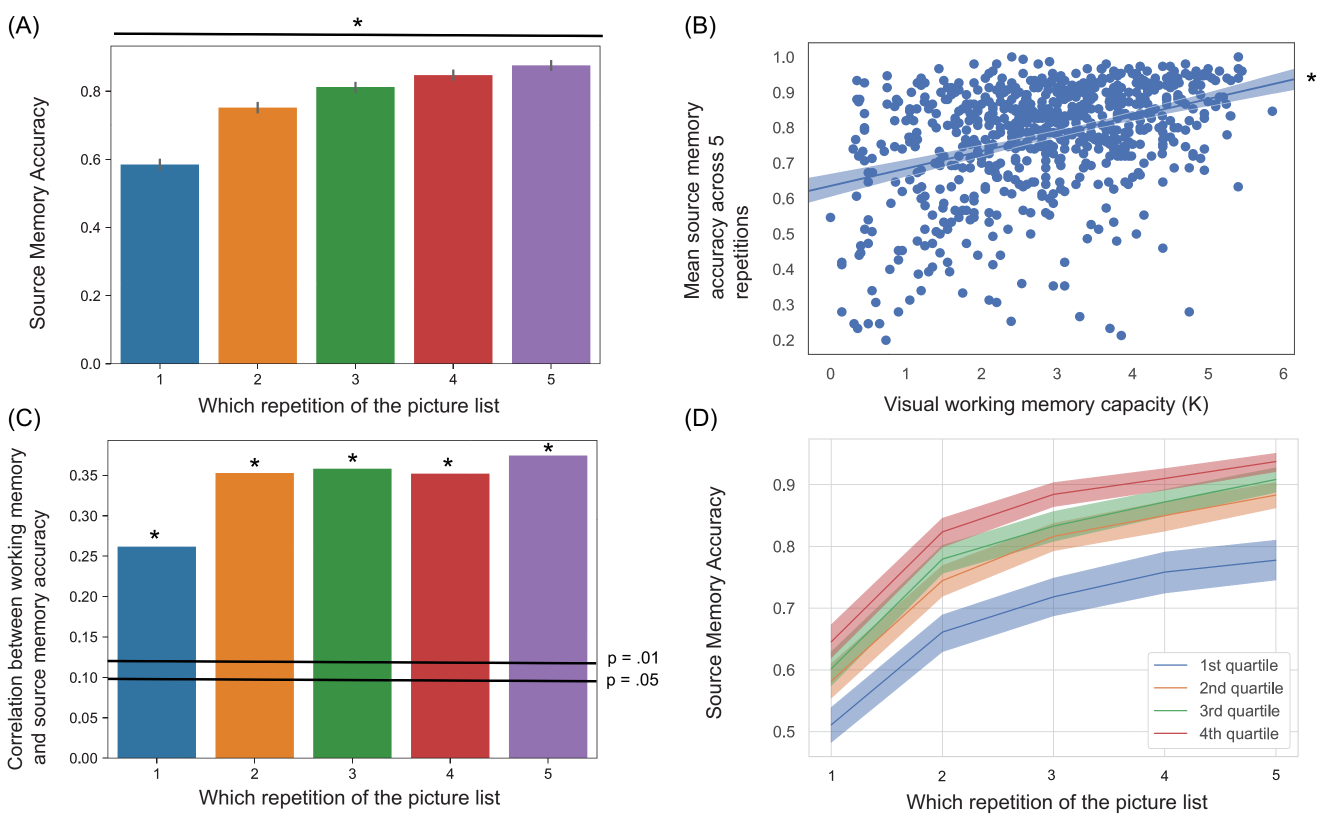
A power analysis was conducted using InteractionPoweR (Baranger et al., 2023) to determine the minimum sample size required to test the study hypothesis (i.e., Aptitude × Treatment interaction effect). We ran 1,000 simulations for each of the power estimation hyperparameters and assumed that our working memory measures and LTM 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 1,000 simulations with a smaller effect size ($r = 0.1$). Results indicated that 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 VWM 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 to the same image sequence resulted in improvement in source memory accuracy suggesting that participants showed significant improvement in LTM via learning, $F(4, 694) = 291.35$, $p < .001$, $\eta^2 = 0.30$ (Figure 3A). More importantly, across 700 participants, we observed that VWM capacity positively correlated to the mean source memory accuracy of the five repetitions of the same picture list, $r(699) = 0.39$, $p < .001$ (Figure 3B). If the *slow starter hypothesis* held true for visual

Figure 3

Visual Working Memory Capacity Consistently Predicted Source Memory Performance, Even as People Started Building Expertise for the Source Memory List



Note. (A) Source memory accuracy increased as participants repeatedly learned the same list of item–location bindings. (B) The visual working memory capacity, estimated by the change detection task of Set Size 6, positively correlated to the mean accuracy of source memory task for all five 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. See the online article for the color version of this figure.

