Formation Mechanism of Offline-State Representations in Visual Working Memory

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Abstract

Visual working memory plays a vital role in human comprehension of dynamically changing visual environments. According to the working memory state model, visual working memory representations can be stored in either an online state or an offline state, and can be flexibly switched between these two storage states according to task demands. However, it remains unclear how offline-state memory representations are transformed from online-state representations. The present study experimentally examines two possible transformation processing hypotheses: the consolidation hypothesis and the decay hypothesis. By adopting a sequential presentation and retrieval paradigm to effectively guide memory representations to be stored in two distinct representational states, this study manipulates the stimulus interval time and presentation time associated with the state transformation process. The results reveal that when the time allocated to the state transformation process is insufficient, it leads to an overlap between the memory representation state transformation process and the online processing of new stimuli, thereby resulting in resource competition. This outcome is consistent with the consolidation hypothesis of memory representation state transformation, which posits that offline-state representations in working memory are formed through the consolidation of memory items from the online state into the offline state.

Full Text

Cognitive Mechanisms Underlying the Formation of Offline Representations in Visual Working Memory

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Visual working memory (VWM) plays a foundational role in advanced cognitive functions. According to state-based models of working memory, visual working memory representations can be stored in either an online or offline state and can flexibly switch between these two storage states based on task demands. However, it remains unclear how offline memory representations are generated from online representations. This study tests two possible conversion hypotheses—the consolidation hypothesis and the fade-away hypothesis—using a sequential memory extraction paradigm to effectively guide memory representations into two distinct storage states. By manipulating the stimulus interval time and presentation time associated with the state conversion process, we found that insufficient time for state conversion leads to overlapping resource competition between the conversion process of memory representations and the online processing of new stimuli. These results support the consolidation hypothesis, which posits that offline representations in working memory are formed through the consolidation of memory items from the online state into the offline state.

Keywords: visual working memory, state-based models, offline representations, state transformation, consolidation

Visual working memory (VWM) serves as a critical system for temporarily maintaining and manipulating visual information, providing an operational platform between sensation, long-term visual memory, decision-making, and action, and forming the basis for complex cognitive processing based on visual information (Aben et al., 2012; Baddeley, 1992; Eriksson et al., 2015; Miller et al., 2018). The capacity of VWM is severely limited, yet daily cognitive tasks are often complex and dynamic, requiring us to maintain multiple pieces of information simultaneously and retrieve them sequentially according to task demands. This necessitates representing and storing working memory information in different neural states based on current task requirements. Accordingly, researchers have proposed state-based models of working memory, which posit that the brain stores working memory information in different states according to priority: online and offline states (de Vries et al., 2020; Nee & Jonides, 2013; Oberauer, 2002; LaRocque et al., 2014; Chota & Van der Stigchel, 2021). Memory representations relevant to the current task are assigned higher priority and stored in the online state, which is accompanied by sustained neural activity that can be detected through EEG or neuroimaging, such as contralateral delay activity (CDA) (Lewis-Peacock et al., 2012; LaRocque et al., 2013; Stokes, 2015; Oliver, 2011). In contrast, memory representations temporarily irrelevant to the current task are assigned lower priority, unloaded from the online state, and briefly stored in the offline state; when needed for subsequent tasks, these offline representations are reactivated into the online state to complete cognitive processing (Manohar et al., 2019; Stokes et al., 2020; Rose, 2020). Unlike online storage, offline storage does not involve sustained neural activity and is thought to store memory information by temporarily altering synaptic connection weights, making it undetectable by neuroimaging devices (Mongillo et al., 2008; Kamiński & Rutishauser, 2020; Muhle-Karbe et al., 2021).

