Sustained Attention Is More Closely Related to Long-term Memory than to Attentional Control

Chong Zhao[1], Anna Corriveau[1], Jin Ke[1,2], Edward K. Vogel[1], and Monica D. Rosenberg[1]

Abstract

■ Individuals differ in their ability to sustain attention. However, whether differences in sustained attention reflect differences in processes related to attentional control and working memory or long-term memory (LTM) remains underexplored. In Experiment 1, we conducted an online study (n = 136) measuring participants' sustained attention, attention control and working memory, and LTM. We measured sustained attention with an audiovisual continuous performance task in which participants responded to images while inhibiting responses to infrequent targets; attention control and working memory with flanker, change localization, and Simon tasks; and LTM with recognition and source memory tests. Factor analyses revealed that sustained attention formed a distinct factor from attention control and working memory and LTM. Individual differences in the Sustained attention factor robustly predicted individual differences in LTM and, to a lesser extent, attention control and working memory. In Experiment 2, to test how neural signatures of sustained attention related to attention control and working memory and LTM, we analyzed fMRI functional connectivity patterns collected as 20 participants performed the audiovisual continuous performance task. A pretrained connectome-based model of sustained attention predicted participants' performance on out-of-scanner LTM tasks, but not attention control and working memory tasks. Together, these results suggest that individual differences in sustained attention, although correlated with attention control and working memory, are more closely related to LTM. ■

INTRODUCTION

"Everyone knows what attention is." Over a century ago, William James (1890) described the concept of attention in *The Principles of Psychology*. He defined attention as the ability to concentrate on targets and effectively inhibit distractors, which he saw as essential for higher-level processes such as memory and learning (James, 1890). Importantly, James also emphasized that voluntary attention could not be sustained for "more than a few seconds at a time." Instead, he saw the goal of sustaining attention as successively bringing relevant items back into mind. Mirroring these descriptions of attention by James (1890), contemporary research divides visual attention into multiple subcomponents including sustained attention (SA) and attentional control (Rosenberg & Chun, 2020; Chun, Golomb, & Turk-Browne, 2011).

One line of attentional research has focused on participants' ability to focus on task goals throughout a longer timeframe or sustain attention (Esterman & Rothlein, 2019). SA fluctuates across various time scales (Rosenberg, 2026; Rosenberg et al., 2020) and is typically measured with continuous performance tasks (CPTs), in which participants are instructed to respond to frequent targets and inhibit response to infrequent nontargets (Rosenberg, Noonan, DeGutis, & Esterman, 2013; Robertson, Manly, Andrade, Baddeley, & Yiend, 1997). In assessing SA, errors in responding to infrequent nontargets are considered lapses in attention, whereas greater variability in RTs is indicative of lower attentional states (Chidharom, Krieg, & Bonnefond, 2021; Esterman, Noonan, Rosenberg, & DeGutis, 2013; Rosenberg et al., 2013).

In studying another aspect of attention, attentional control, researchers have primarily focused on how individuals prioritize task-relevant information, effectively attending to targets and filtering out distractors (Burgoyne, Tsukahara, Mashburn, Pak, & Engle, 2023). Tasks measuring attentional control abilities often require participants to resolve conflicting cognitive and motor demands (Draheim, Pak, Draheim, & Engle, 2022) or detect targets amidst multiple distractors (Martin et al., 2021). Researchers have argued that this ability impacts complex cognitive task performance (Burgoyne & Engle, 2020). The ability to control attention is closely related to the function of working memory, a short-term memory store that deals with the maintenance of targets and the filtering of distractors (Vogel, McCollough, & Machizawa, 2005). Suggesting that these two processes share common neural mechanisms, a multivariate classifier trained on fMRI data to predict attentional selection can also decode working memory content (Zhou, Curtis, Sreenivasan, & Fougnie, 2022). Crucially, individual differences in working memory capacity have been shown to predict performance on attentional control tasks, including the

[1]University of Chicago, [2]Yale University

Journal of Cognitive Neuroscience 38:7, pp. 1355–1371
https://doi.org/10.1162/JOCN.a.2488

antisaccade task, Stroop task, and flanker task (Meier & Kane, 2017; Unsworth, Fukuda, Awh, & Vogel, 2014; Colom, Abad, Quiroga, Shih, & Flores-Mendoza, 2008; Schweizer & Moosbrugger, 2004; Kane, Bleckley, Conway, & Engle, 2001). Given the strong correlations among these measures, we combined them into a single attentional control and working memory factor for our analyses, while still reporting correlations for each individual working memory and attentional control task.

Because SA is often studied separately from attentional control and working memory, an open question is how they are related to each other. One possibility is that variance in SA and attentional control is highly overlapping. Supporting this perspective, one study measured performance on multiple attention tasks, including complex working memory and attentional control tasks, and found evidence for a general attention factor, although it did not test SA (Huang, Mo, & Li, 2012). In addition, individual differences in both SA (Corriveau, Ke, Terashima, Kondo, & Rosenberg, 2025) and attentional control (Zhao & Vogel, 2025a, 2025b) predict long-term memory (LTM) differences, suggesting that both forms of attention play significant roles in the formation and maintenance of LTM. Although behavioral evidence suggested that these two attentional processes may share overlapping variance, fewer neural studies have explored the relationship between SA and attentional control.

However, emerging neuroimaging research has begun to suggest that common functional brain networks may support multiple forms of attention. A growing body of work uses individual differences in patterns of fMRI functional brain connectivity—coordinated activity between spatially distinct brain regions—to predict individual differences in task performance and behavior (Shen et al., 2017; Finn et al., 2015). To construct the model, whole-brain fMRI data were grouped into nodes, and the functional connections between these nodes were used to train and predict cognitive abilities. This work has revealed, for example, that functional connectivity patterns reliably predict abilities such as SA in novel individuals and data sets (Rosenberg, Finn, et al., 2016). The same model that predicts individual differences in SA task performance also predicted overall performance on the attention network task, which assesses alerting, orienting, and executive control (Rosenberg, Hsu, Scheinost, Todd Constable, & Chun, 2018). Furthermore, a similar connectome-based model trained to predict performance on a sustained attentional task (i.e., CPT) predicted performance on attentional control and working memory tasks (Avery et al., 2020).

An alternative perspective is that SA and attentional control, although related, are distinct types of attention. Specifically, SA affects the monitoring of ongoing cognitive processes, whereas attentional control is more closely related to task switching and working memory capacity (Chun et al., 2011). Empirical evidence supporting this claim has shown that lapses in attention, measured through in a psychometric vigilance task requiring participants to respond to changes in color on the screen for 5–10 min, SA to cues, and whole-report working memory tasks, form a distinct factor from attentional control measured with Stroop and visual search tasks (Unsworth, Robison, & Miller, 2021). Crucially, a two-factor model with distinct attentional control and lapse factors outperformed a one-factor attention model, suggesting that a separate lapse factor would fit the empirical data better than combining both forms of attention into one factor. However, whether attentional control and SA play similar roles in affecting visual LTM differences remained unresolved.

Our primary goal was to characterize individual differences in SA, attention control and working memory, and LTM. First, with an online sample (n = 136), we asked whether and how individual differences in SA reflected differences in attentional control and working memory. We next tested whether SA explained unique variance in LTM differences even when accounting for attentional control differences, given that SA (Corriveau et al., 2025) and attention control and working memory (Zhao & Vogel, 2025a) predict incidental and intentional LTM, respectively. Second, using fMRI data from a distinct sample of 20 individuals, we tested whether a validated connectome-based model of SA predicted out-of-scanner SA, attention control and working memory, and LTM performance long after participants were scanned (0.5–1.5 years). Collectively, this work fills the gap in understanding how SA, both behaviorally (Experiment 1) and neurally (Experiment 2), is related to attentional control, working memory, and LTM.

EXPERIMENT 1 (BEHAVIORAL)

In Experiment 1, we aimed to examine relationships between SA, attention control, working memory, and LTM. Some studies have proposed that attentional performance might be explained by a single underlying factor (i.e., Huang et al., 2012), whereas other research indicated that SA and attentional control may be distinct constructs (i.e., Unsworth et al., 2021). With an online sample (n = 136), we are able to dissect the latent psychological factors underlying performance on seven attention and memory tasks through both exploratory and confirmatory factor analyses. The sample size was estimated based on a medium effect size (Zhao & Vogel, 2025b; r = .3) from prior research, with power = 0.9 (estimated n = 113).

Methods

SA Task

In Experiment 1, data were collected from an online platform (Prolific). We recruited participants who were living in the United States and 18–35 years old, with normal or corrected-to-normal vision, no color blindness, no

ongoing psychological and neurological disorder, and 90% or above approval rate for previous studies. One hundred fifty participants were recruited, and 136 participants performed numerically above chance for all tasks (inclusion criteria used in Burgoyne et al., 2023; Zhao, Vogel, & Awh, 2023; mean age = 28.57 years). Study procedures were approved by the University of Chicago institutional review board, and participants were compensated ($15/hr) for their participation.

During the SA task phase of the study, participants completed a 10-min audiovisual CPT (avCPT; Corriveau et al., 2025; see Figure 1G). Throughout the avCPT, trial-unique images and sounds were presented simultaneously, with images displayed for 1 sec each and sounds lasting 1 sec with a 200-msec intertrial interval to distinguish individual sounds. Each task run included 500 trials, with images of indoor and outdoor scenes sourced from the SUN image database (Xiao, Hays, Ehinger, Oliva, & Torralba, 2010) and sound stimuli consisting of natural and manmade sounds cropped to 1 sec from online databases. Full details on stimulus curation are provided in Corriveau et al. (2025). Participants were instructed to press a button for frequent stimuli (90%) from the task-relevant modality and to withhold a response for infrequent stimuli (10%). The nonrelevant modality stimuli were to be ignored. All participants in Experiment 1 were assigned to the visual condition, responding to images and ignoring sounds. The frequent stimulus category was counterbalanced across participants (i.e., indoor vs. outdoor). Correct responses for frequent trials required a button press before the onset of a new stimulus (within 1200 msec of trial start). Performance during the avCPT was calculated as sensitivity (d'), as well as RT consistency (reciprocal of the variation of RTs, 1/(variance RT/mean RT)).

Visual and auditory memory task for avCPT stimuli. After the avCPT, participants underwent recognition memory testing for the stimuli presented (see Figure 1G). Recognition for stimuli in the task-relevant modality (images in Experiment 1) was assessed first, followed by recognition for stimuli in the task-irrelevant modality (sounds). Each memory task, for both task-relevant and task-irrelevant stimuli, consisted of 150 trials (75 old and 75 new). In each task, memory stimuli included 25 old stimuli from the frequent category, 25 old stimuli from the infrequent category, 25 stimuli that had been paired with the infrequent category of the opposite modality (always from the frequent category of the modality being tested), and 75 category-matched foil stimuli. Participants reported their confidence in their recognition memory on a scale from 1 to 4 (1 = *definitely new*, 2 = *maybe new*, 3 = *maybe old*, 4 = *definitely old*). The memory task was self-paced, ending each trial after a memory judgment was made. However, to prevent participants from pausing and resuming after an extended period, memory trials timed out if no response was made within 20 sec. Timed-out trials were excluded from analyses. Images remained on the screen until a memory judgment was made. Sounds were presented at the trial's onset, and participants were able to replay sounds as many times as needed before making a memory judgment.