$^{*}p < .05$.

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 Figure 1B). However, we observed sustained positive correlations between working memory and source memory accuracy for all five repetitions of the sequence, $r(699) > 0.26$, $p < .001$ (Figure 3C). 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 practiced the same materials (Figure 3D). Indeed, the performance advantage for the high working memory subjects remained constant despite substantial learning across the five 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.*

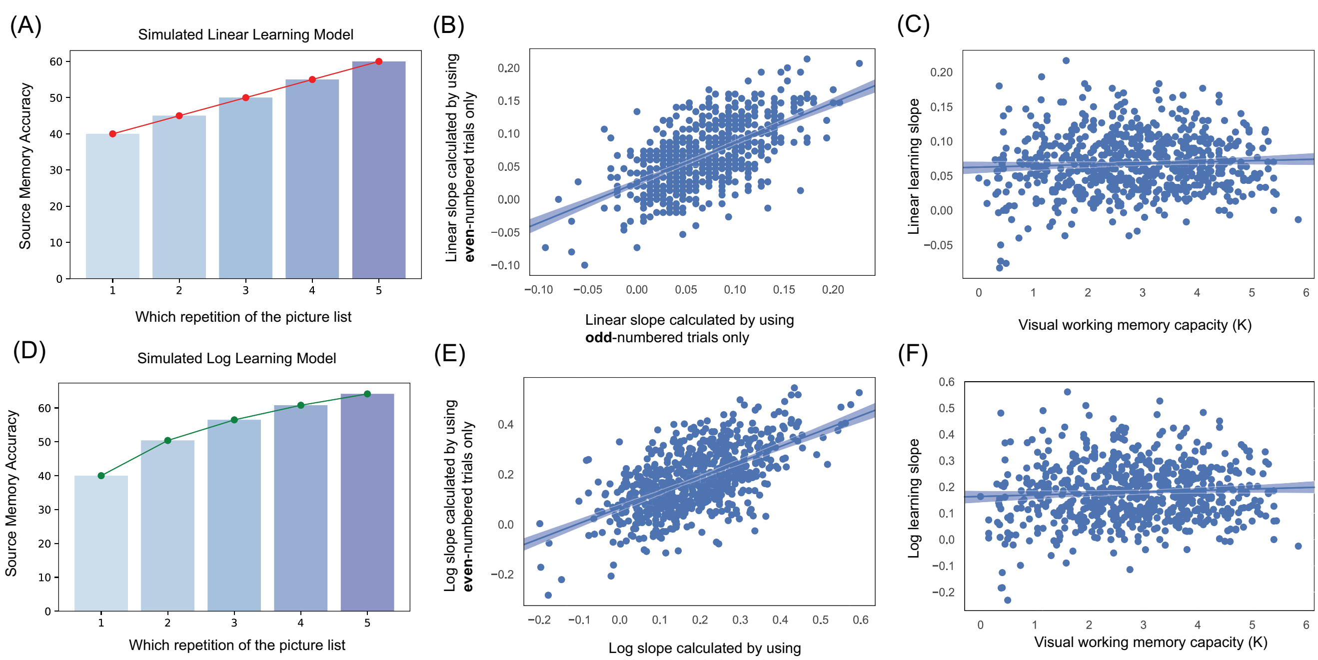
Individual Differences in Learning Rate Are Not Related to Working Memory Ability

As shown in Figure 3D, 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 five 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 (Figure 4A). We tested the reliability of these linear learning slopes in Experiment 1 data by performing an odd–even split-half correlational analysis. The source memory trials were evenly divided into two halves, and the 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 (Figure 4B). 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 (Figure 4D). Similarly, we then tested the reliability of the log-linear learning

Figure 4

Visual Working Memory Capacity Predicted Neither Linear or Log Learning Slope



Note. (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 Experiment 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 Experiment 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. See the online article for the color version of this figure.

slopes using Experiment 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 high reliability (Figure 4E). Different from its sustained predictive power in expertise performance, VWM capacity did not predict the linear learning slope, $r(699) = 0.055$, $p = .10$ (Figure 4C), or the log learning slope, $r(699) = 0.063$, $p = .15$ (Figure 4F).

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, $r(699) = 0.045$, $p = .23$, and the Bayes factor (BF) strongly favored the null (BF = 10.42 favoring null). Similarly, the partial correlation between VWM capacity and log slope was also close to zero, $r(699) = 0.047$, $p = .21$, BF = 9.80 favoring null. In addition to directly modeling the learning slope, we performed a linear mixed-effect analysis with fixed effects for the 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 nonsignificant interaction between working memory ability and the 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 the number of repetitions remained not significant ($\beta = 0.002$, 95% CI [−0.001, 0.004], $p = .07$). Together, these results suggest that VWM capacity does not predict the rate of learning via repetitions, supporting the *stable demands hypothesis*.