Although offline memory representations cannot be directly observed or measured, substantial evidence supports their existence. For instance, researchers have found that when memorizing multiple items simultaneously, if a cue indicates that one item will be probed soon while other uncued items will be tested after a delay following the cued item's probe, the neural activation associated with uncued items returns to baseline before the cued item is probed, and their neural decoding accuracy drops to chance level. However, if transcranial magnetic stimulation (TMS) is applied to the cortex maintaining the uncued items during the retention period, or if a strong visual stimulus is presented at the location of the uncued items, the decoding accuracy for these items increases significantly above chance, demonstrating a reactivation effect. Notably, this reactivation does not occur if the uncued items are no longer probed after the cue appears (Rose et al., 2016; Wolff et al., 2015, 2017). These findings provide strong evidence that offline storage operates through changes in synaptic weights. Zhang et al. (2022) first validated the sequential memory extraction paradigm as an effective method for inducing offline storage using EEG. In this paradigm, participants memorized two arrays presented sequentially, with the second memory array (Array 2) probed before the first (Array 1). The authors argued that because Array 2 was probed first, participants' current task was only relevant to Array 2 from its presentation until its probe. An efficient strategy would be to temporarily store Array 1 in the offline state. This hypothesis aligned with their EEG results: the CDA component associated with online storage of Array 1 disappeared after Array 2 appeared, yet memory performance for Array 1 remained significantly above chance. This indicated that Array 1 could be effectively transferred to the offline memory system after Array 2 presentation in the sequential memory extraction paradigm. Building on this paradigm, Zhang et al. (2022) manipulated cognitive interference and storage duration during offline memory maintenance, finding that offline storage serves as an important protective mechanism that shields memory representations from irrelevant stimulus interference and temporal decay. Li et al. (2021) further demonstrated that online and offline memory storage do not interfere with each other by independently manipulating their memory loads, suggesting that these two states have independent storage resources.

From studies investigating offline storage, memory items first enter the online state for representation and are then transferred to the offline state for temporary storage when they become temporarily irrelevant to the current task but need to be retrieved later. However, no research has examined the cognitive mechanisms underlying the conversion of memory representations from the online to the offline state. Investigating this question will deepen our understanding of representational state transformation, clarify how offline representations are generated, and provide new empirical evidence for the dynamic storage model of working memory. Here, we propose two possible hypotheses regarding representational state transformation and test them experimentally. The first, consistent with traditional theoretical views, posits that stimulus information entering a memory system requires a specific consolidation process. The conversion of memory representations from online to offline states also necessitates such a consolidation process, requiring time and cognitive resources to transform the information representation mode from the online to the offline storage system. We term this the consolidation hypothesis. Under this hypothesis, stimulus information is first encoded into the online state, maintained through neural activation patterns, and then transferred to the offline state when task demands require it, with the state transformation involving a shift from neural activation patterns to synaptic patterns. However, an online-to-offline consolidation process may not be necessary. The "activity-silent" model of working memory suggests that when stimulus information is encoded into the online state, the resulting neural activation simultaneously alters synaptic connection weights between neurons (Stokes, 2015). According to this view, the offline representation of stimulus information is generated synchronously with the online representation, but during online maintenance, the offline representation remains dependent on the online representation and is not yet independent. If the online representation is disrupted and changes, the offline representation changes accordingly. Only when the memory information becomes temporarily irrelevant to the current task, causing its neural activation pattern to disappear and leaving only the synaptic pattern, does an independent and stable offline memory representation truly form. Under this alternative hypothesis, forming an offline memory representation may not require a specific consolidation process—only the natural decay of the memory information's neural activation pattern. We term this the fade-away hypothesis.

In this study, we test these two state transformation hypotheses using the sequential memory extraction paradigm. When a 0.8-second interval and 0.2-second presentation time are used, although the CDA associated with Array 1 (offline storage) disappears after Array 2 (online storage) appears, offline memory performance is affected by changes in online storage load. This result contradicts the resource-dissociation account, which proposes independent storage resources for the two states. We argue that this occurs because Array 1 has not completed its state transformation from online to offline by 0.8 seconds post-stimulus. Consequently, the encoding of Array 2 interferes with Array 1's conversion process. This interference can be interpreted differently depending on the state transformation hypothesis. According to the consolidation hypothesis, when Array 2 appears, it must be consolidated into working memory's online state while Array 1's representation must be consolidated from the online to the offline state. Because Array 2's presentation is brief (0.2 seconds), its stimulus information may disappear before Array 1's consolidation is complete. To perform the task efficiently, the brain may allocate consolidation time between the two stimulus arrays, forcing the two consolidation processes to overlap and compete for resources. This leads to online storage load (Array 2) affecting Array 1's consolidation into the offline state, impairing Array 1's memory performance. According to the fade-away hypothesis, Array 1's neural activation pattern has not fully decayed 0.8 seconds after stimulus offset, so the visual presentation of Array 2 disrupts Array 1's online representation, similarly impairing its memory performance. The key difference between these hypotheses lies in whether Array 2's presentation time can modulate the impact of online processing on offline memory performance when state transformation remains incomplete during the 0.8-second delay. Specifically, the consolidation hypothesis predicts that extending Array 2's presentation time allows Array 1's offline consolidation and Array 2's online consolidation to occur sequentially, eliminating the effect of Array 2's load on Array 1's performance. In contrast, the fade-away hypothesis predicts that because Array 1's neural activation pattern has not vanished by 0.8 seconds, Array 2 will disrupt Array 1's online representation regardless of its presentation duration, making it impossible to eliminate Array 2's impact on Array 1's offline storage by manipulating presentation time.