Attention Control Tasks

Flanker square. The flanker square task was adapted from the flanker task (Burgoyne et al., 2023; see Figure 1C). In each trial, participants were presented with a target stimulus and two possible response options, both consisting of sets of five arrows arranged horizontally (e.g., < < > < <). Participants were instructed to choose the response option where the middle arrow aligned in direction with the outer arrows of the target stimulus. For example, if the target stimulus displayed arrows pointing left and right (e.g., < < > < <), participants were to select the response option with a central arrow pointing left (e.g., > > < > >). Thus, the task required participants to focus on the outer arrows of the target stimulus and the central arrow of the response options, while ignoring the central arrow of the target stimulus and the outer arrows of the response options. Each participant completed 30 sec of practice followed by a 90-sec test phase. The flanker square score was calculated as the difference between the number of correct and incorrect responses. Higher scores in flanker square corresponded to better attentional control abilities.

Simon square. The Simon square task was adapted from the Simon task (Burgoyne et al., 2023; see Figure 1D). In each trial, participants were presented with a target stimulus, an arrow, and two response options: the words "RIGHT" and "LEFT." Participants were instructed to select the response option that matched the direction indicated by the arrow. For example, if the arrow pointed to the left, participants would choose the response option with the word "LEFT." The target stimulus and response options could appear on either side of the screen with equal probability. Therefore, participants needed to focus on the direction of the arrow while interpreting the response options' meaning, ignoring the screen's side where the stimuli appeared. Each participant completed 30 sec of practice followed by a 90-sec test phase. The Simon square score was calculated as the difference between the number of correct and incorrect responses. Higher scores in the Simon square task corresponded to better attentional control abilities.

Working Memory Tasks

Change localization. The change localization task was derived from the color change localization task utilized in previous studies (Zhao et al., 2022; see Figure 1A). In each trial, six colored squares were presented simultaneously for 250 msec, followed by a blank retention interval of 1000 msec. Subsequently, the same six squares

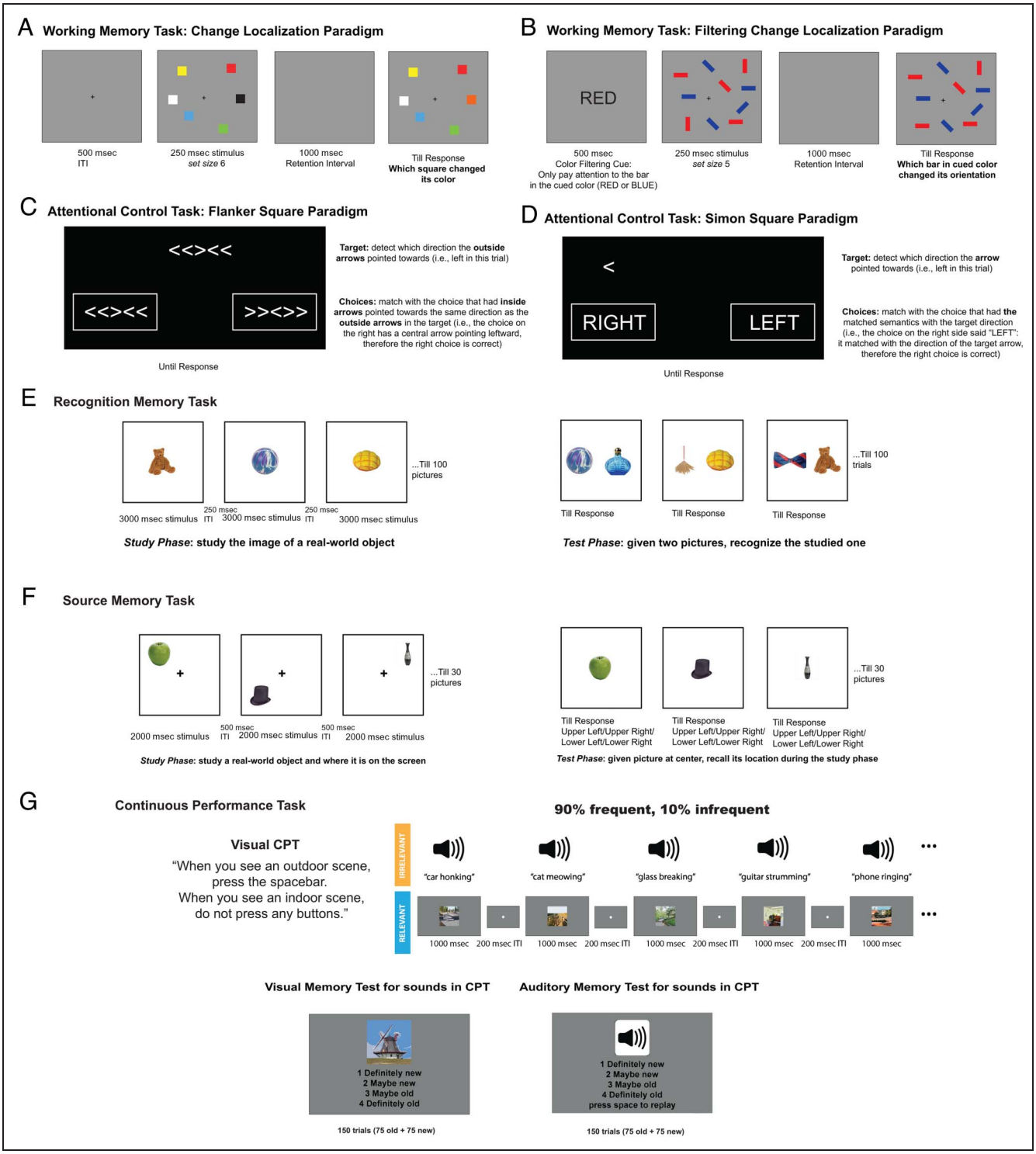

Figure 1. Working memory, attentional control, LTM, and SA tasks used in Experiment 1. (A) Schema of the change localization task (adapted from Zhao, Vogel, & Awh, 2023). (B) Schema of the filtering change localization task (adapted from Zhao & Vogel, 2025a). (C) Schema of the flanker square task (adapted from Burgoyne et al., 2023). (D) Schema of the Simon square task (adapted from Burgoyne et al., 2023). (E) A sample of the source memory paradigm (adapted from Zhao & Vogel, 2025a). (F) A sample of the recognition memory paradigm (adapted from Zhao & Vogel, 2025a). (G) A sample of the avCPT task with visual stimuli as the relevant stimuli (adapted from Corriveau, Yoo, Kwon, Chun, & Rosenberg, 2023).

reappeared in their original positions, with one color altered to a hue not previously presented in that trial. Each square was numbered from 1 to 6, and participants were instructed to press the corresponding key to identify the square that had changed color. The spatial arrangement of the six numbers was randomized across trials. Our behavioral measure of interest was accuracy in the change localization task.

Filtering change localization. The filtering change localization task was adapted from the filtering change detection task (Martin et al., 2021; Luck & Vogel, 1997; see Figure 1B). In each trial, a word, either "RED" or "BLUE," indicating the color of the items to be attended to (the selection instruction) was presented for 200 msec, followed by a 100-msec interval. Subsequently, 10 bars were displayed for 250 msec, with half of them in the designated color, creating a set size 5 condition. After a 900-msec delay, only the bars in the attended color reappeared. During the test phase, one of the bars changed its orientation compared to the encoding phase. Participants were required to identify which one of the five bars had changed its orientation. This filtering localization phase was composed of 60 trials. Our behavioral measure of interest was the accuracy in the filtering change localization task.

LTM Tasks

Recognition memory task (behavioral) data acquisition. In the study phase, participants were presented with 100 images of real-world objects (see Figure 1E). The average picture size was approximately 4.6° × 4.6° of visual angle, assuming a viewing distance of 80 cm from the screen. Each image was centered on the screen during both the study and test phases.

Each trial in the study phase began with a 250-msec fixation cross, followed by the display of an image at the center of the screen for 3000 msec. In the test phase, participants were presented with 100 pairs of images, one on the left side of the screen and the other on the right side. Each pair consisted of one image from the study phase and one novel image. Participants performed a two-alternative forced-choice task to identify which image had been presented during the study phase.

Each test phase trial began with a 250-msec fixation cross, followed by the presentation of the test images until the participant made a button press to indicate their old versus new response and confidence level. Participants used the number keys on a keyboard to indicate their confidence and which image was previously studied: the number keys 1 and 2 for the left-side image with high and low confidence, respectively, and the number keys 9 and 8 for the right-side image with high and low confidence, respectively. The stimuli were sourced from a previously published set of real-world objects (Brady, Konkle, Alvarez, & Oliva, 2008). Our behavioral measure of interest was the accuracy in the recognition memory task.

Source memory task (behavioral) data acquisition. During the study phase, participants were presented with 30 images of real-world objects, each averaging approximately 4.6° × 4.6° of visual angle, assuming a viewing distance of 80 cm from the screen (Zhao & Vogel, 2025a, 2025b; see Figure 1F).

Each trial in the study phase began with a 500-msec fixation cross, followed by the display of an image at the center of the screen for 2000 msec. Participants were instructed to memorize both the visual appearance and the spatial location of each image. In the test phase, participants were presented with the same 30 images, one at a time, and were asked to press W/E/S/D to indicate which quadrant the image was originally located in (W for upper left, E for upper right, S for lower left, and D for lower right).

Each test phase trial began with a 500-msec fixation cross, followed by the presentation of the test image 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). Our behavioral measure of interest was the accuracy in the source memory task.