Experiment 2: Stable Working Memory Demands When Memory Performance Approaches Ceiling

Method

Participants

One hundred participants were recruited at a rate of $9.50 per hour from Prolific, an online platform for participant recruitment. All participants were 18–35 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 Experiment 1.

Procedure

The VWM task was the same as in Experiment 1. After completing the VWM task, participants were then administered a source memory and learning task. The procedures remained the same as in Experiment 1, except that the study and the test phases were repeated 12 times in the same order to facilitate the learning of the sequence in Experiment 2.

Power Estimation

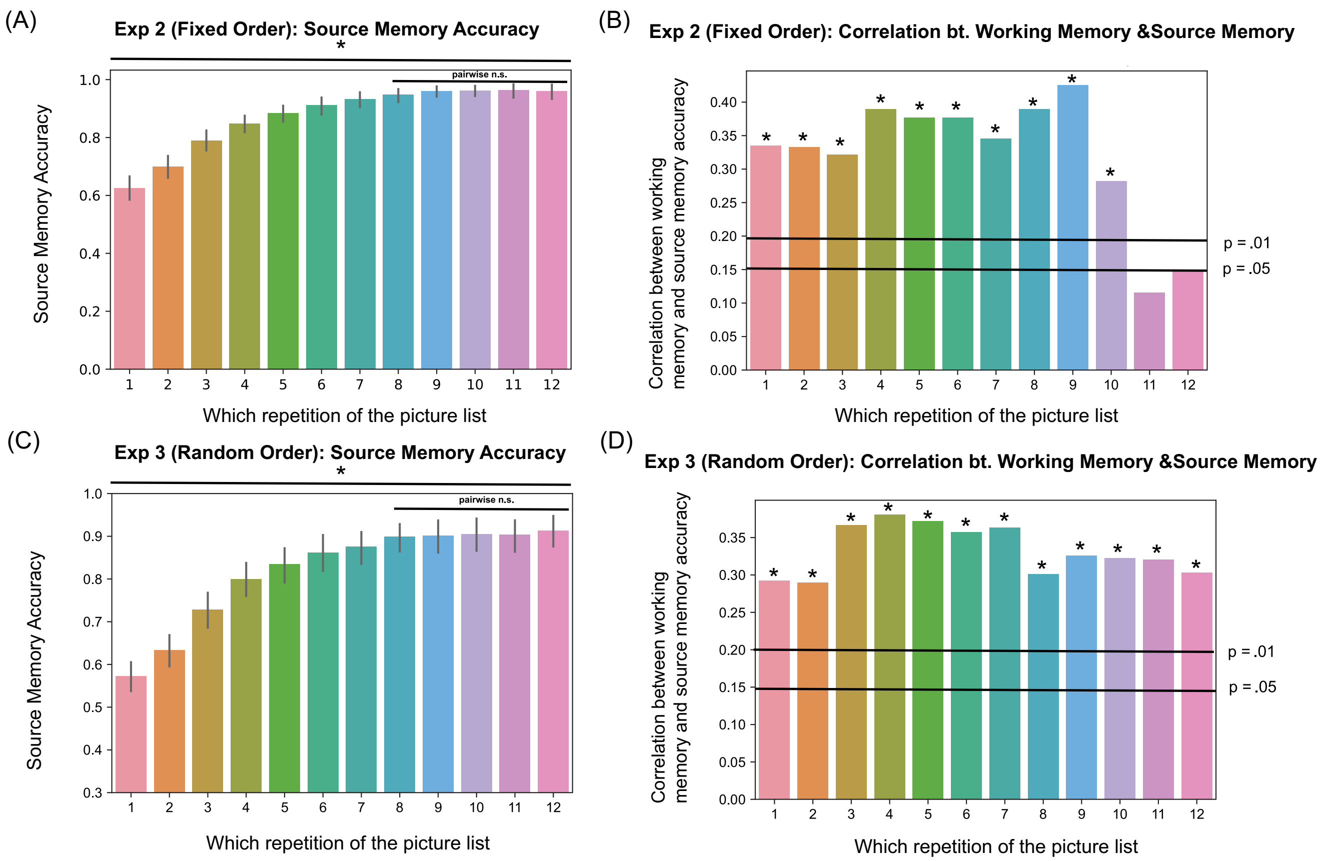
From our Experiment 1 data, we simulated sample sizes that were enough to observe small effect using the correlations that we observed in Experiment 1. The median estimated power for our sample size ($N = 95$) in Experiment 2 was 0.802 (100 iterations of 1,000 time simulation). We plotted our power simulations with $N =$ 100, 150, 200, 250, 300, and 700 in 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 the fourth repetition, $M = 84.72\%$, $t(699) = 8.42$, $p < .001$. That is, despite an over 25% improvement in memory accuracy from the first to the fifth repetition, 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 five times as in Experiment 1. As we expected, participants showed a significant learning effect across repetitions as in Experiment 1, $F(11, 82) = 60.74$, $p < .001$, $\eta^2 = 0.42$ (Figure 5A). 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 > .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, $r(94) = 0.24$, $p = .02$. It is difficult to accurately measure correlations when performance on one task is at or near the 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 the 10th repetition of the list, corrected $r(94) = 0.35$, 0.39, 0.43, and 0.28 for seventh, eighth, nineth, and 10th repetitions, respectively, ps < .01, Figure 5B, ps > .05 for the 11th and 12th 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-effect analysis with fixed effects for the number of repetitions, working memory ability, and their interaction, with random slopes and intercepts by participants. If the *stable demands hypothesis* held, we would expect a nonsignificant interaction between working memory ability and the 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 the number of repetitions remained not significant ($\beta = 0.004$, 95% CI [−0.007, 0.014], $p = .49$). Furthermore, although response time decreased as more repetitions of the task were shown, it reached an asymptote at the seventh