Based on these predictions, Experiment 1 manipulated the delay interval between memory arrays and the load of Array 2 to verify that insufficient delay causes offline memory performance to be affected by online memory load, thereby determining the time required for Array 1 to complete its representational state transformation. Experiment 2 then manipulated Array 2's presentation time and load under the identified delay interval to test the two state transformation hypotheses. If extending Array 2's presentation time eliminates the effect of online load on offline memory performance when Array 1 cannot complete state transformation during the delay interval, the consolidation hypothesis would be supported. Otherwise, the fade-away hypothesis would be supported.

Experiment 1

This experiment aimed to verify that the observation by Zhang et al. (2022)—that online memory load affects offline memory performance—was due to the short 0.8-second interval between memory arrays being insufficient for Array 1 to complete its transformation from online to offline. Using the sequential memory extraction paradigm with a fixed load for Array 1, we manipulated the load of Array 2 and, critically, added a 1-second interval condition to Zhang et al.'s original 0.8-second interval. If Array 1 requires longer than 0.8 seconds to complete the online-to-offline state transformation, we predicted that the 0.8-second interval condition would replicate Zhang et al.'s findings, showing a significant effect of Array 2 load on Array 1 performance. In contrast, the 1-second interval condition should significantly reduce or eliminate this interference effect.

2.1 Method

2.1.1 Participants Sample size was calculated using G*Power 3.1 software, which indicated that 28 participants would achieve 80% statistical power with an effect size (dz) of 0.65 and α level of 0.05. We recruited 30 participants for each experiment. In Experiment 1, the 30 participants included 5 males, with a mean age of 21.97 years (SD: 2.70). All had normal or corrected-to-normal vision and no color vision deficiencies. Participants signed informed consent before the experiment and received 30 yuan compensation afterward.

All experiments complied with the Helsinki Declaration and were approved by the Institutional Review Board of Sichuan Normal University.

2.1.2 Apparatus and Stimuli We used E-prime 2.0 software to run the experiment on a 19-inch LCD monitor with a 60Hz refresh rate (1920$×1080pixels).Thescreenbackgroundwasgray(125×125×125),withablackfixationpoint(0.23°)continuou
blue,black,red,magenta,green,cyan,white,yellow,andpurple.Colorsneverrepeatedwithinatrial.Itemsinboth
centered on the fixation point. Array 1 items appeared at the left and right horizontal positions relative to fixation, while Array 2 items appeared at the top and bottom vertical positions (for two-item arrays) or at all four corners (for four-item arrays). Two probe arrays were presented sequentially, first probing Array 2 and then Array 1. Probe 1 displayed black-bordered squares matching Array 2's positions and quantity, with one square colored. Probe 2 displayed black-bordered squares matching Array 1's positions and quantity, with one square colored. Participants viewed the screen from 70 cm and were instructed to maintain focus throughout the task, responding via keypress.

2.1.3 Procedure [Figure 1: see original paper] Schematic illustration of the experimental procedure for both experiments

As shown in Figure 1, Array 1 containing two memory items was presented for 0.2 seconds, followed by a blank interval of either 0.8 seconds (short-interval condition) or 1 second (long-interval condition). Array 2 then appeared for 0.2 seconds, containing either two or four items. After Array 2 disappeared, a 1-second blank preceded the sequential presentation of the two probe arrays, which tested Array 2 first and then Array 1 with a 1-second interval between them. Participants judged whether the colored square in each probe array matched the color of the corresponding item in the memory array, pressing "z" for same and "m" for different. We emphasized accuracy over speed, so probe arrays remained visible until a response was made. Same and different trials occurred with equal probability (50%). On "different" trials, the probe color was unique within that trial. The delay interval between arrays was manipulated in blocks, while Array 2 set size (2 vs. 4) varied randomly within each trial. Each participant completed five blocks of 32 trials for both the long- and short-interval conditions, with block order counterbalanced across participants. Before the experiment, participants read instructions and completed at least eight practice trials to familiarize themselves with the procedure. To prevent verbal encoding from interfering with visual working memory, participants were required to continuously pronounce "da-da-da" during each block.