Results

Individual Differences in SA Predict Attentional Control, Working Memory, and LTM Measures

We first investigated if individual differences in SA were related to attentional control, working memory, and LTM (see Table 1 for descriptive statistics). Our first metric of SA was avCPT d'. A higher d' suggested that participants

Table 1. Descriptive Statistics of All Task Performance Measures Used in Experiment 1

Task	*Mean*	*SD*	*Skewness*	*Kurtosis*
Simon square accuracy (# correct − # incorrect)	38.82	17.56	−0.89	0.34
Flanker square accuracy (# correct − # incorrect)	19.79	14.75	0.01	−0.72
Change localization accuracy	0.50	0.15	−0.59	0.15
Filtering localization accuracy	0.47	0.15	−0.01	−0.34
Source memory accuracy	0.53	0.19	0.08	−0.51
Recognition memory accuracy	0.74	0.18	−1.22	2.72
Visual memory in CPT accuracy	0.67	0.11	−1.18	1.38
d' CPT	2.75	0.85	−1.20	1.70
RT consistency (*SD*/mean)	4.17	1.08	0.01	0.02

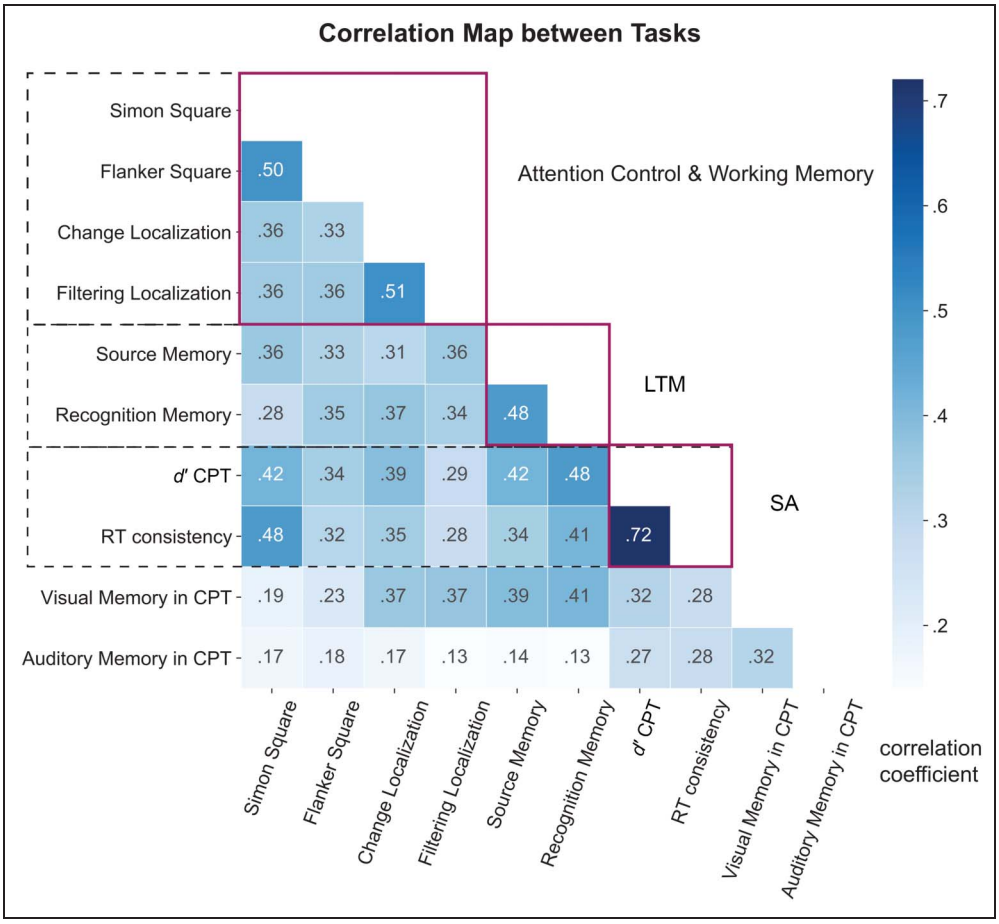

Figure 2. Spearman correlation matrix of individual differences in attentional control and working memory, LTM, and vSA tasks. The red squares highlighted the correlations between tasks within the same hypothesized construct (attention control and working memory, LTM, and SA, respectively), which were supposed to be higher than with other tasks.

were more likely to correctly respond to frequent targets and inhibit their responses when infrequent-category images were shown on screen. We found that participants with higher levels of SA (i.e., a higher d') also showed better performance in attentional control (Simon square: $r(134) = .42$; flanker square: $r(134) = .34$), working memory (change localization: $r(134) = .39$; filter change localization: $r(134) = .29$; $ps < .01$), and LTM (recognition memory: $r(134) = .42$; source memory: $r(134) = .48$; incidental visual recognition memory of CPT: $r(134) = .32$; $ps < .01$) tasks (Figure 2).

Researchers have also quantified SA in terms of the fluctuations of RT during the task. The higher the variance of the RTs across a session, the more attention lapses participants tend to experience (Chidharom et al., 2021; Esterman et al., 2013). Therefore, higher standardized RT variances suggested lower SA levels. With standardized RT variance as our measure of SA, we found that participants with higher RT consistency (i.e., lower RT variability) showed better performance in attentional control and working memory tasks (Simon square: $r(134) = .48$; flanker square: $r(134) = .32$; change localization: $r(134) = .35$; filter change localization: $r(134) = .28$; $ps < .01$) as well as LTM tasks (recognition memory: $r(134) = .34$; source memory: $r(134) = .41$; incidental visual recognition memory of CPT: $r(134) = .28$; $ps < .01$; see Figure 2).

Exploratory Factor Analysis Suggested That a Three-Factor Model Best Explains Performance on Attention and Memory Tasks

The task battery included four distinct families of cognitive measures: SA, attention control, working memory, and LTM. To investigate how these measures clustered together, we first conducted an exploratory factor analysis on the data. Our task performance metrics were standardized (i.e., z scored across participants) to ensure comparability across variables. Then, we used the Kaiser criterion, in combination with scree plots, to determine our optimal number of factors. We found that the first three eigenvalues were larger than or equal to 1 (eigenvalues of 4.5, 1.1 and 1.0, respectively). Therefore, we concluded that a three-factor model best fit our task structure (18.85%, 18.82%, and 14.17% variance explained, respectively; 51.85% explained with all three factors). With the model specification, principal axis factoring was used for factor extraction, and an oblique promax rotation was applied to allow for correlations between factors. Finally, factor loadings were examined, with loadings greater than .30 deemed significant for interpreting the factors (Tavakol & Wetzel, 2020; see Supplemental Figure S1).

In our exploratory factor analysis, d' and RT consistency in the avCPT loaded significantly onto Factor 2, suggesting that the factor reflected SA abilities. In addition, LTM measures,

source and recognition memory, loaded positively onto Factor 1. The visual memory test for stimuli used in the avCPT and working memory tasks also loaded positively on Factor 1. These findings suggested that Factor 1 was likely a visual memory factor. Finally, Simon Square, flanker square, change localization, and filtering localization all positively loaded onto Factor 3, indicating that this factor reflected attentional control and working memory abilities (attention control and working memory). The auditory memory test for task-irrelevant stimuli used in the CPT did not significantly load onto the LTM factor. Therefore, incidental auditory recognition memory performance was excluded from further model buildings with confirmatory factor analysis.

Confirmatory Factor Analysis Model Comparison Supported the Validity of the Three-Factor Model

In our exploratory factor analysis, a three-factor model was preferred, and we assumed that the three factors reflected SA, Attentional control and working memory, and LTM. To confirm that the statistical model fit with our theoretical prediction, we performed a confirmatory factor analysis on our data.

The first model we proposed was a three-factor model, with SA, Attentional control and working memory, and LTM as separate factors (Figure 3A). In this model, Simon square, flanker square, change localization, and filtering

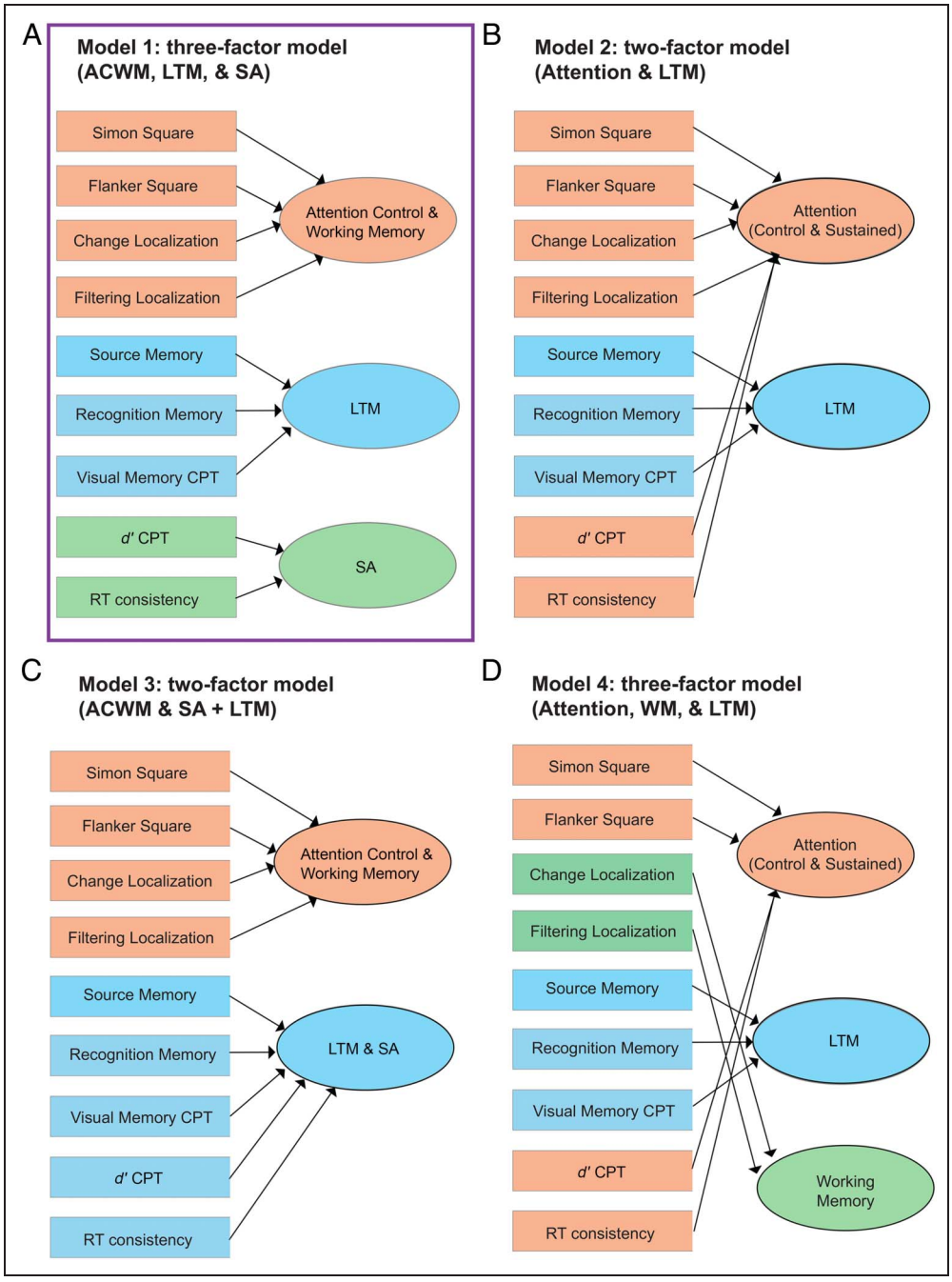

Figure 3. Confirmatory factor analysis results. The model structures of all our potential two- and three-factor models. The best fitting model was highlighted in the purple box (A), in which attention control and working memory, LTM, and SA tasks loaded separately onto three distinct factors. The model fits for all four models were displayed in Table 1. ACWM = attention control and working memory; WM = working memory.

change localization loaded onto the Attention control and working memory factor. Furthermore, source memory, recognition memory, and avCPT visual memory were loaded onto the LTM factor. Finally, avCPT RT consistency and d' were loaded onto the SA factor. The model achieved a satisfactory fit, with a comparative fit index (CFI; higher = better) of 0.94, a Tucker–Lewis Index (TLI; higher = better) of 0.91, and root mean square error of approximation (RMSEA; lower = better) of 0.093. Therefore, our findings suggested that SA formed a distinct factor from attentional control and LTM.