Figure 5

Visual Working Memory Capacity Predicted the Accuracy in Each Repetition of Source Memory List in Experiments 2 and 3



Note. (A) Source memory accuracy increased as participants repeatedly learned the same list of item–location bindings for 12 times in Experimet 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 Experiment 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. Exp = experiment; bt. = between; n.s. = not significant. See the online article for the color version of this figure.
$^* p < .05$.

repetition and did not reliably correlate with working memory abilities (Supplemental Figure 1A and 1B). 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 one participants were recruited at a rate of \$9.50 per hour from Prolific, an online platform for participant recruitment. All participants were 18–35 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 Experiments 1 and 2.

Procedure

The VWM task was the same as in Experiments 1 and 2. After completing the VWM task, participants were then administered a source memory and learning task. The procedures remained the same as in Experiment 2, except that the items in the study and the test phases were repeated 12 times, but in randomized order instead of the fixed order used in Experiments 1 and 2.

Power Estimation

From our Experiment 1 data, we simulated sample sizes that were enough to observe small effects using the correlations that we observed in Experiment 1. The median estimated power for our sample size (N = 101) in Experiment 3 was 0.823 (100 iterations of 1,000 time simulation). We plotted our power simulations with N = 100, 150, 200, 250, 300, and 700 in Supplemental Material.

Results

To facilitate learning of the visual bindings, we tested the image–location bindings in the same sequence order as the order during the encoding phase in Experiments 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, $F(11, 88) = 30.07$, $p < .001$, $\eta^2 = 0.38$ (Figure 5C). 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, ps > .0045 starting seventh list, except from the eighth list). Replicating Experiments 1 and 2, we observed sustained positive correlations between VWM capacity and source memory accuracy, raw Pearson $r(100) \geq 0.29$, ps < .001 (Figure 5D). To further investigate the interactions between working memory and learning, we performed a linear mixed-effect analysis with fixed effects for the number of repetitions, working memory ability, and their interaction, with random slopes and intercepts by participants. If the *stable demands hypothesis* held, we would expect a nonsignificant interaction between working memory ability and the 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 the number of repetitions remained not significant ($\beta = -0.001$, 95% CI [−0.015, 0.013], $p = .90$). Furthermore, although response time decreased as more repetitions of task were shown, it reached asymptote at the sixth repetition and did not consistently correlate with working memory abilities (Supplemental Figure 1C and 1D). In conclusion, we successfully validated our findings in Experiments 1 and 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 a rate of $9.50 per hour from Prolific, an online platform for participant recruitment. All participants were 18–35 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 Experiments 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 was 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.

Procedure

The VWM task was the same as in Experiment 1. After completing the VWM 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 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 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 Figure 6A).