2.1.4 Data Analysis The primary dependent measure was behavioral accuracy. All data were analyzed using JASP software (Love et al., 2019). We report ^{2}p as the effect size for repeated-measures ANOVA results, with small, medium, and large effect sizes defined as 0.01, 0.06, and 0.14, respectively. Paired-samples t-tests were used to analyze the effects of online memory load on online and offline memory performance, with Cohen's d as the effect size measure: $0.2 \leq d < 0.5$ indicates a small effect, $0.5 \leq d < 0.8$ a medium effect, and $d \geq 0.8$ a large effect.

[Figure 2: see original paper] Behavioral accuracy results for Experiment 1. Note: ** indicates $p < 0.01$, * indicates $p < 0.05$.

2.2 Results and Discussion

Figure 2 presents the behavioral results for Experiment 1. Probe 1 reflects online memory performance, while Probe 2 reflects offline memory performance, with all variables as within-subject factors. We first conducted a 2 (online load: 2 vs. 4) × 2 (memory state: online vs. offline) × 2 (delay interval: 0.8s vs. 1s) repeated-measures ANOVA. Results showed significant main effects of online load, memory state, and delay interval, Fs > 16.10, ps < 0.001, ^{2}ps > 0.36. The interaction between online load and memory state was significant, F(1, 29) = 45.26, p < 0.001, ^{2}p = 0.61. We then analyzed memory performance separately for short- and long-interval conditions.

For the short-interval condition, a 2 (online load: 2 vs. 4) × 2 (memory state: online vs. offline) repeated-measures ANOVA revealed significant main effects of memory state and online load, Fs > 10.09, ps < 0.004, ^{2}ps > 0.26, and a significant interaction, F(1, 29) = 17.52, p < 0.001, ^{2}p = 0.38. Paired-samples t-tests showed that online memory performance was significantly lower under high load than low load, t(29) = 6.75, p < 0.001, Cohen's d = 1.23, 95% CI [0.75, 1.70]. Similarly, offline memory performance decreased significantly as online memory load increased, t(29) = 3.044, p = 0.005, Cohen's d = 0.56, 95% CI [0.16, 0.94].

For the long-interval condition, a 2 × 2 repeated-measures ANOVA also showed significant main effects of memory state and online load, Fs > 16.02, ps < 0.001, ^{2}ps > 0.36, and a significant interaction, F(1, 29) = 36.24, p < 0.001, ^{2}p = 0.56. Paired-samples t-tests indicated that online memory performance declined significantly with increased load, t(29) = 8.68, p < 0.001, Cohen's d = 1.59, 95% CI [1.04, 2.12]. However, offline memory performance was unaffected by online load changes, t(29) = 0.81, p = 0.42, Cohen's d = 0.15, 95% CI [–0.21, 0.50].

The short-interval results replicate Zhang et al. (2022). Critically, when the interval between memory arrays was extended to 1 second, Array 1's memory performance (offline storage) was no longer affected by Array 2's load (online storage). This suggests that when the inter-array interval is sufficiently long, Array 1 can complete its consolidation process from online to offline (consolidation hypothesis), or its online activation pattern can fully decay, leaving only the synaptic pattern (fade-away hypothesis), thereby preventing Array 2's online processing from affecting Array 1's performance. Although these results cannot definitively distinguish between the two hypotheses, they provide partial explanation for why Zhang et al.'s findings contradicted the resource-dissociation theory: the 0.8-second interval was insufficient for Array 1 to complete its state transformation, causing this process to persist into Array 2's presentation period.