In addition to the three-factor model that converged with our exploratory factor analysis, we also examined two 2-factor models that resembled the predictions of the unitary attention model. For model comparison, because EFA suggested that three-factor solutions fit our data the best, we focused on two- and three-factor models of CFA. The first metric we used here was the RMSEA measure: The lower the mean square error was, the better the model. Because most of our candidate models were simple, prior research suggested that RMSEA may suggest poor fit even when the model actually fits the data well for simple models (Kenny, Kaniskan, & McCoach, 2015; Hu & Bentler, 1999). Therefore, we introduced two additional fit indices, CFI and TLI, which are more reliable in the context of simpler models. Both values range from 0 to 1, and higher values indicate better fit of the model to empirical data. First, we proposed a two-factor model that combined SA, attentional control, and working memory into one attention factor, with the second factor as LTM (Figure 3B). The model achieved reasonable fit (CFI = 0.85, TLI = 0.79, and RMSEA = 0.144; Table 1). In addition, we also proposed a two-factor model that allowed SA and LTM tasks to be our first factor, with attentional control and working memory (attention control and working memory) tasks forming a distinct second factor (Figure 3C). This model achieved a similarly reasonable fit (CFI = 0.86, TLI = 0.80, and RMSEA = 0.138), slightly better than the two-factor unitary attention model, suggesting that SA may be closer to LTM tasks than attentional control tasks. Crucially, both of the two-factor models fit worse than the three-factor model.

Finally, we proposed an alternative three-factor model, with an attention factor (Simon square, flanker square, d' in CPT and RT consistency), a working memory factor (change localization and filtering localization), and an LTM factor (source memory and recognition memory). This model achieved a similarly reasonable fit (CFI = 0.93, TLI = 0.89, and RMSEA = 0.102; Figure 3D), better than the two-factor models but slightly worse than the three-factor model with SA, attentional control/working memory, and LTM. Therefore, our findings endorsed SA as a separate factor from attentional control and LTM (model fits shown in Table 2).

Under the three-factor model, we proposed that the two square tasks and working memory tasks loaded on an Attentional control and working memory factor, LTM tasks loaded on an LTM factor, and d' and RT consistency in avCPT loaded on an SA factor. The confirmatory factor analysis loadings were all significant with our proposed framework (loadings ≥ .59; Figure 4A). Moreover, the covariance values between our three factors were all significant, suggesting that attentional control and working memory, LTM, and SA were related to each other on the construct level (Figure 4B). To further validate our findings, we also tried to fit a four-factor model, with separate attentional control, working memory, LTM, and SA factors. We found that all four factors were related to each other on the construct level, replicating our findings with the three-factor model combining attentional control and working memory together (see Supplemental Figure S2).

Individual Differences in SA Predicted LTM More Robustly than Working Memory and Attentional Control

With our three-factor model, we next tested whether SA was more robustly related to attentional control and working memory or LTM. We first calculated composite scores separately for SA, attention control and working memory, and LTM. To account for potential error variances not captured by the confirmatory factor analysis covariance matrix, we performed a correlational analysis relating the three factors. Results suggested that attention control and working memory and LTM were significantly correlated, $r(134) = .51$, $ps < .01$ (Figure 5A). More crucially, SA differences significantly predicted differences in attention control and working memory, $r(134) = .45$, $ps < .01$ (Figure 5B), and LTM, $r(134) = .73$, $ps < .01$ (Figure 5C). In comparing the two correlation coefficients, we found that LTM predicted SA more robustly than attention control and working memory measures predicting SA, $z(134) = 4.48$, $p < .01$.

Table 2. Goodness of Fit for Confirmatory Factor Analysis Models

Model	χ^2	*CFI*	*TLI*	*RMSEA*	*Number of Factors*
Model 1 (SA, AC + WM, LTM)	**51.74**	**0.94**	**0.91**	**0.093**	**3**
Model 2 (Attention [SA + AC + WM], Memory [LTM])	98.45	0.85	0.79	0.144	2
Model 3 (SA + LTM, AC + WM)	93.10	0.86	0.80	0.138	2
Model 4 (Attention [SA + AC], WM, LTM)	57.63	0.93	0.89	0.103	3

A lower χ^2 and RMSEA, and a higher CFI and TLI suggested a better model fit. Model 1 achieved the lowest χ^2 and RMSEA, and a highest CFI and TLI. Therefore, Model 1 (SA, attention control and working memory, LTM) (highlighted in **bold**) was selected as the best model among the 4 possible CFA models.

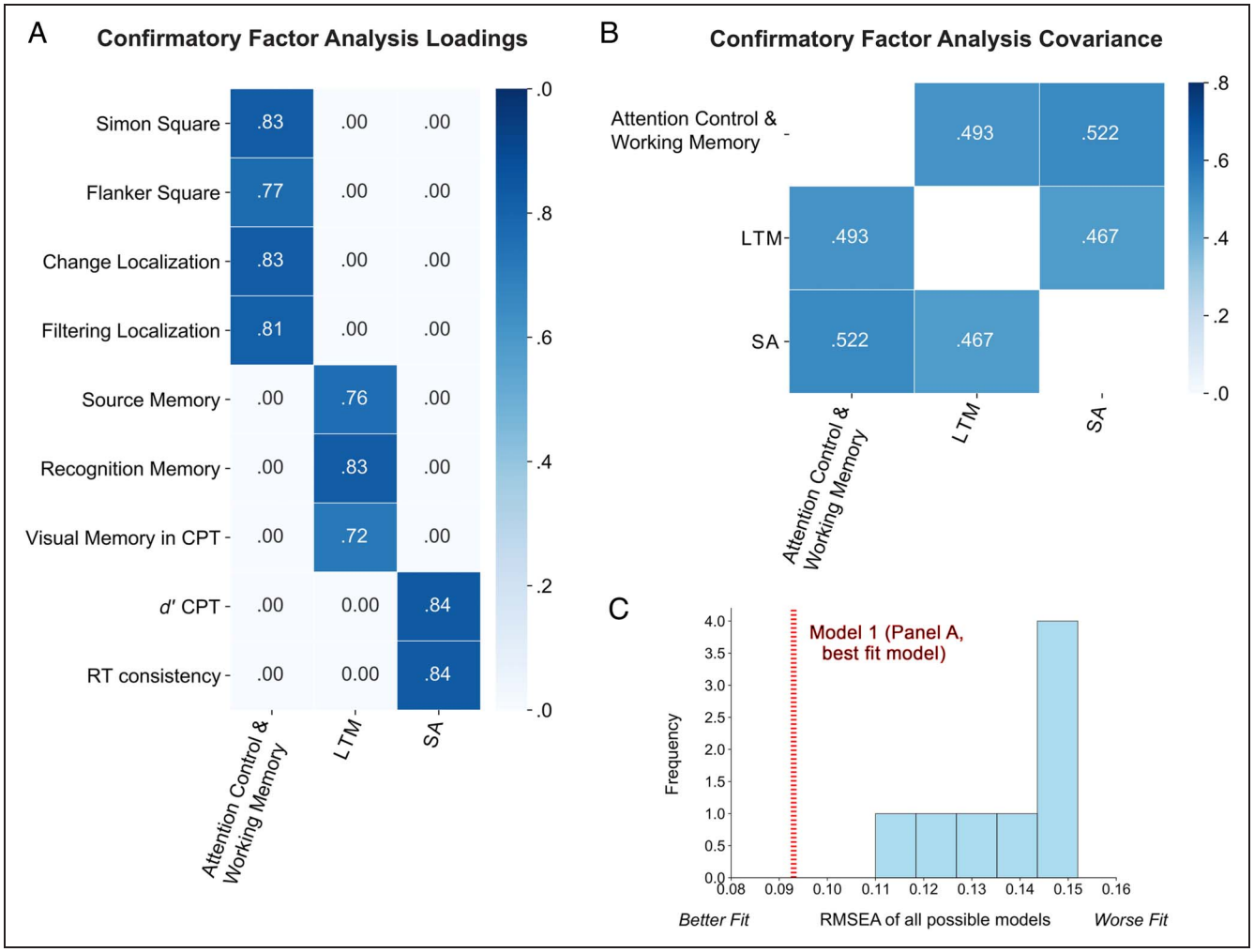

Figure 4. Confirmatory factor analysis results. (A) The CFA model fit with Attention control and working memory, LTM, and SA factors. The loadings were all significantly positive, indicating a good model fit for our Model 1. (B) The covariance loadings between Attention control and working memory, LTM, and SA factors. The three factors were positively loaded onto each other. (C) Distribution of RMSEA values across all possible models. Model 1 demonstrated the best fit (red vertical line), exhibiting the lowest RMSEA among them.

To account for general cognitive abilities (e.g., task difficulty) that could influence all three factors, we conducted a partial correlation analysis among SA, attention control, working memory, and LTM performance. In addition, all measures were z scored before factor analysis, helping to minimize the impact of individual task difficulty. We found that despite the significantly shared variance between each two out of the three constructs (Figure 6D), LTM predicted SA more robustly than attention control and working memory predicted SA, $z(134) = 5.17$, $p < .01$. Therefore, our result converged with the confirmatory factor analysis model comparison (Model 3) in that SA was more closely related to LTM abilities than attentional control or working memory abilities.

Summary of Experiment 1

In Experiment 1, we investigated the relationship between SA, attentional control, working memory, and LTM. Exploratory and confirmatory factor analyses revealed that a three-factor structure—comprising SA, attentional control plus working memory, and LTM—best fit the data compared with alternative models. Once this structure was established, we found that although the aggregate scores for all three factors were correlated, SA showed a stronger relationship with LTM than with attentional control and working memory. To account for the influence of general cognitive abilities, we conducted a partial regression analysis. The results confirmed that SA was more strongly associated with LTM than attentional control and working memory. Overall, these findings suggest that SA and LTM are more closely related than SA and attentional control and working memory, indicating the presence of distinct types of attention involved in cognitive tasks.