Power Estimation

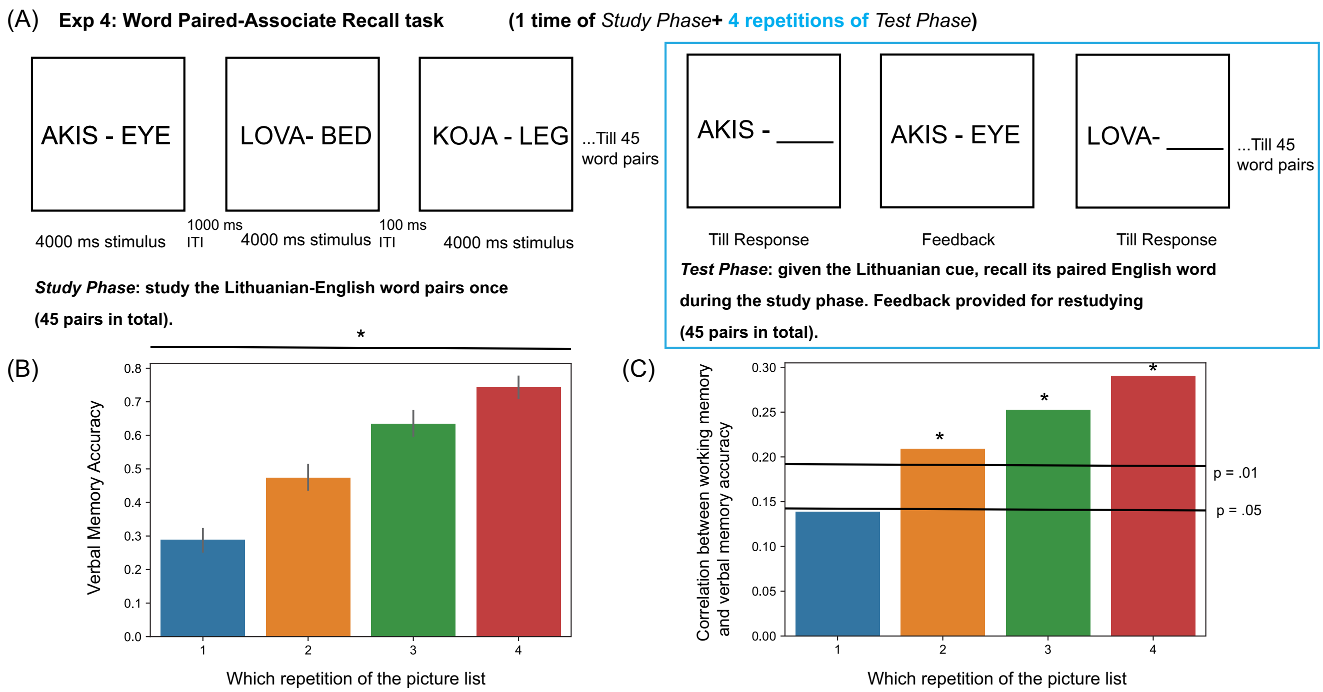
From our Experiment 1 data, we simulated sample sizes that were enough to observe small effect using the correlations that we observed in Experiment 1. The median estimated power for our sample size (N = 188) in Experiment 4 was 0.954 (100 iterations of 1,000 time simulation). We plotted our power simulations with N = 100, 150, 200, 250, 300, and 700 in 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 LTM, such as memory for verbal paired associates. In Experiment 4, we examined the relationship between working memory and verbal LTM 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 asked to type out the associated English word during test (see Figure 6A). Each participant repeated the test procedures for four 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, $F(3, 185) = 124.83$, $p < .001$, $\eta^2 = 0.40$ (Figure 6B). Right after the first exposure

Figure 6

Visual Working Memory Capacity Predicted the Accuracy in Each Repetition of Verbal Associative Memory List in Experiment 4



Note. (A) A sample of the word paired-associate recall task used in Experiment 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 asked to type out its paired English word. The correct answer would be presented as feedback after every test trial, and the participants were expected to learn from this immediate feedback. The test phase was repeated four times to facilitate the learning of verbal paired associates. (B) Source memory accuracy increased as participants repeatedly learned the same list of verbal associative memory for four times in Experiment 4. (C) Visual working memory capacity positively correlated to the mean accuracy of source memory task across two to four repetitions. Exp = experiment. See the online article for the color version of this figure.
$^{*}p < .05$.

of the paired associates, working memory abilities were not predictive of their verbal LTM performance, $r(186) = 0.14$, $p = .058$. However, as participants started building expertise on the English–Lithuanian pairs, their working memory abilities started to positively correlate to their verbal LTM accuracy, second repetition: $r(186) = 0.21$, $p = .004$; third repetition: $r(186) = 0.25$, $p < .001$; fourth repetition: $r(186) = 0.29$, $p < .001$ (Figure 6C). If the *slow starter hypothesis* held, we would expect that working memory abilities predicted verbal LTM the best when participants were inexperienced with the pair associates. In contrast 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 Experiments 1 to 3, suggesting that individual differences in VWM 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, $r(186) = 0.14$, $p = .06$, 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-effect analysis with fixed effects for the 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 nonsignificant interaction between working memory ability and the 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 the number of repetitions remained insignificant ($\beta = 0.012$, 95% CI [−0.001, 0.025], $p = .07$). Together, these results suggest that VWM capacity does not predict the rate of learning via repetitions, thus supporting the *stable demands hypothesis*.