Experiment 2

Experiment 1 demonstrated that the 0.8-second interval was insufficient for Array 1 to complete its representational state transformation, causing this process to continue into Array 2's presentation period, whereas a 1-second interval allowed the transformation to complete successfully. In Experiment 2, we used the 0.8-second interval and presented Array 2 for either 0.2 seconds or 0.5 seconds. We predicted that under the 0.2-second condition, we would continue to observe the effect of Array 2 load on Array 1 performance. However, under the 0.5-second condition, the two state transformation hypotheses make different predictions. If the consolidation hypothesis holds, we expect Array 1's performance (offline storage) to be unaffected by Array 2's load (online storage) because Array 1's state transformation would complete within 1 second after stimulus offset, while Array 2 would continue for an additional 0.3 seconds, providing sufficient time for its encoding. In this scenario, Array 2's consolidation into the online state could be delayed until after Array 1's offline consolidation finished, avoiding process overlap. If the fade-away hypothesis holds, because the 0.8-second interval is insufficient for Array 1's neural activation pattern to decay naturally, Array 2 would disrupt Array 1's online representation regardless of whether it is presented for 0.2 or 0.5 seconds, impairing Array 1's performance equally in both duration conditions.

3.1 Method

3.1.1 Participants Thirty new participants were recruited for Experiment 2, with similar demographic characteristics as Experiment 1.

3.1.2 Apparatus and Stimuli The apparatus and stimuli were identical to Experiment 1, but the procedure differed slightly (see Figure 1). In this experiment, the interval between the two memory arrays was fixed at 0.8 seconds. Array 2 was presented for either 0.2 seconds (short-presentation condition) or 0.5 seconds (long-presentation condition), still randomly containing two or four items. Presentation time was manipulated in blocks, with each participant completing five blocks of 32 trials for both conditions, with block order counterbalanced. Before the formal experiment, participants read instructions and completed at least eight practice trials.

[Figure 3: see original paper] Behavioral accuracy results for Experiment 2. Note: ** indicates $p < 0.01$, * indicates $p < 0.05$.

3.2 Results and Discussion

Figure 3 presents the behavioral results for Experiment 2. The analysis followed the same approach as Experiment 1. A 2 (online load: 2 vs. 4) × 2 (memory state: online vs. offline) × 2 (presentation time: 0.2s vs. 0.5s) repeated-measures ANOVA revealed significant main effects of memory state and online load, Fs > 22.96, ps < 0.001, ^{2}ps > 0.44. The interaction between presentation time and online load was significant, F(1, 29) = 8.23, p = 0.008, ^{2}p = 0.22, as was the interaction between memory state and online load, F(1, 29) = 81.68, p < 0.001, ^{2}p = 0.74. We then analyzed memory performance separately for short- and long-presentation conditions.

For the short-presentation condition, a 2 (online load: 2 vs. 4) × 2 (memory state: online vs. offline) repeated-measures ANOVA showed significant main effects of memory state and online load, Fs > 19.56, ps < 0.001, ^{2}ps > 0.40, and a significant interaction, F(1, 29) = 35.60, p < 0.001, ^{2}p = 0.55. Paired-samples t-tests indicated that online performance was significantly worse under high load than low load, t(29) = 14.70, p < 0.001, Cohen's d = 2.68, 95% CI [1.90, 3.45]. Similarly, offline performance decreased significantly when online load increased from 2 to 4 items, t(29) = 3.66, p = 0.001, Cohen's d = 0.67, 95% CI [0.27, 1.06].

For the long-presentation condition, the 2 × 2 repeated-measures ANOVA also revealed a significant interaction, F(1, 29) = 62.28, p < 0.001, ^{2}p = 0.68, with significant main effects of memory state and online load, Fs > 18.14, ps < 0.001, ^{2}ps > 0.39. Paired-samples t-tests showed that online memory performance was significantly worse under high load, t(29) = 8.85, p < 0.001, Cohen's d = 1.62, 95% CI [1.06, 2.16]. However, offline memory performance did not differ between high and low online load conditions, t(29) = 1.12, p = 0.27, Cohen's d = 0.21, 95% CI [–0.57, 0.16].

These results confirm that Array 1 cannot complete its state transformation within the 0.8-second interval, causing the process to continue into Array 2's presentation period. Importantly, extending Array 2's presentation time eliminated the effect of Array 2's load on Array 1's performance. This pattern supports the consolidation hypothesis: the extended presentation time allowed Array 1's state transformation and Array 2's online consolidation to occur sequentially, preventing process overlap. Thus, representational state transformation involves consolidating memory representations from the online storage system into the offline storage system. This explains why Zhang et al.'s (2022) results contradicted the resource-dissociation theory—the 0.8-second interval was insufficient for Array 1 to complete its transformation, and Array 2's brief presentation forced the consolidation processes for both arrays to overlap, creating resource competition that impaired Array 1's memory performance.