EXPERIMENT 2 (fMRI)

In Experiment 2, we sought to conceptually extend our findings from Experiment 1, where SA was a stronger

predictor of LTM than attentional control and working memory. To do so, we tested if neural markers of SA predicted behavioral measures of attention control and working memory and LTM. We aimed to generalize our results in Experiment 1 even when the LTM and attention control and working memory tasks were administered 0.5–1.5 years after the SA fMRI scanning session. Furthermore, we were interested in if neural markers of SA, calculated with fMRI connectivity, resembled the behavioral findings that robustly predicted LTM.

Methods

Participants

In Experiment 2, data were collected at the MRI Research Center at the University of Chicago. Participants (n = 60) took part in at least one session of a two-session fMRI study, with sessions 10.90 days apart on average (SD = 9.61). During each session, participants completed a 10-min avCPT (Corriveau et al., 2025), performed an annotated rest task, and watched or listened to narratives. Only avCPT data are analyzed here. Study procedures were approved by the relevant University of Chicago institutional review board, and participants were compensated for their participation.

SA Task (fMRI) Data Acquisition

fMRI data were collected on a 3-T Philips Ingenia scanner at the MRI Research Center at the University of Chicago. Functional images were collected with a 32-channel head coil (repetition time/echo time = 1000/28 msec, flip angle = 62°, whole-brain coverage = 27 slices of 3-mm thickness, in-plane resolution = 2.5 × 2.5 mm^2, matrix size = 80 × 80, field of view = 202 × 202 mm^2, and MultiBand SENSE factor 3). Structural images were acquired using a high-resolution T1-weighted magnetization prepared rapid gradient echo sequence (1.000-mm^3 resolution; Corriveau et al., 2025). The avCPT task was the same as in Experiment 1, with the exception that images were presented for the full trial duration, 1.2 sec, with no intertrial interval. Performance during the avCPT was calculated as sensitivity (d').

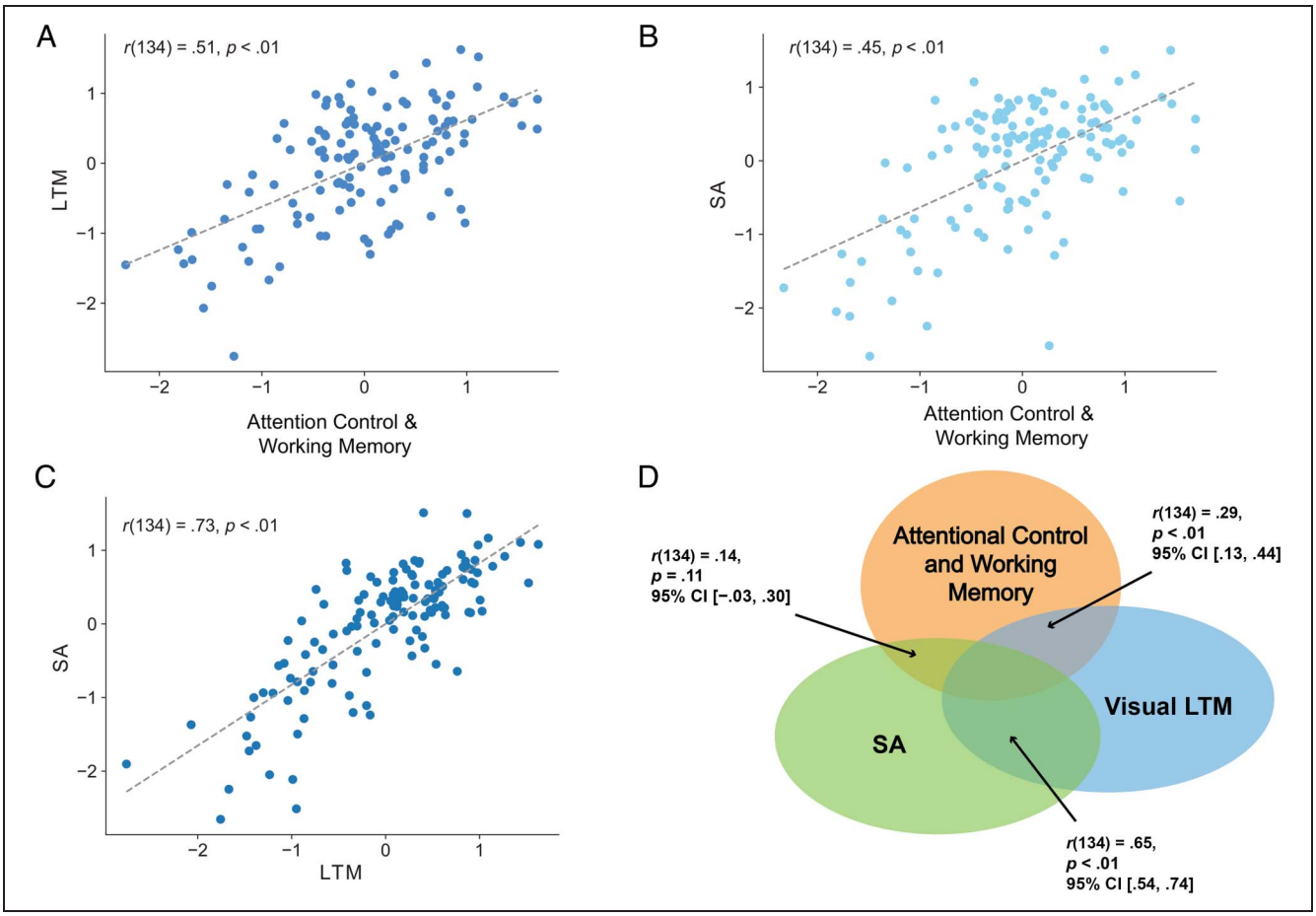

Figure 5. Visual LTM predicted SA more robustly than attentional control and working memory abilities. (A) Attentional control and working memory differences predicted LTM differences. (B) Attentional control and working memory differences predicted SA differences. (C) LTM differences predicted SA differences. (D) Partial regression between attention control and working memory, LTM, and SA. LTM and SA shared significantly larger variance than attention control and working memory as well as SA.

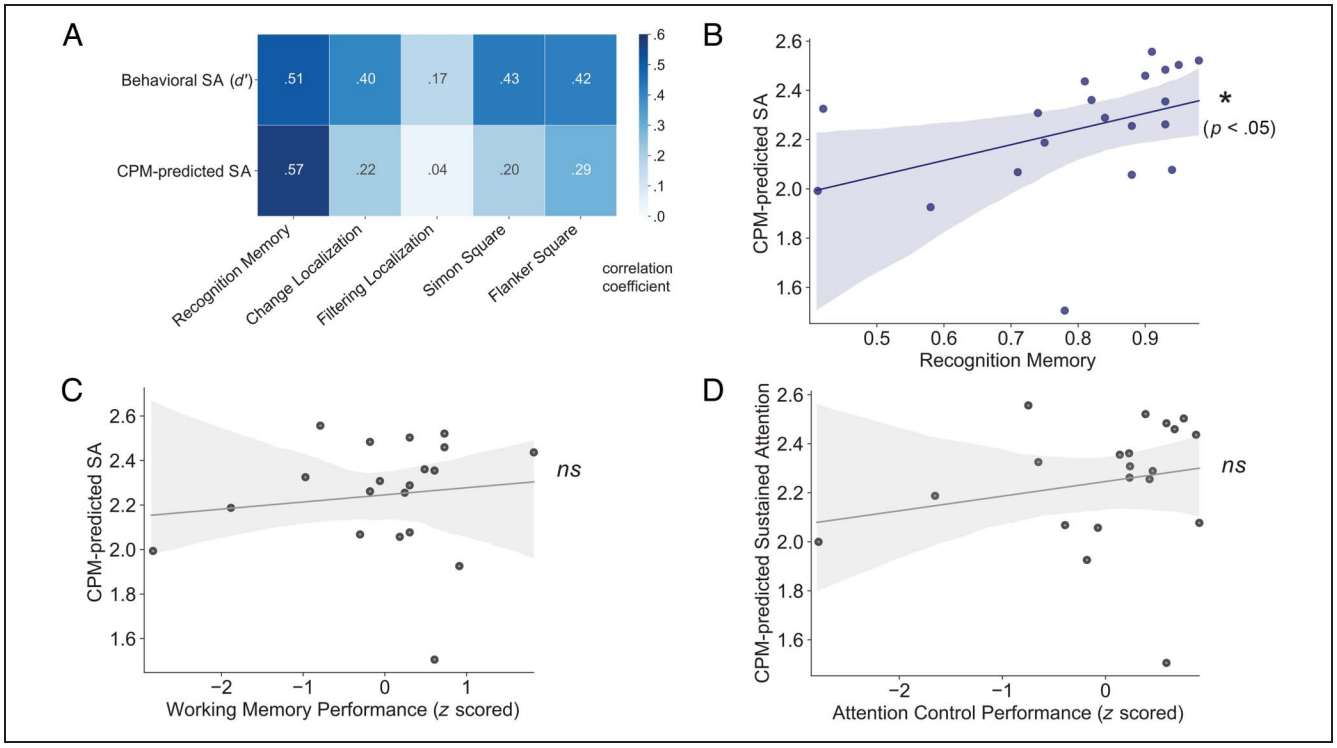

Figure 6. Connectome-predicted SA predicted recognition memory more robustly than attentional control and working memory. (A) The correlation between behaviorally and neurally predicted SA (column) and offline behavioral measures of attention control and working memory as well as LTM (row). (B) Recognition memory and saCPM-predicted SA were significantly correlated. (C) Working memory and saCPM-predicted SA were not significantly correlated. (D) Attentional control and saCPM-predicted SA were not significantly correlated.

fMRI preprocessing and functional connectivity calculation. Three volumes were discarded at the beginning of each scan. The fMRI data were preprocessed using a consistent pipeline in AFNI (Corriveau et al., 2025). Preprocessing steps included discarding initial repetition times as specified, aligning the functional images to Montreal Neurological Institute space, and regressing out nuisance covariates. These covariates included a 24-parameter head motion model (six motion parameters, their temporal derivatives, and squared terms), mean signals from participant-specific white matter and ventricle masks, and the global mean signal. Volumes were censored if the derivative of motion parameters exceeded 0.25 mm or if more than 10% of the brain was classified as outliers.

Functional network nodes were defined with a whole-brain brain atlas designed to maximize the similarity of voxel-wise time series within each node (Shen, Tokoglu, Papademetris, & Constable, 2013). For each participant, a time course was generated for each node by averaging the preprocessed time series of all constituent voxels within a node. Pairwise Pearson correlation coefficients were computed between the time courses of all node pairs, and these were Fisher-normalized to produce 268 × 268 symmetric correlation matrices, reflecting each participant's task-based functional connectivity profile.

SA connectome-based predictive model. The SA connectome-based predictive model (saCPM) was defined to predict individual differences in CPT sensitivity (d') using a data-driven approach, CPM, in previous work (Rosenberg, Finn, et al., 2016). The saCPM includes two sets of functional connections: one associated with better attention (757 connections) and one with worse attention (630 connections), spanning cortical, subcortical, and cerebellar regions. High-attention connections linked the motor cortex, occipital lobes, and cerebellum, whereas low-attention connections were found within the temporal lobe, cerebellum, and between temporal and parietal regions.