Experiment 5: Stable Attentional Control Demands Following Repetitive Learning

In Experiment 5, we examined the relationship between WMAC 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 WMAC 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 (see Figure 1B).

Method

Participants

In Experiment 5, 145 young residents of the United States (18–35 years old) were recruited through Prolific and received monetary compensation ($10.00/hr). 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

In 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 Figure 7), followed by a visuospatial source memory and learning task, as in Experiment 1.

WMAC Tasks: Change Localization, Filtering Change Localization, Flanker Square, and Simon Square.

Change Localization. The change localization task was adopted from the color change localization task used in prior research (Zhao et al., 2023). 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.

Filtering Change Localization. The filtering change localization task was modified from the filtering change detection task (Luck & Vogel, 1997; 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.

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 s of practice and 90 s of test phase. The Flanker square score was calculated as the difference between the number of correct and incorrect responses.

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 is pointed to the left, 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 are presented. Each participant completed 30 s of practice and 90 s 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: Visuospatial Source Memory. The source memory and learning task was the same as in Experiment 1.

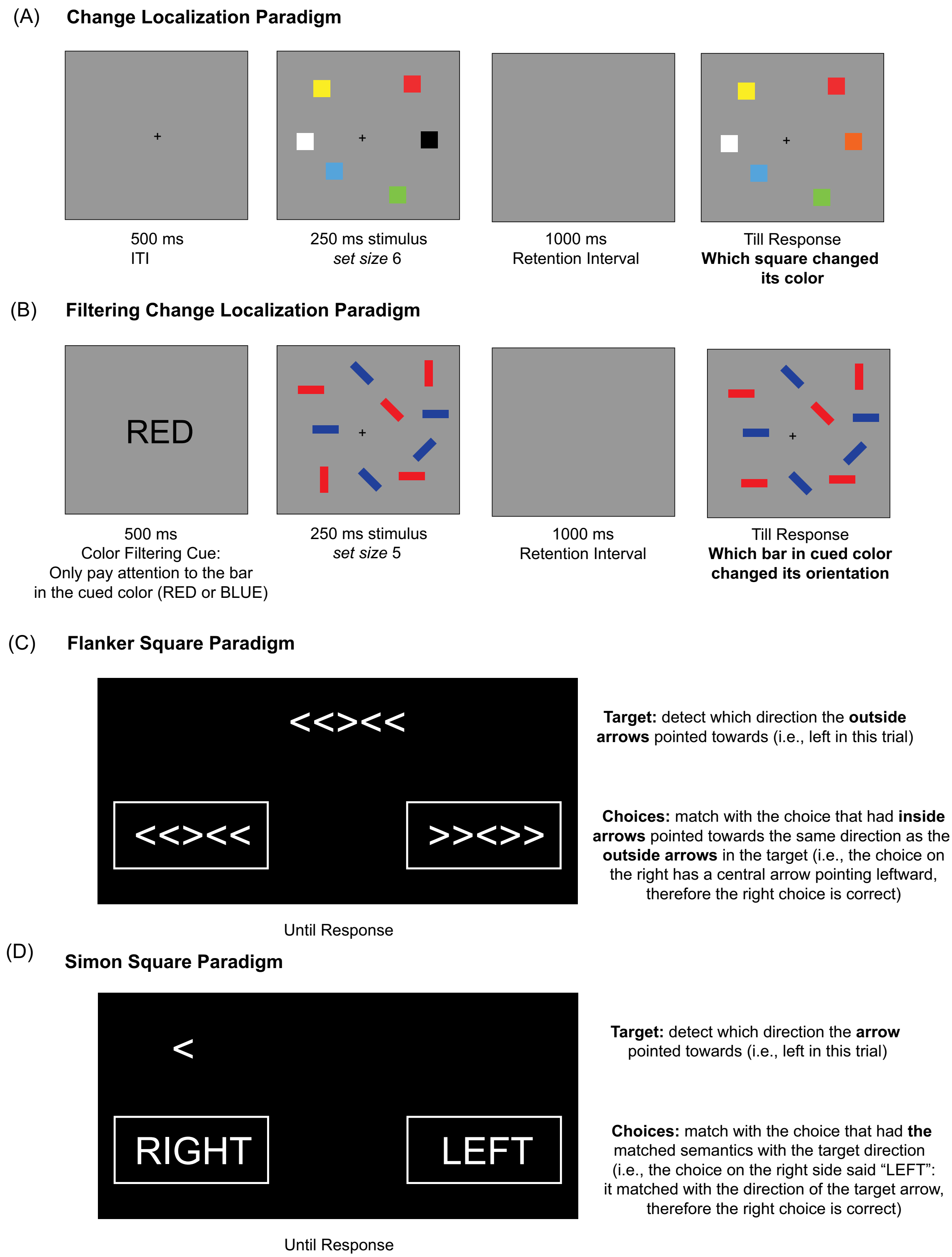
Power Estimation

From our Experiment 1 data, we simulated sample sizes that were enough to observe small effect using the correlations that we observed in Experiment 1. The median estimated power for our sample size ($N = 145$) in Experiment 5 was 0.880 (100 iterations of 1,000 time simulation). We plotted our power simulations with $N =$ 100, 150, 200, 250, 300, and 700 in Supplemental Material.