General Discussion

This study investigated how offline representations in working memory are generated from online representations using the sequential memory extraction paradigm. In Experiment 1, we manipulated the inter-array interval (0.8s vs. 1s) and Array 2's memory load. We found that under the 0.8-second interval, Array 2's load (online storage) significantly affected Array 1's performance (offline storage), but this effect disappeared under the 1-second interval. This indicates that Array 1's representational state transformation continues beyond 0.8 seconds after stimulus offset but completes within 1 second. Based on Experiment 1's results, Experiment 2 used a 0.8-second interval and manipulated Array 2's presentation time (0.2s vs. 0.5s). Extending Array 2's presentation time from 0.2 to 0.5 seconds eliminated the effect of Array 2's load on Array 1's performance. These findings support the consolidation hypothesis, demonstrating that offline representations are formed through a consolidation process that transfers online representations into the offline storage system.

Experiment 1's results show that the transformation from online to offline states completes fully within a 1-second retention interval, consistent with previous EEG findings. For example, Wolf et al. (2017) found that representational decoding accuracy returned to baseline after a 1-second interval, while LaRocque et al. (2013) observed that neural activity for uncued memory representations disappeared approximately 1.25 seconds after cue presentation. These results suggest that stable offline representations can be generated roughly 1 second after stimulus offset. Furthermore, these findings indicate that the state transformation process is not triggered by the onset of the next memory array but begins at a fixed time after stimulus offset. Additionally, Li et al. (2020) manipulated inter-array intervals in a sequential memory extraction paradigm and found that a 0.4-second interval was insufficient to initiate Array 1's state transformation, causing both arrays to be stored online, whereas a 0.8-second interval enabled separate online and offline storage. This suggests that a sufficiently long delay is necessary to trigger state transformation for information temporarily irrelevant to the current task. Thus, generating offline representations involves two temporal factors: an initiation time when the transformation process begins (presenting the next memory stimulus during this period prevents offline representation formation) and a transformation processing time (presenting memory stimuli during this period interferes with offline representation generation).

The current findings provide the first evidence that offline representation formation does not result from the natural decay of neural activation patterns but involves a consolidation process from the online to offline storage system that unfolds over time and shares cognitive resources with the consolidation of visual stimuli into the online state. These results also advance our understanding of the relationship between short-term offline storage and long-term memory. At the neural level, if synaptic weight connections become stable and long-lasting during memory maintenance, long-term memory is formed; when these connections are temporary and quickly eliminated, short-term offline memory results. Our findings show that memory representations undergo a consolidation process to transition from online to offline for temporary storage. This cognitively controlled state transformation consolidation process undoubtedly trains and strengthens synaptic storage patterns, suggesting that using synaptic connection patterns for short-term storage may facilitate long-term memory formation for these items. As previous research has found, items stored in the offline state show better long-term memory performance (McCabe, 2008; Rose et al., 2014). We can therefore infer that complex working memory tasks requiring offline storage, such as sequential memory probing tasks, may be more effective for learning and training than simple memory tasks relying solely on online storage.

Furthermore, our results demonstrate that representational state transformation involves an information consolidation process from online to offline states. The consolidation process generating online representations has been shown to proceed serially with limited bandwidth (Vogel et al., 2006; Scharff & Palmer, 2008; Hao et al., 2017), with different materials having different consolidation capacities (Mance et al., 2012; Becker et al., 2013; Liu & Becker, 2013). This raises new questions: Does increasing offline storage load extend the initiation time and transformation processing time for consolidating representations from online to offline? Is the representational state transformation time related to stimulus type? Since offline memory load was fixed in the current study, we cannot answer these questions. Future research should manipulate the number of items and types of memory materials in the offline state to deepen our understanding of representational state transformation mechanisms.

In summary, this study investigated the process of transforming working memory representations from online to offline states using a sequential memory extraction paradigm. Our results demonstrate that offline representations are formed through a consolidation process that transfers online representations into the offline storage system. These findings clarify the formation process of offline representations and deepen our understanding of working memory's dynamic storage model.

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Note: Figure translations are in progress. See original paper for figures.