To apply the saCPM to new individuals, we calculated each participant's saCPM score by subtracting mean connectivity in the low-attention network from that in the high-attention network. This score was then transformed into a predicted d' (a behavioral index of SA sensitivity) using the original model's coefficient and intercept. Prediction accuracy was assessed by correlating participants' actual task performance with their predicted d' scores, which are linearly related and thus yield identical correlations in new samples. In Experiment 2, we expected that predicted d' scores would correlate with SA task performance, consistent with prior applications of the model to over 2600 individuals across 15 independent data sets (Corriveau et al., 2023; Chamberlain & Rosenberg, 2022; Kardan, Stier, et al., 2022; Fountain-Zaragoza, Samimy, Rosenberg, & Prakash, 2019; Jangraw et al., 2018; Rosenberg et al., 2018, 2020; Rosenberg, Finn, et al., 2016; Rosenberg,

Zhang, et al., 2016), including the larger version of this sample (Corriveau et al., 2025). This robust prior validation supports the adequacy of our sample size and motivates further testing of saCPM's sensitivity to individual differences in LTM, attentional control, and working memory.

Justification of sample size. Despite the relatively small sample size in Experiment 2, several factors support the robustness of our findings. First, the relationship between the strength of the predefined saCPM and accuracy on the CPT was originally established in the full fMRI sample (n = 60; Corriveau et al., 2025). The current analysis focuses on a subset of this sample (n = 20), as only a portion of the original participants completed the additional online working memory and LTM tasks. Second, the saCPM used in our study has been validated across multiple independent data sets comprising over 2600 participants (e.g. Corriveau et al., 2023; Chamberlain & Rosenberg, 2022; Kardan, Stier, et al., 2022; Fountain-Zaragoza et al., 2019; Jangraw et al., 2018; Rosenberg et al., 2018, 2020; Rosenberg, Finn, et al., 2016), reinforcing confidence in its reliability and supporting the interpretability of our results even with a smaller participant pool in this experiment.

Recognition Memory, Attention Control, and Working Memory Tasks

In Experiment 2, the recognition memory, attention control, and working memory tasks were the same as the one used in Experiment 1. We recontacted the participants 0.5–1.5 years after the fMRI scan sessions in which they performed the avCPT. Twenty out of 60 participants performed the recognition memory, attention control, and working memory tasks online (mean age = 21.66 years, 14 women and six men). Although the gap between the fMRI session and the online cognitive tasks was because of logistical constraints, this separation serves as a strength. Specifically, the observed relationships between brain connectivity and cognitive performance are less likely to be influenced by transient factors such as time of day, fatigue, or daily fluctuations. Instead, the delayed testing increases the likelihood that our results reflect more stable, trait-like individual differences in SA, working memory, and LTM. Study procedures were approved by the relevant University of Chicago institutional review board, and participants were compensated ($20/hr) for their participation.

Results

Behavioral and CPM-Predicted SA Coherently Predict LTM but Not Attention Control and Working Memory Measures

SA (i.e., avCPT) performance during the scan session predicted performance on a recognition memory task collected 0.5–1.5 years later, $r(18) = .51, p = .02$ (Figure 6A), supporting our findings in Experiment 1 that SA is closely related to LTM. In contrast, SA performance measured in the MRI session did not predict later change localization, $r(18) = .40, p = .08$; filtering localization, $r(18) = .17, p = .46$; flanker square, $r(18) = .42$, $p = .07$; or Simon square, $r(18) = .43, p = .06$, tasks (Figure 6A). Fisher z comparison revealed that CPT performance was not significantly more correlated with recognition memory performance than with attentional control, ($z(19) = 0.29, p = .19$, or working memory, $z(19) = 1.02, p = .08$, performance.

We next asked if a neural signature of SA, the saCPM, measured during the fMRI session predicted subsequent LTM and attentional control and working memory performance. Prior work has demonstrated that the saCPM successfully generalizes to predict SA (avCPT performance) in the current data set (Corriveau et al., 2023). In our subsample of 20 fMRI participants who also completed the online behavioral tasks, saCPM-predicted SA correlated with observed sustained attentional performance (d'), $r(18) = .47, p = .03$. We confirmed that the saCPM was not related to mean frame-to-frame head motion in this sample, $r(18) = -.04, p = .85$.

We further investigated whether saCPM-predicted SA correlated with observed measures of attentional control, working memory, and recognition memory. If SA and attentional control rely on shared attentional resources in task performance, we would anticipate that saCPM predictions would be more predictive of attentional control and working memory than LTM performance. Mirroring our findings in Experiment 1, saCPM predictions were correlated with recognition memory, $r(18) = .57, p < .01$, αBonf = .01 (Figure 6B), but not attentional control, $r(18) = .28, p = .23$ (Figure 6D), or working memory, $r(18) = .15, p = .54$ (Figure 6C), performance. Moreover, the correlation between saCPM predictions and recognition memory performance was significantly higher than the correlation between saCPM predictions and attentional control, $z(19) = 1.46, p = .036$, or working memory, $z(19) = 1.67, p = .02$, with a Fisher z comparison of correlation strength test. A partial correlation analysis confirmed that saCPM predictions predicted recognition memory, $r(18) = .49, p = .03$, but not attentional control, $r(18) = .36, p = .13$, or working memory, $r(18) = .15, p = .54$, after the time between the fMRI and online session was regressed out. Therefore, fMRI-predicted SA is more closely related to recognition memory than to attentional control and working memory.

fMRI CPM-predicted and Behaviorally Measured SA Showed Similar Correlation Structure with Offline Cognitive Tasks

Finally, we tested if CPM-predicted SA resembled behavioral SA within our sample. Therefore, we examined if fMRI-predicted and behaviorally measured SA measures shared similar covariance with attentional control,

working memory, and recognition memory tasks. We calculated the Spearman correlation between the behavioral and CPM-predicted SA measures and all five cognitive tasks used in our behavioral session (change localization and filtering change localization for working memory, flanker square and Simon square for attentional control, and recognition memory task). The five correlations were similarly ranked between behavioral and fMRI SA measures (Figure 6A). To quantify the strength of rank correlation, we found that the Spearman correlation between the five correlation coefficients using behavioral SA and those using fMRI SA was .84. Thus, fMRI-predicted SA showed similar ranks in its predictive power to cognitive tasks when compared with behaviorally measured SA. This suggests that the brain measures of SA (i.e., CPM predictions) are specifically capturing aspects of SA, as evidenced by their similar patterns of correlations with out-of-scanner task performance. In conclusion, we conceptually extended our findings in Experiment 1 that SA is more closely related to LTM than to attentional control and working memory.

DISCUSSION

Here, we first established that SA—although correlated with attentional control, working memory, and LTM ability—forms a distinct psychological factor with a well-powered sample in Experiment 1. Contrary to an intuitive hypothesis that components of attention are more similar to each other than they are to components of memory, aggregated scores in SA tasks were more predictive of LTM scores than attentional control and working memory scores. To test if our hypotheses could be generalized to neural patterns, we collected attentional control, working memory, and LTM measures 0.5–1.5 years after an independent sample of participants performed an SA task during fMRI. Mirroring findings from Experiment 1, predictions of a validated connectome-based neuromarker of SA correlated more strongly with LTM than attentional control and working memory measures. Therefore, we concluded that SA was likely a separate, although not necessarily independent, factor from attention control, working memory, and LTM. Moreover, SA differences, both behaviorally and neurally, were more predictive of LTM performance than attentional control and working memory task performance.

Our results suggest that attentional control and SA are separable components of attention. In particular, we propose that a separate SA factor, alongside an LTM factor and an attentional control/working memory factor, best explains the underlying factor structure of attention. The identification of the SA factor supports previous claims that attentional lapses account for distinct variance from attentional control and working memory (Unsworth et al., 2021). However, one significant difference between our studies is that the original lapse factor contained attentional lapses from a whole-report working memory task (Adam, Vogel, & Awh, 2017). Because previous research has shown that low-working-memory-capacity participants tend to experience more lapses (Adam, Mance, Fukuda, & Vogel, 2015), the attentional lapse factor in Unsworth et al. (2021) contains more working memory components than the factor made up of our avCPT measures. Moreover, the whole-report task measured an attentional lapse by capturing trials that had one or fewer items correct. Because each trial required responses to six items in a visual array, the sampling rate for lapses was far more sparse than CPTs used in our experiments. Therefore, future research is needed to test if continuous response tasks that capture lapse at a faster speed, as well as whole-report tasks that measure lapses with working memory arrays over a longer timescale, require the same sustained attentional resources. In addition, more measures of SA measured with other paradigms are needed in future studies to make a more generalized SA factor.

Our neural model of SA did not predict offline attentional control or working memory performance as robustly as it did LTM measures. This finding extends previous research, which shows that brain connectome models trained with working memory abilities have significant but limited shared edges with models trained for SA abilities (Kardan, Stier, et al., 2022; Avery et al., 2020). Interestingly, the neural connectivity representations between working memory and fluid intelligence were significantly more similar than those with SA (Avery et al., 2020). Our findings suggest that LTM networks may share greater variance with SA than with attentional control or working memory. This result aligns with previous evidence indicating that SA influences LTM encoding (Wakeland-Hart, Cao, deBettencourt, Bainbridge, & Rosenberg, 2022; deBettencourt, Williams, Vogel, & Awh, 2021; deBettencourt, Norman, & Turk-Browne, 2018). We speculate that the robust predictive relationship between SA and LTM performance in our task may stem from a bidirectional interaction between these constructs. When SA is high, LTM encoding improves (Corriveau et al., 2023; Decker, Duncan, & Finn, 2023; Wakeland-Hart et al., 2022; deBettencourt et al., 2018). Conversely, participants with better LTM performance may be better able to maintain goal-relevant information (i.e., Hu et al., 2024), which is critical for SA tasks. Further research is required to clarify the precise roles that SA plays in shaping LTM and vice versa.

One possible explanation for the link between SA and LTM is that SA plays a role in LTM encoding (Chun & Turk-Browne, 2007). Behavioral research has shown that information tends to be better remembered if it was presented in a better SA state during encoding (Corriveau et al., 2023, 2025; Decker et al., 2023; Wakeland-Hart et al., 2022; deBettencourt et al., 2018). Building on this, EEG studies have found that when participants were asked to remember items and recall their spatial locations, trials that coincided with low SA at encoding were associated with poorer LTM performance (deBettencourt

et al., 2021) or after an attentional lapse (Smallwood, Riby, Heim, & Davies, 2006). Another line of evidence using EEG and pupillometry has shown that attentional lapses at retrieval are associated with reduced memory performance (Madore & Wagner, 2022; Madore et al., 2020). Thus, fluctuations in SA may influence both the encoding and retrieval of episodic memories (Schwartz, Yang, Xue, & Wagner, 2025) and even free recall of verbal materials (Jangraw et al., 2018). Collectively, this body of evidence suggests a close relationship between SA and LTM, which aligns with the findings from our study. Future research is needed to disentangle the distinct encoding and retrieval processes underlying working memory and LTM, which may account for their differing relationships with SA.