Results

Across five iterations of learning and testing, participants showed significant learning effect for the item–location bindings, replicating our results from Experiments 1 to 3, $F(4, 139) = 105.11$, $p < .001$, $\eta^2 = 0.43$. 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: rs(143) > 0.35, ps < .001; filtering change localization: rs(143) > 0.27, ps < .002; Flanker square: rs(143) > 0.29, ps < .001; Simon square: rs(143) > 0.25, ps < .002 (Figure 8). To further investigate the interactions between attentional control and learning, we performed a linear mixed-effect analysis with fixed effects for the 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 nonsignificant interaction

Figure 7
Experimental Procedures for Experiment 4



Note. (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. ITI = intertrial interval. See the online article for the color version of this figure.

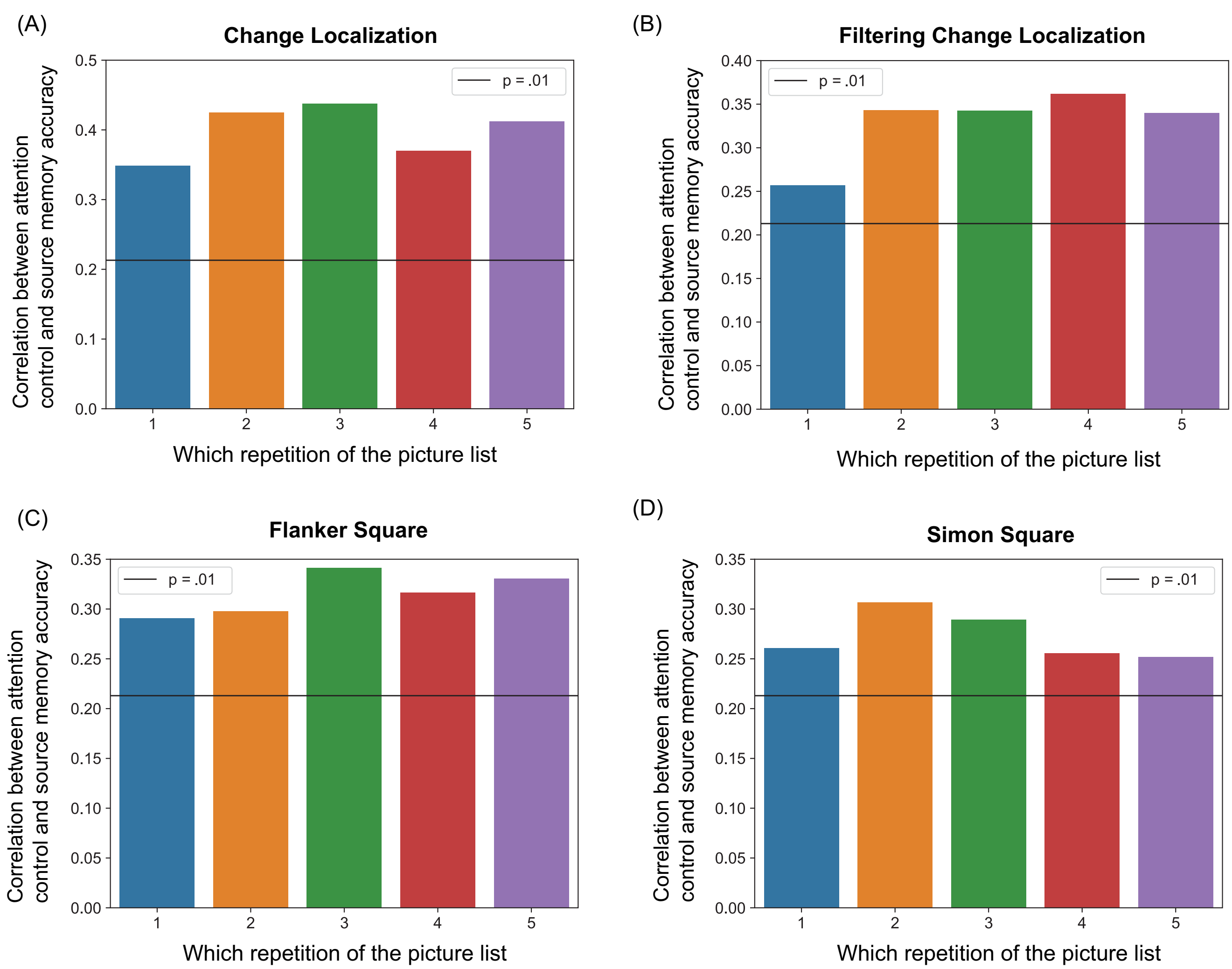
between attentional control ability and the number of repetitions. Alternatively, the *rich-get-richer hypothesis* would result in a significant interaction with a positive coefficient, and the *slow starter hypothesis* would produce a significantly negative coefficient on the interaction term. Echoing our previous findings, we discovered that the interaction between all four attentional control tasks and the number of repetitions remained not significant (change localization: $\beta = -0.028$, 95% CI [−0.079, 0.023], $p = .28$; filtering change localization: $\beta = -0.001$, 95% CI [−0.054, 0.051], $p = .97$; Flanker square: $\beta < -0.001$, 95% CI [−0.001, 0.000], $p = .31$; Simon square: < -0.001, 95% CI [−0.001, 0.000], $p = .41$). Therefore, the performance advantage for the high attention control subjects remained constant despite substantial learning across the five 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 WMAC abilities remain predictive of LTM task performance even after participants reached asymptote level performance for the visual sequence. Importantly, individual differences in VWM abilities affected LTM performance in a source memory task when the visual sequence