A limitation of this work is the size of the fMRI sample in Experiment 2, which is small for individual difference studies. Although the results align with prior work relating connectome-based models of attention to individual differences in reading recall (Jangraw et al., 2018) and within-subject differences in narrative event memory (Song, Finn, & Rosenberg, 2021), future studies with larger samples are needed to replicate the association between individual differences in neural signatures of SA and LTM. Interestingly, work relating connectome-based models of SA and working memory to recognition memory performance in 9- to 11-year-olds found that the working memory CPM—but not saCPM—predicted recognition memory (Kardan, Kaplan, et al., 2022). One caveat is that the recognition memory task used stimuli that had been encoded during the working memory task, raising the possibility that the observed relationship was stimulus- and task-specific within this data set. Future studies that include SA, working memory, and LTM tasks within the same scanning session will facilitate direct comparison of predictive model features and generalizability across cognitive domains.

In conclusion, we demonstrated that SA, although correlated with attentional control, working memory, and LTM, constitutes a distinct psychological factor. Contrary to the intuitive hypothesis that attentional components are more related to each other than to memory components, SA was more predictive of LTM than either attentional control or working memory. These findings were conceptually extended in a follow-up study using fMRI, where both behavioral and neural markers of SA correlated with LTM but not attentional control or working memory performance. Thus, SA appears to be a distinct factor that more robustly predicts LTM performance than attentional control and working memory. More broadly, our findings challenge conventional models that emphasize the unity of attentional processes and instead highlight the unique role of SA in the formation, maintenance, or even retrieval of LTM. These insights open new directions for research on cognitive training, educational interventions, and the neurobiological basis of SA's role in shaping memory outcomes.

Acknowledgments

We would like to acknowledge that this work was supported by the Office of Naval Research Multidisciplinary University Research Initiative (MURI) grants N00014-22-1-2123 (to E. K. V.) and N00014-23-1-2768 (to E. K. V. and M. D. R.), as well as the National Science Foundation grant BCS-2043740 (to M. D. R.). Additional support was provided by resources from the University of Chicago Research Computing Center. We also thank the MRI Research Center at the University of Chicago (RRID: SCR_024723) for assistance with MRI data collection.

Corresponding authors: Chong Zhao and Monica D. Rosenberg, The University of Chicago, 940 E. 57th St., Chicago, IL 60637-1476, e-mails: chongzhao@uchicago.edu, mdrosenberg@uchicago.edu.

Data Availability Statement

The data are available as open data on Open Science Framework data repository: https://osf.io/sajfn/. Supplemental Material can be accessed on this article's homepage: https://doi.org/10.1162/JOCN.a.2488.

Author Contributions

Chong Zhao: Conceptualization; Data curation; Formal analysis; Project administration; Writing—Original draft; Writing—Review & editing. Anna Corriveau: Data curation; Writing—Review & editing. Jin Ke: Data curation; Writing—Review & editing. Edward K. Vogel: Conceptualization; Funding acquisition; Resources; Supervision; Writing—Review & editing. Monica D. Rosenberg: Conceptualization; Funding acquisition; Project administration; Resources; Supervision; Writing—Review & editing.

Funding Information

Monica D. Rosenberg, Division of Behavioral and Cognitive Sciences (https://dx.doi.org/10.13039/100000169), grant number: BCS-2043740. Monica D. Rosenberg, Office of Naval Research (https://dx.doi.org/10.13039/100000006), grant number: N00014-22-1-2123. Edward K. Vogel, Office of Naval Research (https://dx.doi.org/10.13039/100000006), grant numbers: N00014-22-1-2123 and N00014-23-1-2768.

Diversity in Citation Practices

Retrospective analysis of the citations in every article published in this journal from 2010 to 2021 reveals a persistent pattern of gender imbalance: Although the proportions of authorship teams (categorized by estimated gender identification of first author/last author) publishing in the *Journal of Cognitive Neuroscience* (*JoCN*) during this period were M(an)/M = .407, W(oman)/M = .32, M/W = .115, and W/W = .159, the comparable proportions for the articles that these authorship teams cited were M/M = .549, W/M = .257, M/W = .109, and W/W = .085 (Postle and Fulvio, *JoCN*, 34:1, pp. 1–3). Consequently, *JoCN* encourages all authors to consider gender balance explicitly when

selecting which articles to cite and gives them the opportunity to report their article's gender citation balance.

REFERENCES

Adam, K. C. S., Mance, I., Fukuda, K., & Vogel, E. K. (2015). The contribution of attentional lapses to individual differences in visual working memory capacity. *Journal of Cognitive Neuroscience*, *27*, 1601–1616. https://doi.org/10.1162/jocn_a_00811, PubMed: 25811710

Adam, K. C. S., Vogel, E. K., & Awh, E. (2017). Clear evidence for item limits in visual working memory. *Cognitive Psychology*, *97*, 79–97. https://doi.org/10.1016/j.cogpsych.2017.07.001, PubMed: 28734172

Avery, E. W., Yoo, K., Rosenberg, M. D., Greene, A. S., Gao, S., Na, D. L., et al. (2020). Distributed patterns of functional connectivity predict working memory performance in novel healthy and memory-impaired individuals. *Journal of Cognitive Neuroscience*, *32*, 241–255. https://doi.org/10.1162/jocn_a_01487, PubMed: 31659926

Brady, T. F., Konkle, T., Alvarez, G. A., & Oliva, A. (2008). Visual long-term memory has a massive storage capacity for object details. *Proceedings of the National Academy of Sciences, U.S.A.*, *105*, 14325–14329. https://doi.org/10.1073/pnas.0803390105, PubMed: 18787113

Burgoyne, A. P., & Engle, R. W. (2020). Attention control: A cornerstone of higher-order cognition. *Current Directions in Psychological Science*, *29*, 624–630. https://doi.org/10.1177/0963721420969371

Burgoyne, A. P., Tsukahara, J. S., Mashburn, C. A., Pak, R., & Engle, R. W. (2023). Nature and measurement of attention control. *Journal of Experimental Psychology: General*, *52*, 2369–2402. https://doi.org/10.1037/xge0001408, PubMed: 37079831

Chamberlain, T. A., & Rosenberg, M. D. (2022). Propofol selectively modulates functional connectivity signatures of sustained attention during rest and narrative listening. *Cerebral Cortex*, *32*, 5362–5375. https://doi.org/10.1093/cercor/bhac020, PubMed: 35285485

Chidharom, M., Krieg, J., & Bonnefond, A. (2021). Impaired frontal midline theta during periods of high reaction time variability in schizophrenia. *Biological Psychiatry: Cognitive Neuroscience and Neuroimaging*, *6*, 429–438. https://doi.org/10.1016/j.bpsc.2020.10.005, PubMed: 33431347

Chun, M. M., Golomb, J. D., & Turk-Browne, N. B. (2011). A taxonomy of external and internal attention. *Annual Review of Psychology*, *62*, 73–101. https://doi.org/10.1146/annurev.psych.093008.100427, PubMed: 19575619

Chun, M. M., & Turk-Browne, N. B. (2007). Interactions between attention and memory. *Current Opinion in Neurobiology*, *17*, 177–184. https://doi.org/10.1016/j.conb.2007.03.005, PubMed: 17379501

Colom, R., Abad, F. J., Quiroga, M. Á., Shih, P. C., & Flores-Mendoza, C. (2008). Working memory and intelligence are highly related constructs, but why? *Intelligence*, *36*, 584–606. https://doi.org/10.1016/j.intell.2008.01.002

Corriveau, A., Ke, J., Terashima, H., Kondo, H. M., & Rosenberg, M. D. (2025). Functional brain networks predicting sustained attention are not specific to perceptual modality. *Network Neuroscience*, *9*, 303–325. https://doi.org/10.1162/netn_a_00430, PubMed: 40161982

Corriveau, A., Yoo, K., Kwon, Y. H., Chun, M. M., & Rosenberg, M. D. (2023). Functional connectome stability and optimality are markers of cognitive performance. *Cerebral Cortex*, *33*, 5025–5041. https://doi.org/10.1093/cercor/bhac396, PubMed: 36408606

deBettencourt, M. T., Norman, K. A., & Turk-Browne, N. B. (2018). Forgetting from lapses of sustained attention. *Psychonomic Bulletin & Review*, *25*, 605–611. https://doi.org/10.3758/s13423-017-1309-5, PubMed: 28585055

deBettencourt, M. T., Williams, S. D., Vogel, E. K., & Awh, E. (2021). Sustained attention and spatial attention distinctly influence long-term memory encoding. *Journal of Cognitive Neuroscience*, *33*, 2132–2148. https://doi.org/10.1162/jocn_a_01748, PubMed: 34496022

Decker, A. L., Duncan, K., & Finn, A. S. (2023). Fluctuations in sustained attention explain moment-to-moment shifts in children's memory formation. *Psychological Science*, *34*, 1377–1389. https://doi.org/10.1177/09567976231206767, PubMed: 37930955

Draheim, C., Pak, R., Draheim, A. A., & Engle, R. W. (2022). The role of attention control in complex real-world tasks. *Psychonomic Bulletin & Review*, *29*, 1143–1197. https://doi.org/10.3758/s13423-021-02052-2, PubMed: 35167106

Esterman, M., Noonan, S. K., Rosenberg, M., & DeGutis, J. (2013). In the zone or zoning out? Tracking behavioral and neural fluctuations during sustained attention. *Cerebral Cortex*, *23*, 2712–2723. https://doi.org/10.1093/cercor/bhs261, PubMed: 22941724

Esterman, M., & Rothlein, D. (2019). Models of sustained attention. *Current Opinion in Psychology*, *29*, 174–180. https://doi.org/10.1016/j.copsyc.2019.03.005, PubMed: 30986621

Finn, E. S., Shen, X., Scheinost, D., Rosenberg, M. D., Huang, J., Chun, M. M., et al. (2015). Functional connectome fingerprinting: Identifying individuals using patterns of brain connectivity. *Nature Neuroscience*, *18*, 1664–1671. https://doi.org/10.1038/nn.4135, PubMed: 26457551

Fountain-Zaragoza, S., Samimy, S., Rosenberg, M. D., & Prakash, R. S. (2019). Connectome-based models predict attentional control in aging adults. *Neuroimage*, *186*, 1–13. https://doi.org/10.1016/j.neuroimage.2018.10.074, PubMed: 30394324

Hu, B., Guan, X., Zhai, H., Han, X., Hu, C., & Gong, J. (2024). Cognitive and cortical network alterations in pediatric temporal lobe space-occupying lesions: An fMRI study. *Frontiers in Human Neuroscience*, *18*, 1509899. https://doi.org/10.3389/fnhum.2024.1509899, PubMed: 39717148

Hu, L., & Bentler, P. M. (1999). Cutoff criteria for fit indexes in covariance structure analysis: Conventional criteria versus new alternatives. *Structural Equation Modeling: A Multidisciplinary Journal*, *6*, 1–55. https://doi.org/10.1080/10705519909540118

Huang, L., Mo, L., & Li, Y. (2012). Measuring the interrelations among multiple paradigms of visual attention: An individual differences approach. *Journal of Experimental Psychology: Human Perception and Performance*, *38*, 414–428. https://doi.org/10.1037/a0026314, PubMed: 22250865

James, W. (1890). *The principles of psychology*. Henry Holt. https://doi.org/10.1037/10538-000

Jangraw, D. C., Gonzalez-Castillo, J., Handwerker, D. A., Ghane, M., Rosenberg, M. D., Panwar, P., et al. (2018). A functional connectivity-based neuromarker of sustained attention generalizes to predict recall in a reading task. *Neuroimage*, *166*, 99–109. https://doi.org/10.1016/j.neuroimage.2017.10.019, PubMed: 29031531

Kane, M. J., Bleckley, M. K., Conway, A. R., & Engle, R. W. (2001). A controlled-attention view of working-memory capacity. *Journal of Experimental Psychology: General*, *130*, 169–183. https://doi.org/10.1037/0096-3445.130.2.169, PubMed: 11409097

Kardan, O., Kaplan, S., Wheelock, M. D., Feczko, E., Day, T. K., Miranda-Domínguez, Ó., et al. (2022). Resting-state

functional connectivity identifies individuals and predicts age in 8-to-26-month-olds. *Developmental Cognitive Neuroscience*, *56*, 101123. https://doi.org/10.1016/j.dcn.2022.101123, PubMed: 35751994

Kardan, O., Stier, A. J., Cardenas-Iniguez, C., Schertz, K. E., Pruin, J. C., Deng, Y., et al. (2022). Differences in the functional brain architecture of sustained attention and working memory in youth and adults. *PLoS Biology*, *20*, e3001938. https://doi.org/10.1371/journal.pbio.3001938, PubMed: 36542658

Kenny, D. A., Kaniskan, B., & McCoach, D. B. (2015). The performance of RMSEA in models with small degrees of freedom. *Sociological Methods & Research*, *44*, 486–507. https://doi.org/10.1177/0049124114543236

Luck, S. J., & Vogel, E. K. (1997). The capacity of visual working memory for features and conjunctions. *Nature*, *390*, 279–284. https://doi.org/10.1038/36846, PubMed: 9384378

Madore, K. P., Khazenzon, A. M., Backes, C. W., Jiang, J., Uncapher, M. R., Norcia, A. M., et al. (2020). Memory failure predicted by attention lapsing and media multitasking. *Nature*, *587*, 87–91. https://doi.org/10.1038/s41586-020-2870-z, PubMed: 33116309

Madore, K. P., & Wagner, A. D. (2022). Readiness to remember: Predicting variability in episodic memory. *Trends in Cognitive Sciences*, *26*, 707–723. https://doi.org/10.1016/j.tics.2022.05.006, PubMed: 35786366

Martin, J. D., Tsukahara, J. S., Draheim, C., Shipstead, Z., Mashburn, C. A., Vogel, E. K., et al. (2021). The visual arrays task: Visual storage capacity or attention control? *Journal of Experimental Psychology: General*, *150*, 2525–2551. https://doi.org/10.1037/xge0001048, PubMed: 34591545

Meier, M. E., & Kane, M. J. (2017). Attentional control and working memory capacity. In T. Egner (Ed.), *The Wiley handbook of cognitive control* (pp. 50–63). Wiley. https://doi.org/10.1002/9781118920497.ch3

Robertson, I. H., Manly, T., Andrade, J., Baddeley, B. T., & Yiend, J. (1997). Oops!': Performance correlates of everyday attentional failures in traumatic brain injured and normal subjects. *Neuropsychologia*, *35*, 747–758. https://doi.org/10.1016/S0028-3932(97)00015-8, PubMed: 9204482

Rosenberg, M., Noonan, S., DeGutis, J., & Esterman, M. (2013). Sustaining visual attention in the face of distraction: A novel gradual-onset continuous performance task. *Attention, Perception, & Psychophysics*, *75*, 426–439. https://doi.org/10.3758/s13414-012-0413-x, PubMed: 23299180

Rosenberg, M. D. (2026). A temporal hierarchy of sustained attention dynamics. *Current Directions in Psychological Science*, *35*, 3–39. https://doi.org/10.1177/09637214251342976

Rosenberg, M. D., & Chun, M. M. (2020). Network models of attention and working memory. In D. Poeppel, G. R. Mangun, & M. S. Gazzaniga (Eds.), *The cognitive neurosciences* (6th ed.). MIT Press. https://doi.org/10.7551/mitpress/11442.003.0037

Rosenberg, M. D., Finn, E. S., Scheinost, D., Papademetris, X., Shen, X., Constable, R. T., et al. (2016). A neuromarker of sustained attention from whole-brain functional connectivity. *Nature Neuroscience*, *19*, 165–171. https://doi.org/10.1038/nn.4179, PubMed: 26595653

Rosenberg, M. D., Hsu, W.-T., Scheinost, D., Todd Constable, R., & Chun, M. M. (2018). Connectome-based models predict separable components of attention in novel individuals. *Journal of Cognitive Neuroscience*, *30*, 160–173. https://doi.org/10.1162/jocn_a_01197, PubMed: 29040013

Rosenberg, M. D., Scheinost, D., Greene, A. S., Avery, E. W., Kwon, Y. H., Finn, E. S., et al. (2020). Functional connectivity predicts changes in attention observed across minutes, days, and months. *Proceedings of the National Academy of Sciences, U.S.A.*, *117*, 3797–3807. https://doi.org/10.1073/pnas.1912226117, PubMed: 32019892

Rosenberg, M. D., Zhang, S., Hsu, W.-T., Scheinost, D., Finn, E. S., Shen, X., et al. (2016). Methylphenidate modulates functional network connectivity to enhance attention. *Journal of Neuroscience*, *36*, 9547–9557. https://doi.org/10.1523/JNEUROSCI.1746-16.2016, PubMed: 27629707

Schwartz, S. T., Yang, H., Xue, A. M., & Wagner, A. D. (2025). Attending to remember: Recent advances in methods and theory. *Current Directions in Psychological Science*. https://doi.org/10.1177/09637214251339452, PubMed: 40964066

Schweizer, K., & Moosbrugger, H. (2004). Attention and working memory as predictors of intelligence. *Intelligence*, *32*, 329–347. https://doi.org/10.1016/j.intell.2004.06.006

Shen, X., Finn, E. S., Scheinost, D., Rosenberg, M. D., Chun, M. M., Papademetris, X., et al. (2017). Using connectome-based predictive modeling to predict individual behavior from brain connectivity. *Nature Protocols*, *12*, 506–518. https://doi.org/10.1038/nprot.2016.178, PubMed: 28182017

Shen, X., Tokoglu, F., Papademetris, X., & Constable, R. T. (2013). Groupwise whole-brain parcellation from resting-state fMRI data for network node identification. *Neuroimage*, *82*, 403–415. https://doi.org/10.1016/j.neuroimage.2013.05.081, PubMed: 23747961

Smallwood, J., Riby, L., Heim, D., & Davies, J. B. (2006). Encoding during the attentional lapse: Accuracy of encoding during the semantic sustained attention to response task. *Consciousness and Cognition*, *15*, 218–231. https://doi.org/10.1016/j.concog.2005.03.003, PubMed: 16115782

Song, H., Finn, E. S., & Rosenberg, M. D. (2021). Neural signatures of attentional engagement during narratives and its consequences for event memory. *Proceedings of the National Academy of Sciences, U.S.A., 118*, e2021905118. https://doi.org/10.1073/pnas.2021905118, PubMed: 34385312

Tavakol, M., & Wetzel, A. (2020). Factor analysis: A means for theory and instrument development in support of construct validity. *International Journal of Medical Education*, *11*, 245–247. https://doi.org/10.5116/ijme.5f96.0f4a, PubMed: 33170146

Unsworth, N., Fukuda, K., Awh, E., & Vogel, E. K. (2014). Working memory and fluid intelligence: Capacity, attention control, and secondary memory retrieval. *Cognitive Psychology*, *71*, 1–26. https://doi.org/10.1016/j.cogpsych.2014.01.003, PubMed: 24531497

Unsworth, N., Robison, M. K., & Miller, A. L. (2021). Individual differences in lapses of attention: A latent variable analysis. *Journal of Experimental Psychology: General*, *150*, 1303–1331. https://doi.org/10.1037/xge0000998, PubMed: 40474404

Vogel, E. K., McCollough, A. W., & Machizawa, M. G. (2005). Neural measures reveal individual differences in controlling access to working memory. *Nature*, *438*, 500–503. https://doi.org/10.1038/nature04171, PubMed: 16306992

Wakeland-Hart, C. D., Cao, S. A., deBettencourt, M. T., Bainbridge, W. A., & Rosenberg, M. D. (2022). Predicting visual memory across images and within individuals. *Cognition*, *227*, 105201. https://doi.org/10.1016/j.cognition.2022.105201, PubMed: 35868240

Xiao, J., Hays, J., Ehinger, K. A., Oliva, A., & Torralba, A. (2010). SUN database: Large-scale scene recognition from abbey to zoo. In *Proceedings of the IEEE Computer Society Conference on Computer Vision and Pattern Recognition* (pp. 3485–3492). https://doi.org/10.1109/CVPR.2010.5539970

Zhao, C., Vogel, E., & Awh, E. (2023). Change localization: A highly reliable and sensitive measure of capacity in visual working memory. *Attention, Perception, & Psychophysics*, *85*, 1681–1694. https://doi.org/10.3758/s13414-022-02586-0, PubMed: 36229631

Zhao, C., & Vogel, E. K. (2025a). Working memory and attentional control abilities predict individual differences in

visual long-term memory tasks. *Journal of Memory and Language*, *144*, 104665. https://doi.org/10.1016/j.jml.2025.104665

Zhao, C., & Vogel, E. K. (2025b). Individual differences in working memory and attentional control continue to predict memory performance despite extensive learning. *Journal of Experimental Psychology: General*, *154*, 1268–1283. https://doi.org/10.1037/xge0001728, PubMed: 39869694

Zhou, Y., Curtis, C. E., Sreenivasan, K. K., & Fougnie, D. (2022). Common neural mechanisms control attention and working memory. *Journal of Neuroscience*, *42*, 7110–7120. https://doi.org/10.1523/JNEUROSCI.0443-22.2022, PubMed: 35927036