Figure 8

Working Memory and Attentional Control Abilities Predicted the Accuracy in Each Repetition of Verbal Associative Memory List in Experiment 5



Note. (A) Visual working memory capacity, measured by change localization task, positively correlated to the mean accuracy of source memory task performance for all five 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 five repetitions. (C) Attentional control abilities, measured by Flanker square task, positively correlated to the mean accuracy of source memory task performance for all five repetitions. (D) Attentional control abilities, measured by Simon square task, positively correlated to the mean accuracy of source memory task performance for all five repetitions. See the online article for the color version of this figure.

was learned five times (Experiment 1), 12 times (Experiment 2), or 12 times with different orders of encoding (Experiment 3). Moreover, we generalized our findings into the domain of verbal LTM, arguing that differential working memory abilities consistently resulted in differences in retrieval accuracy of verbal paired associates throughout repetitive learning (Experiment 4). Finally, we also showed that WMAC abilities, measured with four highly reliable tasks, continued to be predictive of performance throughout learning (Experiment 5). Our results from all five experiments reject the *slow starter hypothesis*, in that we did not observe a decrease in WMAC requirement as expertise built up. Instead, we observed sustained (Experiments 1, 2, 3, and 5), or even slightly increasing (Experiment 4), involvement of WMAC as people repeatedly learned the test materials. Instead, our findings mostly supported an alternative hypothesis, the *stable demands hypothesis*, which domain-general attentional control abilities may affect domain-specific LTM 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 been shown to have better domain-general laboratory-monitored attentional task performance (Voss et al., 2010). 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 data set, thousands of participants were trained over an 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*.

Although domain-general WMAC 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 Figure 4, we modeled the learning slopes of 700 participants across the five 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 LTM accuracy but not learning speed appears to suggest that learning rate may be independent of 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 × Treatment interactions (e.g., Kaufman et al., 2009) but diverges with the conclusions of other work in that area (Ackerman, 1987; B. A. Williams & Pearlberg, 2006). 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* (B. A. Williams & Pearlberg, 2006). In 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). Last, 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 B. A. Williams and Pearlberg (2006), the 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 Experiments 1–4 and a battery of four WMAC tasks in Experiment 5. We showed that working memory abilities constantly predicted performance across repetitions (Experiments 1–4), and attentional control task also similarly constantly predicted performance with learning (Experiment 5). A related ongoing debate in the field questions whether attentional control abilities form a unitary construct (Kane et al., 2004) or instead reflect 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 multidimensional 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 multifaceted 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. Although 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. Finally, 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 an extended period of time. 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 the 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 & Engle, 2002; Hambrick et al., 2014; Meinz & Hambrick, 2010). Although beyond the scope of our present study, further research is needed to determine whether attentional control and working memory abilities continue to play a role once the task performance becomes more automatized. Overall, our results help demonstrate the persisting role of individual differences in WMAC in contributing to domain-specific learning.

Constraints of Generality

Our experiments used real-world objects (Experiments 1–3 and 5) as well as words as our stimuli (Experiment 4). We replicated our key findings that working memory capacity as well as attentional control abilities consistently predicted memory performance with repetitions but not the rate of learning. Therefore, we expect our key findings to generalize to a wide range of visual and verbal stimuli. Furthermore, our experiments contained online participants from Prolific. Therefore, we believe that our results are generalizable to samples of human populations in real life outside of laboratory settings.

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Received October 23, 2023
Revision received December 5, 2024
Accepted December 15, 2024 ■